WARESHOUSE SELECTION: A HYBRID FUZZY MULTI-CRITERIA DECISION-MAKING APPROACH

BY

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ABSTRACT

Warehouse location selection requires the consideration of multiple, often conflicting criteria such as cost, space availability, and accessibility, as the warehouse itself plays a critical role in optimizing logistics costs and enhancing customer service. To accommodate the selection efforts, this study presents an integrated fuzzy multi-criteria decision-making approach that combines the Fuzzy Best-Worst Method (FBWM) with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to identify the most suitable warehouse location. The former is employed to determine the relative weights of criteria, taking into account the uncertainty inherent in expert judgments, while the later is used to rank the alternative locations with respective to the criteria and its weights.

A case study, which involves three warehouse alternatives evaluated based on area, rental rate, and distance to the airport is conducted to demonstrate the effectiveness of the proposed method. Closeness coefficients were calculated across multiple methodological configurations using three normalization techniques (linear vector, linear sum, and max) and two distance metrics (Euclidean and Manhattan).

To further explore the robustness of the rankings, combinations of weight generated using a complementary weighting strategy was experimented. From a discrete set of weights ranging from 0.05 to 0.90, a total of 5,832 possible combinations were generated. Two filtering conditions were applied to eliminate invalid weight combinations: all the weights must sum to one, and the weight for the rental cost criterion must be the largest one. This process yielded 45 valid weight combinations. These combinations of weight were later put into usage to evaluate the consistency of ranking outcomes.

Sensitivity and robustness analyses reveal that the top-ranked warehouse (Alternative S2) consistently outperforms others regardless of methodological configurations and weights combinations. This confirms the reliability of the decision. In addition, Analysis of variance (ANOVA) results indicate that both weight combinations and distance metrics significantly affect the closeness coefficient ($\boldsymbol{CC_i}$), while the normalization method shows minimal impact. Moreover, Manhattan distance provides higher discrimination among alternatives, whereas Euclidean distance offers more stable and consistent rankings. Overall, the proposed approach is robust and practical, providing decision-makers with a clear and reliable framework for selecting warehouse locations.

Keywords: Warehouse selection, FBWM, TOPSIS, MCDM, Normalization techniques, Distance metrics, Sensitivity analysis, Robustness analysis, two-way ANOVA

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Nay Chi Moe Oo

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LIST OF SYMBOLS/ABBREVIATIONS

Symbols/Abbreviations	**Terms**
AHP	Analytic hierarchy process
AI	Absolutely important (linguistic term)
ANOVA	Analysis of variance
BWM	Best-worst method
CC_i	Closeness coefficient of alternative
cu.m.	Cubic meter
EI	Equally important (linguistic term)
FBWM	Fuzzy best-worst method
FI	Fairly important (linguistic term)
Fuzzy AHP	Fuzzy analytic hierarchy process
Fuzzy TOPSIS	Fuzzy technique for order preference by similarity to ideal solution
GLM	General linear model
GMIR	Graded mean integration representation
km	Kilometer
m^2	Square meter
MCDM	Multi-criteria decision-making
NIS	Negative ideal solution
PIS	Positive ideal solution
SIIT	Sirindhorn International Institute of Technology
TFN	Triangular fuzzy number
THB	Thai baht
TU	Thammasat University
TOPSIS	Technique for order preference by similarity to ideal solution
VI	Very important (linguistic term)
WI	Weakly important (linguistic term)

CHAPTER 1
INTRODUCTION

The selection of a warehouse is a critical aspect of logistics and supply chain management, playing a pivotal role in ensuring operational efficiency, logistics costs, and service performance. Warehouses serve as essential nodes within supply chains, connecting suppliers, manufacturers, and customers while enabling the storage, handling, and distribution of goods. Beyond their functional roles, warehouses significantly influence broader supply chain performance by optimizing inventory levels, reducing transportation costs, and enhancing service quality. Despite their importance, warehouse selection is a complex decision-making process requiring careful consideration of multiple, often conflicting criteria.

1.1 Background

As supply chains become increasingly complex and customer expectations for speed and reliability continue to grow, the strategic role of warehouse location has become more significant than ever. A well-chosen warehouse location not only enhances operational efficiency but also contributes to cost optimization and service performance across the entire supply chain network (Singh et al., 2018).

Selecting the optimal warehouse requires the consideration of multiple, often conflicting criteria, such as rental cost, available storage space, proximity to transportation infrastructure, and accessibility to markets. For instance, a location with lower rent may be far from distribution hubs, while a more central location might incur higher operating costs (Dey et al., 2016; Yang & Hung, 2007). Additionally, many of these factors are qualitative and subjective, relying on expert judgment, which introduces uncertainty and imprecision into the decision-making process.

To address this complexity, researchers and practitioners frequently apply MCDM methods. In particular, fuzzy set theory, introduced by Zadeh (1965), has been widely adopted to manage the vagueness and subjectivity in human judgment. FBWM, an advancement in fuzzy MCDM techniques, enables decision-makers to identify and compare criteria efficiently by focusing on the most and least important ones. It reduces the cognitive burden and improves consistency in the weight elicitation process (Guo & Zhao, 2017; Rezaei, 2015).

Once the criteria weights are determined using FBWM, TOPSIS is often employed to rank alternatives. TOPSIS evaluates each option based on its geometric distance to an ideal and a negative-ideal solution, identifying the most favorable choice overall (Ocampo et al., 2020; Omrani et al., 2018).However, recent studies have highlighted that TOPSIS outcomes can be sensitive to methodological configurations, particularly the choice of normalization technique (e.g., vector, max, or sum) and distance metric (Euclidean vs. Manhattan). These variations can significantly affect closeness coefficient (CC_i) values and thus alter the final rankings (Bánhidi & Dobos, 2024; Vafaei et al., 2021).

To address this concern, this study develops a hybrid fuzzy MCDM framework that combines FBWM and TOPSIS with robustness and sensitivity analyses. Alongside expert-derived weights, 45 valid random weight combinations are used to examine how changes in decision-maker preferences affect the results. The framework systematically evaluates multiple normalization methods and distance metrics to assess the stability, reliability, and consistency of the results. This methodological approach aims to enhance the transparency and robustness of warehouse location decisions, particularly under conditions of uncertainty and subjectivity inherent in expert-based evaluations.

1.2 Problem statement

Selecting an appropriate warehouse location is a critical and complex decision in logistics and supply chain management. The location directly impacts operational costs, such as transportation and inventory holding, and influences service quality, delivery speed, and overall supply chain responsiveness. With growing customer expectations, intensified global competition, and increasing supply chain complexity, the importance of selecting warehouses accurately and strategically has become increasingly significant.

However, warehouse location selection is inherently a multi-criteria decision-making process, involving the assessment of both quantitative factors (e.g., rental cost, available space, proximity to airports) and qualitative factors (e.g., contract conditions, flexibility, reputation). These criteria often conflict, making trade-offs challenging to evaluate using conventional methods. Furthermore, many assessments rely on subjective expert judgments expressed in linguistic terms, which introduce uncertainty and ambiguity into the decision-making process.

Traditional MCDM methods, such as the Analytic Hierarchy Process (AHP), have been widely used for such evaluations, but they tend to be time-consuming and inconsistent when dealing with many criteria. The FBWM offers an efficient and consistent alternative by reducing the number of pairwise comparisons and effectively handling vagueness in expert input (Guo & Zhao, 2017; Rezaei, 2015). When integrated with TOPSIS, this hybrid framework allows for the structured ranking of alternatives based on their relative closeness to an ideal solution.

Nevertheless, studies have shown that TOPSIS results can be sensitive to the choice of normalization technique and distance metric, which can significantly impact the closeness coefficients and resulting rankings (Çelen, 2014; Shyur & Shih, 2024). Without addressing this sensitivity, decision-makers may unknowingly rely on rankings that lack robustness and consistency.

Therefore, this research aims to fill this gap by developing a hybrid fuzzy MCDM framework for warehouse location selection and conducting a comprehensive robustness analysis. This includes exploring how different normalization techniques, distance metrics, and weight combinations affect ranking outcomes. The goal is to provide a reliable, transparent, and methodologically sound tool for warehouse selection under uncertainty.

1.3 Research objectives

The primary objective of this research is to develop a structured, transparent, and reliable decision-making framework for warehouse selection under uncertainty, using a hybrid fuzzy multi-criteria decision-making (MCDM) approach. Given the strategic importance of warehouse location in logistics and supply chain performance, it is necessary to systematically evaluate multiple and often conflicting decision criteria.

This study first identifies and validates key warehouse selection criteria such as rental cost, storage area, and proximity to transportation hubs through expert input and a review of relevant literature. The relative importance of these criteria is then determined using FBWM, which enables experts to express preferences through fuzzy linguistic terms while minimizing the number of pairwise comparisons required. By constructing best-to-others and others-to-worst matrices, the FBWM generates consistent and reliable fuzzy weight vectors for each criterion.

These weights are then integrated into TOPSIS, which evaluates and ranks the warehouse alternatives according to their relative closeness to an ideal solution. To ensure the robustness of the ranking results, this study further investigates the effect of different methodological configurations, specifically, three normalization techniques (linear vector, linear sum, and max) and two distance metrics (Euclidean and Manhattan) within the TOPSIS model.

Additionally, a set of 45 valid random weight combinations is systematically generated to simulate variations in expert preferences. These are used to test the sensitivity of the decision model. Finally, statistical analyses, including two-way ANOVA by general linear model (GLM), are performed to evaluate the significance of methodological choices on ranking outcomes.

Through this integrated approach, the study aims to provide a practical and robust decision-support tool for warehouse selection that is capable of handling uncertainty, expert subjectivity, and methodological variability.

1.4 Significance of study

This study addresses these challenges by developing a structured decision-making model that improves both the reliability and transparency of warehouse selection under uncertainty by integrating FBWM with TOPSIS. FBWM enables the derivation of consistent and efficient criteria weights using fuzzy linguistic input, thereby reducing the cognitive load on experts while maintaining high decision quality. These weights are then applied within the TOPSIS model to generate a rational, data-driven ranking of warehouse alternatives, providing decision-makers with robust and transparent guidance.

In addition to providing a practical decision-support tool, this study contributes to the literature by incorporating a comprehensive robustness and sensitivity analysis, an area often overlooked in traditional MCDM studies. By systematically examining the effects of different normalization techniques and distance metrics on the final rankings, the model ensures greater reliability in various decision-making contexts.

Furthermore, the application of statistical methods such as two-way ANOVA within the GLM model is used to validate the stability of the results. Ultimately, this research offers both academic and practical value by delivering a robust, adaptable framework for warehouse location decisions in real-world supply chain environments.

1.5 Scope and limitations

This study develops a structured and robust decision-making framework for warehouse selection using a hybrid fuzzy MCDM approach. The model integrates the FBWM for criteria weighting and TOPSIS for alternative ranking, supported by robustness and sensitivity analyses to evaluate the stability of results under varying methodological conditions.

The scope of this research is limited to three key quantitative decision criteria: rental cost, warehouse area, and distance to the airport selected through expert consultation, as well as their relevance to logistics operations. The framework is demonstrated through a case study with three warehouse alternatives. While this ensures a focused and manageable analysis, it may not fully reflect the complexity of larger-scale or more diverse decision scenarios involving additional qualitative or strategic factors.

For robustness testing, random weight combinations were generated under practical constraints, such as prioritizing rental cost. While this increases realism, it also restricts the generalizability of results to other contexts where the criteria priorities may differ. Similarly, although fuzzy logic helps address uncertainty in expert judgments, subjectivity may still arise from differences in interpreting linguistic terms.

Two-way ANOVA was applied specifically to examine the effects of normalization techniques and distance metrics on closeness coefficients. These analyses provide useful insights but are limited to the parameters and configurations selected for this case study.Despite these limitations, the proposed framework offers both methodological and practical value. It provides a transparent and reliable foundation for warehouse location decisions and can be extended in future research to include additional criteria, alternatives, or decision contexts. decision-making contexts.

CHAPTER 2
LITERATURE REVIEW

As global supply chains become more dynamic and complex, selecting an optimal warehouse location requires a structured decision-making framework that can address multiple, often conflicting, criteria such as rental cost, facility size, and access to key transportation infrastructure. Traditional approaches, though foundational, often fail to adequately capture the uncertainty and subjectivity present in real-world logistics decisions.

To address these limitations, MCDM methods have been widely adopted. Techniques such as AHP, TOPSIS, and the BWM provide structured approaches for evaluating and ranking alternatives based on various decision criteria. However, these methods frequently rely on precise numerical input, which can be unrealistic in practice. In response, researchers have integrated fuzzy logic into classical MCDM frameworks, resulting in Fuzzy MCDM models that effectively manage linguistic judgments and imprecise evaluations.

Among these, the FBWM offers notable advantages by reducing the cognitive burden on decision-makers while maintaining consistency in pairwise comparisons. This hybrid framework is robust for supporting warehouse selection decisions when combined with TOPSIS, which ranks alternatives based on relative closeness to ideal solutions.

Additionally, methodological choices within the TOPSIS process, such as normalization techniques (e.g., linear vector, linear sum, max) and distance metrics (e.g., Euclidean, Manhattan), can significantly influence the final rankings. Despite their impact, these elements are often overlooked in sensitivity analysis. Therefore, recent studies have emphasized the importance of evaluating the robustness of decision outcomes by analyzing how such variations affect consistency and reliability.

This chapter critically examines the existing literature on warehouse selection, emphasizing the evolution of MCDM methodologies, the integration of fuzzy logic, and the influence of methodological parameters on decision outcomes. The review identifies research gaps, particularly in robustness testing through weight variation and sensitivity analysis, and establishes the foundation for the hybrid FBWM–TOPSIS framework proposed in this study.

2.1 Warehouse selection in supply chain management

Warehouse selection is a crucial decision in supply chain management, as it directly impacts cost efficiency, service quality, and overall operational performance. A strategically located and well-equipped warehouse reduces transportation and operational costs and enhances a firm's responsiveness to fluctuating market demands and customer expectations. With supply chains becoming increasingly complex and time-sensitive, identifying an optimal warehouse location requires the careful evaluation of multiple criteria, often involving trade-offs between cost, accessibility, infrastructure, and flexibility (Singh et al., 2018; Vafaei et al., 2021).

Modern warehouses serve far more than just storage purposes; they are critical nodes in the logistics network, supporting operations such as cross-docking, packaging, and real-time inventory management. As such, selecting an appropriate warehouse requires careful evaluation of several key quantitative factors. These include warehouse area (m^2), which affects storage capacity and operational layout; rental cost (THB/ m^2/month), which influences financial viability; and distance to transportation hubs such as airports, which is crucial for time-sensitive deliveries (Ocampo et al., 2020). Additionally, material handling fees (THB/move/cu.m.) and fulfillment rates (THB/order) serve as important indicators of cost-efficiency and processing performance in warehouse operations (Dey et al., 2016)

Due to numerous conflicting criteria and the inherent uncertainty in expert evaluations, traditional decision-making approaches are often insufficient. Therefore, MCDM methods such as AHP, TOPSIS, and BWM have gained prominence in academic and practical applications. These methods allow structured and systematic evaluation of multiple alternatives against diverse criteria. The following sections will explore these methodologies, with a focus on their fuzzy extensions and hybrid applications, particularly the integration of FBWM with TOPSIS and the use of robustness analysis to validate decision reliability

2.2 Multi-criteria decision-making (MCDM) Methods

Warehouse selection is a complex, multi-criteria decision problem that requires careful evaluation of conflicting factors such as cost, accessibility, space availability, and operational efficiency. Traditional decision-making methods cannot often incorporate subjective judgments or handle the inherent uncertainty in real-world logistics environments. To overcome these limitations, MCDM approaches have become essential tools for systematically analyzing and ranking alternatives in warehouse selection.

Among the widely applied MCDM techniques are the AHP, TOPSIS, and BWM. These methods enable decision-makers to evaluate both qualitative and quantitative criteria, providing a more structured and transparent approach to warehouse evaluation (Guo & Zhao, 2017).

AHP structures complex decisions into a hierarchical model and utilizes pairwise comparisons to derive priority weights (Yang & Hung, 2007) . While effective, AHP becomes cumbersome with many criteria, leading to inconsistencies in judgments (Patil & Kant, 2014) . On the other hand, TOPSIS ranks alternatives based on their relative distance from an ideal and anti-ideal solution, making it suitable for balancing multiple trade-offs. However, its outcomes are sensitive to the choice of normalization technique and distance metric, which may impact the stability of final rankings (Çelen, 2014; Vafaei et al., 2021) .

The BWM, particularly in its fuzzy extension (FBWM), offers a more consistent and efficient alternative. By asking decision-makers to identify only the best and worst criteria and compare others relative to them, it significantly reduces the number of required comparisons while improving consistency (Rezaei, 2015) . Fuzzy BWM further enhances this method by incorporating linguistic assessments to deal with the vagueness in expert opinions (Guo & Zhao, 2017) .

To leverage the strengths of multiple techniques and mitigate their limitations, hybrid approaches have gained popularity. One such approach, FBWM integrated with TOPSIS, combines robust weight determination with effective alternative ranking under uncertainty. Furthermore, recent studies have highlighted the importance of robustness and sensitivity analysis in MCDM applications. Variations in normalization methods (e.g., linear vector, linear sum, max) and distance metrics (e.g., Euclidean, Manhattan) can significantly influence the ranking results, raising concerns about the reliability of decision outcomes (Bánhidi & Dobos, 2024; Shyur & Shih, 2024). To address this issue, the current research employs expert-derived fuzzy weights and a wide range of randomly generated weight combinations. This strategy supports a thorough sensitivity and robustness assessment, providing insights into the stability of the ranking under different methodological settings.

2.3 Fuzzy logic in decision-making

The Warehouse selection involves uncertainty and subjective judgments that traditional MCDM methods struggle to handle. Fuzzy logic, introduced by Zadeh, 1965, provides a framework to address imprecision by expressing criteria in linguistic terms (e.g., low, medium, high) rather than exact numerical values. This approach enhances decision models by incorporating human-like reasoning, making it particularly useful for evaluating qualitative factors such as facility quality, contract conditions, and reputation (Guo & Zhao, 2017) .

Fuzzy logic is commonly integrated with MCDM techniques like Fuzzy AHP, which refines pairwise comparisons by reducing inconsistencies (Patil & Kant, 2014) , Fuzzy TOPSIS, which ranks alternatives based on their relative closeness to an ideal solution, improves the evaluation of warehouse cost efficiency, fulfillment rate, and infrastructure quality (Sun, 2010) . FBWM, a more recent method, simplifies the decision-making process by prioritizing the most and least important criteria while minimizing subjective bias (Guo & Zhao, 2017) .

The primary advantage of fuzzy logic is its ability to handle uncertainty and enhance decision accuracy (Dong et al., 2021). However, defining membership functions and fuzzification rules can be complex, requiring expert input and increasing computational intensity (Foroozesh et al., 2022) . Despite these challenges, hybrid fuzzy MCDM models continue to improve the robustness of warehouse selection, making them essential for handling real-world logistics decisions.

2.4 Normalization methods in MCDM

Normalization is a fundamental step in MCDM that transforms criteria with different units into a comparable scale, ensuring fair evaluation across alternatives.

Since MCDM techniques rely on aggregating multiple criteria, normalization helps mitigate bias caused by varying measurement units. The most used normalization methods include Linear vector normalization, Max normalization, and Linear sum normalization, each affecting decision outcomes differently (Vafaei et al., 2021).

- Linear vector normalization adjusts each criterion value relative to the overall magnitude, ensuring that all criteria contribute proportionally to the decision process. This method is commonly applied in TOPSIS and other ranking-based techniques.
- Linear sum normalization standardizes each criterion by dividing values by their total sum. While this preserves proportional relationships, extreme values can sometimes affect it, distorting the results.
- Max normalization scales each criterion by dividing values by the maximum value in the dataset. This makes interpretation straightforward but can exaggerate differences among alternatives.

The choice of normalization method significantly impacts ranking consistency and decision reliability in MCDM applications. Studies have shown that different normalization approaches can lead to rank reversal issues, affecting the final selection of alternatives (Çelen, 2014).

2.5 Robustness and sensitivity in decision analysis

Robustness and sensitivity analysis are essential components of decision analysis, especially in fuzzy MCDM frameworks, where variations can influence the ranking of alternatives in model parameters, weighting schemes, normalization techniques, or distance metrics. Mukhametzyanov & Pamucar, 2018 highlighted a key limitation of traditional MCDM models, the lack of formal validation mechanisms to assess the stability of decision outcomes. They emphasized the importance of statistical sensitivity analysis, particularly for strategic decisions such as warehouse location selection, where unstable rankings can compromise practical reliability. Bánhidi & Dobos, 2024 , further investigated the role of normalization techniques in TOPSIS, namely, Vector linear, Max, and Linear sum, and demonstrated that even minor differences in these methods can lead to substantial shifts in closeness coefficients (CC_i), thereby impacting final rankings.

Building on this foundation, the current study employs a hybrid FBWM–TOPSIS approach complemented by a comprehensive robustness analysis. The study evaluates how methodological choices influence ranking stability by applying various normalization methods (linear vector, linear sum, and max), distance metrics (Euclidean and Manhattan), and valid random weight combinations. Statistical tools such as Two-Way ANOVA and GLM quantify the sensitivity of closeness coefficients to these variations.

2.6 Research gaps and justification for the study

Despite the growing application of fuzzy MCDM techniques in logistics and warehouse selection, several critical gaps persist in the literature. Although FBWM and TOPSIS have been successfully applied to facility location problems, few studies have integrated these methods into a unified framework incorporating robustness and sensitivity analysis. While FBWM enhances efficiency and consistency in criteria weighting, its application with TOPSIS has primarily been limited to case-specific studies, without systematic evaluation under different methodological assumptions.

A significant gap in the literature concerns the limited investigation of methodological parameters within TOPSIS, specifically normalization methods (Linear vector, linear sum, and max) and distance metrics (Euclidean, Manhattan) that affect the final rankings. Existing studies (Bánhidi & Dobos, 2024; Çelen, 2014; Shyur & Shih, 2024) have shown that these components can significantly alter closeness coefficient values (CC_i), yet few have examined their combined effect within a fuzzy decision-making framework. Furthermore, the interaction between these methodological parameters and fuzzy-derived weights remains underexplored in warehouse selection contexts, where accuracy and consistency are crucial for strategic decision-making.

Another underexplored area is large-scale random weight combinations to capture decision variability and evaluate model robustness. Most existing MCDM applications rely exclusively on expert-derived weights, which may not reflect the full range of decision-making scenarios encountered in practice. Incorporating valid weight sets provides a more comprehensive understanding of how changes in criteria importance influence alternative rankings. Furthermore, while robustness is a core concern in real-world applications, many studies still lack formal statistical testing to validate model stability. Techniques like two-way ANOVA are rarely applied, resulting in limited insights into the statistical significance of methodological choices.

To address these gaps, this study proposes a hybrid fuzzy MCDM framework that integrates FBWM with TOPSIS, supported by systematic testing of normalization methods and distance metrics. The framework incorporates valid random weight combinations and applies statistical analysis through ANOVA and GLM. This approach aims to deliver a transparent, robust, and adaptable decision-support model for warehouse selection, capable of addressing uncertainty, subjectivity, and methodological variation in real-world supply chain environments.

CHAPTER 3
METHODOLOGY

This chapter describes the research design and methodological framework used to solve the warehouse location selection problem. The approach integrates two weighting methods, the Fuzzy Best-Worst Method (FBWM) and random weight generation with TOPSIS. As shown in Figure 3.1, the methodology begins with identifying decision criteria based on expert input and market observations. Next, the criteria are assigned weights using FBWM and random weight combinations, and the alternatives are evaluated to generate the normalized comparison matrix. The results are then processed through TOPSIS to calculate the closeness coefficient CC_i values, which are compared to assess ranking robustness.

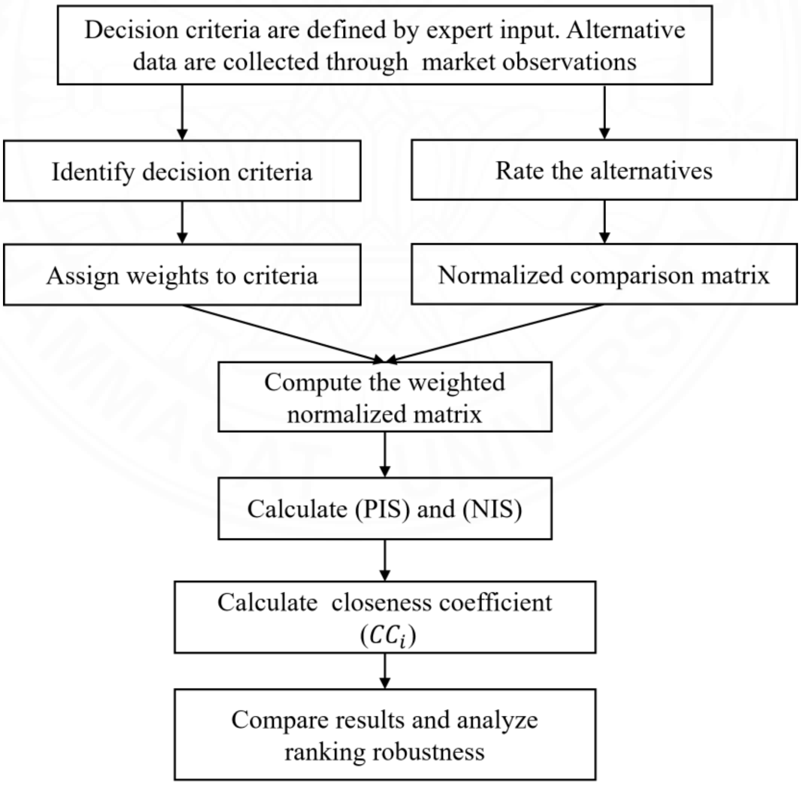

Figure 3.1 Framework for research methodology

3.1 Research Framework

This study adopts a hybrid multi-criteria decision-making approach to evaluate and rank warehouse alternatives under uncertain and variable conditions. The objective is to combine expert judgment with structured mathematical techniques to ensure accuracy and robustness in the selection process. The research design can be divided into three broad stages:

- Criteria definition and weighting: Identify relevant decision criteria and determine their weights.
- Alternative evaluation: Compute a ranking of the warehouse location using TOPSIS.
- Robustness analysis: Test the stability of the rankings by varying input weights of the criteria and methodological parameters.

The process begins by identifying the decision criteria through literature review and expert consultation. For this warehouse selection case, three quantitative criteria were chosen based on their practical importance: warehouse area, rental rate, and distance to the airport. Data for each alternative on these criteria was obtained through market surveys and expert estimates, reflecting real-world conditions.

To determine the relative importance of each criterion, two weighting strategies were applied. The first method uses FBWM, incorporating expert input expressed through linguistic comparisons. F-BWM is particularly effective in handling imprecise judgments and translating them into structured fuzzy weights using triangular fuzzy numbers (TFNs). In addition to the expert-derived weights, a second strategy involving randomly generated weight combinations was employed to assess the robustness of the methodology.

Once the criteria weights are established, the warehouse alternatives are evaluated using TOPSIS method. In this study, TOPSIS is configured in several ways: three normalization techniques (linear vector, linear sum, and max normalization) and two distance metrics (Euclidean and Manhattan) are applied to evaluate the ranking.

A robustness analysis was performed to validate the stability of the outcomes. This involved applying the randomly generated weight sets to the TOPSIS framework and statistically analyzing the variation in rankings. A two-way ANOVA, applied within the General Linear Model (GLM) framework used to examine the effects of different normalization and distance methods on the closeness coefficient of each alternative. This statistical analysis helps identify which methodological configurations yield the most consistent and reliable rankings.

The research design integrates expert knowledge, fuzzy logic, and statistical validation into a comprehensive decision-making framework. It ensures that the selected warehouse alternative is optimal based on expert judgment and robust across a wide range of input scenarios.

3.2 Selection of criteria and alternatives

This study involves a Thai logistics service provider seeking a warehouse to support its regional distribution operations. There are three candidate locations (S1, S2, and S3) for the warehouse. These facilities are located within the Bangkok metropolitan area. The company seeks to lease one of these warehouses. The evaluation is based on three quantitative criteria selected to reflect key operational aspects: area (C1, measured in m^2), rental rate (C2, in THB/m^2/month), and distance to the airport (C3, in km). The area is classified as a benefit criterion, with which higher values are preferred, while rental rate and distance to the airport are regarded as cost criteria, where lower values are more desirable. As summarized in Table 3.1, the three criteria are initially identified through a review of relevant literature and later retained through expert consultations with logistics practitioners and academic researchers to ensure both theoretical validity and practical relevance.

Table 3.1 Criteria for warehouse selection

Code	Criteria	Description
C1	Area	Physical size of the warehouse (m^2).
C2	Rental rate	Cost associated with leasing the warehouse space (THB/m^2/month).
C3	Distance to airport	Proximity to major transportation hubs (km).

In addition, expert evaluations of the relative importance of these criteria are conducted using fuzzy linguistic terms, such as “Equally Important (EI),” “Weakly

Important (WI)," and "Fairly Important (FI)." These qualitative judgments are then translated into TFNs, which serve as inputs to the fuzzy MCDM framework employed in this study.

The finalized criteria are listed in Table 3.1, forming the foundation for the evaluation process. These are organized hierarchically to reflect the structure of the decision-making model as shown in Figure 3.2.

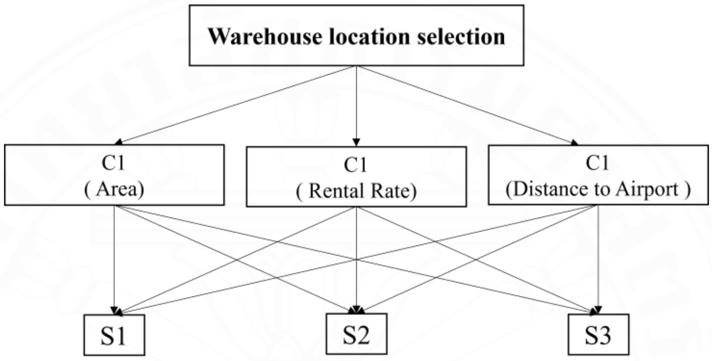

Figure 3.2 Overview of criteria hierarchy.

3.3 Weighting approaches for criteria

3.3.1 Fuzzy set theory

Expert opinions often expressed using linguistic terms such as "equally important (EI)", "weakly important (WI)", "fairly important (FI)" (see Table 3-2), can be translated into TFNs, preserving the vagueness of human judgment. A TFN, denoted as $\tilde{A} = (l, m, u)$, is a special type of fuzzy set represented by a triplet of values: the lower bound (l), the most likely or modal value (m), and the upper bound (u). The membership function $\mu_{\tilde{A}}(x)$ of a TFN is defined by Zadeh, 1965 as:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, x < l \\ \dfrac{x-l}{m-l}, l \leq x \leq m \\ \dfrac{u-x}{u-m}, m \leq x \leq u \\ 0, x > m \end{cases} \tag{3.1}$$

Table 3.2 Linguistic terms and corresponding TFNs

Symbol	Linguistic term	Scale	Triangular fuzzy scale
EI	Equally important	$\tilde{1}$	(1,1,1)
WI	Weakly important	$\tilde{2}$	(2/3 ,1,3/2)
FI	Fairly Important	$\tilde{3}$	(3/2 ,2,5/2)
VI	Very important	$\tilde{4}$	(5/2 ,3,7/2)
AI	Absolutely important	$\tilde{5}$	(7/2 ,4,9/2)

To obtain crisp values from fuzzy evaluations, defuzzification is applied to convert fuzzy numbers into representative real values. One widely used method is the graded mean integration representation (GMIR), first introduced by (Chen & Hsieh, 2000), which ranks TFNs by computing a weighted average emphasizing the most likely value.

For a TFN of $\tilde{A} = (l_i, m_i, u_i)$, the defuzzified value $R(\tilde{A})$ is calculated using the following equation:

$$R(\tilde{A}) = \frac{l_i + 4m_i + u_i}{6} \tag{3.2}$$

The GMIR approach has been successfully applied in fuzzy MCDM contexts, including FAHP and FBWM, due to its computational simplicity, clarity, and effectiveness in handling imprecise evaluations.

3.3.2 Criteria weighting using FBWM

FBWM is employed to derive the weights of decision criteria using fuzzy theory and an optimization model. The following steps summarize the FBWM procedure:

Step 1: Construct a set of decision criteria $\{C_1, C_2, \dots, C_n\}$

Step 2: Determine the most important criteria (best) and the least important (worst) criteria.

Step 3: Construct fuzzy best-to-others (BO) and fuzzy others-to-worst (OW) vectors. The best criterion is compared with all other criteria using linguistic terms (see Table 2). Each linguistic term is converted into a TFN: $\tilde{a}_{B,j} = (l_{B,j}, m_{B,j}, u_{B,j})$, where $\tilde{a}_{B,j}$ represents the fuzzy preference of the best criteria over the criteria j. The fuzzy BO vector is then constructed as: $\tilde{A}_B = (\tilde{a}_{B,1}, \tilde{a}_{B,2}, \dots, \tilde{a}_{B,n})$. Similarly, each criterion j is compared to the worst criterion using linguistic terms, resulting in: $\tilde{a}_{j,w} = (l_{j,W}, m_{j,W}, u_{j,W})$, where $\tilde{a}_{j,w}$ represents the fuzzy preference of criterion j over the worst criteria. The fuzzy OW vector is then constructed as: $\tilde{A}_W = (\tilde{a}_{1,W}, \tilde{a}_{2,W}, \dots, \tilde{a}_{n,W})$.

Step 4: Compute fuzzy weights by optimization.

The fuzzy weights $\widetilde{w}_j = (w_j^l, w_j^m, w_j^u)$ for each criterion are computed by solving the following optimization model adopted from Dong et al., 2021:

$$\min k^*$$

$$s.t \begin{cases} \left|\dfrac{\widetilde{w}_B}{\widetilde{w}_j} - \tilde{a}_{B,j}\right| \le k^* \\ \left|\dfrac{\widetilde{w}_j}{\widetilde{w}_W} - \tilde{a}_{j,w}\right| \le k^* \\ \sum_{j=1}^{n} R(\widetilde{w}_j) = 1 \\ w_j^l \le w_j^m \le w_j^u \\ w_j^l \ge 0 \\ j = 1,2,\dots,n \end{cases} \tag{3.3}$$

$R(\widetilde{w}_j)$ can be calculated by using the GMIR method as shown below:

$$R(\widetilde{w}_j) = \frac{w_j^l + 4w_j^m + w_j^u}{6} \tag{3.4}$$

Step 5: Consistency Ratio (CR) is computed as follows:

$$CR = \frac{k^*}{CI_{max}} \tag{3.5}$$

where CI_{max} is obtained as per Table 3. If CR < threshold (e.g., 0.1 or 0.05), the comparisons are deemed consistent. Otherwise, the decision-maker must revise the judgments.

Table 3. 3 Consistency index (CI_{max}) values

Linguistic Terms	Equally important (EI)	Weakly important (WI)	Fairly Important (FI)	Very important (VI)	Absolutely Important (AI)
$\tilde{a}_{BW}$	(1,1,1)	(2/3 ,1,3/2)	(3/2 ,2,5/2)	(5/2 ,3,7/2)	(7/2 ,4,9/2)
CI_{max}	3.00	3.80	5.29	6.69	8.04

3.3.3 Criteria weighting using random weight combinations.

In addition to the expert-derived FBWM weights, this study incorporates a complementary approach based on random weight combinations to perform a structured sensitivity and robustness analysis. This method allows for the exploration of how variations in criteria importance can influence the final rankings of warehouse alternatives

In this approach, three criteria weights w_1, w_2, w_3 were assigned values from a discrete set ranging from 0.05 to 0.90 in increments of 0.05, resulting in 18 possible values for each criterion, as $w_j = \{0.10, 0.15, 0.20, \ldots, 0.90\}$, $\forall\, j = 1,2,\ldots, n$. This produced a total of $18^3 = 5{,}832$ potential weight combinations. To ensure that these combinations were both valid and meaningful, two constraints were applied. First, the weights had to sum to one, as shown in Equation (3.6).

$$\sum_{j=1}^{n} w_j = 1 \tag{3.6}$$

Second, to reflect the assumption that rental cost is the most important criterion in the decision-making process, the condition $w_2 \geq w_1$ and $w_2 \geq w_3$ was applied. Only the weight combinations that satisfied both conditions were applied for analysis. These valid weight combinations were later used in the TOPSIS model to perform a comparative assessment of decision robustness across different weighting scenarios.

3.4 TOPSIS evaluation

In this phase, TOPSIS is applied to evaluate and rank warehouse alternatives based on their proximity to the ideal solution.

Step 1: Establish alternatives, criteria, and construct the decision matrix.

The alternatives S_i are evaluated against a set of quantitative criteria that include area (m^2), rental rate (THB/m^2/month), and distance to the airport (km). These criteria are categorized into benefit criteria (e.g., area where higher values are preferred) and cost criteria (e.g., rental rate, where lower values are selected). Let $A = [x_{ij}]$ be the decision matrix consisting of p alternatives and n criteria, where x_{ij} denotes the performance score of alternatives i with respect to the criteria j, for $i = 1,2,3, \dots, p$ and $j = 1,2,3, \dots n$. The matrix is structured as follows:

$$A = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pn} \end{bmatrix}, \text{ where } i = 1,2,3, \dots, p \text{ and } j = 1,2,3, \dots n.$$

Step 2: The decision matrix defined in Step 1 is normalized by using either of the three following techniques.

Linear vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{p} x_{ij}^2}}, \ j = 1,2,3, \dots n, \text{ where } i = 1,2,3, \dots, p \tag{3.7}$$

Linear sum normalization:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{p} x_{ij}}, \ j = 1,2,3, \dots n, \text{ where } i = 1,2,3, \dots, p \tag{3.8}$$

Max normalization:

$$r_{ij} = \frac{x_{ij}}{\max x_{ij}}, \qquad j = 1,2,3, \dots n, i = 1,2,3, \dots, p \tag{3.9}$$

Here, r_{ij} represents the normalized value of the criterion j for alternative i, while x_{ij} denotes the raw value of the criterion j for alternative i.

Step 3: Construction of the weighted normalized decision matrix.

The weighted normalized values are calculated using the equation:

$$v_{ij} = r_{ij} \cdot w_j, \ \ i = 1,2,3, \dots, p \text{ and } j = 1,2,3, \dots n \tag{3.10}$$

Here, v_{ij} is the weighted normalized value of the criteria j for alternative i, and w_j represents the weight for the criteria j.

Step 4: Determination of positive and negative ideal solutions

The positive ideal solution (PIS) and negative ideal solution (NIS) are determined for each criterion based on their nature:

For benefit criteria,

$$v_j^+ = \max_i\{v_{ij}\}, \quad j = 1,2,\dots,n$$
$$v_j^- = \min_i\{v_{ij}\}, \quad j = 1,2,\dots,n \tag{3.11}$$

For cost criteria,

$$v_j^+ = \min\{v_{ij}\}, \quad j = 1,2,\dots,n$$
$$v_j^- = \max\{v_{ij}\}, \quad j = 1,2,\dots,n \tag{3.12}$$

For beneficial criteria, such as area, the maximum value is selected as the ideal solution. For non-beneficial criteria, such as cost, the minimum value is selected.

Step 5: Calculation of distances to ideal solutions.

Each alternative’s distance from the ideal solutions is calculated using both the Euclidean and Manhattan distance formulas. The Euclidean distance quantifies the straight-line distance from each alternative to the ideal solution and is computed as follows:

Euclidean distance calculation.

$$d_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2}, \quad i = 1,2,3,\dots,p \tag{3.13}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}, \quad i = 1,2,3,\dots,p \tag{3.14}$$

The Manhattan distance is calculated by summing the absolute differences between each alternative.

Manhattan distance calculation

$$d_i^+ = \sum_{j=1}^{n} \left| v_{ij} - v_j^+ \right|, \quad i = 1,2,3,\dots,p \tag{3.15}$$

$$d_i^- = \sum_{j=1}^{n} \left| v_{ij} - v_j^- \right|, \quad i = 1,2,3,\dots,p \tag{3.16}$$

Step 6: Closeness coefficient calculation

The closeness coefficient (CC_i), indicating the relative proximity of each alternative to the ideal solution, was calculated using:

$$CC_i = \frac{d_i^-}{(d_i^+ + d_i^-)}, \quad i = 1,2,3,\dots,p \tag{3.17}$$

A higher CC_i value indicates a closer proximity to the PIS, reflecting better performance.

Step 7: Ranking of alternatives

The alternatives are ranked based on their CC_i values, with the highest CC_i corresponding to the most suitable warehouse location.

3.5 Robustness and sensitivity analysis

A comprehensive robustness and sensitivity analysis was conducted to evaluate the proposed decision-making framework's reliability. The analysis examined how variations in criterion weights, normalization techniques, and distance metrics influence the final rankings of warehouse alternatives.

Robustness was assessed by comparing CC_i values across different methodological configurations, which combined two weighting approaches (FBWM and random weights generation), three normalization methods (linear vector, linear sum, and max), and two distance metrics (Euclidean and Manhattan). For each configuration, the CC_i values were calculated, and the resulting rankings were analyzed for consistency.

Sensitivity analysis focused on how normalization methods and distance metrics affected the TOPSIS results. Each combination was applied to the weighted decision matrices, and changes in CC_i values were used to observe shifts in rankings.

Finally, a two-way ANOVA was performed within the General Linear Model (GLM) framework to test the effects of these methodological variations statistically. The factors analyzed were weight combinations, normalization method, and distance metric, with CC_i as the response variable. Significant main and interaction effects were further examined using Tukey's post-hoc tests to identify which specific configurations produced statistically distinct results. This approach provides deeper insight into the model's sensitivity and highlights the methodological choices that lead to more stable and discriminative rankings.

CHAPTER 4
RESULTS AND DISCUSSION

This chapter presents the results of the proposed approach to warehouse location selection. The approach consists of three stages: (1) determining the importance of criteria using the Fuzzy Best-Worst Method (FBWM) and random weight generation, (2) ranking the warehouse alternatives using TOPSIS under various methodological settings, and (3) conducting a robustness analysis to evaluate the stability of the results across different configurations. Furthermore, a sensitivity analysis is performed to investigate how methodological variations influence the final rankings.

4.1 Fuzzy Best-Worst method (FBWM)

The FBWM is applied to derive the importance weights of the three criteria: Area (C1), Rental rate (C2), and Distance to airport (C3). Rental rate (C2) is identified as the most important criterion, while Distance to airport (C3) is considered the least important based on the decision context. Linguistic preferences are expressed by expert judgments and converted into TFNs to form comparison matrices. The best-to-others (BO) vector represents the relative importance of the best criterion (C2) over the other criteria.

Table 4.1 Best-to-others (BO) fuzzy comparison matrix

Best-to-Others (BO)		C1	C2	C3
C2	Linguistic Scale	FI	EI	AI
	TFNs ($a_{B,j}$)	(3/2 ,2,5/2)	(1,1,1)	(7/2 ,4,9/2)
	Lower ($l_{B,j}$)	3/2	1	7/2
	Medium ($m_{B,j}$)	2	1	4
	Upper ($u_{B,j}$)	5/2	1	9/2

Table 4.1 shows that C2 is “Fairly important” over C1, “Equally important” to itself, and “Absolutely important” over C3. These linguistic terms correspond to the TFNs (1.5, 2, 2.5), (1, 1, 1), and (3.5, 4, 4.5), respectively. The others-to-worst (OW) vector reflects the importance of each criterion relative to the worst one (C3). As presented in Table 4.2, C1 is considered “Weakly important” compared to C3, C2 is

"Absolutely important," and C3 is "Equally important" to itself. The corresponding TFNs are (0.666, 1, 1.5), (3.5, 4, 4.5), and (1, 1, 1), respectively.

Table 4.2 Others-to-worst (OW) fuzzy comparison matrix

Others-to-Worst (OW)	C3				
	Linguistic Scale	TFNs ($\tilde{a}_{j,W}$)	Lower ($l_{j,W}$)	Medium ($m_{j,W}$)	Upper ($u_{j,W}$)
C1	WI	(2/3 ,1,3/2)	2/3	1	3/2
C2	AI	(7/2 ,4,9/2)	7/2	4	9/2
C3	EI	(1,1,1)	1	1	1

These fuzzy comparisons are then used to construct the fuzzy optimization model as shown in Equation (3.3). The results obtained from solving the model are as follows: the weight of Area (C1) is 0.250, Rental rate (C2) is 0.593, and Distance to airport (C3) is 0.157. These weights reflect the relative importance of each criterion and are used in the next phase for alternative ranking via TOPSIS.

To ensure the reliability of the expert judgments used in the FBWM model, a consistency check is conducted using the approach proposed by (Dong et al., 2021). The consistency ratio (CR) is calculated as the ratio between the maximum deviation value k^* obtained from the optimization model and the corresponding CI_{max}, which is determined based on the fuzzy linguistic scale used in the comparisons, as shown in Table 3.3.

In this study, the maximum deviation $k^* = 0.07$, and the value of k^* is obtained from the optimal solution of the FBWM optimization model (solved using Excel Solver), which minimizes the maximum deviation between the derived weights and the expert comparison ratio. The corresponding $CI_{max} = 8.04$, and CR was computed using Equation (3.5). Since the $CR = 0.07/8.04 = 0.0087$ is significantly lower than the commonly accepted threshold of 0.1, the comparisons are considered consistent, and the derived fuzzy weights are valid for further analysis.

4.2 Alternatives ranking using TOPSIS

To evaluate the alternatives, a decision matrix was constructed based on three alternatives $S_i = \{S_1, S_2, S_3\}$ and three criteria: Area ($C_1, benefit$), Rental Rate

($C_2, cost$), and Distance to Airport ($C_3, cost$). The evaluation matrix is presented in Table 4.3, which serves as the input for the TOPSIS procedure.

Table 4.3 Evaluation matrix for warehouse alternatives

Alternative (S_i)	Benefit Criteria	Cost Criteria	Cost Criteria
	C1	C2	C3
S1	1000.00	159.00	30.00
S2	700.00	79.50	25.00
S3	500.00	95.40	40.00

Table 4.4 Normalized matrix by linear vector normalization

Alternative (S_i)	Benefit Criteria	Cost Criteria	Cost Criteria
	C1	C2	C3
S1	0.758	0.788	0.537
S2	0.531	0.394	0.447
S3	0.379	0.473	0.716

Table 4.5 Normalized matrix by linear sum normalization

Alternative (S_i)	Benefit Criteria	Cost Criteria	Cost Criteria
	C1	C2	C3
S1	0.455	0.476	0.316
S2	0.318	0.238	0.263
S3	0.227	0.286	0.421

Table 4.6 Normalized matrix by max normalization

Alternative (S_i)	Benefit Criteria	Cost Criteria	Cost Criteria
	C1	C2	C3
S1	1.000	1.000	0.750
S2	0.700	0.500	0.625
S3	0.500	0.600	1.000

The matrix was normalized using linear vector, linear sum, and max normalization as defined in Equations (3.7) to (3.9). Tables 4.4, 4.5, and 4.6 present the corresponding normalized values for each method, respectively.

Next, the normalized values r_{ij} were multiplied by the previously obtained fuzzy weights w_j (from FBWM), to obtain the weighted normalized values v_{ij} , using Equation (3.10). The weighted normalized values were then used to compute the distances of each alternative from the PIS and NIS, based on whether the criteria were classified as benefit or cost types, as shown in Equations (3.11) and (3.12). Tables (4.7) – (4.9) present the weighted normalized matrices for linear vector, linear sum, and max normalization methods, along with the corresponding PIS and NIS values for each criterion. Two distance metrics were applied: Euclidean distance, computed using Equations (3.13) and (3.14), and Manhattan distance, based on Equations (3.15) and (3.16). Finally, CC_i is computed using Equation (3.17).

Table 4.7 Weighted normalized matrix using linear vector normalization

Alternative (S_i)	Benefit Criteria	Cost Criteria	Cost Criteria
	C1	C2	C3
S1	0.190	0.467	0.084
S2	0.133	0.234	0.070
S3	0.095	0.280	0.112
PIS	0.190	0.234	0.070
NIS	0.095	0.467	0.112

Table 4.8 Weighted normalized matrix using linear sum normalization

Alternative (S_i)	Benefit Criteria	Cost Criteria	Cost Criteria
	C1	C2	C3
S1	0.114	0.282	0.050
S2	0.080	0.141	0.041
S3	0.057	0.169	0.066
PIS	0.114	0.141	0.041
NIS	0.057	0.282	0.066

Table 4.9 Weighted normalized matrix using max normalization

Alternative (S_i)	Benefit Criteria	Cost Criteria	Cost Criteria
	C1	C2	C3
S1	0.900	0.050	0.038
S2	0.630	0.025	0.031
S3	0.450	0.030	0.050
PIS	0.900	0.025	0.031
NIS	0.450	0.050	0.050

The final ranking results of the three alternatives using TOPSIS under all combinations of three normalization techniques (linear vector, linear sum, and max) and two distance metrics (Euclidean and Manhattan) are presented in Table 4.10.

Table 4.10 Ranking results of alternatives using FBWM and TOPSIS

Ranking by FBWM and TOPSIS									
Normalizati-on Method	S_i	Euclidean Distance				Manhattan Distance			
		d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
Linear vector	S1	0.234	0.099	0.297	3	0.248	0.123	0.332	3
	S2	0.057	0.240	0.809	1	0.057	0.314	0.847	1
	S3	0.114	0.187	0.622	2	0.184	0.187	0.504	2
Linear sum	S1	0.141	0.059	0.295	3	0.149	0.073	0.329	3
	S2	0.034	0.145	0.810	1	0.034	0.189	0.847	1
	S3	0.068	0.113	0.624	2	0.110	0.113	0.507	2
Max	S1	0.297	0.131	0.306	3	0.316	0.164	0.342	3
	S2	0.075	0.306	0.803	1	0.075	0.405	0.844	1
	S3	0.150	0.237	0.612	2	0.243	0.237	0.494	2

4.3 Analysis of FBWM–TOPSIS rankings across normalization and distance methods

The rankings derived from applying FBWM weights within the TOPSIS framework are presented in Table 4.10. The results compare the impact of three normalization methods (linear vector, linear sum, and max normalization) and two distance measures (Euclidean and Manhattan) on the final warehouse rankings.

Across all configurations, alternative S2 consistently ranked first, with closeness coefficient (CC_i) values ranging from 0.803 to 0.847. This stability across all normalization and distance methods confirms S2 as the most robust and preferred option. Warehouse alternative (S1) consistently ranked last, with CC_i values between 0.295 and 0.342. Warehouse alternative (S3) ranked in second place across all methods but showed more variation in results than S2 and S1. Specifically, under linear vector normalization, its CC_i dropped from 0.622 with Euclidean distance to 0.504 with Manhattan distance. Under linear sum normalization, the variation was smaller, with CC_i values between 0.612 and 0.624. These differences indicate that S3's ranking is moderately affected by the choice of normalization and distance method.

In terms of distance metrics, the Manhattan distance generally produces higher CC_i values across alternatives compared to Euclidean distance. Additionally, Manhattan distance showed greater discrimination between top and bottom-ranked alternatives, particularly under the linear sum normalization. This indicates that Manhattan distance is more sensitive to variations in normalized performance values.

Regarding normalization techniques, linear vector normalization and linear sum normalization presented similar ranking patterns, with slightly more pronounced differences in CC_i. These small deviations highlight the importance of carefully selecting a normalization technique, as even small computational differences can influence how alternatives are distinguished.

Overall, while the top and bottom rankings remained stable across all methods (S2 and S1, respectively), the middle-ranked alternative (S3) demonstrated some degree of sensitivity. This highlights that the choice of normalization and distance methods can influence the differentiation between alternatives, particularly those that are closely matched in performance, when methodological choices are varied.

4.4 Evaluation using valid weight combinations

To evaluate the robustness of the decision-making model beyond expert-derived FBWM weights, an additional analysis was conducted using systematically generated random weight combinations. A total of 5,832 potential weight combinations were generated by assigning discrete values ranging from 0.05 to 0.90 (in increments of 0.05) to each of the three criteria (w_1, w_2, w_3). To ensure only meaningful and realistic configurations, two filtering conditions were applied:

(1) The weights must sum to one $(w_1 + w_2 + w_3 = 1)$

(2) the weight assigned to the rental rate (w_2) must be greater than or equal to the weights of the other two criteria $(w_2 \geq w_1, w_2 \geq w_3)$. After applying these constraints, 45 valid weight distributions remained, as in Table 4.11.

These were then applied in the TOPSIS framework across all combinations of normalization (linear vector, linear sum, and max) and distance methods (Euclidean and Manhattan). This procedure allowed for 270 evaluation runs (45 weight combinations × 3 normalization methods × 2 distance metrics) for each alternative, enabling a detailed assessment of how rankings respond to varying inputs.

The closeness coefficient (CC_i) was calculated for each alternative under every scenario, and the resulting rankings were recorded. This approach provided a rich dataset for understanding the sensitivity of warehouse rankings to weight for identifying patterns of consistency across different methodological settings.

Table 4.11 Valid weight combinations

Weight Comb-ination	W1	W2	W3		Weight Comb-ination	W1	W2	W3		Weight Comb-ination	W1	W2	W3
1	0.05	0.50	0.45		16	0.10	0.80	0.10		31	0.25	0.50	0.25
2	0.05	0.55	0.40		17	0.10	0.85	0.05		32	0.25	0.55	0.20
3	0.05	0.6	0.35		18	0.15	0.50	0.35		33	0.25	0.6	0.15
4	0.05	0.65	0.30		19	0.15	0.55	0.30		34	0.25	0.65	0.10
5	0.05	0.70	0.25		20	0.15	0.60	0.25		35	0.25	0.70	0.05
6	0.05	0.75	0.20		21	0.15	0.65	0.20		36	0.30	0.50	0.20
7	0.05	0.80	0.15		22	0.15	0.70	0.15		37	0.30	0.55	0.15
8	0.05	0.85	0.10		23	0.15	0.75	0.10		38	0.30	0.60	0.10
9	0.05	0.90	0.05		24	0.15	0.80	0.05		39	0.30	0.65	0.05
10	0.10	0.50	0.40		25	0.20	0.50	0.30		40	0.35	0.50	0.15
11	0.10	0.55	0.35		26	0.20	0.55	0.25		41	0.35	0.55	0.10
12	0.10	0.60	0.30		27	0.20	0.60	0.20		42	0.35	0.60	0.05
13	0.10	0.65	0.25		28	0.20	0.65	0.15		43	0.40	0.50	0.10
14	0.10	0.70	0.20		29	0.20	0.70	0.10		44	0.40	0.55	0.05
15	0.10	0.75	0.15		30	0.20	0.75	0.05		45	0.45	0.50	0.05

Table 4.12 Dataset components used for robustness and sensitivity analysis.

Component	**Description**	**Quantity**
Alternatives	Warehouse location options (S1, S2, S3)	3
Valid weight combinations	Valid weight sets generated for robustness analysis	45
Normalization methods	Linear vector, linear sum, and max normalization	3
Distance metrics	Euclidean and Manhattan distance calculations	2
Closeness coefficient values	Total number of CC_i values computed	810

The full dataset consists of 810 closeness coefficient values (denoted as CC_i), covering every alternative (S1, S2, S3) across the 270 scenarios. For each evaluation, the following parameters were recorded in Table 4.12.

4.5 Statistical analysis of ranking robustness

To evaluate the influence of methodological variation on warehouse selection outcomes, a two-way ANOVA was conducted in Minitab. The analysis examined the effects of three factors: valid weight combinations, normalization method (linear vector, linear sum, and max), and distance metric (Euclidean and Manhattan) on the CC_i of each warehouse alternative. The dataset consisted of 810 CC_i values, generated from 45 valid weight combinations across all methodological configurations. Residual analysis indicated no major violations of normality or homogeneity, confirming the suitability of the model. Finally, Tukey post-hoc tests were performed to identify specific method pairs with significant differences in their impact on CC_i. The analysis included the following three factors, as shown in Table 4.13.

Table 4.13 Factor information for S1, S2 and S3 for ANOVA model

Factor	Type	Levels	Values
Weight Combination	Fixed	45	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30,31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44,45
Distance Calculation	Fixed	2	Euclidean, Manhattan
Normalization Method	Fixed	3	Max, Sum, Vector

4.5.1 Statistical analysis of results for alternative 1 (S1)

The evaluation shows that weight combination, distance metric, and normalization method all have a substantial impact on the CC_i values for Alternative 1 (S1). The ANOVA results demonstrated that all three factors significantly influenced CC_i values of S1, with p-values less than 0.001, indicating strong statistical significance (see Table 4.14).

Table 4.14 Analysis of variance for alternative 1 (S1)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Weight Combination	44	2.62660	0.059695	1120.51	0.000
Distance Calculation	1	0.05553	0.055526	1042.25	0.000
Normalization Method	2	0.00767	0.003836	72.01	0.000
Error	222	0.01183	0.000053		
Total	269	2.70162			

The model summary metrics further confirmed the strength of the analysis. The adjusted R-squared value was 99.47%, indicating that the model explained nearly all of the variation in CC_i values. The predicted R-squared was also high at 99.35%, suggesting strong predictive accuracy in Table 4.15.

Table 4.15 Model summary for alternative 1 (S1)

S	R-sq	R-sq(adj)	R-sq(pred)
0.0072990	99.56%	99.47%	99.35%

To further identify which specific factor differed significantly, Tukey's post-hoc pairwise comparisons were conducted for both distance metrics and normalization methods in Tables 4.16 and 4.17.

Table 4.16 Tukey pairwise comparisons: distance calculation for alternative 1 (S1)

Grouping Information Using the Tukey Method and 95% Confidence				
Distance Calculation	**N**	**Mean**	**Grouping**	
Manhattan	135	0.280956	A	
Euclidean	135	0.252275		B

Table 4.17 Tukey pairwise comparisons: normalization method for alternative 1 (S1)

Grouping Information Using the Tukey Method and 95% Confidence				
Normalization Method	**N**	**Mean**	**Grouping**	
Max	90	0.274036	A	
Vector	90	0.264059		B
Sum	90	0.261752		B

For alternative S1, the Manhattan distance produced a significantly higher mean CC_i (0.280956) than the Euclidean distance (0.252275), as indicated by their different statistical groupings A and B. This suggests that Manhattan distance offers greater discriminative power in differentiating performance. Regarding normalization methods, max normalization yielded the highest mean CC_i (0.274036), significantly above both Vector (0.264059) and Sum (0.261752) normalization, which were statistically similar and as in grouped together.

The normal probability plot of residuals (Figure 4.1) supports the validity of the ANOVA assumptions, with residuals closely following a straight line, indicating approximate normality and homoscedasticity.

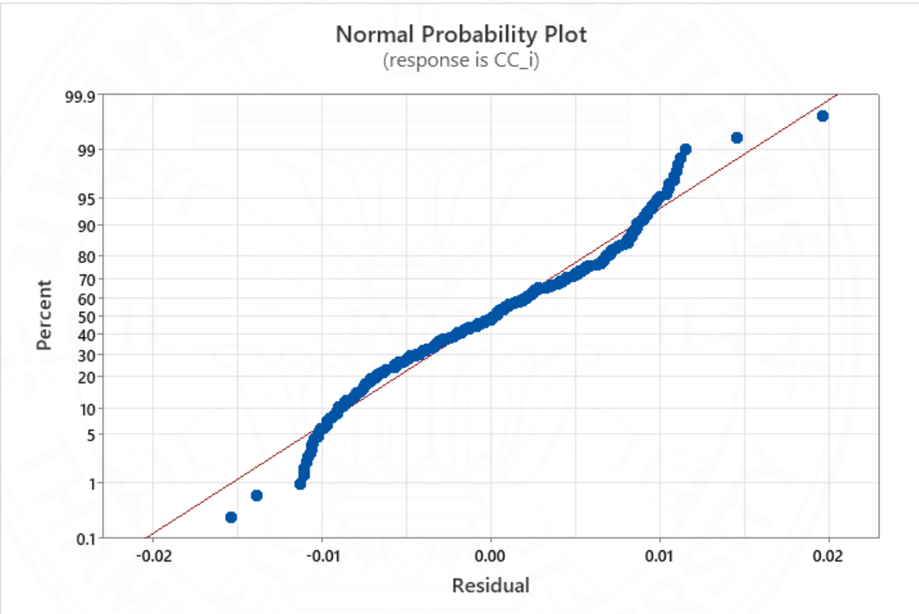

Figure 4.1 Normal probability plot of residuals for alternative 1(S1)

The statistical analysis confirms that the selection of distance metric, and weight combination significantly influences the closeness coefficient (CC_i) values for Alternative 1 (S1).

4.5.2 Statistical analysis of results for alternative 2 (S2)

To evaluate the sensitivity and robustness of the ranking outcome for Alternative 2 (S2), a two-way ANOVA was performed in Minitab, considering the same factors outlined in Table 4.13. The ANOVA results, presented in Table 4.18, show that weight combination and distance metric are statistically significant effects on CC_i.

In contrast, the normalization method had only a marginal effect , indicating a weaker influence compared to the other factors.

As shown in the model summary in Table 4.19, the R-squared value is 98.60%, with an adjusted R-squared at 98.30% and predicted R-squared at 97.92%. It indicates that the model is statistically valid and provides a reliable fit for analyzing CC_i in alternative 2.

Tukey's pairwise comparisons (Tables 4.20 and 4.21) show that Alternative 2 (S2) is strongly influenced by distance metrics, while normalization methods have no significant effect.

Table 4.18 Analysis of variance for alternative 2 (S2)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Weight Combination	44	1.50545	0.034215	342.99	0.000
Distance Calculation	1	0.04957	0.049569	496.91	0.000
Normalization Method	2	0.00059	0.000296	2.97	0.053
Error	222	0.02215	0.000100		
Total	269	1.57776			

Table 4.19 Model summary for alternative2 (S2)

S	R-sq	R-sq(adj)	R-sq(pred)
0.0099877	98.60%	98.30%	97.92%

Table 4.20 Tukey pairwise comparisons: distance calculation for alternative 2 (S2)

Grouping Information Using the Tukey Method and 95% Confidence				
Distance Calculation	N	Mean	Grouping	
Manhattan	135	0.887083	A	-
Euclidean	135	0.859984	-	B

Table 4.21 Tukey pairwise comparisons: normalization method for alternative 2 (S2)

Grouping Information Using the Tukey Method and 95% Confidence				
Normalization Method	N	Mean	Grouping	
Max	90	0.874825	A	-
Vector	90	0.874317	A	-
Sum	90	0.871458	A	-

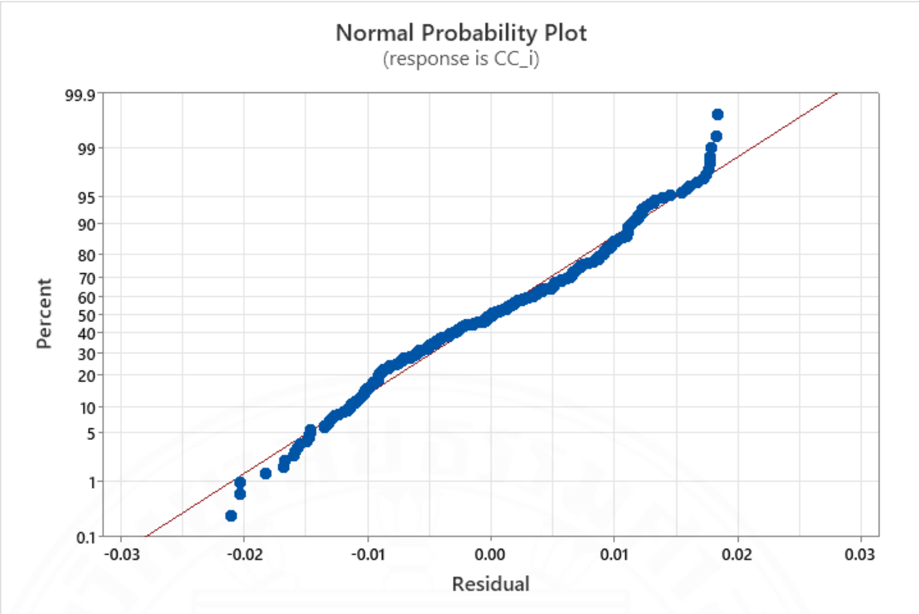

Figure 4.2 Normal probability plot of residuals for alternative 2(S2).

The normal probability plot of residuals (Figure 4.2) confirms that the assumption of normality was satisfied.

4.5.3 Statistical analysis of results for alternative 3 (S3)

For alternative 3 (S3), the same statistical approach was applied, using the GLM as the response variable and the same factors listed in Table 4.13. The ANOVA results are presented in Table 4.22. All three factors exhibited statistically significant effects on the CC_i values, as indicated by their p-values being less than 0.05. The model summary in Table 4.23 reveals a high goodness-of-fit, with an R-squared value of 99.03%, adjusted R-squared of 98.82%, and predicted R-squared of 98.56%, confirming that the model explains nearly all variability in the data.

Table 4.22 Analysis of variance for alternative 3 (S3)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Weight Combination	44	1.84942	0.042032	367.46	0.000
Distance Calculation	1	0.72113	0.721133	6304.32	0.000
Normalization Method	2	0.00877	0.004384	38.33	0.000
Error	222	0.02539	0.000114		
Total	269	2.60471			

Table 4.23 Model summary for alternative3 (S3)

S	R-sq	R-sq(adj)	R-sq(pred)
0.0099877	99.03%	98.82%	98.56%

Post-hoc comparisons using Tukey's test were conducted to examine pairwise differences between levels of the distance and normalization methods. For the distance calculation method comparison, there is a significant influence on CC_i for S3, as indicated by their assignment to distinct groups (A and B, respectively) in Table 4.24.

Table 4.24 Tukey pairwise comparisons: distance calculation for alternative 3 (S3)

Grouping Information Using the Tukey Method and 95% Confidence				
Distance Calculation	N	Mean	Grouping	
Manhattan	135	0.641491	A	-
Euclidean	135	0.538130	-	B

Table 4.25 Tukey pairwise comparisons: normalization method for alternative 3 (S3)

Grouping Information Using the Tukey Method and 95% Confidence				
Normalization Method	N	Mean	Grouping	
Max	90	0.595045	A	-
Vector	90	0.592501	A	-
Sum	90	0.581887	-	B

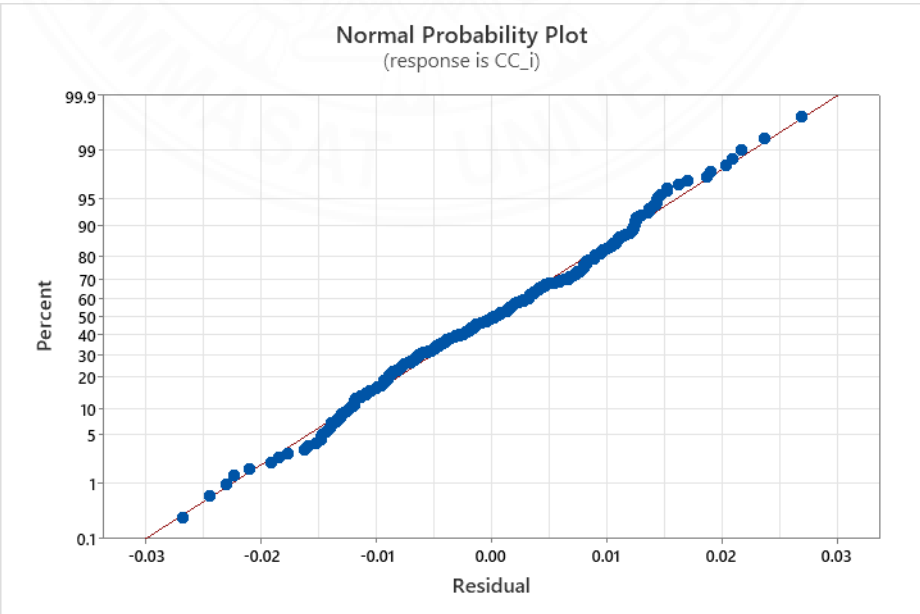

Figure 4.3 Normal probability plot of residuals for alternative 3 (S3).

Table 4.25 shows a comparison of the normalization methods, which were not significantly different, even though the results are in groups A and B. Furthermore, the normal probability plot of residuals (Figure 4.3) confirms that the residuals follow a normal distribution, supporting the validity of the ANOVA assumptions.

4.6 Interpretation of sensitivity and robustness

The sensitivity and robustness analysis shows that the overall ranking pattern is stable, with S2 consistently in the top-ranked position. However, the variations CC_i values and the magnitude difference between alternatives were changed depending on the weight combinations, normalization methods, and distance metrics used. These results highlight the importance of sensitivity analysis in MCDM, particularly in real-world situations where judgments and methodological choices can vary.

The robustness of the proposed decision-making framework is substantiated through evaluation, using 45 weight combinations, and statistical analysis via two-way ANOVA. The findings reveal that weight combinations and distance metrics are statistically significant effects on CC_i values across all three alternatives. Among the distance metrics, the Manhattan distance demonstrated greater discriminatory capability by generating a wider dispersion of CC_i scores, whereas the Euclidean distance yielded more stable and consistent rankings across methodological variations. In contrast, normalization methods did not exhibit a statistically significant influence, suggesting their negligible effect on CC_i values. Overall, the results demonstrate that the TOPSIS-based framework ensures reliable and adaptable warehouse location decisions, even under varying inputs and methodological settings.

CHAPTER 5
CONCLUSION

This study developed a hybrid fuzzy multi-criteria decision-making framework for warehouse location selection, integrating the FBWM for criteria weighting with the TOPSIS for alternative ranking. The approach was designed to address the uncertainty inherent in expert judgments and the variability in methodological configurations. A case study involving three warehouse candidates (S1, S2, and S3) within the Bangkok metropolitan area was conducted, evaluated against three quantitative criteria: warehouse area, rental cost, and distance to the airport.

In addition to expert-derived weights from FBWM, the study applied 45 valid random weight combinations to simulate variations in decision-maker preferences. Rankings were generated under three normalization methods (linear vector, linear sum, and max) and two distance metrics (Euclidean and Manhattan), followed by robustness and sensitivity analysis using Two-Way ANOVA.

5.1 Key findings and contributions

The results demonstrated that alternative S2 consistently ranked as the most suitable warehouse location across all evaluation scenarios, with closeness coefficient values ranging from 0.803 to 0.847. Alternative S1 consistently ranked last, while S3 ranked second.

Robustness analysis confirmed that variations in criteria weights and distance metrics significantly influenced closeness coefficients, whereas normalization methods had minimal effect. Manhattan distance provided greater discrimination among alternatives, while Euclidean distance yielded more stable results.

This research contributes to theory by demonstrating the integration of FBWM and TOPSIS within a warehouse location selection context, and by incorporating a comprehensive robustness and sensitivity analysis supported by statistical validation. Practically, it offers decision-makers a transparent and replicable framework capable of producing reliable results under varying decision preferences.

5.2 Limitations and recommendations for future research

The study was limited to three quantitative criteria, excluding qualitative considerations such as facility condition, contract flexibility, and accessibility to labor markets. The case study involved only three alternatives within a single metropolitan area, limiting generalizability. The robustness analysis assumed rental cost to be the most important criterion, which may not hold in all contexts. Finally, while FBWM accounted for fuzziness in weighting, the TOPSIS stage used deterministic performance scores.

Future research could integrate fuzzy TOPSIS in the ranking stage, expand the criteria set to include qualitative and sustainability-related factors, apply the framework to a broader range of alternatives and contexts, and use real-time data for dynamic decision-making.

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APPENDIX

APPENDIX A

Dataset of CC_i Values for Alternative S1

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
1	1	0.05	0.50	0.45	Euclidean	Vector	S1	0.2914
2	1	0.05	0.50	0.45	Euclidean	Max	S1	0.3102
3	1	0.05	0.50	0.45	Euclidean	Sum	S1	0.2864
4	1	0.05	0.50	0.45	Manhattan	Vector	S1	0.2953
5	1	0.05	0.50	0.45	Manhattan	Max	S1	0.3099
6	1	0.05	0.50	0.45	Manhattan	Sum	S1	0.2915
7	2	0.05	0.55	0.40	Euclidean	Vector	S1	0.2520
8	2	0.05	0.55	0.40	Euclidean	Max	S1	0.2694
9	2	0.05	0.55	0.40	Euclidean	Sum	S1	0.2474
10	2	0.05	0.55	0.40	Manhattan	Vector	S1	0.2639
11	2	0.05	0.55	0.40	Manhattan	Max	S1	0.2778
12	2	0.05	0.55	0.40	Manhattan	Sum	S1	0.2602
13	3	0.05	0.60	0.35	Euclidean	Vector	S1	0.2152
14	3	0.05	0.60	0.35	Euclidean	Max	S1	0.2309
15	3	0.05	0.60	0.35	Euclidean	Sum	S1	0.2111
16	3	0.05	0.60	0.35	Manhattan	Vector	S1	0.2335
17	3	0.05	0.60	0.35	Manhattan	Max	S1	0.2466
18	3	0.05	0.60	0.35	Manhattan	Sum	S1	0.2301
19	4	0.05	0.65	0.30	Euclidean	Vector	S1	0.1810
20	4	0.05	0.65	0.30	Euclidean	Max	S1	0.1946
21	4	0.05	0.65	0.30	Euclidean	Sum	S1	0.1775
22	4	0.05	0.65	0.30	Manhattan	Vector	S1	0.2042
23	4	0.05	0.65	0.30	Manhattan	Max	S1	0.2162
24	4	0.05	0.65	0.30	Manhattan	Sum	S1	0.2011
25	5	0.05	0.70	0.25	Euclidean	Vector	S1	0.1493
26	5	0.05	0.70	0.25	Euclidean	Max	S1	0.1608
27	5	0.05	0.70	0.25	Euclidean	Sum	S1	0.1464
28	5	0.05	0.70	0.25	Manhattan	Vector	S1	0.1760
29	5	0.05	0.70	0.25	Manhattan	Max	S1	0.1867
30	5	0.05	0.70	0.25	Manhattan	Sum	S1	0.1732
31	6	0.05	0.75	0.20	Euclidean	Vector	S1	0.1203
32	6	0.05	0.75	0.20	Euclidean	Max	S1	0.1295
33	6	0.05	0.75	0.20	Euclidean	Sum	S1	0.1180
34	6	0.05	0.75	0.20	Manhattan	Vector	S1	0.1487
35	6	0.05	0.75	0.20	Manhattan	Max	S1	0.1579
36	6	0.05	0.75	0.20	Manhattan	Sum	S1	0.1463
37	7	0.05	0.80	0.15	Euclidean	Vector	S1	0.0943

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
38	7	0.05	0.80	0.15	Euclidean	Max	S1	0.1012
39	7	0.05	0.80	0.15	Euclidean	Sum	S1	0.0926
40	7	0.05	0.80	0.15	Manhattan	Vector	S1	0.1223
41	7	0.05	0.80	0.15	Manhattan	Max	S1	0.1299
42	7	0.05	0.80	0.15	Manhattan	Sum	S1	0.1204
43	8	0.05	0.85	0.10	Euclidean	Vector	S1	0.0722
44	8	0.05	0.85	0.10	Euclidean	Max	S1	0.0768
45	8	0.05	0.85	0.10	Euclidean	Sum	S1	0.0711
46	8	0.05	0.85	0.10	Manhattan	Vector	S1	0.0968
47	8	0.05	0.85	0.10	Manhattan	Max	S1	0.1026
48	8	0.05	0.85	0.10	Manhattan	Sum	S1	0.0954
49	9	0.05	0.90	0.05	Euclidean	Vector	S1	0.0558
50	9	0.05	0.90	0.05	Euclidean	Max	S1	0.0585
51	9	0.05	0.90	0.05	Euclidean	Sum	S1	0.0552
52	9	0.05	0.90	0.05	Manhattan	Vector	S1	0.0721
53	9	0.05	0.90	0.05	Manhattan	Max	S1	0.0759
54	9	0.05	0.90	0.05	Manhattan	Sum	S1	0.0712
55	10	0.10	0.50	0.40	Euclidean	Vector	S1	0.2879
56	10	0.10	0.50	0.40	Euclidean	Max	S1	0.3048
57	10	0.10	0.50	0.40	Euclidean	Sum	S1	0.2836
58	10	0.10	0.50	0.40	Manhattan	Vector	S1	0.3198
59	10	0.10	0.50	0.40	Manhattan	Max	S1	0.3333
60	10	0.10	0.50	0.40	Manhattan	Sum	S1	0.3164
61	11	0.10	0.55	0.35	Euclidean	Vector	S1	0.2505
62	11	0.10	0.55	0.35	Euclidean	Max	S1	0.2657
63	11	0.10	0.55	0.35	Euclidean	Sum	S1	0.2466
64	11	0.10	0.55	0.35	Manhattan	Vector	S1	0.2884
65	11	0.10	0.55	0.35	Manhattan	Max	S1	0.3014
66	11	0.10	0.55	0.35	Manhattan	Sum	S1	0.2851
67	12	0.10	0.60	0.30	Euclidean	Vector	S1	0.2164
68	12	0.10	0.60	0.30	Euclidean	Max	S1	0.2297
69	12	0.10	0.60	0.30	Euclidean	Sum	S1	0.2130
70	12	0.10	0.60	0.30	Manhattan	Vector	S1	0.2581
71	12	0.10	0.60	0.30	Manhattan	Max	S1	0.2703
72	12	0.10	0.60	0.30	Manhattan	Sum	S1	0.2550
73	13	0.10	0.65	0.25	Euclidean	Vector	S1	0.1857
74	13	0.10	0.65	0.25	Euclidean	Max	S1	0.1969
75	13	0.10	0.65	0.25	Euclidean	Sum	S1	0.1829
76	13	0.10	0.65	0.25	Manhattan	Vector	S1	0.2288
77	13	0.10	0.65	0.25	Manhattan	Max	S1	0.2400

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
78	13	0.10	0.65	0.25	Manhattan	Sum	S1	0.2260
79	14	0.10	0.70	0.20	Euclidean	Vector	S1	0.1586
80	14	0.10	0.70	0.20	Euclidean	Max	S1	0.1677
81	14	0.10	0.70	0.20	Euclidean	Sum	S1	0.1565
82	14	0.10	0.70	0.20	Manhattan	Vector	S1	0.2005
83	14	0.10	0.70	0.20	Manhattan	Max	S1	0.2105
84	14	0.10	0.70	0.20	Manhattan	Sum	S1	0.1981
85	15	0.10	0.75	0.15	Euclidean	Vector	S1	0.1357
86	15	0.10	0.75	0.15	Euclidean	Max	S1	0.1427
87	15	0.10	0.75	0.15	Euclidean	Sum	S1	0.1341
88	15	0.10	0.75	0.15	Manhattan	Vector	S1	0.1732
89	15	0.10	0.75	0.15	Manhattan	Max	S1	0.1818
90	15	0.10	0.75	0.15	Manhattan	Sum	S1	0.1712
91	16	0.10	0.80	0.10	Euclidean	Vector	S1	0.1173
92	16	0.10	0.80	0.10	Euclidean	Max	S1	0.1226
93	16	0.10	0.80	0.10	Euclidean	Sum	S1	0.1162
94	16	0.10	0.80	0.10	Manhattan	Vector	S1	0.1468
95	16	0.10	0.80	0.10	Manhattan	Max	S1	0.1538
96	16	0.10	0.80	0.10	Manhattan	Sum	S1	0.1452
97	17	0.10	0.85	0.05	Euclidean	Vector	S1	0.1042
98	17	0.10	0.85	0.05	Euclidean	Max	S1	0.1081
99	17	0.10	0.85	0.05	Euclidean	Sum	S1	0.1033
100	17	0.10	0.85	0.05	Manhattan	Vector	S1	0.1213
101	17	0.10	0.85	0.05	Manhattan	Max	S1	0.1266
102	17	0.10	0.85	0.05	Manhattan	Sum	S1	0.1201
103	18	0.15	0.50	0.35	Euclidean	Vector	S1	0.2977
104	18	0.15	0.50	0.35	Euclidean	Max	S1	0.3123
105	18	0.15	0.50	0.35	Euclidean	Sum	S1	0.2941
106	18	0.15	0.50	0.35	Manhattan	Vector	S1	0.3435
107	18	0.15	0.50	0.35	Manhattan	Max	S1	0.3562
108	18	0.15	0.50	0.35	Manhattan	Sum	S1	0.3404
109	19	0.15	0.55	0.30	Euclidean	Vector	S1	0.2636
110	19	0.15	0.55	0.30	Euclidean	Max	S1	0.2765
111	19	0.15	0.55	0.30	Euclidean	Sum	S1	0.2605
112	19	0.15	0.55	0.30	Manhattan	Vector	S1	0.3121
113	19	0.15	0.55	0.30	Manhattan	Max	S1	0.3243
114	19	0.15	0.55	0.30	Manhattan	Sum	S1	0.3092
115	20	0.15	0.60	0.25	Euclidean	Vector	S1	0.2335
116	20	0.15	0.60	0.25	Euclidean	Max	S1	0.2445
117	20	0.15	0.60	0.25	Euclidean	Sum	S1	0.2309

S/N	Weigh t Combi nation	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
118	20	0.15	0.60	0.25	Manhattan	Vector	S1	0.2819
119	20	0.15	0.60	0.25	Manhattan	Max	S1	0.2933
120	20	0.15	0.60	0.25	Manhattan	Sum	S1	0.2791
121	21	0.15	0.65	0.20	Euclidean	Vector	S1	0.2074
122	21	0.15	0.65	0.20	Euclidean	Max	S1	0.2166
123	21	0.15	0.65	0.20	Euclidean	Sum	S1	0.2053
124	21	0.15	0.65	0.20	Manhattan	Vector	S1	0.2526
125	21	0.15	0.65	0.20	Manhattan	Max	S1	0.2632
126	21	0.15	0.65	0.20	Manhattan	Sum	S1	0.2502
127	22	0.15	0.70	0.15	Euclidean	Vector	S1	0.1854
128	22	0.15	0.70	0.15	Euclidean	Max	S1	0.1931
129	22	0.15	0.70	0.15	Euclidean	Sum	S1	0.1838
130	22	0.15	0.70	0.15	Manhattan	Vector	S1	0.2244
131	22	0.15	0.70	0.15	Manhattan	Max	S1	0.2338
132	22	0.15	0.70	0.15	Manhattan	Sum	S1	0.2222
133	23	0.15	0.75	0.10	Euclidean	Vector	S1	0.1678
134	23	0.15	0.75	0.10	Euclidean	Max	S1	0.1740
135	23	0.15	0.75	0.10	Euclidean	Sum	S1	0.1665
136	23	0.15	0.75	0.10	Manhattan	Vector	S1	0.1971
137	23	0.15	0.75	0.10	Manhattan	Max	S1	0.2051
138	23	0.15	0.75	0.10	Manhattan	Sum	S1	0.1953
139	24	0.15	0.80	0.05	Euclidean	Vector	S1	0.1544
140	24	0.15	0.80	0.05	Euclidean	Max	S1	0.1597
141	24	0.15	0.80	0.05	Euclidean	Sum	S1	0.1533
142	24	0.15	0.80	0.05	Manhattan	Vector	S1	0.1707
143	24	0.15	0.80	0.05	Manhattan	Max	S1	0.1772
144	24	0.15	0.80	0.05	Manhattan	Sum	S1	0.1693
145	25	0.20	0.50	0.30	Euclidean	Vector	S1	0.3184
146	25	0.20	0.50	0.30	Euclidean	Max	S1	0.3309
147	25	0.20	0.50	0.30	Euclidean	Sum	S1	0.3155
148	25	0.20	0.50	0.30	Manhattan	Vector	S1	0.3664
149	25	0.20	0.50	0.30	Manhattan	Max	S1	0.3784
150	25	0.20	0.50	0.30	Manhattan	Sum	S1	0.3636
151	26	0.20	0.55	0.25	Euclidean	Vector	S1	0.2877
152	26	0.20	0.55	0.25	Euclidean	Max	S1	0.2988
153	26	0.20	0.55	0.25	Euclidean	Sum	S1	0.2852
154	26	0.20	0.55	0.25	Manhattan	Vector	S1	0.3352
155	26	0.20	0.55	0.25	Manhattan	Max	S1	0.3467
156	26	0.20	0.55	0.25	Manhattan	Sum	S1	0.3325
157	27	0.20	0.60	0.20	Euclidean	Vector	S1	0.2612

S/N	Weigh t Combi nation	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
158	27	0.20	0.60	0.20	Euclidean	Max	S1	0.2708
159	27	0.20	0.60	0.20	Euclidean	Sum	S1	0.2591
160	27	0.20	0.60	0.20	Manhattan	Vector	S1	0.3050
161	27	0.20	0.60	0.20	Manhattan	Max	S1	0.3158
162	27	0.20	0.60	0.20	Manhattan	Sum	S1	0.3025
163	28	0.20	0.65	0.15	Euclidean	Vector	S1	0.2387
164	28	0.20	0.65	0.15	Euclidean	Max	S1	0.2470
165	28	0.20	0.65	0.15	Euclidean	Sum	S1	0.2369
166	28	0.20	0.65	0.15	Manhattan	Vector	S1	0.2758
167	28	0.20	0.65	0.15	Manhattan	Max	S1	0.2857
168	28	0.20	0.65	0.15	Manhattan	Sum	S1	0.2735
169	29	0.20	0.70	0.10	Euclidean	Vector	S1	0.2201
170	29	0.20	0.70	0.10	Euclidean	Max	S1	0.2274
171	29	0.20	0.70	0.10	Euclidean	Sum	S1	0.2186
172	29	0.20	0.70	0.10	Manhattan	Vector	S1	0.2476
173	29	0.20	0.70	0.10	Manhattan	Max	S1	0.2564
174	29	0.20	0.70	0.10	Manhattan	Sum	S1	0.2456
175	30	0.20	0.75	0.05	Euclidean	Vector	S1	0.2053
176	30	0.20	0.75	0.05	Euclidean	Max	S1	0.2118
177	30	0.20	0.75	0.05	Euclidean	Sum	S1	0.2040
178	30	0.20	0.75	0.05	Manhattan	Vector	S1	0.2203
179	30	0.20	0.75	0.05	Manhattan	Max	S1	0.2278
180	30	0.20	0.75	0.05	Manhattan	Sum	S1	0.2187
181	31	0.25	0.50	0.25	Euclidean	Vector	S1	0.3457
182	31	0.25	0.50	0.25	Euclidean	Max	S1	0.3568
183	31	0.25	0.50	0.25	Euclidean	Sum	S1	0.3433
184	31	0.25	0.50	0.25	Manhattan	Vector	S1	0.3887
185	31	0.25	0.50	0.25	Manhattan	Max	S1	0.4000
186	31	0.25	0.50	0.25	Manhattan	Sum	S1	0.3861
187	32	0.25	0.55	0.20	Euclidean	Vector	S1	0.3178
188	32	0.25	0.55	0.20	Euclidean	Max	S1	0.3278
189	32	0.25	0.55	0.20	Euclidean	Sum	S1	0.3156
190	32	0.25	0.55	0.20	Manhattan	Vector	S1	0.3575
191	32	0.25	0.55	0.20	Manhattan	Max	S1	0.3684
192	32	0.25	0.55	0.20	Manhattan	Sum	S1	0.3550
193	33	0.25	0.60	0.15	Euclidean	Vector	S1	0.2937
194	33	0.25	0.60	0.15	Euclidean	Max	S1	0.3027
195	33	0.25	0.60	0.15	Euclidean	Sum	S1	0.2919
196	33	0.25	0.60	0.15	Manhattan	Vector	S1	0.3274
197	33	0.25	0.60	0.15	Manhattan	Max	S1	0.3377

S/N	Weigh t Combi nation	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
198	33	0.25	0.60	0.15	Manhattan	Sum	S1	0.3251
199	34	0.25	0.65	0.10	Euclidean	Vector	S1	0.2734
200	34	0.25	0.65	0.10	Euclidean	Max	S1	0.2816
201	34	0.25	0.65	0.10	Euclidean	Sum	S1	0.2718
202	34	0.25	0.65	0.10	Manhattan	Vector	S1	0.2982
203	34	0.25	0.65	0.10	Manhattan	Max	S1	0.3077
204	34	0.25	0.65	0.10	Manhattan	Sum	S1	0.2962
205	35	0.25	0.70	0.05	Euclidean	Vector	S1	0.2565
206	35	0.25	0.70	0.05	Euclidean	Max	S1	0.2641
207	35	0.25	0.70	0.05	Euclidean	Sum	S1	0.2550
208	35	0.25	0.70	0.05	Manhattan	Vector	S1	0.2701
209	35	0.25	0.70	0.05	Manhattan	Max	S1	0.2785
210	35	0.25	0.70	0.05	Manhattan	Sum	S1	0.2683
211	36	0.30	0.50	0.20	Euclidean	Vector	S1	0.3760
212	36	0.30	0.50	0.20	Euclidean	Max	S1	0.3862
213	36	0.30	0.50	0.20	Euclidean	Sum	S1	0.3739
214	36	0.30	0.50	0.20	Manhattan	Vector	S1	0.4102
215	36	0.30	0.50	0.20	Manhattan	Max	S1	0.4211
216	36	0.30	0.50	0.20	Manhattan	Sum	S1	0.4078
217	37	0.30	0.55	0.15	Euclidean	Vector	S1	0.3498
218	37	0.30	0.55	0.15	Euclidean	Max	S1	0.3594
219	37	0.30	0.55	0.15	Euclidean	Sum	S1	0.3479
220	37	0.30	0.55	0.15	Manhattan	Vector	S1	0.3791
221	37	0.30	0.55	0.15	Manhattan	Max	S1	0.3896
222	37	0.30	0.55	0.15	Manhattan	Sum	S1	0.3769
223	38	0.30	0.60	0.10	Euclidean	Vector	S1	0.3273
224	38	0.30	0.60	0.10	Euclidean	Max	S1	0.3362
225	38	0.30	0.60	0.10	Euclidean	Sum	S1	0.3255
226	38	0.30	0.60	0.10	Manhattan	Vector	S1	0.3491
227	38	0.30	0.60	0.10	Manhattan	Max	S1	0.3590
228	38	0.30	0.60	0.10	Manhattan	Sum	S1	0.3470
229	39	0.30	0.65	0.05	Euclidean	Vector	S1	0.3081
230	39	0.30	0.65	0.05	Euclidean	Max	S1	0.3165
231	39	0.30	0.65	0.05	Euclidean	Sum	S1	0.3064
232	39	0.30	0.65	0.05	Manhattan	Vector	S1	0.3200
233	39	0.30	0.65	0.05	Manhattan	Max	S1	0.3291
234	39	0.30	0.65	0.05	Manhattan	Sum	S1	0.3182
235	40	0.35	0.50	0.15	Euclidean	Vector	S1	0.4067
236	40	0.35	0.50	0.15	Euclidean	Max	S1	0.4165
237	40	0.35	0.50	0.15	Euclidean	Sum	S1	0.4047

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
238	40	0.35	0.50	0.15	Manhattan	Vector	S1	0.4311
239	40	0.35	0.50	0.15	Manhattan	Max	S1	0.4416
240	40	0.35	0.50	0.15	Manhattan	Sum	S1	0.4289
241	41	0.35	0.55	0.10	Euclidean	Vector	S1	0.3816
242	41	0.35	0.55	0.10	Euclidean	Max	S1	0.3910
243	41	0.35	0.55	0.10	Euclidean	Sum	S1	0.3797
244	41	0.35	0.55	0.10	Manhattan	Vector	S1	0.4002
245	41	0.35	0.55	0.10	Manhattan	Max	S1	0.4103
246	41	0.35	0.55	0.10	Manhattan	Sum	S1	0.3980
247	42	0.35	0.60	0.05	Euclidean	Vector	S1	0.3599
248	42	0.35	0.60	0.05	Euclidean	Max	S1	0.3690
249	42	0.35	0.60	0.05	Euclidean	Sum	S1	0.3581
250	42	0.35	0.60	0.05	Manhattan	Vector	S1	0.3702
251	42	0.35	0.60	0.05	Manhattan	Max	S1	0.3797
252	42	0.35	0.60	0.05	Manhattan	Sum	S1	0.3683
253	43	0.40	0.50	0.10	Euclidean	Vector	S1	0.4363
254	43	0.40	0.50	0.10	Euclidean	Max	S1	0.4461
255	43	0.40	0.50	0.10	Euclidean	Sum	S1	0.4344
256	43	0.40	0.50	0.10	Manhattan	Vector	S1	0.4514
257	43	0.40	0.50	0.10	Manhattan	Max	S1	0.4615
258	43	0.40	0.50	0.10	Manhattan	Sum	S1	0.4493
259	44	0.40	0.55	0.05	Euclidean	Vector	S1	0.4120
260	44	0.40	0.55	0.05	Euclidean	Max	S1	0.4215
261	44	0.40	0.55	0.05	Euclidean	Sum	S1	0.4101
262	44	0.40	0.55	0.05	Manhattan	Vector	S1	0.4206
263	44	0.40	0.55	0.05	Manhattan	Max	S1	0.4304
264	44	0.40	0.55	0.05	Manhattan	Sum	S1	0.4186
265	45	0.45	0.50	0.05	Euclidean	Vector	S1	0.4643
266	45	0.45	0.50	0.05	Euclidean	Max	S1	0.4740
267	45	0.45	0.50	0.05	Euclidean	Sum	S1	0.4624
268	45	0.45	0.50	0.05	Manhattan	Vector	S1	0.4712
269	45	0.45	0.50	0.05	Manhattan	Max	S1	0.4810
270	45	0.45	0.50	0.05	Manhattan	Sum	S1	0.4691

Dataset of CC_i Values for Alternative S2

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
1	1	0.05	0.50	0.45	Euclidean	Vector	S2	0.9531
2	1	0.05	0.50	0.45	Euclidean	Max	S2	0.9526
3	1	0.05	0.50	0.45	Euclidean	Sum	S2	0.9531
4	1	0.05	0.50	0.45	Manhattan	Vector	S2	0.9662
5	1	0.05	0.50	0.45	Manhattan	Max	S2	0.9662
6	1	0.05	0.50	0.45	Manhattan	Sum	S2	0.9662
7	2	0.05	0.55	0.40	Euclidean	Vector	S2	0.9551
8	2	0.05	0.55	0.40	Euclidean	Max	S2	0.9543
9	2	0.05	0.55	0.40	Euclidean	Sum	S2	0.9552
10	2	0.05	0.55	0.40	Manhattan	Vector	S2	0.9668
11	2	0.05	0.55	0.40	Manhattan	Max	S2	0.9667
12	2	0.05	0.55	0.40	Manhattan	Sum	S2	0.9668
13	3	0.05	0.60	0.35	Euclidean	Vector	S2	0.9572
14	3	0.05	0.60	0.35	Euclidean	Max	S2	0.9562
15	3	0.05	0.60	0.35	Euclidean	Sum	S2	0.9574
16	3	0.05	0.60	0.35	Manhattan	Vector	S2	0.9674
17	3	0.05	0.60	0.35	Manhattan	Max	S2	0.9671
18	3	0.05	0.60	0.35	Manhattan	Sum	S2	0.9675
19	4	0.05	0.65	0.30	Euclidean	Vector	S2	0.9594
20	4	0.05	0.65	0.30	Euclidean	Max	S2	0.9582
21	4	0.05	0.65	0.30	Euclidean	Sum	S2	0.9596
22	4	0.05	0.65	0.30	Manhattan	Vector	S2	0.9680
23	4	0.05	0.65	0.30	Manhattan	Max	S2	0.9676
24	4	0.05	0.65	0.30	Manhattan	Sum	S2	0.9681
25	5	0.05	0.70	0.25	Euclidean	Vector	S2	0.9615
26	5	0.05	0.70	0.25	Euclidean	Max	S2	0.9603
27	5	0.05	0.70	0.25	Euclidean	Sum	S2	0.9617
28	5	0.05	0.70	0.25	Manhattan	Vector	S2	0.9686
29	5	0.05	0.70	0.25	Manhattan	Max	S2	0.9680
30	5	0.05	0.70	0.25	Manhattan	Sum	S2	0.9687
31	6	0.05	0.75	0.20	Euclidean	Vector	S2	0.9635
32	6	0.05	0.75	0.20	Euclidean	Max	S2	0.9623
33	6	0.05	0.75	0.20	Euclidean	Sum	S2	0.9638
34	6	0.05	0.75	0.20	Manhattan	Vector	S2	0.9691
35	6	0.05	0.75	0.20	Manhattan	Max	S2	0.9684
36	6	0.05	0.75	0.20	Manhattan	Sum	S2	0.9692
37	7	0.05	0.80	0.15	Euclidean	Vector	S2	0.9655
38	7	0.05	0.80	0.15	Euclidean	Max	S2	0.9642

S/N	Weigh t Comb inatio n	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
39	7	0.05	0.80	0.15	Euclidean	Sum	S2	0.9657
40	7	0.05	0.80	0.15	Manhattan	Vector	S2	0.9696
41	7	0.05	0.80	0.15	Manhattan	Max	S2	0.9688
42	7	0.05	0.80	0.15	Manhattan	Sum	S2	0.9698
43	8	0.05	0.85	0.10	Euclidean	Vector	S2	0.9673
44	8	0.05	0.85	0.10	Euclidean	Max	S2	0.9660
45	8	0.05	0.85	0.10	Euclidean	Sum	S2	0.9675
46	8	0.05	0.85	0.10	Manhattan	Vector	S2	0.9701
47	8	0.05	0.85	0.10	Manhattan	Max	S2	0.9692
48	8	0.05	0.85	0.10	Manhattan	Sum	S2	0.9703
49	9	0.05	0.90	0.05	Euclidean	Vector	S2	0.9690
50	9	0.05	0.90	0.05	Euclidean	Max	S2	0.9678
51	9	0.05	0.90	0.05	Euclidean	Sum	S2	0.9692
52	9	0.05	0.90	0.05	Manhattan	Vector	S2	0.9706
53	9	0.05	0.90	0.05	Manhattan	Max	S2	0.9696
54	9	0.05	0.90	0.05	Manhattan	Sum	S2	0.9708
55	10	0.10	0.50	0.40	Euclidean	Vector	S2	0.9082
56	10	0.10	0.50	0.40	Euclidean	Max	S2	0.9069
57	10	0.10	0.50	0.40	Euclidean	Sum	S2	0.9083
58	10	0.10	0.50	0.40	Manhattan	Vector	S2	0.9336
59	10	0.10	0.50	0.40	Manhattan	Max	S2	0.9333
60	10	0.10	0.50	0.40	Manhattan	Sum	S2	0.9335
61	11	0.10	0.55	0.35	Euclidean	Vector	S2	0.9123
62	11	0.10	0.55	0.35	Euclidean	Max	S2	0.9105
63	11	0.10	0.55	0.35	Euclidean	Sum	S2	0.9126
64	11	0.10	0.55	0.35	Manhattan	Vector	S2	0.9347
65	11	0.10	0.55	0.35	Manhattan	Max	S2	0.9342
66	11	0.10	0.55	0.35	Manhattan	Sum	S2	0.9347
67	12	0.10	0.60	0.30	Euclidean	Vector	S2	0.9167
68	12	0.10	0.60	0.30	Euclidean	Max	S2	0.9145
69	12	0.10	0.60	0.30	Euclidean	Sum	S2	0.9171
70	12	0.10	0.60	0.30	Manhattan	Vector	S2	0.9359
71	12	0.10	0.60	0.30	Manhattan	Max	S2	0.9351
72	12	0.10	0.60	0.30	Manhattan	Sum	S2	0.9360
73	13	0.10	0.65	0.25	Euclidean	Vector	S2	0.9210
74	13	0.10	0.65	0.25	Euclidean	Max	S2	0.9187
75	13	0.10	0.65	0.25	Euclidean	Sum	S2	0.9215
76	13	0.10	0.65	0.25	Manhattan	Vector	S2	0.9370
77	13	0.10	0.65	0.25	Manhattan	Max	S2	0.9360

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
78	13	0.10	0.65	0.25	Manhattan	Sum	S2	0.9371
79	14	0.10	0.70	0.20	Euclidean	Vector	S2	0.9252
80	14	0.10	0.70	0.20	Euclidean	Max	S2	0.9228
81	14	0.10	0.70	0.20	Euclidean	Sum	S2	0.9257
82	14	0.10	0.70	0.20	Manhattan	Vector	S2	0.9381
83	14	0.10	0.70	0.20	Manhattan	Max	S2	0.9368
84	14	0.10	0.70	0.20	Manhattan	Sum	S2	0.9383
85	15	0.10	0.75	0.15	Euclidean	Vector	S2	0.9292
86	15	0.10	0.75	0.15	Euclidean	Max	S2	0.9268
87	15	0.10	0.75	0.15	Euclidean	Sum	S2	0.9297
88	15	0.10	0.75	0.15	Manhattan	Vector	S2	0.9391
89	15	0.10	0.75	0.15	Manhattan	Max	S2	0.9377
90	15	0.10	0.75	0.15	Manhattan	Sum	S2	0.9394
91	16	0.10	0.80	0.10	Euclidean	Vector	S2	0.9330
92	16	0.10	0.80	0.10	Euclidean	Max	S2	0.9306
93	16	0.10	0.80	0.10	Euclidean	Sum	S2	0.9335
94	16	0.10	0.80	0.10	Manhattan	Vector	S2	0.9401
95	16	0.10	0.80	0.10	Manhattan	Max	S2	0.9385
96	16	0.10	0.80	0.10	Manhattan	Sum	S2	0.9405
97	17	0.10	0.85	0.05	Euclidean	Vector	S2	0.9365
98	17	0.10	0.85	0.05	Euclidean	Max	S2	0.9342
99	17	0.10	0.85	0.05	Euclidean	Sum	S2	0.9370
100	17	0.10	0.85	0.05	Manhattan	Vector	S2	0.9411
101	17	0.10	0.85	0.05	Manhattan	Max	S2	0.9392
102	17	0.10	0.85	0.05	Manhattan	Sum	S2	0.9415
103	18	0.15	0.50	0.35	Euclidean	Vector	S2	0.8655
104	18	0.15	0.50	0.35	Euclidean	Max	S2	0.8632
105	18	0.15	0.50	0.35	Euclidean	Sum	S2	0.8658
106	18	0.15	0.50	0.35	Manhattan	Vector	S2	0.9019
107	18	0.15	0.50	0.35	Manhattan	Max	S2	0.9014
108	18	0.15	0.50	0.35	Manhattan	Sum	S2	0.9019
109	19	0.15	0.55	0.30	Euclidean	Vector	S2	0.8720
110	19	0.15	0.55	0.30	Euclidean	Max	S2	0.8690
111	19	0.15	0.55	0.30	Euclidean	Sum	S2	0.8725
112	19	0.15	0.55	0.30	Manhattan	Vector	S2	0.9037
113	19	0.15	0.55	0.30	Manhattan	Max	S2	0.9027
114	19	0.15	0.55	0.30	Manhattan	Sum	S2	0.9037
115	20	0.15	0.60	0.25	Euclidean	Vector	S2	0.8786
116	20	0.15	0.60	0.25	Euclidean	Max	S2	0.8753

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
117	20	0.15	0.60	0.25	Euclidean	Sum	S2	0.8792
118	20	0.15	0.60	0.25	Manhattan	Vector	S2	0.9053
119	20	0.15	0.60	0.25	Manhattan	Max	S2	0.9040
120	20	0.15	0.60	0.25	Manhattan	Sum	S2	0.9055
121	21	0.15	0.65	0.20	Euclidean	Vector	S2	0.8851
122	21	0.15	0.65	0.20	Euclidean	Max	S2	0.8815
123	21	0.15	0.65	0.20	Euclidean	Sum	S2	0.8857
124	21	0.15	0.65	0.20	Manhattan	Vector	S2	0.9070
125	21	0.15	0.65	0.20	Manhattan	Max	S2	0.9053
126	21	0.15	0.65	0.20	Manhattan	Sum	S2	0.9072
127	22	0.15	0.70	0.15	Euclidean	Vector	S2	0.8913
128	22	0.15	0.70	0.15	Euclidean	Max	S2	0.8877
129	22	0.15	0.70	0.15	Euclidean	Sum	S2	0.8920
130	22	0.15	0.70	0.15	Manhattan	Vector	S2	0.9085
131	22	0.15	0.70	0.15	Manhattan	Max	S2	0.9065
132	22	0.15	0.70	0.15	Manhattan	Sum	S2	0.9089
133	23	0.15	0.75	0.10	Euclidean	Vector	S2	0.8972
134	23	0.15	0.75	0.10	Euclidean	Max	S2	0.8936
135	23	0.15	0.75	0.10	Euclidean	Sum	S2	0.8979
136	23	0.15	0.75	0.10	Manhattan	Vector	S2	0.9100
137	23	0.15	0.75	0.10	Manhattan	Max	S2	0.9077
138	23	0.15	0.75	0.10	Manhattan	Sum	S2	0.9105
139	24	0.15	0.80	0.05	Euclidean	Vector	S2	0.9027
140	24	0.15	0.80	0.05	Euclidean	Max	S2	0.8992
141	24	0.15	0.80	0.05	Euclidean	Sum	S2	0.9033
142	24	0.15	0.80	0.05	Manhattan	Vector	S2	0.9115
143	24	0.15	0.80	0.05	Manhattan	Max	S2	0.9089
144	24	0.15	0.80	0.05	Manhattan	Sum	S2	0.9120
145	25	0.20	0.50	0.30	Euclidean	Vector	S2	0.8254
146	25	0.20	0.50	0.30	Euclidean	Max	S2	0.8220
147	25	0.20	0.50	0.30	Euclidean	Sum	S2	0.8259
148	25	0.20	0.50	0.30	Manhattan	Vector	S2	0.8713
149	25	0.20	0.50	0.30	Manhattan	Max	S2	0.8703
150	25	0.20	0.50	0.30	Manhattan	Sum	S2	0.8713
151	26	0.20	0.55	0.25	Euclidean	Vector	S2	0.8342
152	26	0.20	0.55	0.25	Euclidean	Max	S2	0.8302
153	26	0.20	0.55	0.25	Euclidean	Sum	S2	0.8350
154	26	0.20	0.55	0.25	Manhattan	Vector	S2	0.8735
155	26	0.20	0.55	0.25	Manhattan	Max	S2	0.8720

S/N	Weigh t Comb inatio n	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
156	26	0.20	0.55	0.25	Manhattan	Sum	S2	0.8737
157	27	0.20	0.60	0.20	Euclidean	Vector	S2	0.8431
158	27	0.20	0.60	0.20	Euclidean	Max	S2	0.8386
159	27	0.20	0.60	0.20	Euclidean	Sum	S2	0.8439
160	27	0.20	0.60	0.20	Manhattan	Vector	S2	0.8757
161	27	0.20	0.60	0.20	Manhattan	Max	S2	0.8737
162	27	0.20	0.60	0.20	Manhattan	Sum	S2	0.8760
163	28	0.20	0.65	0.15	Euclidean	Vector	S2	0.8516
164	28	0.20	0.65	0.15	Euclidean	Max	S2	0.8470
165	28	0.20	0.65	0.15	Euclidean	Sum	S2	0.8525
166	28	0.20	0.65	0.15	Manhattan	Vector	S2	0.8778
167	28	0.20	0.65	0.15	Manhattan	Max	S2	0.8753
168	28	0.20	0.65	0.15	Manhattan	Sum	S2	0.8782
169	29	0.20	0.70	0.10	Euclidean	Vector	S2	0.8597
170	29	0.20	0.70	0.10	Euclidean	Max	S2	0.8552
171	29	0.20	0.70	0.10	Euclidean	Sum	S2	0.8606
172	29	0.20	0.70	0.10	Manhattan	Vector	S2	0.8798
173	29	0.20	0.70	0.10	Manhattan	Max	S2	0.8769
174	29	0.20	0.70	0.10	Manhattan	Sum	S2	0.8803
175	30	0.20	0.75	0.05	Euclidean	Vector	S2	0.8673
176	30	0.20	0.75	0.05	Euclidean	Max	S2	0.8629
177	30	0.20	0.75	0.05	Euclidean	Sum	S2	0.8682
178	30	0.20	0.75	0.05	Manhattan	Vector	S2	0.8818
179	30	0.20	0.75	0.05	Manhattan	Max	S2	0.8785
180	30	0.20	0.75	0.05	Manhattan	Sum	S2	0.8824
181	31	0.25	0.50	0.25	Euclidean	Vector	S2	0.7882
182	31	0.25	0.50	0.25	Euclidean	Max	S2	0.7836
183	31	0.25	0.50	0.25	Euclidean	Sum	S2	0.7890
184	31	0.25	0.50	0.25	Manhattan	Vector	S2	0.8416
185	31	0.25	0.50	0.25	Manhattan	Max	S2	0.8400
186	31	0.25	0.50	0.25	Manhattan	Sum	S2	0.8417
187	32	0.25	0.55	0.20	Euclidean	Vector	S2	0.7993
188	32	0.25	0.55	0.20	Euclidean	Max	S2	0.7942
189	32	0.25	0.55	0.20	Euclidean	Sum	S2	0.8003
190	32	0.25	0.55	0.20	Manhattan	Vector	S2	0.8443
191	32	0.25	0.55	0.20	Manhattan	Max	S2	0.8421
192	32	0.25	0.55	0.20	Manhattan	Sum	S2	0.8446
193	33	0.25	0.60	0.15	Euclidean	Vector	S2	0.8103
194	33	0.25	0.60	0.15	Euclidean	Max	S2	0.8048

S/N	Weigh t Comb inatio n	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
195	33	0.25	0.60	0.15	Euclidean	Sum	S2	0.8113
196	33	0.25	0.60	0.15	Manhattan	Vector	S2	0.8469
197	33	0.25	0.60	0.15	Manhattan	Max	S2	0.8442
198	33	0.25	0.60	0.15	Manhattan	Sum	S2	0.8474
199	34	0.25	0.65	0.10	Euclidean	Vector	S2	0.8207
200	34	0.25	0.65	0.10	Euclidean	Max	S2	0.8153
201	34	0.25	0.65	0.10	Euclidean	Sum	S2	0.8218
202	34	0.25	0.65	0.10	Manhattan	Vector	S2	0.8495
203	34	0.25	0.65	0.10	Manhattan	Max	S2	0.8462
204	34	0.25	0.65	0.10	Manhattan	Sum	S2	0.8501
205	35	0.25	0.70	0.05	Euclidean	Vector	S2	0.8306
206	35	0.25	0.70	0.05	Euclidean	Max	S2	0.8252
207	35	0.25	0.70	0.05	Euclidean	Sum	S2	0.8316
208	35	0.25	0.70	0.05	Manhattan	Vector	S2	0.8519
209	35	0.25	0.70	0.05	Manhattan	Max	S2	0.8481
210	35	0.25	0.70	0.05	Manhattan	Sum	S2	0.8527
211	36	0.30	0.50	0.20	Euclidean	Vector	S2	0.7541
212	36	0.30	0.50	0.20	Euclidean	Max	S2	0.7485
213	36	0.30	0.50	0.20	Euclidean	Sum	S2	0.7551
214	36	0.30	0.50	0.20	Manhattan	Vector	S2	0.8128
215	36	0.30	0.50	0.20	Manhattan	Max	S2	0.8105
216	36	0.30	0.50	0.20	Manhattan	Sum	S2	0.8130
217	37	0.30	0.55	0.15	Euclidean	Vector	S2	0.7674
218	37	0.30	0.55	0.15	Euclidean	Max	S2	0.7613
219	37	0.30	0.55	0.15	Euclidean	Sum	S2	0.7686
220	37	0.30	0.55	0.15	Manhattan	Vector	S2	0.8159
221	37	0.30	0.55	0.15	Manhattan	Max	S2	0.8130
222	37	0.30	0.55	0.15	Manhattan	Sum	S2	0.8164
223	38	0.30	0.60	0.10	Euclidean	Vector	S2	0.7803
224	38	0.30	0.60	0.10	Euclidean	Max	S2	0.7740
225	38	0.30	0.60	0.10	Euclidean	Sum	S2	0.7815
226	38	0.30	0.60	0.10	Manhattan	Vector	S2	0.8190
227	38	0.30	0.60	0.10	Manhattan	Max	S2	0.8154
228	38	0.30	0.60	0.10	Manhattan	Sum	S2	0.8196
229	39	0.30	0.65	0.05	Euclidean	Vector	S2	0.7924
230	39	0.30	0.65	0.05	Euclidean	Max	S2	0.7862
231	39	0.30	0.65	0.05	Euclidean	Sum	S2	0.7937
232	39	0.30	0.65	0.05	Manhattan	Vector	S2	0.8220
233	39	0.30	0.65	0.05	Manhattan	Max	S2	0.8177

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
234	39	0.30	0.65	0.05	Manhattan	Sum	S2	0.8228
235	40	0.35	0.50	0.15	Euclidean	Vector	S2	0.7232
236	40	0.35	0.50	0.15	Euclidean	Max	S2	0.7167
237	40	0.35	0.50	0.15	Euclidean	Sum	S2	0.7245
238	40	0.35	0.50	0.15	Manhattan	Vector	S2	0.7848
239	40	0.35	0.50	0.15	Manhattan	Max	S2	0.7818
240	40	0.35	0.50	0.15	Manhattan	Sum	S2	0.7853
241	41	0.35	0.55	0.10	Euclidean	Vector	S2	0.7384
242	41	0.35	0.55	0.10	Euclidean	Max	S2	0.7316
243	41	0.35	0.55	0.10	Euclidean	Sum	S2	0.7398
244	41	0.35	0.55	0.10	Manhattan	Vector	S2	0.7884
245	41	0.35	0.55	0.10	Manhattan	Max	S2	0.7846
246	41	0.35	0.55	0.10	Manhattan	Sum	S2	0.7891
247	42	0.35	0.60	0.05	Euclidean	Vector	S2	0.7530
248	42	0.35	0.60	0.05	Euclidean	Max	S2	0.7461
249	42	0.35	0.60	0.05	Euclidean	Sum	S2	0.7544
250	42	0.35	0.60	0.05	Manhattan	Vector	S2	0.7919
251	42	0.35	0.60	0.05	Manhattan	Max	S2	0.7873
252	42	0.35	0.60	0.05	Manhattan	Sum	S2	0.7928
253	43	0.40	0.50	0.10	Euclidean	Vector	S2	0.6956
254	43	0.40	0.50	0.10	Euclidean	Max	S2	0.6884
255	43	0.40	0.50	0.10	Euclidean	Sum	S2	0.6970
256	43	0.40	0.50	0.10	Manhattan	Vector	S2	0.7577
257	43	0.40	0.50	0.10	Manhattan	Max	S2	0.7538
258	43	0.40	0.50	0.10	Manhattan	Sum	S2	0.7584
259	44	0.40	0.55	0.05	Euclidean	Vector	S2	0.7125
260	44	0.40	0.55	0.05	Euclidean	Max	S2	0.7052
261	44	0.40	0.55	0.05	Euclidean	Sum	S2	0.7139
262	44	0.40	0.55	0.05	Manhattan	Vector	S2	0.7617
263	44	0.40	0.55	0.05	Manhattan	Max	S2	0.7570
264	44	0.40	0.55	0.05	Manhattan	Sum	S2	0.7626
265	45	0.45	0.50	0.05	Euclidean	Vector	S2	0.6712
266	45	0.45	0.50	0.05	Euclidean	Max	S2	0.6636
267	45	0.45	0.50	0.05	Euclidean	Sum	S2	0.6727
268	45	0.45	0.50	0.05	Manhattan	Vector	S2	0.7314
269	45	0.45	0.50	0.05	Manhattan	Max	S2	0.7266
270	45	0.45	0.50	0.05	Manhattan	Sum	S1	0.7323

Dataset of CC_i Values for Alternative S3

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
1	1	0.05	0.50	0.45	Euclidean	Vector	S3	0.5510
2	1	0.05	0.50	0.45	Euclidean	Max	S3	0.5294
3	1	0.05	0.50	0.45	Euclidean	Sum	S3	0.5568
4	1	0.05	0.50	0.45	Manhattan	Vector	S3	0.4681
5	1	0.05	0.50	0.45	Manhattan	Max	S3	0.4507
6	1	0.05	0.50	0.45	Manhattan	Sum	S3	0.4727
7	2	0.05	0.55	0.40	Euclidean	Vector	S3	0.5965
8	2	0.05	0.55	0.40	Euclidean	Max	S3	0.5764
9	2	0.05	0.55	0.40	Euclidean	Sum	S3	0.6018
10	2	0.05	0.55	0.40	Manhattan	Vector	S3	0.5055
11	2	0.05	0.55	0.40	Manhattan	Max	S3	0.4889
12	2	0.05	0.55	0.40	Manhattan	Sum	S3	0.5099
13	3	0.05	0.60	0.35	Euclidean	Vector	S3	0.6390
14	3	0.05	0.60	0.35	Euclidean	Max	S3	0.6210
15	3	0.05	0.60	0.35	Euclidean	Sum	S3	0.6438
16	3	0.05	0.60	0.35	Manhattan	Vector	S3	0.5415
17	3	0.05	0.60	0.35	Manhattan	Max	S3	0.5260
18	3	0.05	0.60	0.35	Manhattan	Sum	S3	0.5456
19	4	0.05	0.65	0.30	Euclidean	Vector	S3	0.6781
20	4	0.05	0.65	0.30	Euclidean	Max	S3	0.6627
21	4	0.05	0.65	0.30	Euclidean	Sum	S3	0.6821
22	4	0.05	0.65	0.30	Manhattan	Vector	S3	0.5763
23	4	0.05	0.65	0.30	Manhattan	Max	S3	0.5622
24	4	0.05	0.65	0.30	Manhattan	Sum	S3	0.5799
25	5	0.05	0.70	0.25	Euclidean	Vector	S3	0.7128
26	5	0.05	0.70	0.25	Euclidean	Max	S3	0.7006
27	5	0.05	0.70	0.25	Euclidean	Sum	S3	0.7159
28	5	0.05	0.70	0.25	Manhattan	Vector	S3	0.6098
29	5	0.05	0.70	0.25	Manhattan	Max	S3	0.5973
30	5	0.05	0.70	0.25	Manhattan	Sum	S3	0.6130
31	6	0.05	0.75	0.20	Euclidean	Vector	S3	0.7424
32	6	0.05	0.75	0.20	Euclidean	Max	S3	0.7335
33	6	0.05	0.75	0.20	Euclidean	Sum	S3	0.7446
34	6	0.05	0.75	0.20	Manhattan	Vector	S3	0.6422
35	6	0.05	0.75	0.20	Manhattan	Max	S3	0.6316
36	6	0.05	0.75	0.20	Manhattan	Sum	S3	0.6449
37	7	0.05	0.80	0.15	Euclidean	Vector	S3	0.7657
38	7	0.05	0.80	0.15	Euclidean	Max	S3	0.7602
39	7	0.05	0.80	0.15	Euclidean	Sum	S3	0.7671

S/N	Weigh t Combi nation	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
40	7	0.05	0.80	0.15	Manhattan	Vector	S3	0.6735
41	7	0.05	0.80	0.15	Manhattan	Max	S3	0.6649
42	7	0.05	0.80	0.15	Manhattan	Sum	S3	0.6757
43	8	0.05	0.85	0.10	Euclidean	Vector	S3	0.7822
44	8	0.05	0.85	0.10	Euclidean	Max	S3	0.7794
45	8	0.05	0.85	0.10	Euclidean	Sum	S3	0.7829
46	8	0.05	0.85	0.10	Manhattan	Vector	S3	0.7038
47	8	0.05	0.85	0.10	Manhattan	Max	S3	0.6974
48	8	0.05	0.85	0.10	Manhattan	Sum	S3	0.7054
49	9	0.05	0.90	0.05	Euclidean	Vector	S3	0.7917
50	9	0.05	0.90	0.05	Euclidean	Max	S3	0.7907
51	9	0.05	0.90	0.05	Euclidean	Sum	S3	0.7919
52	9	0.05	0.90	0.05	Manhattan	Vector	S3	0.7331
53	9	0.05	0.90	0.05	Manhattan	Max	S3	0.7291
54	9	0.05	0.90	0.05	Manhattan	Sum	S3	0.7340
55	10	0.10	0.50	0.40	Euclidean	Vector	S3	0.5668
56	10	0.10	0.50	0.40	Euclidean	Max	S3	0.5467
57	10	0.10	0.50	0.40	Euclidean	Sum	S3	0.5721
58	10	0.10	0.50	0.40	Manhattan	Vector	S3	0.4605
59	10	0.10	0.50	0.40	Manhattan	Max	S3	0.4444
60	10	0.10	0.50	0.40	Manhattan	Sum	S3	0.4647
61	11	0.10	0.55	0.35	Euclidean	Vector	S3	0.6115
62	11	0.10	0.55	0.35	Euclidean	Max	S3	0.5933
63	11	0.10	0.55	0.35	Euclidean	Sum	S3	0.6162
64	11	0.10	0.55	0.35	Manhattan	Vector	S3	0.4974
65	11	0.10	0.55	0.35	Manhattan	Max	S3	0.4822
66	11	0.10	0.55	0.35	Manhattan	Sum	S3	0.5014
67	12	0.10	0.60	0.30	Euclidean	Vector	S3	0.6524
68	12	0.10	0.60	0.30	Euclidean	Max	S3	0.6367
69	12	0.10	0.60	0.30	Euclidean	Sum	S3	0.6565
70	12	0.10	0.60	0.30	Manhattan	Vector	S3	0.5331
71	12	0.10	0.60	0.30	Manhattan	Max	S3	0.5189
72	12	0.10	0.60	0.30	Manhattan	Sum	S3	0.5367
73	13	0.10	0.65	0.25	Euclidean	Vector	S3	0.6889
74	13	0.10	0.65	0.25	Euclidean	Max	S3	0.6761
75	13	0.10	0.65	0.25	Euclidean	Sum	S3	0.6921
76	13	0.10	0.65	0.25	Manhattan	Vector	S3	0.5674
77	13	0.10	0.65	0.25	Manhattan	Max	S3	0.5547
78	13	0.10	0.65	0.25	Manhattan	Sum	S3	0.5706
79	14	0.10	0.70	0.20	Euclidean	Vector	S3	0.7201

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
80	14	0.10	0.70	0.20	Euclidean	Max	S3	0.7104
81	14	0.10	0.70	0.20	Euclidean	Sum	S3	0.7224
82	14	0.10	0.70	0.20	Manhattan	Vector	S3	0.6006
83	14	0.10	0.70	0.20	Manhattan	Max	S3	0.5895
84	14	0.10	0.70	0.20	Manhattan	Sum	S3	0.6034
85	15	0.10	0.75	0.15	Euclidean	Vector	S3	0.7450
86	15	0.10	0.75	0.15	Euclidean	Max	S3	0.7385
87	15	0.10	0.75	0.15	Euclidean	Sum	S3	0.7465
88	15	0.10	0.75	0.15	Manhattan	Vector	S3	0.6327
89	15	0.10	0.75	0.15	Manhattan	Max	S3	0.6234
90	15	0.10	0.75	0.15	Manhattan	Sum	S3	0.6350
91	16	0.10	0.80	0.10	Euclidean	Vector	S3	0.7631
92	16	0.10	0.80	0.10	Euclidean	Max	S3	0.7592
93	16	0.10	0.80	0.10	Euclidean	Sum	S3	0.7639
94	16	0.10	0.80	0.10	Manhattan	Vector	S3	0.6637
95	16	0.10	0.80	0.10	Manhattan	Max	S3	0.6564
96	16	0.10	0.80	0.10	Manhattan	Sum	S3	0.6654
97	17	0.10	0.85	0.05	Euclidean	Vector	S3	0.7742
98	17	0.10	0.85	0.05	Euclidean	Max	S3	0.7721
99	17	0.10	0.85	0.05	Euclidean	Sum	S3	0.7747
100	17	0.10	0.85	0.05	Manhattan	Vector	S3	0.6937
101	17	0.10	0.85	0.05	Manhattan	Max	S3	0.6886
102	17	0.10	0.85	0.05	Manhattan	Sum	S3	0.6949
103	18	0.15	0.50	0.35	Euclidean	Vector	S3	0.5747
104	18	0.15	0.50	0.35	Euclidean	Max	S3	0.5568
105	18	0.15	0.50	0.35	Euclidean	Sum	S3	0.5793
106	18	0.15	0.50	0.35	Manhattan	Vector	S3	0.4532
107	18	0.15	0.50	0.35	Manhattan	Max	S3	0.4384
108	18	0.15	0.50	0.35	Manhattan	Sum	S3	0.4570
109	19	0.15	0.55	0.30	Euclidean	Vector	S3	0.6169
110	19	0.15	0.55	0.30	Euclidean	Max	S3	0.6011
111	19	0.15	0.55	0.30	Euclidean	Sum	S3	0.6209
112	19	0.15	0.55	0.30	Manhattan	Vector	S3	0.4897
113	19	0.15	0.55	0.30	Manhattan	Max	S3	0.4757
114	19	0.15	0.55	0.30	Manhattan	Sum	S3	0.4932
115	20	0.15	0.60	0.25	Euclidean	Vector	S3	0.6545
116	20	0.15	0.60	0.25	Euclidean	Max	S3	0.6413
117	20	0.15	0.60	0.25	Euclidean	Sum	S3	0.6577
118	20	0.15	0.60	0.25	Manhattan	Vector	S3	0.5249
119	20	0.15	0.60	0.25	Manhattan	Max	S3	0.5120

S/N	Weigh t Combi nation	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
120	20	0.15	0.60	0.25	Manhattan	Sum	S3	0.5281
121	21	0.15	0.65	0.20	Euclidean	Vector	S3	0.6867
122	21	0.15	0.65	0.20	Euclidean	Max	S3	0.6764
123	21	0.15	0.65	0.20	Euclidean	Sum	S3	0.6892
124	21	0.15	0.65	0.20	Manhattan	Vector	S3	0.5589
125	21	0.15	0.65	0.20	Manhattan	Max	S3	0.5474
126	21	0.15	0.65	0.20	Manhattan	Sum	S3	0.5617
127	22	0.15	0.70	0.15	Euclidean	Vector	S3	0.7129
128	22	0.15	0.70	0.15	Euclidean	Max	S3	0.7053
129	22	0.15	0.70	0.15	Euclidean	Sum	S3	0.7147
130	22	0.15	0.70	0.15	Manhattan	Vector	S3	0.5917
131	22	0.15	0.70	0.15	Manhattan	Max	S3	0.5818
132	22	0.15	0.70	0.15	Manhattan	Sum	S3	0.5941
133	23	0.15	0.75	0.10	Euclidean	Vector	S3	0.7326
134	23	0.15	0.75	0.10	Euclidean	Max	S3	0.7273
135	23	0.15	0.75	0.10	Euclidean	Sum	S3	0.7338
136	23	0.15	0.75	0.10	Manhattan	Vector	S3	0.6235
137	23	0.15	0.75	0.10	Manhattan	Max	S3	0.6154
138	23	0.15	0.75	0.10	Manhattan	Sum	S3	0.6253
139	24	0.15	0.80	0.05	Euclidean	Vector	S3	0.7458
140	24	0.15	0.80	0.05	Euclidean	Max	S3	0.7420
141	24	0.15	0.80	0.05	Euclidean	Sum	S3	0.7466
142	24	0.15	0.80	0.05	Manhattan	Vector	S3	0.6542
143	24	0.15	0.80	0.05	Manhattan	Max	S3	0.6481
144	24	0.15	0.80	0.05	Manhattan	Sum	S3	0.6555
145	25	0.20	0.50	0.30	Euclidean	Vector	S3	0.5732
146	25	0.20	0.50	0.30	Euclidean	Max	S3	0.5577
147	25	0.20	0.50	0.30	Euclidean	Sum	S3	0.5769
148	25	0.20	0.50	0.30	Manhattan	Vector	S3	0.4461
149	25	0.20	0.50	0.30	Manhattan	Max	S3	0.4324
150	25	0.20	0.50	0.30	Manhattan	Sum	S3	0.4495
151	26	0.20	0.55	0.25	Euclidean	Vector	S3	0.6116
152	26	0.20	0.55	0.25	Euclidean	Max	S3	0.5983
153	26	0.20	0.55	0.25	Euclidean	Sum	S3	0.6147
154	26	0.20	0.55	0.25	Manhattan	Vector	S3	0.4821
155	26	0.20	0.55	0.25	Manhattan	Max	S3	0.4693
156	26	0.20	0.55	0.25	Manhattan	Sum	S3	0.4853
157	27	0.20	0.60	0.20	Euclidean	Vector	S3	0.6447
158	27	0.20	0.60	0.20	Euclidean	Max	S3	0.6338
159	27	0.20	0.60	0.20	Euclidean	Sum	S3	0.6472

S/N	Weigh t Combi nation	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
160	27	0.20	0.60	0.20	Manhattan	Vector	S3	0.5169
161	27	0.20	0.60	0.20	Manhattan	Max	S3	0.5053
162	27	0.20	0.60	0.20	Manhattan	Sum	S3	0.5197
163	28	0.20	0.65	0.15	Euclidean	Vector	S3	0.6721
164	28	0.20	0.65	0.15	Euclidean	Max	S3	0.6635
165	28	0.20	0.65	0.15	Euclidean	Sum	S3	0.6740
166	28	0.20	0.65	0.15	Manhattan	Vector	S3	0.5505
167	28	0.20	0.65	0.15	Manhattan	Max	S3	0.5403
168	28	0.20	0.65	0.15	Manhattan	Sum	S3	0.5530
169	29	0.20	0.70	0.10	Euclidean	Vector	S3	0.6935
170	29	0.20	0.70	0.10	Euclidean	Max	S3	0.6868
171	29	0.20	0.70	0.10	Euclidean	Sum	S3	0.6949
172	29	0.20	0.70	0.10	Manhattan	Vector	S3	0.5830
173	29	0.20	0.70	0.10	Manhattan	Max	S3	0.5744
174	29	0.20	0.70	0.10	Manhattan	Sum	S3	0.5850
175	30	0.20	0.75	0.05	Euclidean	Vector	S3	0.7090
176	30	0.20	0.75	0.05	Euclidean	Max	S3	0.7036
177	30	0.20	0.75	0.05	Euclidean	Sum	S3	0.7100
178	30	0.20	0.75	0.05	Manhattan	Vector	S3	0.6145
179	30	0.20	0.75	0.05	Manhattan	Max	S3	0.6076
180	30	0.20	0.75	0.05	Manhattan	Sum	S3	0.6160
181	31	0.25	0.50	0.25	Euclidean	Vector	S3	0.5625
182	31	0.25	0.50	0.25	Euclidean	Max	S3	0.5494
183	31	0.25	0.50	0.25	Euclidean	Sum	S3	0.5655
184	31	0.25	0.50	0.25	Manhattan	Vector	S3	0.4392
185	31	0.25	0.50	0.25	Manhattan	Max	S3	0.4267
186	31	0.25	0.50	0.25	Manhattan	Sum	S3	0.4423
187	32	0.25	0.55	0.20	Euclidean	Vector	S3	0.5966
188	32	0.25	0.55	0.20	Euclidean	Max	S3	0.5854
189	32	0.25	0.55	0.20	Euclidean	Sum	S3	0.5992
190	32	0.25	0.55	0.20	Manhattan	Vector	S3	0.4748
191	32	0.25	0.55	0.20	Manhattan	Max	S3	0.4632
192	32	0.25	0.55	0.20	Manhattan	Sum	S3	0.4776
193	33	0.25	0.60	0.15	Euclidean	Vector	S3	0.6254
194	33	0.25	0.60	0.15	Euclidean	Max	S3	0.6160
195	33	0.25	0.60	0.15	Euclidean	Sum	S3	0.6274
196	33	0.25	0.60	0.15	Manhattan	Vector	S3	0.5092
197	33	0.25	0.60	0.15	Manhattan	Max	S3	0.4987
198	33	0.25	0.60	0.15	Manhattan	Sum	S3	0.5117
199	34	0.25	0.65	0.10	Euclidean	Vector	S3	0.6486

S/N	Weigh t Combi nation	w_1	w_2	w_3	Distance Calculation	Normaliz ation	S_i	CC_i
200	34	0.25	0.65	0.10	Euclidean	Max	S3	0.6407
201	34	0.25	0.65	0.10	Euclidean	Sum	S3	0.6502
202	34	0.25	0.65	0.10	Manhattan	Vector	S3	0.5425
203	34	0.25	0.65	0.10	Manhattan	Max	S3	0.5333
204	34	0.25	0.65	0.10	Manhattan	Sum	S3	0.5445
205	35	0.25	0.70	0.05	Euclidean	Vector	S3	0.6664
206	35	0.25	0.70	0.05	Euclidean	Max	S3	0.6596
207	35	0.25	0.70	0.05	Euclidean	Sum	S3	0.6677
208	35	0.25	0.70	0.05	Manhattan	Vector	S3	0.5746
209	35	0.25	0.70	0.05	Manhattan	Max	S3	0.5671
210	35	0.25	0.70	0.05	Manhattan	Sum	S3	0.5763
211	36	0.30	0.50	0.20	Euclidean	Vector	S3	0.5447
212	36	0.30	0.50	0.20	Euclidean	Max	S3	0.5333
213	36	0.30	0.50	0.20	Euclidean	Sum	S3	0.5472
214	36	0.30	0.50	0.20	Manhattan	Vector	S3	0.4325
215	36	0.30	0.50	0.20	Manhattan	Max	S3	0.4211
216	36	0.30	0.50	0.20	Manhattan	Sum	S3	0.4353
217	37	0.30	0.55	0.15	Euclidean	Vector	S3	0.5750
218	37	0.30	0.55	0.15	Euclidean	Max	S3	0.5650
219	37	0.30	0.55	0.15	Euclidean	Sum	S3	0.5771
220	37	0.30	0.55	0.15	Manhattan	Vector	S3	0.4677
221	37	0.30	0.55	0.15	Manhattan	Max	S3	0.4571
222	37	0.30	0.55	0.15	Manhattan	Sum	S3	0.4702
223	38	0.30	0.60	0.10	Euclidean	Vector	S3	0.6001
224	38	0.30	0.60	0.10	Euclidean	Max	S3	0.5914
225	38	0.30	0.60	0.10	Euclidean	Sum	S3	0.6019
226	38	0.30	0.60	0.10	Manhattan	Vector	S3	0.5017
227	38	0.30	0.60	0.10	Manhattan	Max	S3	0.4923
228	38	0.30	0.60	0.10	Manhattan	Sum	S3	0.5038
229	39	0.30	0.65	0.05	Euclidean	Vector	S3	0.6203
230	39	0.30	0.65	0.05	Euclidean	Max	S3	0.6124
231	39	0.30	0.65	0.05	Euclidean	Sum	S3	0.6218
232	39	0.30	0.65	0.05	Manhattan	Vector	S3	0.5346
233	39	0.30	0.65	0.05	Manhattan	Max	S3	0.5266
234	39	0.30	0.65	0.05	Manhattan	Sum	S3	0.5363
235	40	0.35	0.50	0.15	Euclidean	Vector	S3	0.5224
236	40	0.35	0.50	0.15	Euclidean	Max	S3	0.5122
237	40	0.35	0.50	0.15	Euclidean	Sum	S3	0.5245
238	40	0.35	0.50	0.15	Manhattan	Vector	S3	0.4261
239	40	0.35	0.50	0.15	Manhattan	Max	S3	0.4156

S/N	Weight Combination	w_1	w_2	w_3	Distance Calculation	Normalization	S_i	CC_i
240	40	0.35	0.50	0.15	Manhattan	Sum	S3	0.4285
241	41	0.35	0.55	0.10	Euclidean	Vector	S3	0.5495
242	41	0.35	0.55	0.10	Euclidean	Max	S3	0.5402
243	41	0.35	0.55	0.10	Euclidean	Sum	S3	0.5514
244	41	0.35	0.55	0.10	Manhattan	Vector	S3	0.4608
245	41	0.35	0.55	0.10	Manhattan	Max	S3	0.4513
246	41	0.35	0.55	0.10	Manhattan	Sum	S3	0.4630
247	42	0.35	0.60	0.05	Euclidean	Vector	S3	0.5721
248	42	0.35	0.60	0.05	Euclidean	Max	S3	0.5634
249	42	0.35	0.60	0.05	Euclidean	Sum	S3	0.5738
250	42	0.35	0.60	0.05	Manhattan	Vector	S3	0.4945
251	42	0.35	0.60	0.05	Manhattan	Max	S3	0.4861
252	42	0.35	0.60	0.05	Manhattan	Sum	S3	0.4963
253	43	0.40	0.50	0.10	Euclidean	Vector	S3	0.4979
254	43	0.40	0.50	0.10	Euclidean	Max	S3	0.4884
255	43	0.40	0.50	0.10	Euclidean	Sum	S3	0.4999
256	43	0.40	0.50	0.10	Manhattan	Vector	S3	0.4198
257	43	0.40	0.50	0.10	Manhattan	Max	S3	0.4103
258	43	0.40	0.50	0.10	Manhattan	Sum	S3	0.4219
259	44	0.40	0.55	0.05	Euclidean	Vector	S3	0.5228
260	44	0.40	0.55	0.05	Euclidean	Max	S3	0.5137
261	44	0.40	0.55	0.05	Euclidean	Sum	S3	0.5246
262	44	0.40	0.55	0.05	Manhattan	Vector	S3	0.4542
263	44	0.40	0.55	0.05	Manhattan	Max	S3	0.4456
264	44	0.40	0.55	0.05	Manhattan	Sum	S3	0.4560
265	45	0.45	0.50	0.05	Euclidean	Vector	S3	0.4731
266	45	0.45	0.50	0.05	Euclidean	Max	S3	0.4638
267	45	0.45	0.50	0.05	Euclidean	Sum	S3	0.4749
268	45	0.45	0.50	0.05	Manhattan	Vector	S3	0.4137
269	45	0.45	0.50	0.05	Manhattan	Max	S3	0.4051
270	45	0.45	0.50	0.05	Manhattan	Sum	S3	0.4155

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