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Full Length Research Paper

Application of PROMETHEE II Model Technique to Evaluate Water Loss Management Strategies in Water Supply Systems

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Abstract

This paper presents combination of hydraulic modelling and multi-criteria aiding approaches in water loss management using Alexandra township, Johannesburg, South Africa as case study. Hydraulic analysis of Alexandra' water losses as a component of non-revenue showed an increases from 87.02% to 95.21% in 2016 and 2022.The authors used PROMETHEE-II'D-Sight' built-in sensitivity analysis software to evaluate decision makers' strategic preferences to finally integrate group decisions for water-loss reduction technique. For this purpose, six strategic objectives and ten evaluation criteria abstracted from the water utility' strategic thrust were evaluated by eight decision-makers by employing PROMETHEE II' weighted-preference outranking method to draw group divergence. The study objectives criteria for decision makers were characterized by environmental, institutional, technical capacity, public health, socioeconomic and financial governance. Applying a sequencing water loss hydraulic prioritization supported by decision-makers, a multi-criteria decision-analysis method explicated systematic preference-outranking, normalizing and elicitation of single-sided decisions into a combined global group-decision. The study' results expounded that high preferred integrated water loss reduction options for water managers should aim to enhance (i) technical capacity, (ii) financial reliability, (iii) socioeconomic and (iv) institutional governance objectives. The research shows how that decision-theory model can be integrated with practical hydraulic engineering research approaches.

Keywords: Decision-Theory, Evaluation Criteria, Multi-Criteria Decision Technique, Water Loss Management, Strategic Objectives, PROMETHEE II, D-Sight, Water Supply Systems.

1. INTRODUCTION

Water losses in the water supply networks (WSN) have grown particularly in many developing nations. Water loss is a primary drawback for the performance and economic sustainability of water utilities and is a key indicator of WSN inefficiencies. Water loss reduction is one efficient measure for reducing water shortage. Managing water loss. within the water supply system has become a crucial concern nowadays (Zyoud and Fuchs-Hanusch 2019). Emphasis is placed on ensuring the water meter's accuracy, water distribution stability as well as physical and apparent water losses. Accessibility to sufficient safe and good drinking water at an affordable cost is among the basic human rights. However, many water utilities are confronted with water shortages (Helmecke et al., 2020). In other studies Zese et al., 2021) highlighted water losses due to pipe bursts, leaking meters and even domestic household leakages. In most developing countries, there has been a failure to provide adequate water supply to the consumers, because of high water losses within WSS. Many studies have comprehensively confirmed that some countries have record water losses as a component of non-revenue water (NRW) as high as 50% of the total system input volume (SIV) in the water distribution network, and early 70% of water loss could be caused by poor network construction and design, exposed pipe damage, pipe theft, aging of pipes and poor sealing connection (Boztaş and Özdemir 2019 and Shushu et al., 2021).

Furthermore, the water-loss within the WDS is linked to environmental, social, public health and economic effects. Besides this, the WSS water losses minimize revenue, inflate the firm's operation and maintenance costs and potentially deteriorate water quality (Chini and Stillwell 2018; Ougougdal et al., 2020 and Mathye et al., 2022a). Therefore, water loss management is assumed to be the primary objective for effectively protecting scarce water resources (Oberascher 2019; Kisakye et al., 2022). At an economic scale, water losses reduce water utility revenue while increasing high production, transmission and production costs Al-Washali et al., 2017; Chini and Stillwell 2018 and Mathye et al. 2022a). Some studies have confirmed that prevailing socio-economic factors such as population growth, poverty, urbanization, increasing domestic demand, continuous industrialization and limited financial capacity contribute to water losses (Ougougdal et al., 2020). Most developing countries have had water losses associated with socio-economic factors (Ilaya-Ayza et al. 2017 and Mathye et al., 2022a). Furthermore, aging infrastructure, limited financial resources, poor active leak control methodologies, reduced speed of repair action, poor quality repair, lack of new pipeline upgrade, poor customer awareness of water accountability and background leakages are among the factors that cause high water losses. Therefore, many evolving pressure-driven and hydraulic modelling tools and methods were engineered to further manage water losses (Mathye et al, 2022a). These tools differ by complexity level and vary in software development, benchmarking and performance indicators (PI). Because no single water loss method or tool alone is sufficient to significantly reduce water losses (Al-Washali et al., 2017). It is therefore important that water managers select and implement well-structured, systematic and transparent water loss reduction tools in complex water loss reduction scenarios. Transparent and systematic water loss tools integrate the roles of all relevant stakeholders and decision-makers (DM) involved in the decision-support objective formulation concerning water loss reduction (Al-Washali et al., 2017 and Alves et al., 2018). Multi-criteria-decision analysis methods (Alves et al., 2018) to evaluate water losses in the water distribution system may have the potential to contribute to new concepts of systematic decision support guidelines for water loss reduction. MCDA is a tool designed in the decision theory stream to resolve operational research problems having finite decision option counts (Abdullah et al, 2021). Decision-makers assess and rank weights depending on evaluation criteria (EC). Discrete MCDA approaches account for different ranges of qualitative and quantitative criteria above financial criteria and can handle uncertainties during their optimized decision-making process (Pematangsiantar, 2017). An MCDA framework can provide rational, objective, transparent, consistent and well-structured solutions towards complex decision challenges in the water resources planning and management sector (Ilaya-Ayza et al., 2017).

The MCDA technique can complement measures of quantitative and qualitative criteria beyond a single criterion that can, for example, be aimed at financial savings (Moon, 2020). According to Bera and Kartic (2019), most water utilities in developing countries confirmed that in water resource planning and management (Ferdowsi et al., 2021), MCDA is the most used strategic water infrastructure and stakeholder management technique. Although not adequately available in most developing countries, MCDA techniques as decision-support tools have been implemented by several researchers in water loss management studies. Hence, the knowledge gap of MCDA in developing countries resulting in non-application is understood and validated (Golfam et al., 2019; Waris et al., 2019 and Noori et al., 2021). Furthermore, the development of decision support in the form of MCDA makes it possible for water managers to select adequate priority strategies for specific local water loss conditions or contexts faced by water utilities. From a comprehensive water resource management globally, MCDA (Noori et al., 2021) techniques have been extensively researched and applied in a decision-making environment. Therefore, some of the most widely developed and utilized multi-criteria techniques in water resources management are highlighted in this article.

1.1 Critical Review MCDA Methods

The concept of MCDA has evolved over a period of time within the water resource management sector as well as outside the water sector. A recent MCDA review (Golfam et al., 2019) for water resources management and planning revealed that MCDA is prominently utilized to evaluate water policies, infrastructure and strategic planning. The research implies that the most prevalent applied techniques are compromise programming (CP), fuzzy set-analysis, analytic hierarchy process (AHP) (Waris et al., 2019), preference ranking and organization method for enrichment evaluation (PROMETHEE), and elimination "et choixtraduisant la realité" (ELECTRE; in English: elimination and choice expressing the R´ reality). A recent MCDA review (Golfam et al., 2019) for water resources management and planning revealed that MCDA is prominently utilized to evaluate water policies, infrastructure and strategic planning. The research implies that the most prevalent applied techniques are compromise programming (CP), fuzzy set-analysis, analytic hierarchy process (AHP) (Waris et al., 2019), preference ranking and organization method for enrichment evaluation (PROMETHEE), and ELECTRE.

Research in decision-making is sometimes assisted by methods designed to rectify operational challenges. Researchers (Adili and Işik, 2016) compared additive ratio assessment (ARAS) and COPRAS methods with each to select appropriate operational air conditioners for a specific projects using decision making and preference process. Both methods had similar performance characteristics. Nurmalini and Rahim (2017) investigated the comparative performance of weighted product-model(WPM), CORPRAS, AHP, TOPSIS, and weighted sum model (WSM) to determine sustainable house affordability assessment technique. They utilized CP, TOPSIS and the simple additive-method (SAW) Nurmalini and Rahim (2017) in creating a water resource management model to delineated the best prominent alternative water loss technique. Banihabib and Hashemi Madani (2017), performed a comparative assessment of non-compensatory and compensatory multi-criteria techniques for the strategic management of water resources. AHP and SAW represent the compensatory approach, and ELECTRE III is a non-compensatory technique. The inferences depicted that the ELECTRE-III approach explicated low sensitivity compared to the AHP and SAW methods in weight changes. Moreover, the obtained ranking from the ELECTRE-III approach was highly reliable in terms of decision-making processes. Cambrainha and Fontana (2018) formulated different decisions abstracted from decision makers (DM) to the hierarchy of EC. The study utilized a pairwise comparison approach to elicit the group preferences in water-loss management. These group preferences of the water-loss framework from DM were then aggregated to recommend AHP (Ilaya-Ayza et al., 2017). The PROMOTHEE method and its family of related techniques were used in certain outranking methods (Sureeyatanapas, 2016). In the compensatory approach, the assessment of alternatives assumes the trade-offs among different criteria. However, in non-compensatory techniques, the loss of alternative criteria could not be compensated through other criteria (Zardari et al., 2015). In other studies, the weighted sum model (WSM) which is a simplified technique that represents AHP, wherein every water-loss reduction alternative is assessed with various EC expressed in the same measure units, was established by adding every alternative score to every EC and multiplying it by the average weight of the EC. The outcome was used to develop divergence of various scores into final group decision (Samanta et al., 2016). Although not exhaustive in this paper, finally, Kumar and Qin (2016) demonstrated the elimination and choice-translating reality (ELECTRE) method, which belongs to the family of MCDA approaches. In this study the researchers used the outranking of the alternatives in selecting, sorting and ranking the appropriate water-loss reduction alternative within the decision-making process. The ELECTRE method utilizes priority ranks to recommend specific water-loss reduction alternatives. The research objectives of this article are to (a) propose a MCDA model for the water distribution system to evaluate strategies of water-loss management; (b) frame out an efficient and reliable MCDA approach using the PROMETHEE-II method to assess different preferences of decision-makers as well as integrating and prioritization of water-loss reduction options; and (c) determine the most preferred options of decision-makers in enhancing technical capacity, financial reliability as well as socio-economic and institutional governance. The authors made preliminary deduction that the identified challenge of high water losses could possibly be addressed with integrated MCDA design strategies using methods such as PROMETHEE-II and D-Sight Software with its sensitivity analysis. Such an approach could address strategic goals of health, safety, environmental, institutional, socio-economic, technical and financial governance. The proposed models are based on multi-criteria decision-aiding design methods.

1.2 Scenario Planning and Setting

The MCDA approach to evaluate water-loss management strategies for WDS was applied to Alexandra township in Johannesburg (South Africa) , which is representative to other informal settlements in Africa, South America and Asia (Mathye et al., 2022b).The case study is characterized by a dense population, serious socio-economic challenges and a deterioration of infrastructure including water supply systems. Figure 1 shows the Alexandra township map which further depicts the dense settlements and water distribution system (figure not to scale). Alexandra is a socio-economic township with high unemployment and less accountable for water payment (Mathye et al., 2022a). In 2016, the estimated annual total system input volume (SIV) was 18.5Mm^3 and 87.02% of the entire SIV was reported as NRW, which equates to a USD revenue loss of USD 49,882M (Mathye et al. 2022a). Table 1 shows the computed Alexandra Township water balance for 2019/2020, where 95.2% was estimated as NRW (Mathye et al., 2022a). The scientific and hydraulic results findings are the novelty that motivate MCDA application to assess strategies for water loss reduction.

Figure 1. Alexandra Township Layout Plan.

Table 1. Alexandra water balance for the financial year 2019/2020.

<table>
<tr><td rowspan="6">System Input Volume (SIV)
26,272,578.53 m^3/yr.
100%</td><td rowspan="3">Authorized Consumption
17,676,052 m^3/yr.
67.28%</td><td rowspan="2">Billed Authorized Consumption
1,257,383.25 m^3/yr.
4.79%</td><td>Billed Metered Consumption
873,195.03 m^3/yr.
3.32%</td><td>Free Basic Water
337,902.5 m^3/yr.
1.29%</td></tr>
<tr><td>Billed Unmetered Consumption
384,188 m^3/yr.
1.46%</td><td>Recovered Revenue Water
919,480.71 m^3/yr.
3.5%</td></tr>
<tr><td>Unbilled Authorized Consumption
16,418,668.77 m^3/yr.
62.49%</td><td>Unbilled Metered Consumption
16,418,668.77 m^3/yr.
62.49%</td><td rowspan="4">Non-Revenue Water (NRW)
25,015,195.28 m^3/yr.
95.21%</td></tr>
<tr><td rowspan="3">Water Losses
8,596,526.51 m^3/yr.
32.72%</td><td>Apparent Losses
No Historic Data
0 m^3/yr
0.00%</td><td rowspan="2">Real Looses + Unauthorized Consumption
8,596,526.51 m^3/yr.
32.72%</td></tr>
<tr><td rowspan="2">Real Losses
8,596,526.51 m^3/yr.
32.72%</td></tr>
<tr><td>Reservoir Overflows
<0.01 m^3/yr
<0.01%</td></tr>
</table>

3. MATERIALS AND METHOD

3.1. Overview of methodologies

The novelty the study is combination a scientific and hydraulic modelling in water supply system with decision-making matrix to draw convergence of integrated water loss management strategy. The authors used PROMETHEE II preference outranking method though a D-Sight software to derive synergies of the group's strategic objective in managing water losses. The PROMETHEE method is commonly successful in over 90% of MCDA applications in forestry, finance, chemistry, logistics, transport, water resources and environmental management (Safari et al., 2021). PROMETHEE II allows DMs to group their criteria in a tree to structure a problem sequentially and integrate a group decision through a brainstorming session. In this study, the authors selected eight water loss management experts called DM from the water utility with work experience ranging between 10 and 15 years. The selected 8 DM strategically occupied roles in water loss management in the following classified functional components:

- [DM1-DM2]_Physical Losses Department,
- DM3_Corporate Finance,
- DM4 & DM5_Operations and Maintenance,
- DM6_Metering Department,
- DM7_Stakeholder & Customer Management) and
- DM8_Planning and Policy Monitoring.

The ten EC were taken as a product of the Likert index (1-5) process that the authors applied to prioritize ten EC and six SO for this study. Table 2 shows the Likert scale tabulation.

Table 2. Likert Scale Tabulation.

Linguistic Description	Interval Level
Very Poor (Very Low)	1
Poor	2
Fair (Medium)	3
Good	4
Very Good (Very High)	5

The ECs was a premise through which elicitation of weights apportioned by the DM to strategic objectives (SO) was derived. Table 3 presents the ten priority evaluation criteria (EC) and the corresponding criteria description indexes abstracted from the utility's strategic objective (SO) thrust (Mathye et al., 2022a) through the help of the DM during a brainstorming session. Figure 2 illustrates the three-phase process flow of the methodology.

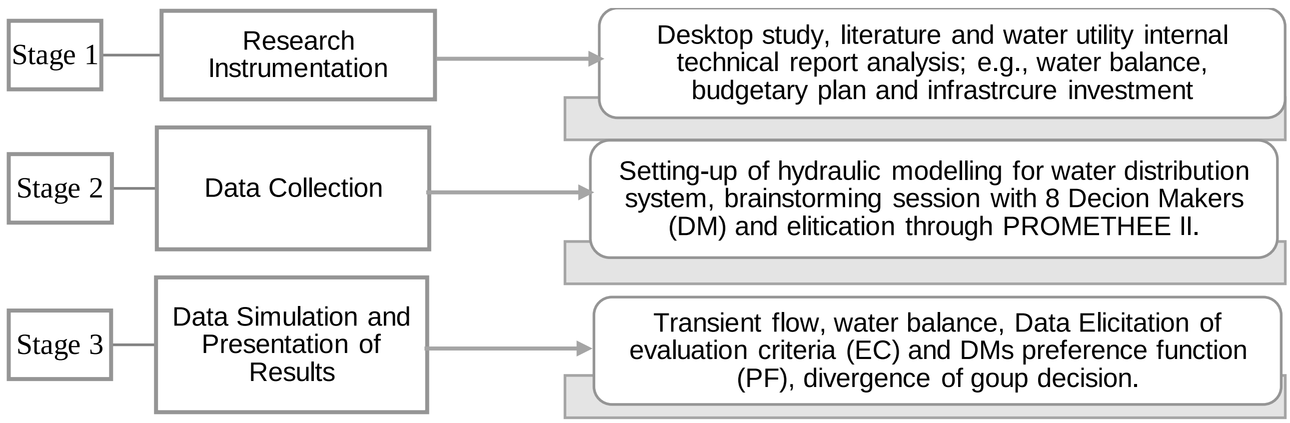

Figure 2. Technical Data Flow Methodology.

Table 3 presents the ten EC and their corresponding description index as well as the respective Likert scale in direct proportion to table 2. The ECs and description index were derived by the DMs from the water utility strategic thrust (Mathye et al. 2022a). The proceeding sections present the flow process, data collection, mathematical formulation followed and results.

Table 3: Evaluation Criteria.

Evaluation Criteria	EC Code	Likert Scale	Criteria Description Index
Revenue collection	EC-1	Maximize (4-5)*	The objective of the utility is to increase revenue generation levels. Therefore, the option is highly preferable, if the potential is high.
Investment of infrastructure	EC-2	Minimize (4-5)*	Implementation and investment costs for new infrastructure: if the cost is low, the option seems highly preferable.
Operation and maintenance costs	EC-3	Minimize (1-3)*	Operation and maintenance expenditure levels: if the cost is low, the option seems highly preferable.
Water saving	EC-4	Maximize (4-5)*	Institutional capacity to reduce water losses: if the potential is high, the option seems highly preferable.
Meter testing	EC-5	Maximize (4-5)*	Ability to improve meter quality to increase meter accuracy: if the potential is high, the option seems highly preferable.
Quality of water	EC-6	Maximize (4-5)*	The capability of the prevailing option in increasing the quality of water: if the potential is high, then this option is highly preferable.
Speed and quality of repairs	EC-7	Maximize (4-5)*	Capability to minimize run time of leakage: the option is preferable, if the potential is high.
Infra-system quality	EC-8	Maximize (4-5)*	The capacity of the available technology; the higher the integration potential, the more preferable this option
Service affordability	EC-9	Minimize (1-3)*	The impact of water pricing and affordability index: if the relative cost seems low, then the option is highly preferred.
Water-Policies	EC-10	Maximize (4-5)*	The ability of institutional water policy at the local level; the higher the viability level of the option, the more preferable the option.

Figure 3 represents a four-phased MCDA Methodological Flow Process for SO and EC as well as steps taken for developing MCDA integrated water loss management mode in water distribution system. The MCDA process flow shows what the authors used to define problem of water losses, integration of decision makers (DM)' EC, SO through MCDA' PROMTHEE II. The process flow also show elicitation process, positive and negative outranking process, D-Sight software programming, sensitivity analysis as well as group decision divergence for final model achievement. Figure 4 shows the MCDA Strategic Objectives and Evaluation Criteria Tree that combines table 2 and table 3 through the four phases presented in figure 3.

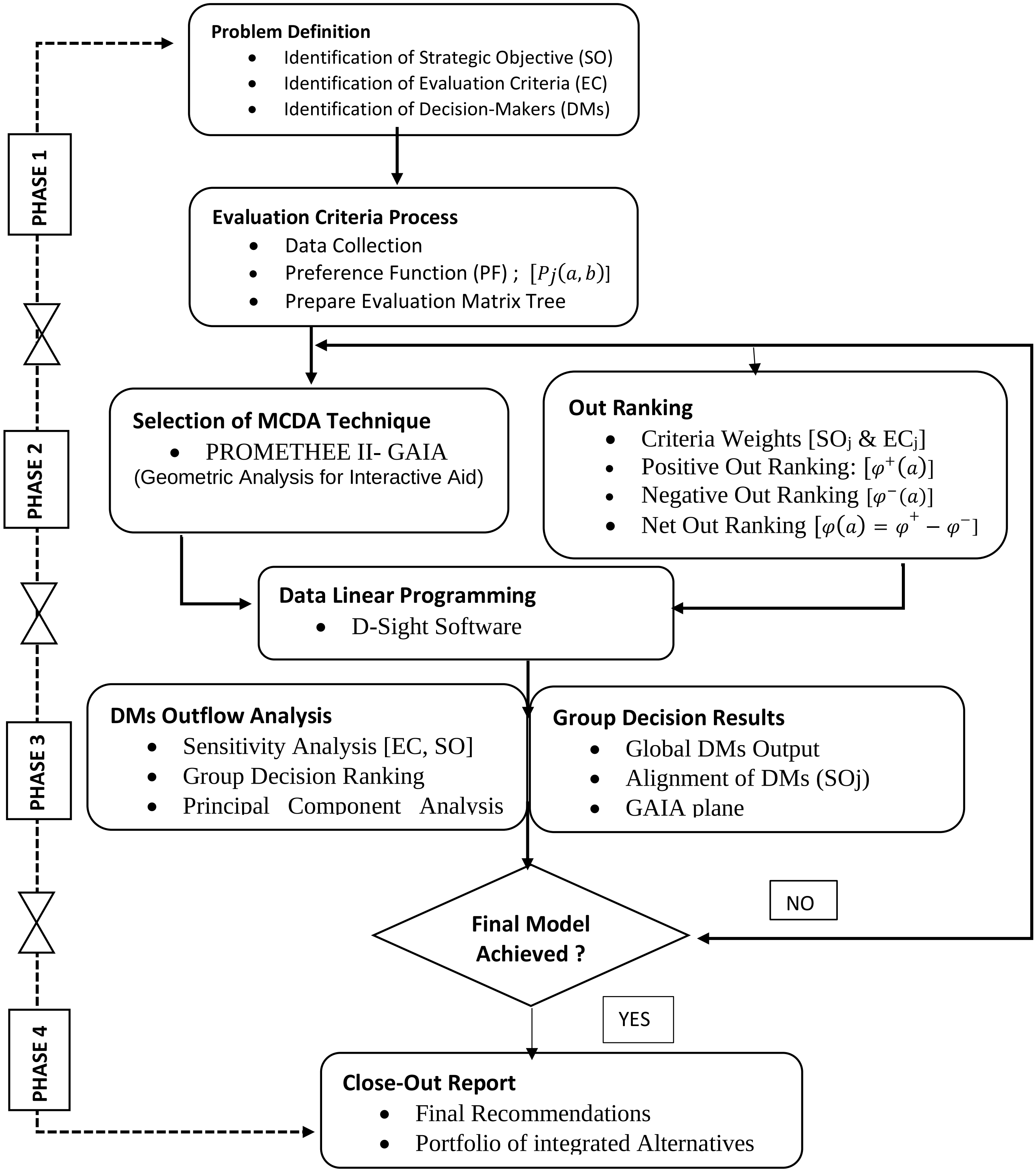

Figure 3. MCDA Methodological Flow Process.

Figure 4 presents the MCDA tree for six corresponding strategic objectives (SO) as well as ten water loss evaluation criteria (EC). The SOs and ECs were abstracted water utility (Johannesburg Water SOC, LTD)' strategic objective thrust and are as follows: (SO1)_ Financial Objectives, (SO2)_ Environmental Objective, (SO3)_ Health Compliance Objective, (SO4)_Technical Objective, (SO5)_ Socioeconomic Aspects and (SO6)_ Institutional Governance. Furthermore, the impact of DM's preference weighting is examined using the PROMETHEE_II tool.

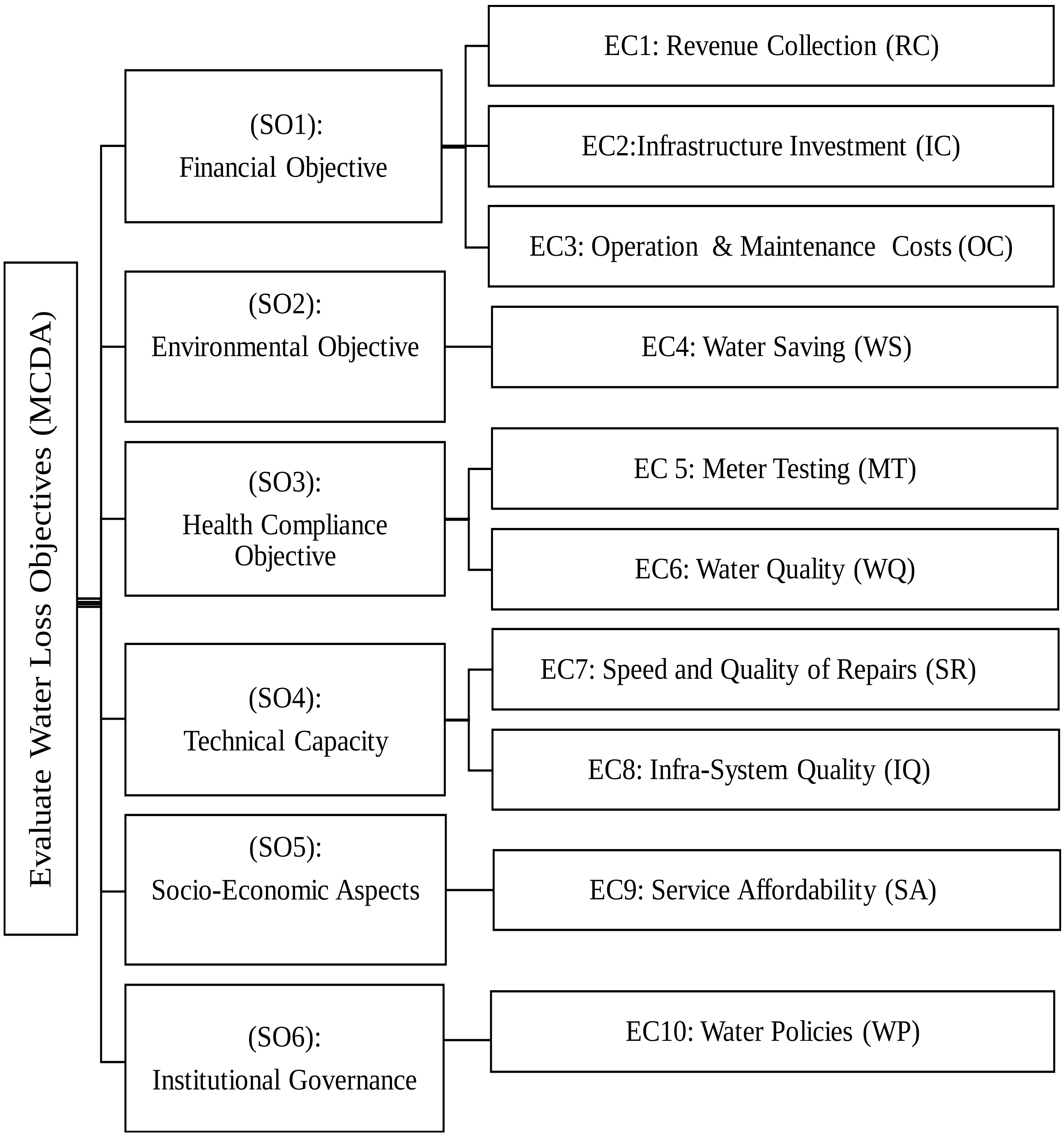

Figure 4. MCDA Strategic Objectives and Evaluation Criteria Tree

3.2. Data Collection Process

The SO and EC in the data collection as well as the weights were independent and non-negative numbers obtained from particular criteria units, where weight criteria were high. It follows that the criterion is likely to be significant. Normalization of weights was performed and the total sum was equated to zero. The weights of SO and EC for each DM are abstracted and computed by the revised SIMOS algorithm obtained from DM questionnaire responses. The SO and EC weights are related to every class, been equally placed evaluation criteria in the arranged pattern of DM and sorted in increasing performance order.

The elicitation process to select six SO and ten EC through Likert scale tabulation was undertaken during a brainstorming session with eight decision-makers. The DMs were presented with six SO cards and ten EC with black cards used for the priority ranking of EC and SO. The DMs were asked to lay out EC and SO cards upon a table. Their ranking implies the significance order based on expert judgement. This was done by moving the EC and SO cards around until agreement was reached. The DMs were further asked to place several blank cards between SO1 and SO2 or EC1 and EC2 (e.g., 2). The EC and SO weights are then calculated for r =1 to a limit of ñ, where ñ represents the ranking level counts as stated below. The SO and EC weights were calculated for r equal to 1, towards the ñ limit, wherein ñ denotes the ranking level count stated in equation (1). In the abstraction and computation of non-normalized weights for every DM, the equally placed SO and EC on the rank are allocated with the same k(r) non-normalized weight

$$\mathrm{k(r)} = 1 + \mathrm{u}(\mathrm{X}_0 + \cdots \mathrm{X}_\mathrm{r}) \qquad (1)$$

where k(r) is the rank of SO or EC, u is the weight value between two EC and SO, $\mathrm{X}_0 = 0$ and X_r is he rank (r) of any criterion is defined in their order of increasing importance in the DM's response priority pattern read from left to right. "X" is the total number of gaps between the highest ranked EC or SO and the lowest ranked EC or SO (e.g. RC and IQ), then it means the parameter "u" is defined as:

$$\mathrm{u} = (\mathrm{z} - 1)/\mathrm{X} \qquad (2)$$

Where the rank (r) of any criterion is defined in their order of increasing importance in the DM's response priority pattern read from left to right. The "z" is a parameter defined by DMs' responses to the questionnaire survey. When abstracting and computing the non-normalized weight for all DMs; the EC placed on rank (r) for all SOs was performed. In addition, all EC were assigned the same non-normalized k(r) weight. All DM were further asked to select the corresponding preference function (PF) type for specific EC. The authors adopted recommendations by DM using the preference function (PF) type to determine (q), which is the threshold of indifference Furthermore, (p) is a threshold of strict preference and (s) is an intermediate value between q and p. After this exercise, all DM ranked the EC and SO and counted the corresponding blank cards. Table 3 presents the preliminary DM preference elicitation questionnaire survey data. The EC and SO weights for each DM were later computed through the "revised SIMOS" algorithm. The data in Table 1 were used and processed by PROMETHEE II-**Geometric Analysis for Interactive Aid (**GAIA). The D-sight software was applied for normalization and analysis. Corresponding results are presented in the proceeding sections.

3.3. Evaluation Criteria Process

The study benefitted from the skills of experts and specialists using D-Sight Software to analyze all collected data. The scores produced by the PROMETHEE II method are between -1 and +1. This software normalizes data on a 0 to 100 scale to ease the readability of results. To compare the different alternatives for each DM preference, the following evaluation criteria process was undertaken:

- evaluation matrix representing the assessment of each alternative against each EC;
- (ii) criteria weights representing the importance of each EC (note that each DM gave a specific set of weights during computation); and
- (iii) preference functions and preference thresholds (if applicable) utilized for computing alternative noncriterion scores. The usual PF (type 1) was selected by each DM for all EC and was applied during the elicitation process.

This process will be done in two stages; (1) Weighting for Evaluation Criteria (EC) and (2) Weighting for higher level objectives. The relative importance of EC is expressed in terms of weights. Each of the ten (10) cards has the name of an EC written on it. A small explanatory note is also given at the back of each card.

- Step 1: - Arrange the cards in a row representing the order of importance starting with the most important EC. For equally important EC, you may group the cards together.
- Step 2: - To express the gaps in importance, insert any number of blank cards that have been given to you. The greater the difference in importance of the EC, the greater the number of blank cards between them.
- Step 3: - Recording the pattern is that the first card (SO/EC) is the most important criterion and the last one is the least important.

3.4 The Weight Normalization

The proceeding sections present the DMs elicitation questionnaire survey data processed by the authors. The SO and EC weights were independent and non-negative numbers obtained from particular criteria units. If the weight criterion is high, then this criterion is likely to be significant. Normalization of weights has generally been performed. The total sum is equal to zero. For every decision-maker, the weights seem to be rather different. Hence, the ranking for every decision-maker is calculated by SO and EC. The weights of SO and EC for each DM are abstracted and computed by the revised SIMOS algorithm obtained from DM questionnaire responses presented in the Table 4.

The rank (r) of the criterion is defined in a particular order to increase the significance in the response priority patterns of DM from the left to the right hand side. The parameter Z is defined through the responses of DM to the survey. By this the DM places no blank cards among any two SO or EC cards. Similarly, if there is one blank card between two SO or EC cards, there are subsequently two gaps. Hence, if this X represents the total count of gaps among the highest ranked SO or EC and the lowest ranked SO or EC (like IQ and RC), then the parameter 'u' can be defined as shown in equations in the proceeding section.

Table 4 : Decision-makers Preference Elicitation Questionnaire Survey Data.

ID	Corporate Strategic Goal				Evaluation Criteria Index (ECI)										Weight Assessment Index Data on DM's EC Priority																			Relative Weight Range on EC	Weight Assessment Index Data on DM's SO Prior											Relative Weight Range on EC
Decision Maker	Fully Agree	Partially Agree	Do Not Agree	Other (Specify	Revenue Collection (RC)	Infratructure Cost (IC)	O & M Cost (OC)	Water Saving (WS)	Meter Tests (MT)	Water Quality (WQ)	Speed & Quality of Repairs (SR)	Infra-System Quality (IQ)	Service Affordability (SA)	Water Policies (WP)																					Financial Objective_(FO) Environmental Objective_(EO) Health Compliance Objective_(HO) Technical Capacity _(TC) Socio-Economic Aspects _(SE) Institutional Governance_(IG)											
Strategic Objctives (SO)					FO			EO	HO		TC		SE	IG	Most Important																		Least Important		Most Important										Least Important	
					Preference Funtion (PF) Types										DMs_EC Ranking																				DMs_ SO Ranking											
DM1	X				Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	RC	1	WS	2	WQ	2	IC	1	SR	1	OC	1	SA	1	MT	2	WP	1	IQ	12	FO	2	EO	1	HO	1	SE	1	TC	1	IG	7
DM2	X				Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	RC	2	WS	3	SR	1	IC	1	WQ	2	SA	1	OC	3	MT	2	IQ	1	WP	16	IG	3	FO	2	SE	2	HO	1	TC	1	EO	9
DM3		X			Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	WS	3	OC	1	RC	2	IC	1	WP	2	WQ	2	SA	1	MT	1	SR	1	IQ	14	FO	2	SE	1	TC	1	EO	1	IG	1	HO	6
DM4	X				Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	RC	1	SA	1	SR	2	IC	2	WQ	2	OC	1	WS	1	IQ	1	WP	1	MT	12	FO	2	SE	1	TC	2	IG	1	HO	1	EO	7
DM5	X				Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	RC	1	IC	2	SA	1	OC	1	SR	1	WS	1	IQ	2	MT	2	WP	1	WQ	12	IG	1	FO	2	TC	2	HO	3	EO	1	SE	9
DM6	X				Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	SA	2	RC	1	WQ	2	OC	2	SR	3	IC	1	WS	2	IQ	1	WP	1	MT	15	FO	1	SE	3	IG	2	TC	2	EO	1	HO	9
DM7		X			Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	RC	2	WS	1	WQ	1	IC	1	MT	3	WP	2	SA	1	SR	3	IQ	1	OC	15	FO	2	TC	2	SE	1	HO	1	EO	1	IG	7
DM8	X				Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	Type I	RC	3	WS	2	WQ	2	IQ	2	SA	1	OC	3	SR	1	IC	3	WP	1	MT	18	TC	1	FO	3	SE	2	IG	3	HO	1	EO	10

3.5 Mathematical Formulation

The following section presents the mathematical formulation applied in this study. Data interpolation is summarized in equation

$$\begin{bmatrix} g_1(a_1)g_2(a_1) \ldots\ldots g_j(a_1) \ldots\ g_n(a_1) \\ . \\ g_1(a_2)\ g_2(a_2)\ \ldots\ldots g_j(a_2) \ldots g_n(a_2 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \\ . \\ g_1(a_i)g_2(a_i) \ldots\ldots g_j(a_i) \ldots\ g_n(a_i) \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \\ . \\ g_1(a_m)g_2(a_m) \ldots\ldots g_j(a_m) \ldots\ g_n(a_m) \end{bmatrix} \quad (3)$$

where $gj(aj)$ is the performance of i^{th} alternative for j^{th} criteria, m is the total number of alternatives, and n is the total number of criteria. Furthermore, $g_j(a_i)$ represents the i^{th} alternative performance upon the j^{th} criterion, *n* denotes the count of criteria, and m defines the count of alternatives. The PROMETHEE-II technique depends upon the pairwise method wherein the deviation between two alternative EC is considered a preference with a value between zero and one. For every criterion, the preference function (PF) can be explained through the mathematical formulation in equation 4

$$\mathrm{Pj(a,b)} = \mathrm{Fj[dj(a,b)]} \forall\ a, b\ \in\ A \quad (4)$$

Where … Pj dj(a,b) = [gj(a) - gj(b)] and 0 ≤ Pj(a,b) ≤ 1

3.5.1 Preference Function Types

Usually, there are six general types of preference functions namely level shape criterion, U-shape criterion, V-shape criterion, usual criterion, Gaussian criterion and V-shape with indifference criterion. The DM can have the privilege to choose from the preference functions. The DM can specify the various threshold parameters such as p, q and s depending upon the application type of preference functions. In cases where DM choose "type 1" ("usual criterion" PF), the evaluation matrix g*j*(.), the relative (weight) of the *j*th criterion (*wj*) and the generalized criterion {g*j*(.), *Pj*(*a*,*b*)} need to be defined (Mutikanga, 2012). Equation 5 presents the type 1 PF for DMs' possible selection.

$$\begin{bmatrix} \pi(a,b) = \sum_{j=1}^{n} \mathrm{Wj}\ \dot{\mathrm{P}}\mathrm{j}(a,b) \\ . \\ . \\ \pi(b,a) = \sum_{j=1}^{n} \mathrm{Wj}\ \dot{\mathrm{P}}\mathrm{j}(b,a) \end{bmatrix} \quad (5)$$

where π(a,b) is the degree of measure for which 'a' is preferable to 'b' for all criteria, and π(b, a) represents the preference of 'b' over 'a' for all criteria. In some cases, a criteria may emerge where "a" > "b" or "b > "a" and therefore π(a,b) and π(b, a) are usually positive.

The method is generally a pair-wise approach in which the variations of two alternative estimation criteria are taken into account as a preference function. From existing research, it has been stated that the preference value generally lies between 0 and 1. The mathematical formulations for the preference functions can be given in equation 6, where $\pi(x,y)$ is the level of measure at which *x* is more preferred than *y* for all criteria. The $\pi(y,x)$ is the level of measure at which *y* is more preferred than *x* for all criteria. In some rare cases, where *x*>*y* or *y*>*x*, π(*x*,*y*) and π(*y*,*x*) are generally positive. Equation 6 shows the preference where divergence preference functions for more DMs are integrated.

$$Pj(x,y) = Fj[dj(x,y)] \forall x, y \in A \quad (6)$$

where … d$j(x,y) = [Gj(x) - Gj(y)]$ presents the PF for more DMS, and the value of $Pj(x,y)$ are between 0 and 1.

The PROMETHEE procedure can be applied once the evaluation matrix $Gj(x)$ is established, the weights Wj and the generalized criteria g_j, Pj $\mathrm{Pj(a,b)} =$ are defined for i = 1,2,...,n; j = 1,2,...,k (Mutikanga et al., 2012)

3.5.2 Beneficial and Non-Beneficial Criterion

The following conditions are applied while implementing beneficial and non-beneficial criteria for either a lower or higher value: In case of beneficial criteria, the alternative *x* is given preference over the alternative *y* in the above equation for the variations among their calculations on the *j*th criterion. In case of non-beneficial criteria, the equation 6 can be rewritten as below. Equation 7 indicates the non-beneficial PF for DMs

$$Pj(x,y) = Fj[-dj(x,y)] \quad (7)$$

where $Pj(x,y)$ is the PF for the DMs in a non-beneficial criteria for higher or lower scores value

3.5.3 PROMETHEE II Outranking Alternatives

In the preference ranking methods for PROMETHEE I and II, the values of π(*x*,*y*) and π(*y*,*x)* are calculated mathematically for each alternative pair in the evaluation matrix for each DM. The comprehensive analysis for outranking graphs is calculated using a mathematical model. The below equations are modeled to develop an equal number of alternatives *x* or *y*.

i. *Positive Outranking*

$$\varphi^{+(x)} = \frac{1}{(m-1)} \sum_{a \in A}^{n} \pi(x,a) \quad (8)$$

w Where: $\varphi^{+(x)}$ outranking, each option a, belonging to the set of options $\sum_{a \in A}^{n} \pi(x,a)$, $\pi(x,a)$ is the overall preference index of a over b, taking into account all the criteria, $\varphi^{+(x)}$

i. Negative Outranking

$$\varphi^{-(x) = \frac{1}{(m-1)} \sum_{a\in A}^{n} \pi(a,x)} \quad (9)$$

Where: $\varphi^{+(x)}$ and $\varphi^{-(x)}$ outranking, each option a, belonging to the set of options $\sum_{a\in A}^{n} \pi(x,a)$, $\pi(x,a)$ is the overall preference index of a over b, taking into account all the criteria, $\varphi^{+(x)}$ and $\varphi^{-(x)}$

The positive and negative outranking measure the strength and weakness, respectively, of a compared decision by a decision-maker to other preference options $\mathrm{Pj}(\mathrm{b},\mathrm{a})$ (Mutikanga, 2012). PROMETHEE II, that is an entire pre-order ranking model in comparison to the partial outranking model.

The positive outranking model is indicated by alternative outranking *x*. All the other estimation criteria are taken as alternatives. A higher value of $\varphi^{+(x)}$ indicates a better alternative. The negative outranking model indicates how the alternative x is outperformed by further evaluation criteria. Thus the minimum value of $\varphi^{-(x)}$ denotes a toward optimal alternative.

ii. Net Outranking

After the completion of negative and positive outrank flows for alternatives, for each alternative the net outranking is provided by equation 10

$$\varphi(x) = \varphi^{+(x) - \varphi^{-(x)}} \quad (10)$$

where φ_x the usual criterion PF that integrates positive outranking towards optimal alternatives $\varphi^{+(x)}$. Hence, to estimate the net outranking value, equation 10 must be rewritten as equation 11.

$$\varphi(x) = \varphi^{+(x) - \varphi^{-(x) = \frac{1}{(m-1)} \sum_{j=1}^{n} \sum_{a\in A}^{n} [Pj(x,a) - Pj(a,x)] Wj}} \quad (11)$$

where $\varphi(x)$ the usual criterion PF, the j^{th} criterion relative weight (WJ), generalized criterion, the evaluation matrix gj(.) and $\mathrm{Pj}(\mathrm{a},)$, the positive outranking towards optimal alternatives $\varphi^{+(x)}$ or negative outranking towards optimal alternatives $\varphi^{-(x)}$. Equation 12 gives a summation of net outranking of usual PF for all DMs

$$\varphi(x) = \sum_{j=1}^{n} Wj\varphi j(x) \quad (12)$$

where $\varphi_x(\mathrm{a})$ the usual criterion PF, the j^{th} criterion relative weight (WJ). Yet, the value of *φj*(*x*) in the net outranking flow for a single criterion concerning the *j*th iteration is given in equation 13.

$$\varphi j(x) = \frac{1}{(m-1)} \sum_{a\in A}^{n}) \quad (13)$$

where $\varphi\mathrm{j}(x)$ the usual criterion PF, n is the sample size e.g. 8 DMs

In net outranking, $\varphi(\mathrm{a})$ represents the Single Criterion and the net flow gained for the j^{th} Criterion equation 14.

$$\varphi\mathrm{j}(\mathrm{a}) = \frac{1}{(\mathrm{m}-1)} \sum_{\mathrm{x}\in\mathrm{A}} [\mathrm{Pj}(\mathrm{a},\mathrm{x}) - \mathrm{Pj}(\mathrm{x},\mathrm{a})] \quad (14)$$

where $\varphi\mathrm{j}(\mathrm{a})$ the usual criterion PF, the j^{th} criterion relative weight (WJ), generalized criterion, the evaluation matrix gj(.) and $\mathrm{Pj}(\mathrm{a},)$.

To determine the complete ranking matrix for the PROMETHEE II – (GAJA), a geometric analysis for the interactive aid plane concerning the relative and graphical position of options for its role to different criteria is used. The entire evaluation matrix $\mathrm{M}_{(\mathrm{m}\times\mathrm{n})}$ is then defined and based on the Single Criterion with net flows of all alternatives. The representative mathematical formula is given in equation 15. The entire evaluation matrix of order M(mxn) depends on a single criterion with net flow alternatives (equation 15),

$$\begin{bmatrix} \varphi_1(a_1)\ \varphi_2(a_1) \dots\ \varphi_j(a_1) \dots\ \varphi_1(a_2) \\ . \\ \varphi_2(a_2)\ \varphi_2(a_2) \dots\ \varphi_j(a_2) \dots\ \varphi_n(a_2) \\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. \\ \varphi_1(a_i)\ \varphi_2(a_i) \dots\ \varphi_j(a_i) \dots\ \varphi_n(a_i) \\ . \\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. \\ \varphi_1(a_m)\ \varphi_2(a_m) \dots\ \varphi_j(a_m) \dots\ \varphi_n(a_m) \end{bmatrix} \quad (15)$$

where $\varphi_1(a_1)$ presents the DM and PF criteria, and $\varphi_j(a_i)$ are indicative of the divergence criteria point for DM in the data sample. In generating the complete evaluation matrix (M), the GAIA plane is modeled by projecting these values in equation 15 on the plane. It is modeled in such a manner that the least information on the preference function's evaluation criteria can be considered as being lost.

In the GAIA plane, the alternatives ($x_1, x_2, \dots x_m$) are modeled through points and the criteria ($c_1, c_2, \dots, c_n$) are indicated by the axis generated from equation 15. Moreover, the implementation of the PROMETHEE II-GAIA model that uses D-sight software has been used commonly in the state-of-the-art literature.

4. RESULTS AND DISCUSSIONS

4.1. Weight Index Results of Decision-Makers

The proceeding sub-sections present an assessment of outcomes and a discussion concerning inferences. Figure 5 presents the elicited EC weights and rankings for each DM, while Fig. 6 shows the corresponding strategic objective ranks and weights. The variable weight index data in Figs. 5 and 6 show the independence of the DM's preference and their ranking of EC in response to the corresponding water loss reduction strategic objectives (SO). Although each DM weight allocation is initially independent of others, the PROMETHEE II methods become useful in integrating final group decisions for each criterion. The decision-maker presents the relative significance of criteria through ordinal preferences, which allows for the definition of the determining function wherein the numerical values denote the weight representation. For instance, in the order of priority weight and ranking, most DM-allocated weight scores are between 17 and 19 with rankings from 8 to 10 for revenue collection (RC). Note that a ranking of one indicates least importance and ten represents the highest importance. This scoring pattern is consistent with the financial objective SO1 (Fig. 5). This means that most DM agree on prioritizing financial capacity to enable the water utility to manage water losses well. However, less priority is given to operation and maintenance costs (OC), speed and quality of repair (SR), meter testing (MT) and water saving (WS), which, in practice, are commonly believed to be variables belonging to a sound strategy for curbing water losses. Furthermore, the low-weight allocation and ranking of EC such as water policies (WP) and service affordability (SA) are not aligned to SO1, which most DMs have prioritized. The authors made a preliminary deduction that, within the water utility, various DMs strategically represent their independent functional analysis of what water loss reduction criteria should entail in terms of their preference function for each corresponding strategic objective. It is the authors' further deduction that, although the DMs are experienced in water loss observations, their functional and operational gaps in water loss control could be why water loss reduction strategies are not efficiently prioritizes by the water utility. The authors' preliminary deduction, are further justified by the NRW of about 95% outlined in Table 1 above.

Figure 5: Rank and evaluation criteria for decision maker (DM) weight indexes.

As indicated in Fig. 6 below, when a water utility's executive personnel have a disintegrated approach towards the reduction of water losses or focus their resources on one strategic objective in this case (SO1), other critical SO such as institutional governance (IG), technical capacity (TC) and socioeconomic (SE) objectives become high risk and difficult to manage. This may collectively lead to results characterized by exponential water loss challenges.

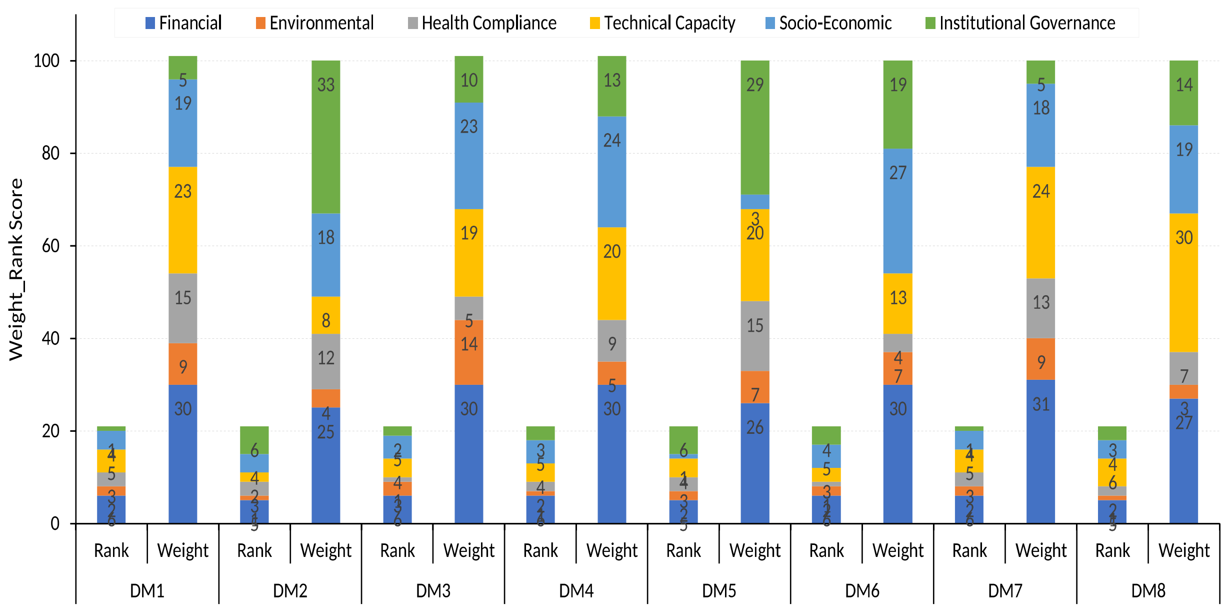

Figure 6: Rank and weights of decision makers (DM) for strategic objective indices.

Figure 7 presents the rounded-off results of normalization of weights for each EC alternative, while Fig. 6 presents the integrated rounded-off EC pattern. The weights of the DM are obtained through the 'Revised Simos' procedure. Figure 5 shows also that when EC weights are normalized for all DM, a more balanced outlook represented by a MCDA can be achieved. For integrated group decisions, the mean and median descriptive statistical values presented in Fig. 6 are assumed to be representative values as they agree with the group's majority perception. Therefore, rounded-up values were used within PROMETHEE-II with the D-Sight software application to normalize and graphically elicit group decisions for analysis and presentation in the proceeding sub-sections. After the normalization process, evaluation criteria such as SR, WQ, SA, WS and IC received more attention. Particularly RC proves that MCDA is a suitable alternative method to establish group decisions for water loss reduction approaches.

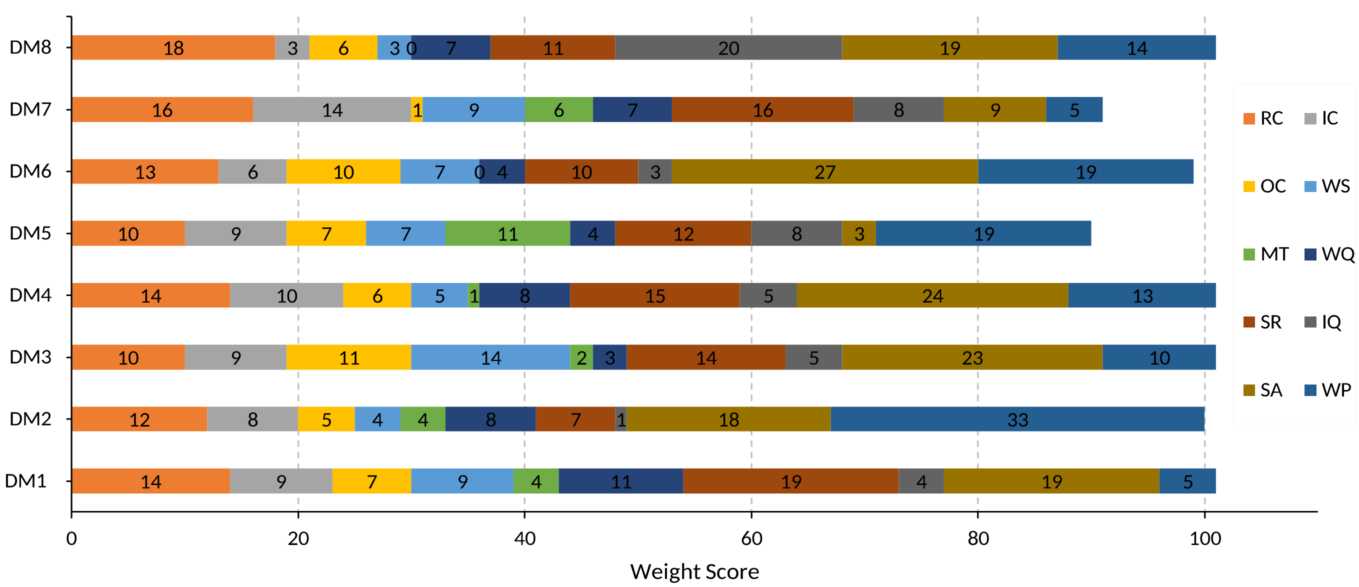

Figure 7: Rounded-off weight index values by decision-makers.

As presented in Fig. 8, the sensitivity normalization of the weighted scores and ranking resulted in integrated linear reduction values (R^2) of 0.1865 and 0.997 with projected constants (C) of 6.2 and 6.8 for the mean (Mn) and median (Md), respectively. Although the R^2 values appear insignificant, it is worth deducing that all EC have the same pattern, except for SA, which is increasing in priority, because its relatively high importance is what may enhance more RC for the respective water utility. Thereby, the author made the further deduction that MCDA design seems to handle qualitative data well and should be used as a tool for planning on appropriate case-based water-loss reduction strategies. Accordingly figure 6 further shows that the sensitivity analysis of all ECs per DMs might not have been initially integrated into an organizational water loss control key performance areas, however the PROMETHEE II' MCDA still offer a more intelligible DMs comprehensive decision and offers optional analysis of what DMs thinks of water loss control in their substantial daily-functions or output.

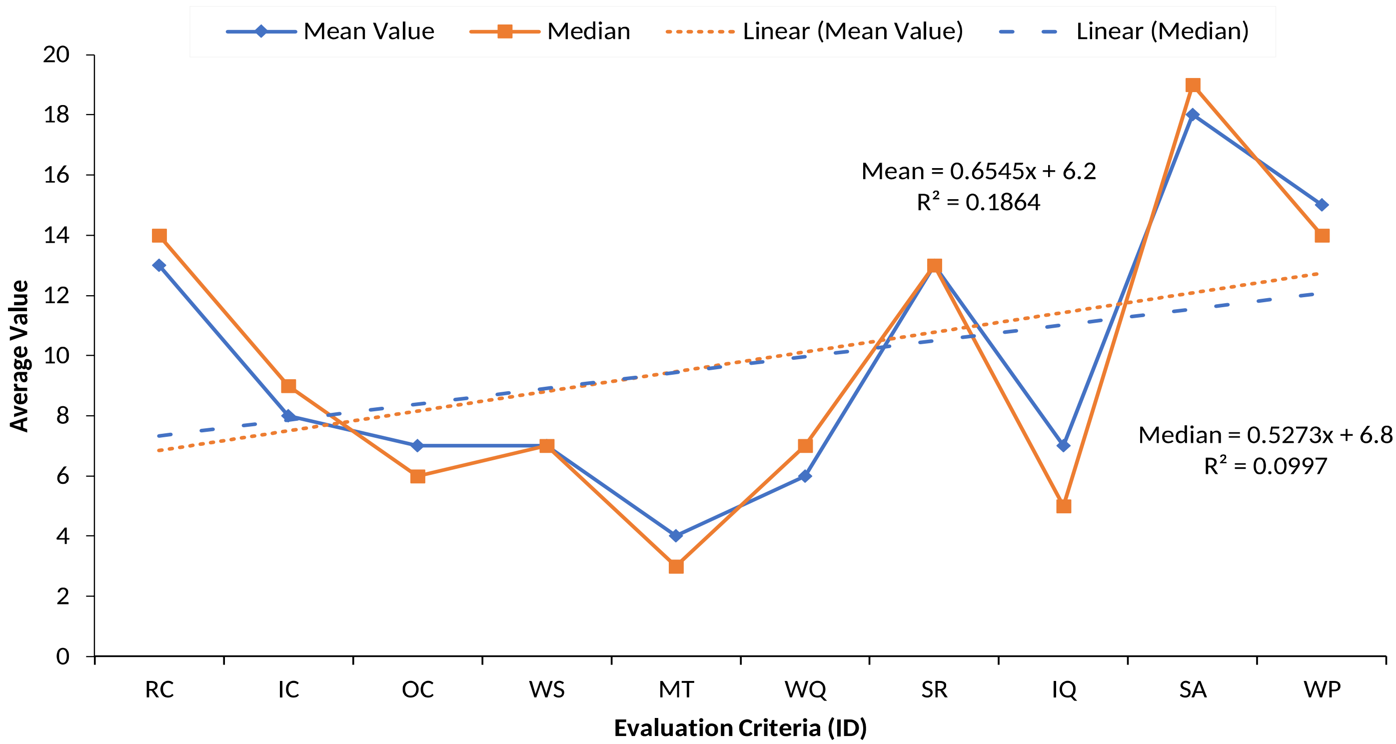

Figure 8: Rounded-off evaluation criteria mean and median outlook

4.2 Comparison of Results for the Different Decision-Makers

Figure 9 shows diverging results and normalized scores for various DM. While it is often efficient to aggregate the preference scores of DM for each SO and the corresponding EC, it is crucial for most group decisions to first promote independent thinking and ideas (resulting in enhanced divergence) before final aggregation can be elicited (Sureeyatanapas, 2016). Further, when applying MCDA, proper visualization for elicited and sensitivity-normalized DM output is required. This will help investigators to draw a more divergent picture of what should be prioritized from a group decision perspective. As demonstrated in Fig. 7, DM are represented by the different colors to allow for improved visual assessment of all alternatives to decide on preferences regarding divergence. For example, EC4 and EC5 are the criteria for which there is a consensus by most DM. EC8 is the best or at least one of the best alternatives identified by all DM. While it has been proven above that the non-normalized and non-elicited independent scores do not paint a picture of consensus, Fig. 7 shows that both PROMETHEE II and D-Sight software may help in drawing more divergence on the DM's view when applying water loss reduction strategies. This suggests that the mixed-method technique of elicitation and normalization of individual scores to group divergence helps to address the limitations of a single-view decision in water loss management. This suggestion is supported by previous studies (Sureeyatanapas, 2016; de Brito et al., 2019; Abdullah et al. 2021).

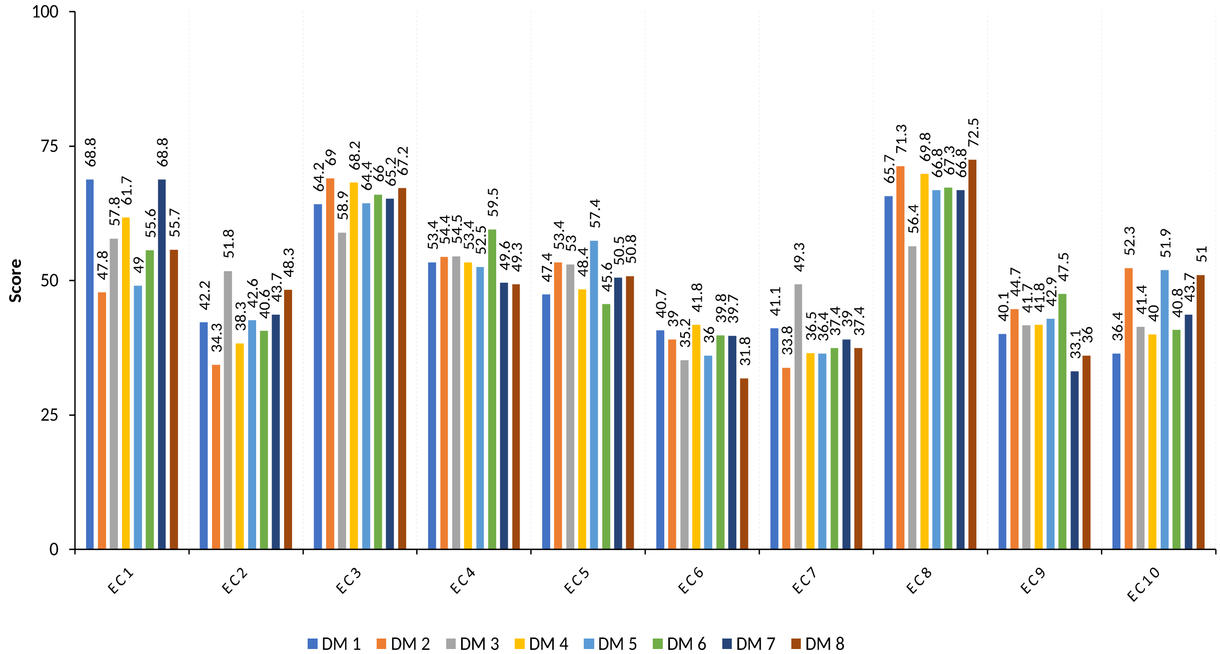

Figure 9: Divergence of decision maker (DM) results

4.3. Alignment between the group decisions

4.3.1. Global Results

Figure 8 presents the global alignment of DMs group decisions. For this analysis, the PROMETTHE-II' D-Sight software application normalized all weights and DMs received the same weights per alternative. This means that no individual DM will have more impact than any other in the determination of the global scores of alternatives. In other words, each alternative's global score equals the average of its scores obtained for all DMs. It is important to assess how the different DMs evaluations are aligned on the global score results. To start with, the weights given by each DM need to be looked at individually and then collectively. Considering figure 8, the normalized average weights given to each category by different DMs are shown dark yellow, which proves that all DM's divergence and consensus are for the common objective of prioritizing the implementation of proper water loss reduction strategies. For instance, the strategic objective (SO) such as "Financial Objective" and "Environmental Objective" have a very low spread. On the other hand, the values for "Technical Capacity," "Socio-Economic Objective," and "Institutional Governance" have considerably different global score averages, which means that there is no global consensus, although the overall pattern is comparable. The authors drew a preliminary deduction from the above findings that although the perception of reducing water losses is somewhat clear from DMs, as represented by a 'dark yellow line", the water utility appears to undervalue the impact of prevailing "Socioeconomic" conditions, lack of "Technical Capacity" and poor "Institutional Governance." This undervaluing of the crucial water loss reduction strategic objective could be a reason to justify further the NRW of about 95% in the case study area, since less efforts are put on these three main water loss reduction strategies (Table 1). As evidenced in Table 5, the strategic objective (SO6) on “Institutional Governance (IG) is receiving a high global score in its level of importance. Other studies have proven that poor institutional governance is what makes curbing water losses in developing countries a real challenge (Makaya 2016; Heryanto et al., 2021; Mathye et al. 2022). Although the “Financial Objective” (FO) was seen as a priority for maximization in the preceding results of this study, the global scoring view suggests that the water utility should prioritize strong "Institutional Governance”, however, its risk parameters (indicated by relatively high standard deviations) are lower when compared to the "Financial Objective. "Concerning the average weight percentage for the "Technical Capacity” objective and the "Socioeconomic Objective", it is worth highlighting that the water utility is comfortable with its "Technical Capacity" and the prevailing "Socioeconomic" dynamics in the example case study area. This is in agreement with the findings by Makaya, 2016 and Heryanto et al. 2021, who concluded that when water utilities in developing countries place less effort on improving the "Technical Capacity" as well as developing socioeconomic intervention plans to address water loss reduction it is a sign that such water utilities lack strong "Institutional Governance.

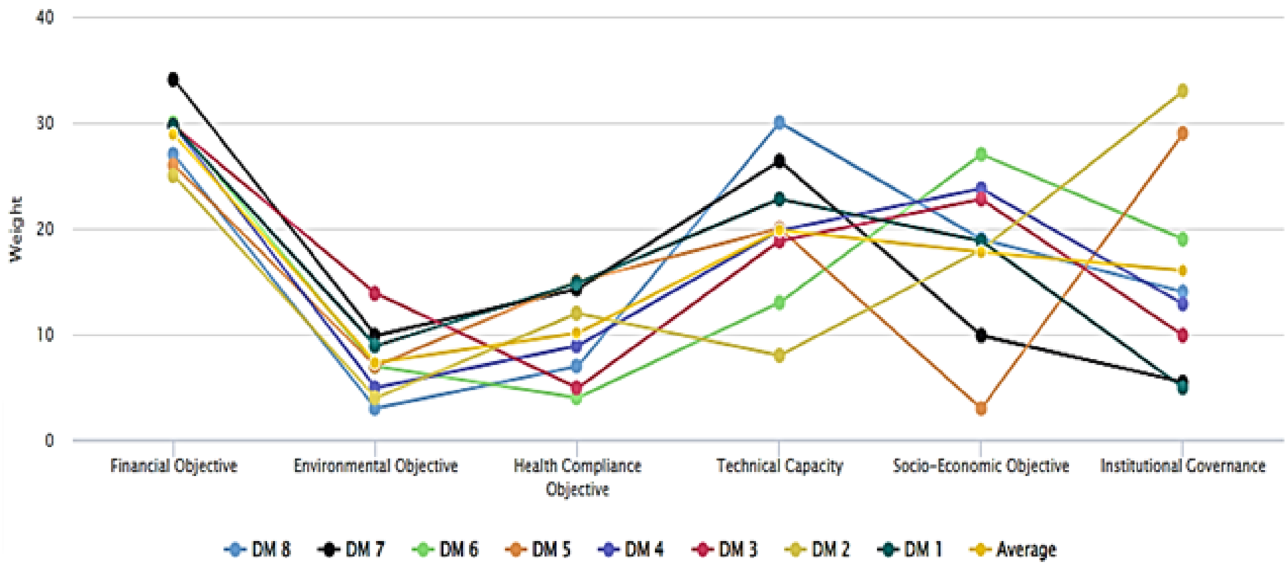

Figure 10: Global Alignment Alternative Scores for Group Decision-making.

Table 5: Global Average Weight Score for Decision Makers' Strategic Objectives

Strategic Objective	Average weight	Standard deviation
Institutional Governance	28.9%	2.9%
Socioeconomic Objective	7.3%	3.5%
Technical Capacity	10.1%	4.5%
Health Compliance	19.8%	7.0%
Environmental Objective	17.8%	7.8%
Financial Objective	16.0%	10.4%

4.3.2. Geometric Analysis for Interactive Aid "GAIA"

As the last step in the proposed assessment process, PROMETHEE II allows use of visualization such as the **Geometric Analysis for Interactive Aid** (GAIA) plane in aiding decision-making. This plane is computed using the principal component analysis (PCA), where each DM will be represented by an axis and each alternative by a dot. The direction of an axis will show the direction where preferred alternatives can be found in the graph such as shown in Fig. 9 (e.g., EC1 for DM1 and DM7). The length of an axis represents the differentiation by a DM concerning various alternatives. The longer the axis is, the greater is the difference (i.e. delta between minimum and maximum scores) between the alternatives for the corresponding decision maker. Hence, a very short axis indicates that all alternatives have a very similar score for that specific DM.' Decision-makers with axes in the same direction have similar results in the ranking of alternatives. Moreover, alternatives close to each other have similar scores and will be preferred by the same stakeholders. The red axis, also known as the "Decision Stick" in the PROMETHEE method is obtained by using the weight values of all DM (i.e. the green axes) and showing the direction of the globally preferred alternatives EC8 and EC3. Finally, the global picture (GAIA-plane) allows for visualization of the three distinct clusters of alternatives that the water utility may implement in the quest to reduce water losses:

- EC2, EC6, EC7 and EC9: these alternatives are either bad (inappropriate) or average (standard) for all DM.
- EC4 and EC5: these alternatives are average for most DM.
- EC3 and EC8: these alternatives are good (appropriate) for all DM.

The technical limitation of a GAIA plane outlook is that there might be some visual “unreliability” (high scope for interpretation) as the authors represent an eight-dimensional dataset into a two-dimensional plane.

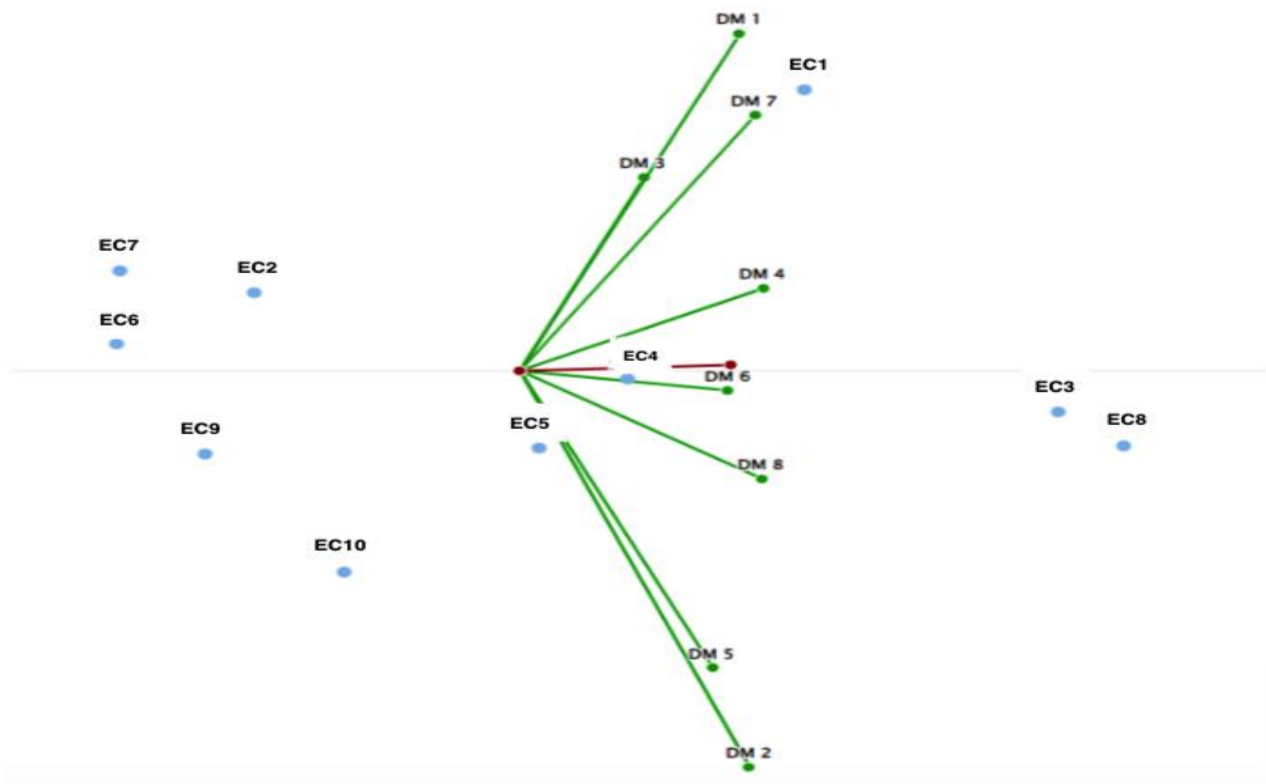

Figure 11: Global GAIA Plane Example Representation.

4.3.3 Integrated Water Loss Management Improvement Project (IWLMIP)

The researcher embarked on the pre-testing phase by incorporating the prioritized water loss reduction strategy options from the first four specific objectives into Integrated Water Loss Management Improvement Project (IWLMIP) in Alexandra, South Africa. Figure 12 present the outcome of a PROMETHEE-II’ MCDA process. The outcome from the 8 DMs indicated four SO with relevant performance indicator (PI) that requires maximizing namely; (i) **financial reliability**, (ii) **technical capacity** and sound (iii) **institutional governance** and (iv) **socio-economic goals.** When compared with the original strategic thrust of water utility (Johannesburg Water SOC, LTD) presented in table 2 and measured through a Likert Scale 1-5, as integrated in table 3, the findings are relevant in that except “socio-economic objective” that required minimizing, the other three findings for (i) **financial reliability and capacity**, (ii) **technical capacity** and sound (iii) **institutional governance,** require maximizing. .Therefore, it is evident that the 8 DM’ convergence through PROMETHEE II’ D-Sight software prioritized the above 4 strategic objectives. The high profile ranking of that institutional governance and financial objectives is therefore key to effective WL management strategies. This outcome is common with other research findings, (Dighade et al., 2014, Mutikanga 2014; Makaya 2014). Figure 12, therefore present the Integrated Water Loss Management Improvement Project (IWLMIP) which the authors used for further practical testing in a real case study in Alexandra urban township. The testing used quantitation principal component analysis (PCA) through a MATLAB algorithm to develop a final socio-technical IWLMM for developing countries.

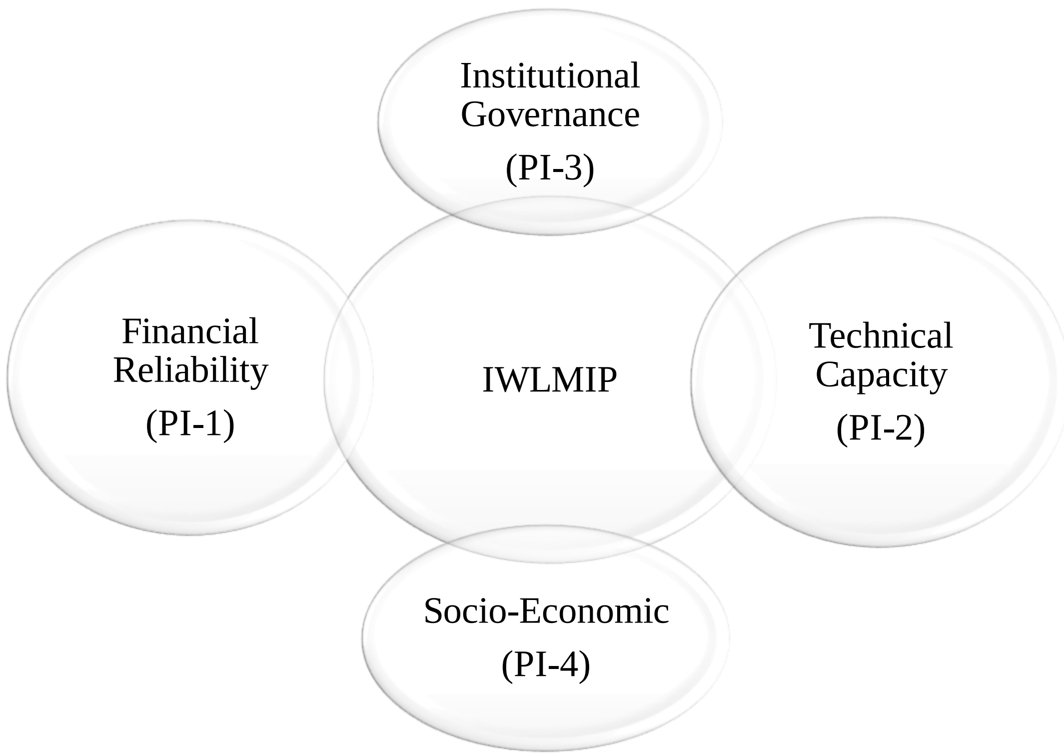

Figure 12 IWLMIP Result for Pre-Testing on IWLMM.

The implementation of IWLMIP was crucial for fine-tuning of the IWLMM for implementation by water utility in Alexandra Township- Johannesburg (South Africa) and for other water managers in developing countries. The pre-testing outcome for PCA was done by sampling of 61 professional personnel from the water entity (Johannesburg Water SOC LTD) and 361 customers (end-users) in Alexandra township. This was done in order to practically developed conceptual IWLMM known as MCDST-OM as well alignment with figure 10 above.

The principal component analysis (PCA) approach that is also known as exploratory factor analysis (EFA) was used in a MATLAB format to determine the number of components or factors that account for much of the variability in the data (Hastie et al., 2009 and Saunders et al., 2016). The final development and presentation of the developed IWLMM for developing counties is presented as a further sub-objective by the same authors of this paper.

5. CONCLUSIONS AND RECOMMENDATIONS

This study elucidated the application of a new multi-criteria decision analysis method to assess the hydraulic-based water-loss management strategies in water supply system, emphasizing the structuring and analysis of group decisions. The research' novelty is highlighted carefully through a comparative and decision making matrix, where basic hydraulic water loss assessment models such as NRW, SIV and water balance index in water supply system were combined with decision based MCDA approach to evaluate water loss management strategy. The proposed MCDA-integrated framework presented in this example case study used the PROMETHEE II methodology and the D-Sight software sensitivity analysis. The study explicitly considered strategic objectives linked to finance, socioeconomic, environmental, health and safety, as well as technical and institutional governance considerations.

Through the step-by-step decision-making process of a group, represented by 8 DM in this example, outcomes explicated that highly preferred options seem to be those which improve financial reliability. Technical capacity and sound institutional governance goals were those criteria that provide an organization with financial soundness. Outcomes also indicated that the crucial goal of financial optimization does not seem to be necessarily the best and most appropriate strategy when water-loss multi-criteria options are linked to a challenging socioeconomic setting such as an informal settlement. The D-Sight software is valuable for dealing with decision-making in the planning of complex water loss challenges and the ranking of the strategic objectives and ECs. The results show that even in cases where multiple criteria options exist, integrated and global results can still be achieved, thereby assisting the water utility in deciding which strategic objective(s) they should prioritize, resource, implement and monitor. The study limitations are that although 8 DMs were selected from the water utility, they may have yet to give a proper group decision and that their ranking of alternatives is solely based on their functional level in the water utility; hence their decision may be subjective. This proposed MCDA application is an effective decision-support tool envisaged to assist policymakers, water managers and water utilities. The tool supports policymakers in assessing and prioritizing overall strategies for water-loss reduction within WDS, specifically in developing nations. This is because some of these countries face socioeconomic and institutional governance challenges. The authors recommend further research on water loss management with larger data samples consisting of water utility DM, customers and other stakeholders. The proposed and other multi-criteria techniques should be tested also in other example regions to improve integrated group decision-making. The developed and other multi-criteria models should serve as an alternative or supportive option to assist water managers, policymakers, planners, social scientists and decision-makers in properly assessing, prioritizing and selecting the best strategic objectives for reducing water losses in water distribution systems.

DATA AVAILABILITY STATEMENT: All generated and collected data, models, and code used during the study were provisionally and ethically granted by Johannesburg Water SOC Ltd. and the University of Johannesburg. Some or all of the data, models, and code that support the findings of this study are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST: The authors declare that there is no conflict on the publication of this research paper.

INSTITUTIONAL REVIEW BOARD STATEMENT: The study was conducted according to the guidelines of the Declaration of the Department of Higher Education and Training of South Africa Government Gazette (No. 39583, Vol 607) of 8 January 2016 and originally approved by the University of Johannesburg on 12 February 2018 and the Institutional Review and Ethical committee of the University of Johannesburg on 24 August 2020 with the Ethical Clearance Number UJ_FEBE_FEPC_00034**.**

INFORMED CONSENT STATEMENT: Informed consent was obtained from all subjects involved in the study and approved under Ethical Clearance Number UJ_FEBE_FEPC_00034.

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