IoT-Driven Sensor Selection for Smart Water and Electricity Systems: A TOPSIS and VIKOR Approach

Oumaima Rhallab[1], Rachid Dehbi[2], Zouhair Ibn Batouta[3], Amine Dehbi[4]
Faculty of Science Aïn Chock, Laboratory of Data Engineering and Intelligent Systems, Hassan II Casablanca, Morocco [1, 2]
Faculty of Science Ben M'Sik, Laboratory of Information Processing, Hassan II Casablanca, Morocco [3]
Faculty of Science Ben M'Sik, LTI Laboratory, Hassan II Casablanca, Morocco [4]
High School of Technology-Dakhla, Ibn Zohr University, Dakhla, Morocco [4]

Abstract—**In the era of smart cities and intelligent resource management, the need for precise and efficient sensing devices is increasingly critical. Among essential infrastructures are water and electricity systems, which necessitate continuous monitoring to optimize consumption, detect anomalies, and reduce operational costs. Several commercial sensors for water metering and electricity metering are available on the market, each differing in precision, power consumption, communication protocols, and durability. This diversity creates a decisional challenge when choosing the best sensor for a certain application. We report herein a comparative study of various water and electricity sensors by means of a multi-criteria decision-making approach. We adopt TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje), two robust quantitative MCDM techniques. The carefully selected set of evaluation criteria and a wide range of sensors commonly used were analyzed. It turned out that the ranking was different based on context and application; therefore, valuable insights have been provided for engineers, system designers, and decision-makers in the IoT domain. It is expected that the present study will be of practical help for choosing the best sensors in smart metering applications and prove the efficiency of integrated decision models in technical evaluations.**

Keywords—Water and electricity system; water metering; electricity metering; MCDM techniques; TOPSIS; VIKOR; IoT; smart metering

I. Introduction

Rapid changes in information and communication technologies are driving modern societies, and one of the strongest paradigms is the Internet of Things. It enables IoT systems to monitor and control in real-time the resources that are part of the network, which helps in achieving sustainable development and smart urban management. The most important infrastructures are water and electricity networks; their correct measurement and smart monitoring offer significant benefits, such as optimizing consumption, detecting anomalies, and reducing operational costs [1], [2].

IoT-enabled sensors and smart meters have become the backbone of this transformation, allowing for a set of functionalities such as automated billing, leak detection, load forecasting, and predictive maintenance [3], [5]. However, the diversity of commercially available devices creates a decision-making problem. In fact, each sensor differs in several aspects: accuracy, cost, communication protocol, energy consumption, durability, and ease of integration. For this reason, selecting the most suitable alternative requires a rigorous and objective evaluation framework [6], [7].

Given this complexity, researchers have widely applied MCDM approaches. Methods such as the Analytic Hierarchy Process (AHP) [8] and COPRAS [9] have been successfully applied in various fields, but they often rely on subjective judgments. This may introduce biases when evaluating real-world technologies. For this reason, alternative methods that provide more robust quantitative evaluations have gained attention. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) are among the most widely used techniques since the late 2000s, offering balanced solutions for ranking alternatives based on proximity to ideal and compromise outcomes [10], [11].

While recent research has investigated the application of TOPSIS and VIKOR in energy systems, water infrastructures, and IoT environments [6], [7], a comparative evaluation that jointly applies both methods to heterogeneous smart metering technologies is rather limited. Indeed, only a few works have so far proposed an integrated assessment covering both water and electricity infrastructures according to a set of unified technical and economic criteria.

Based on this observation, this study, therefore, seeks to perform a comparative analysis of a set of various water and electricity sensors through TOPSIS and VIKOR based on technical and economic criteria. The results obtained offer important remarks to researchers, engineers, utility companies, and policy analysts interested in the deployment of smart metering solutions. The contribution of this study is the development of a multi-criteria evaluation model based on TOPSIS and VIKOR methods to comparatively evaluate smart water and electricity sensor systems and support decision-making processes. The adopted methodology will be described, along with the criteria and the corresponding methods for the final ranking.

The concluding remarks and the perspectives will be presented at the end. Additionally, this work contributes to the growing literature on IoT-based sustainable infrastructure, while offering a decision-support framework that could be extended to other domains of smart city development.

II. Related Work

Nowadays, with the rapid development of information and communication technologies, the adoption of IoT within such critical infrastructures as water and electricity has accelerated. Accordingly, IoT solutions will provide real-time monitoring, anomaly detection, and predictive maintenance that are all essentials toward reaching sustainability and efficiency targets [1], [2].

IoT technologies have already proven to be transformative in the water sector. Obunga et al. [1] reviewed state-of-the-art applications of IoT for water distribution, focusing on leakage detection and reduction of non-revenue water. Similarly, the work of Zyoud [2] presented an in-depth bibliometric analysis of the use of IoT in urban water systems, whereas Bandara et al. [5] discussed integrating IoT sensors into real-time water quality monitoring. Complementing this, the work from Jamadarkhani et al. [12] proposed a non-intrusive IoT-based solution for monitoring consumption in intermittently pressurized networks, further extending the applicability of IoT in challenging environments.

Smart metering, when discussing electricity systems, has really taken off with regard to efficiency and automation. Al-Sammak et al. [4] have developed smart meters equipped with LoRaWAN and NB-IoT adaptive energy optimization algorithms, thus achieving significant consumption reductions. Rivero-Iglesias et al. [7] showed hybrid multi-criteria frameworks for alternative power generation technologies assessment and proved the importance of decision-making models, both qualitative and quantitative, as analytical tools in the energy domain. A systematic literature review by Mathebula and Mbuli [18] demonstrated that TOPSIS-based frameworks are frequently applied in power system evaluation due to their ability to balance technical, economic, and environmental criteria. The increasing complexity of evaluating this kind of technology means that multi-criteria decision-making methods are increasingly applied.

The interest in the TOPSIS and VIKOR methods is growing due to their strength in ranking alternatives under conflicting criteria. Li et al. [11] proposed a dynamic adaptive framework that embeds these methods within federated learning contexts, while Radulescu et al [6] applied them for sustainability assessment. Pramanik et al. [14] further explored the effectiveness of these methods in mobile crowd computing environments. More interestingly, Yang et al. [15] successfully applied the combined VIKOR–TOPSIS model to urban water supply safety assessment in Tianjin, confirming their applicability in real-world resource management. Lin [16] extended these methods to the evaluation of smart cities through the development of a fuzzy-based model; this is bound to underline their versatility in complex infrastructural systems.

Even though the application of MCDM methods is altering the water and electricity domains, many of the related studies still consider specific applications or even single-domain analysis. This points to the necessity for unifying comparative approaches for evaluating numerous heterogeneous smart meter technologies at various critical infrastructures.

III. Methodology

A. Selection of Sensors

In this work, a representative sample of commercially available water and electricity sensors was selected, as shown in Table I. The choice was guided by three main factors: the prevalence in smart metering applications, the availability of technical specifications, and the relevance in both residential and industrial contexts.

TABLE I. SELECTED WATER AND ELECTRICITY SENSORS

Type	Sensor (Model)	Manufacturer	Key Features
Water Sensor	Neptune T-10	Neptune Technology	Mechanical water meter, high accuracy, AMR/AMI compatible
	Sensus iPERL	Xylem Inc.	Solid-state, low-flow detection, long lifespan
	Kamstrup MULTICAL 21	Kamstrup	Ultrasonic, battery life >16 years, wireless M-Bus
	Diehl IZAR Water Meter	Diehl Metering	Smart communication, IoT-ready (LoRaWAN)
	LoRaWAN Ultrasonic WM	Elster / Honeywell	Real-time flow monitoring, remote connectivity
Electricity Sensor	Schneider iEM3000	Schneider Electric	High precision, industrial energy management
	Sense Energy Monitor	Sense Labs	Real-time load monitoring, app integration, residential use
	Shelly EM	Shelly	Wi-Fi based, low-cost, suitable for home automation
	IoTaWatt Energy Monitor	Open source	Multi-channel, IoT integration, low-cost
	Smappee Infinity	Smappee	AI-based analytics, smart grid integration

B. Evaluation Criteria

The assessment of water and electricity sensors was made based on ten technical and economic criteria, deduced from the recent literature and industrial practices. These criteria were chosen to capture measurement performance, operational efficiency, sustainability, and integration with IoT infrastructures.

1) C1 – Measurement accuracy (%): Accuracy has always been one of the key performance indicators in water and energy metering, since it has a direct influence on billing, anomaly detection, and decision-making itself [1], [5], [13].

2) C2 – Cost (€): Initial investments and lifetime affordability are crucial in wide-scale deployments: Cost-performance trade-off is a recurring theme in the sensor and IoT selection studies [2], [12], [17].

3) C3 – Energy Consumption (mW): Energy efficiency is essential for IoT-based systems, especially for batteryoperated smart meters. The recent works ([4], [14], [15]) emphasized the importance of low consumption for extending the lifetime of devices to ensure sustainability in operation.

4) C4 – Communication protocol (1–5): IoT-enabled sensors rely on robust communication standards such as LoRaWAN, NB-IoT and M-Bus. The ability to integrate seamlessly into IoT networks has been widely reported as a determinant of scalability and interoperability [2], [4], [16].

5) C5 – Durability / Robustness (1–5): The sensors employed in outdoor or industrial environments should be reliable under extreme environmental conditions. Robustness and resilience are also considered significant dimensions of evaluation by many works, such as [1], [15], [17].

6) C6 – Ease of installation and integration (1–5): The ability to deploy sensors with minimal effort and integrate them into existing infrastructures influences the adoption rates. Studies on IoT platforms and system selection confirm their importance [12], [16], [19].

7) C7 – Maintenance requirements (1–5): Sensors with low maintenance requirements lower the cost of operation and increase efficiency. This aspect has been highlighted in various recent IoT-enabled monitoring system analyses [5], [13].

8) C8 – Security features (1–5): Smart metering requires data integrity and protection against tampering or cyberattacks. In works on IoT system evaluation, encryption and secure communication are set as required features [6], [16].

9) C9 – Scalability (1–5): From household to utility-level deployments, the capacity to function effectively ensures sensor adaptability for different applications. In most sustainable IoT and systems for groundwater monitoring, scalability has emerged as one of the most identified key requirements [2], [7], [17].

10) C10 – Response time (ms): This may be the latency in measurement and communication, which seriously affects real-time monitoring. Minimizing response time was considered one of the important criteria in IoT water and electricity systems [4], [14].

The selected criteria, therefore, reflect both performance-oriented attributes (C1, C3, C4, C5, C10) and practical/operational aspects (C2, C6, C7, C8, C9), ensuring a balanced evaluation framework consistent with previous studies. The criteria were quantized and employed a well-structured five-level scale, spanning from "Very low" at level 1 to "Very high" at level 5. The quantification was determined through the comparative interpretation of the technical specifications of the devices and was utilized in a similar manner for all alternatives. Table II recaps the qualitative score used.

In the literature, there are different methods for determining criteria weights, such as AHP based on pairwise comparisons. In this study, expert consultation was considered, bringing in domain knowledge about smart metering systems. The developed weighting scheme has been consistently used within both TOPSIS and VIKOR to ensure coherence and comparability of the ranking results. The final weights reflecting the relative importance of each criterion are given as follows [see Eq. (1)]:

$$w = [0.15,0.10,0.08,0.10,0.10,0.08,0.07,0.10,0.07,0.15], \quad \sum wj=1 \quad (1)$$

TABLE II. QUALITATIVE SCORING RUBRIC FOR CRITERIA DISCRETIZATION

Score	Interpretation	Description
1	Very Low	Limited capability or basic functionality
2	Low	Below-average performance
3	Moderate	Standard acceptable performance
4	High	Strong capability with advanced features
5	Very High	Excellent performance and optimized design

C. Decision-Making Framework

To objectively rank the selected water and electricity sensors, two Multi-Criteria Decision-Making (MCDM) methods were applied: TOPSIS and VIKOR. Both approaches are widely used for evaluating alternatives under conflicting criteria, but they differ in their ranking logic: TOPSIS emphasizes closeness to the ideal solution, while VIKOR highlights compromise solutions.

1) TOPSIS method: In 1981, Hwang and Yoon introduced the TOPSIS method, which has since become a reference approach for ranking alternatives in multi-criteria decision-making [20]. The TOPSIS method evaluates the performance of alternatives with respect to different criteria by considering both the ideal-best and the ideal-worst solutions. The principle is that the chosen alternative should simultaneously have the shortest distance from the ideal solution and the farthest distance from the anti-ideal solution. The steps to rank alternatives by the TOPSIS method are as follows [see Eq. (2)]:

a) Normalization of the decision matrix:

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i=1,2,\ldots,m;\ j=1,2,\ldots,n \quad (2)$$

where, x_{ij} is the performance value of alternative i on criterion j; m is the number of alternatives; n is the number of criteria.

b) Weighted normalized decision matrix [see Eq. (3)]:

$$v_{ij}=w_j \cdot r_{ij}, \quad j=1,2,\ldots,n \quad (3)$$

where, w_j is the weight of criterion j.

c) Ideal and anti-ideal solutions [see Eq. (4) and Eq. (5)]:

$$A^{+}=\{v_1^{+},v_2^{+},\ldots,v_n^{+}\}, \quad v_j^{+}=\begin{cases}\max_i(v_{ij}), & \text{if j is benefit}\\ \min_i(v_{ij}), & \text{if j is cost}\end{cases} \quad (4)$$

$$A^{-}=\{v_1^{-},v_2^{-},\ldots,v_n^{-}\}, \quad v_j^{-}=\begin{cases}\min_i(v_{ij}), & \text{if j is benefit}\\ \max_i(v_{ij}), & \text{if j is cost}\end{cases} \quad (5)$$

where, A^+ is the positive ideal solution and A^- is the negative ideal solution.

d) Distance to ideal and anti-ideal solutions [see Eq. (6) and Eq. (7)]:

$$S_i^+=\sqrt{\sum_{j=1}^{n}(v_{ij}-v_j^+)^2} \quad (6)$$

$$S_i^-=\sqrt{\sum_{j=1}^{n}(v_{ij}-v_j^-)^2} \quad (7)$$

where, S_i^+ is the distance of alternative i from the ideal solution, and S_i^- is the distance of alternative i from the anti-ideal solution.

e) Closeness coefficient [see Eq. (8)]:

$$C_i=\frac{S_i^-}{S_i^++S_i^-}, \quad 0\le C_i\le 1 \quad (8)$$

where, C_i is the closeness coefficient of alternative i. A higher C_i indicates a better sensor.

2) VIKOR method: In 2004, Opricovic and Tzeng introduced the VIKOR method, which has since become a widely applied approach for ranking alternatives in multi-criteria decision-making [21]. The VIKOR method evaluates the performance of alternatives by focusing on identifying a compromise solution that provides maximum group utility while minimizing individual regret. The principle is that the selected alternative should represent a balance between closeness to the ideal solution and fairness across all criteria. The steps to rank alternatives by the VIKOR method are as follows:

- Best and worst values [see Eq. (9) and Eq. (10)]:

$$f_j^*=\max_i x_{ij} \quad (9)$$

$$f_j^-=\min_i x_{ij} \quad 10)$$

where, f_j^* is the best value for criterion j, and f_j^- is the worst value for criterion j.

- Utility and regret measures [see Eq. (11)]:

$$S_i=\sum_{j=1}^{n} w_j\cdot\frac{f_j^*-x_{ij}}{f_j^*-f_j^-} \quad (11)$$

where, S_i is the utility measure representing the group utility of alternative i.

$$R_i=\max_j\left[w_j\cdot\frac{f_j^*-x_{ij}}{f_j^*-f_j^-}\right] \quad (12)$$

where, R_i is the regret measure, representing the worst-case performance of the alternative i [see Eq. (12)].

- Compromise index [see Eq. (13)]:

$$Q_i= v\cdot\frac{S_i-S^*}{S^--S^*}+(1-v)\cdot\frac{R_i-R^*}{R^--R^*} \quad (13)$$

where, Q_i is the compromise index of alternative i, and v is the weight assigned to the “majority of criteria” strategy (commonly v=0.5).

- Boundaries [see Eq. (14)]:

$$S^*=\min_i S_i, \quad S^-=\max_i S_i \quad (14)$$

where, S^* and S^- are the best and worst values of the group utility.

$$R^*=\min_i R_i, \quad R^-=\max_i R_i \quad (15)$$

where, R^* and R^- are the best and worst values of the regret measure [see Eq. (15)].

IV. Results and Discussion

1) Decision matrix – water sensors: Table III and Fig. 1 show a multi-criteria comparison between five smart metering sensors about ten technical and functional criteria (C1 to C10). The result shows that Sensus iPERL and Kamstrup Multical 21 are the best overall performers; both have very good performance across measurement accuracy (C1), communication protocol (C4), durability (C5), and scalability (C9), enabling large-scale deployment. From the outcome, one can emphasize that Diehl IZAR LoRa ensures good performance related to its communication capability and ease of integration (C4 and C6), confirming its relevance in IoT architectures based on LoRaWAN. On the other hand, it shows a moderate performance regarding energy consumption (C3) and maintenance requirements (C7). The overall performance of Neptune T-10 and Elster V200 is lower, especially regarding security features (C8), maintenance requirements (C7), and response time (C10); this may limit their use in real-time monitoring environments that require high reliability. In general, these findings confirm the need for a multi-criteria analysis approach toward the optimal selection of sensors, no single device being dominant across all the criteria considered herein, and the final choice strongly depends on application-specific priorities, including cost, performance, security, and scalability.

TABLE III. Decision Matrix for Water Sensors (C1–C10)

Sensor	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Sensus iPERL	5	3	4	5	5	4	4	5	5	4
Kamstrup Multical21	5	4	4	5	5	5	4	4	5	4
Diehl IZAR (LoRa)	4	4	3	5	4	5	3	4	4	3
Neptune T-10	4	3	3	4	4	3	3	3	4	3
Elster V200	3	4	3	4	3	3	3	3	3	3

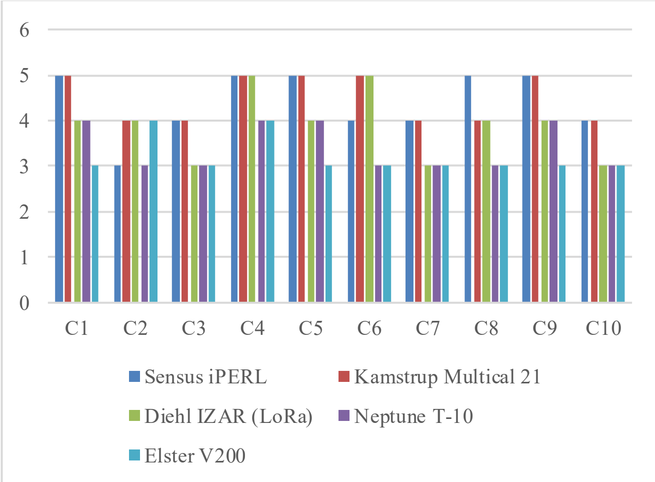

Fig. 1. Decision matrix visualization for water sensors (C1–C10).

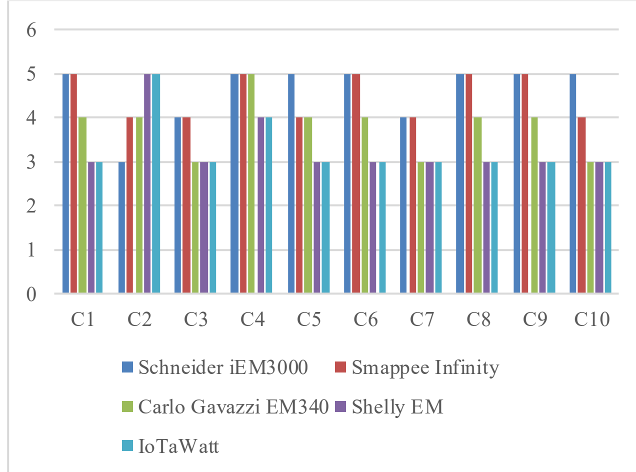

Fig. 2. Decision matrix visualization for electricity sensors (C1–C10).

2) Decision matrix – electricity sensors: Table IV and Fig. 2 show the decision matrix and its graphic visualization for the chosen electricity sensors, which have been assessed for ten criteria (C1–C10). The results point out Schneider iEM3000 as the top-performing device, since it has always reported high values for accuracy (C1), communication protocol (C4), ease of installation (C6), security features (C8), scalability (C9), and response time (C10), allowing it to be adopted in advanced smart grid and industrial monitoring. Smappee Infinity also appears as a very high-performing device with excellent scores regarding communication capability (C4), security (C8), and scalability (C9), but with a better cost score (C2), thus offering the most favourable trade-off between performance and affordability. Carlo Gavazzi EM340 presents moderate results on most of the criteria but shows worse scores in energy consumption (C3), maintenance (C7), and response time (C10), thus limiting its adoption for real-time applications. In contrast, Shelly EM and IoTaWatt present worse general scores, in particular referring to robustness (C5), integration capability (C6), and security (C8), thus considering them more suitable for residential monitoring or small-scale industries rather than wide industrial purposes.

Generally, the integrated analysis of Table IV and Fig. 2 confirms the relevance of multicriteria evaluation for choosing electricity sensors able to satisfy technical requirements together with economic ones.

3) TOPSIS rankings – water sensors: Table V and Fig. 3 present the TOPSIS ranking results of water sensors based on the closeness coefficient C_i , which reflects the relative distance of each sensor from the ideal solution. The analysis indicates that Sensus iPERL achieves the highest coefficient (0.65), confirming its superior overall performance across the considered criteria. It is followed closely by Kamstrup Multical 21 with a coefficient of 0.64, showing that both sensors offer nearly equivalent high-level performance. Diehl IZAR (LoRa) ranks third with a coefficient of 0.58, reflecting solid performance but slightly weaker results in some technical aspects. In contrast, Neptune T-10 and Elster V200 obtain lower coefficients of 0.47 and 0.42, respectively, indicating a greater distance from the ideal solution. These outcomes demonstrate the effectiveness of the TOPSIS method in supporting multicriteria decision-making and identify Sensus iPERL as the most suitable option for smart water metering in the evaluated context.

TABLE IV. DECISION MATRIX FOR ELECTRICITY SENSORS (C1–C10)

Sensor	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Schneider iEM3000	5	3	4	5	5	5	4	5	5	5
Smappee Infinity	5	4	4	5	4	5	4	5	5	4
Carlo Gavazzi EM340	4	4	3	5	4	4	3	4	4	3
Shelly EM	3	5	3	4	3	3	3	3	3	3
IoTaWatt	3	5	3	4	3	3	3	3	3	3

TABLE V. TOPSIS RANKINGS OF WATER SENSORS

Rank	Sensor	Closeness Coefficient C_i
1	Sensus iPERL	0.65
2	Kamstrup MULTICAL 21	0.64
3	Diehl IZAR (LoRa)	0.58
4	Neptune T-10	0.47
5	Elster V200	0.42

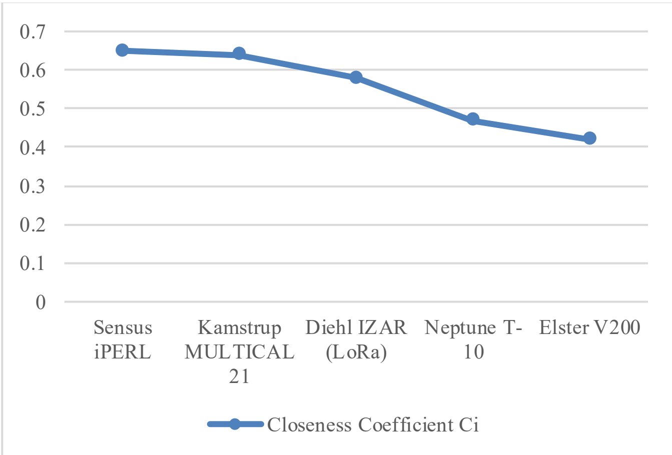

Fig. 3. Ranking of water sensors based on the TOPSIS closeness coefficient C_i.

4) TOPSIS rankings – electricity sensors: Table VI and Fig. 4 show the results of the ranking using the TOPSIS method in terms of the closeness coefficient C_i obtained for electricity sensors. The performed analysis indicates that Schneider iEM3000 reaches the highest value of the coefficient, amounting to 0.68, which translates into the best overall result among the devices under consideration. Equally good competitiveness in terms of functionality and performance manifests in the result of Smappee Infinity, with a coefficient of 0.65. Carlo Gavazzi EM340 takes third place with a value of 0.61, attesting to well-balanced technical capabilities but slightly weaker results with respect to some criteria, including the requirements and time of response. In turn, Shelly EM (0.49) and IoTaWatt (0.45) receive a lower score, reflecting their bigger distance from the ideal solution and significant constraints regarding robustness, possibilities of integration, and security features. In general, the obtained results confirm the reliability of the TOPSIS method for sensor selection and Schneider iEM3000 as the best choice for advanced electricity monitoring systems in the considered context.

5) VIKOR results – water sensors: Table VII and Fig. 5 show the results of the VIKOR ranking of water sensors according to the compromise index Q_i. The solution with the lowest value of the compromise index is Kamstrup Multical 21, with $Q_i = 0.18$, which makes it the most suitable alternative according to the VIKOR method. It is closely followed by Sensus iPERL, which has a Q_i value of 0.20, clearly showing the close competition between the two leading solutions. Diehl IZAR (LoRa) takes third place, with a compromise index of 0.29, reflecting good performance through moderate compromises. On the other hand, Neptune T-10 (0.37) and Elster V200 (0.44) have higher values of the compromise index, representing less favourable compromises due to the weaker performance in several criteria evaluated. These results confirm the capability of VIKOR to identify compromise solutions under conflicting criteria and support the selection of Kamstrup Multical 21 as the best water sensor from the viewpoint of multi-criteria compromise evaluation.

TABLE VI. TOPSIS RANKINGS OF ELECTRICITY SENSORS

Rank	Sensor	Closeness Coefficient C_i
1	Schneider iEM3000	0.68
2	Smappee Infinity	0.65
3	Carlo Gavazzi EM340	0.61
4	Shelly EM	0.49
5	IoTaWatt	0.45

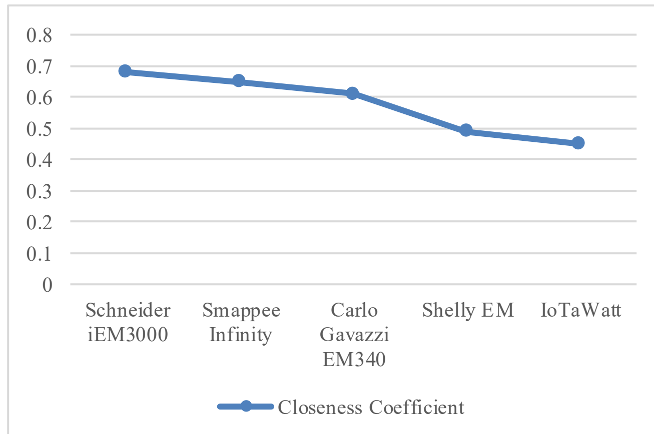

Fig. 4. Ranking of electricity sensors based on TOPSIS closeness coefficient C_i.

TABLE VII. VIKOR RANKINGS OF WATER SENSORS

Rank	Sensor	Compromise Index Q_i
1	Kamstrup MULTICAL 21	0.18
2	Sensus iPERL	0.20
3	Diehl IZAR (LoRa)	0.29
4	Neptune T-10	0.37
5	Elster V200	0.44

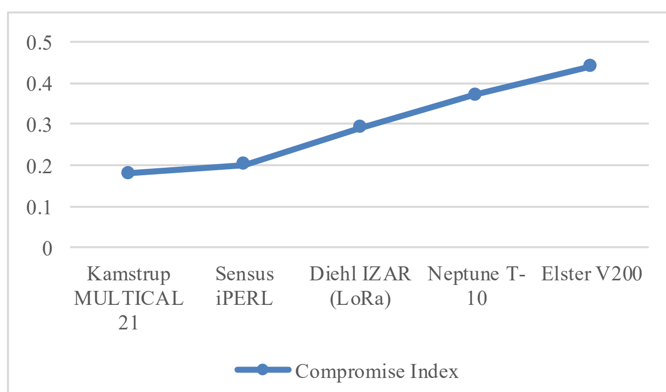

Fig. 5. Ranking of water sensors based on VIKOR closeness coefficient Q_i.

6) VIKOR results – electricity sensors: Table VIII and Fig. 6 present VIKOR evaluation results for electricity sensors based on the compromise index Q_i. It can be seen from this table and figure that the minimum value of the compromise index, 0.17, was obtained in the case of Smappee Infinity, which is ranked as the best alternative by the VIKOR method. This sensor is followed by Schneider iEM3000, with a Q_i value of 0.19, indicating the very tough competition between the two best-ranked solutions. In the third position is Carlo Gavazzi EM340, which has attained a compromise index value of 0.27, reflecting acceptable performances with moderate compromise. In turn, rather high values were noted in the cases of Shelly EM (0.39) and IoTaWatt (0.43), testifying to a less favourable compromise solution due to weaker performances in several evaluation criteria. These results have evidenced the suitability of the VIKOR method in ranking electricity sensors in conflicting criteria and then pointed to Smappee Infinity as the most appropriate choice in electricity monitoring applications, regarding the context of the present study.

TABLE VIII. VIKOR RANKINGS OF ELECTRICITY SENSORS

Rank	Sensor	Compromise Index Q_i
1	Smappee Infinity	0.17
2	Schneider iEM3000	0.19
3	Carlo Gavazzi EM340	0.27
4	Shelly EM	0.39
5	IoTaWatt	0.43

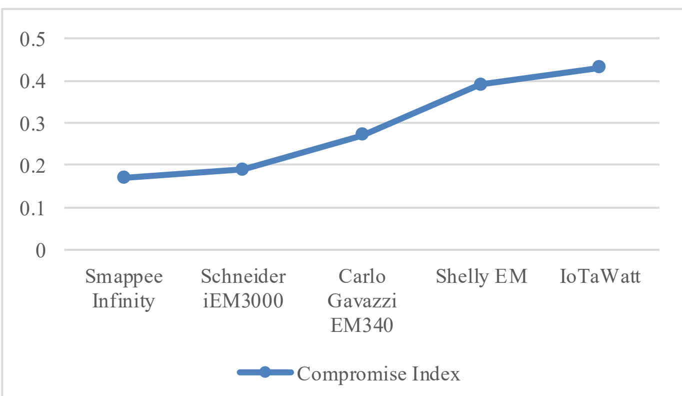

Fig. 6. Ranking of electricity sensors based on VIKOR closeness coefficient Q_i.

V. DISCUSSION

Both TOPSIS and VIKOR confirm Kamstrup Multical 21 and Sensus iPERL as the top-performing water sensors with strong accuracy, durability, and scalability. Schneider iEM3000 and Smappee Infinity consistently occupy the top ranks for electricity sensors, although TOPSIS prioritizes Schneider with a higher closeness coefficient, while VIKOR highlights Smappee with a better compromise index. As expected, the use of weights in Eq. (1) introduced significant changes to the ranking by giving much more importance to accuracy and response time, with ultrasonic and industrial-grade meters always on top. Low-cost devices such as Shelly EM and IoTaWatt remain appealing for the residential context since they are low-cost and easy to deploy, but perform less competitively in terms of durability and security. The combination of TOPSIS, which focuses on proximity to an ideal solution, with VIKOR, which aims towards compromise ranking, ensures that an effective analysis model is provided as part of the proposed methodology, relevant for various application scenarios, be it domestic or industrial.

It is important to state here that the aim of this work is not centered on developing a unique set of protocols for measurement or a unique experimental setup, but it attempts to offer a comparative evaluation of existing smart metering technology based upon existing technical specifications.

VI. CONCLUSION

This study conducted a comparative analysis of water and electricity sensors using two multi-criteria decision-making methods: TOPSIS and VIKOR. Ten technical and economic criteria were considered, with weights emphasizing accuracy and response time. The results showed that Kamstrup Multical 21 and Sensus iPERL are the most suitable water sensors, while Schneider iEM3000 and Smappee Infinity lead among electricity sensors. Lower-cost devices such as Shelly EM and IoTaWatt remain viable for residential applications but perform less favorably in terms of durability and security. Methodologically, TOPSIS highlighted alternatives closest to the ideal solution, whereas VIKOR emphasized compromise solutions. The use of both approaches ensured more reliable and balanced rankings.

The present assessment is mainly based on publicly available technical specifications, and this engenders certain limitations. The lack of experimental validation, real deployment scenarios, or workload-based evaluation constrains the present analysis to a comparative decision-support perspective. Furthermore, possible inconsistencies in data reported by the manufacturers may affect ranking results, although the multi-criteria structure of TOPSIS and VIKOR reduces isolated deviations in the ranking outcome, considering the overall performance.

Future research can be directed toward extending this study by considering experimental data, sensitivity analysis for a weight strategy, and robustness analysis, which will improve the usage of the proposed scheme for smart city applications.

This study contributes significant findings for selecting smart sensors based on the context of applications, resulting in more efficient and sustainable management of water and electricity.

REFERENCES

[1] Obunga, P.O., Rwanga, S.S., Dinka, M.O. et al. Review of the emerging technologies in the water sector with a focus on the deployment of Internet of Things solutions. npj Clean Water 8, 53 (2025).

[2] Zyoud, S. Exploring the promising role of internet of things in urban water systems: a comprehensive global analysis of insights, trends, and research priorities. Discov Internet Things 5, 31 (2025).

[3] Devasena, D., Ramya, Ra, Yuvaraj, Dharshan, Vivek, S., Darshan, T.: IoT based water distribution system. International Journal of Engineering and Advanced Technology 8(6), 132– 135 (2019).

[4] Al-Sammak, K.A., Alenezi, M.N., Alshammari, F.S., Alqahtani, A.: Optimizing IoT energy efficiency for smart meters with LoRaWAN and NB-IoT. Energies 18(4), 987 (2025).

[5] Bandara, R.M.P.N.S.; Jayasignhe, A.B.; Retscher, G. The Integration of IoT (Internet of Things) Sensors and Location-Based Services for Water Quality Monitoring: A Systematic Literature Review. Sensors 2025, 25, 1918.

[6] Radulescu, C., Radulescu, M.: A hybrid group multi-criteria approach based on SAW, TOPSIS, VIKOR, and COPRAS methods for complex IoT selection problems. Electronics 13, 789 (2024).

[7] Rivero-Iglesias, J.M., Puente, J., Fernandez, I., León, O.: A hybrid group multi-criteria decisionmaking model for the selection of power generation technologies. Systems 13(9), 742 (2025).

[8] Saaty, T.L.: Decision making with the Analytic Hierarchy Process. International Journal of Services Sciences 1(1), 83–98 (2008).

[9] Stefano, N., Filho, N., Vergara, L., Rocha, R.: COPRAS (Complex Proportional Assessment): State of the Art Research and its Applications. IEEE Latin America Transactions 13(12), 3899– 3906 (2015).

[10] Govindan, K., Sivakumar, R., Sarkis, J., Murugesan, P.: Multi-criteria decision making approaches for green supplier evaluation and selection: a literature review. Journal of Cleaner Production 387, 135907 (2023).

[11] Li, L., Shi, W., Chen, S., Liu, J., Huang, J., Liu, P.: A dynamic adaptive and resource-allocated selection method based on TOPSIS and VIKOR in federated learning. Neural Processing Letters 56, 11493 (2024).

[12] Diao, X., Rownak, M.R., Olatubosun, S., Vaddi, P.K., Smidts, C.: A multiple-criteria sensor selection framework based on qualitative physical models. Advanced Engineering Informatics 65(B), 103228 (2025).

[13] Jayaraman, P., Nagarajan, K.K., Partheeban, P., Krishnamurthy, V.: Critical review on water quality analysis using IoT and machine learning models. International Journal of Information Management Data Insights 4(1), 100210 (2024).

[14] Essamlali, I., Nhaila, H., El Khaili, M.: Advances in machine learning and IoT for water quality monitoring: A comprehensive review. Heliyon 10(6), e27920 (2024).

[15] Ullah, I., Ali, F., Sharafian, A., Ali, A., Yasir, N.H.M., Bai, X.: Optimizing underwater connectivity through multi-attribute decision-making for underwater IoT deployments using remote sensing technologies. Frontiers in Marine Science 11, 1468481 (2024).

[16] Ilieva, G., Yankova, T.: IoT system selection as a fuzzy multi-criteria problem. Sensors 22(11), 4110 (2022).

[17] Pocco, V., Chucuya, S., Huayna, G., Ingol-Blanco, E., Pino-Vargas, E.: A multi-criteria decision-making technique using remote sensors to evaluate the potential of groundwater in the arid zone basin of the Atacama Desert. Water 15, 1344 (2023).

[18] Mathebula, J., Mbuli, N.: Application of TOPSIS for Multi-Criteria Decision Analysis (MCDA) in Power Systems: A Systematic Literature Review. *Energies* 18(13), 3478 (2025)

[19] Tran, N.-T.: Application of the multi-criteria analysis method MAIRCA, SPOTIS, COMET for the optimisation of sustainable electricity technology development. EUREKA: Physics and Engineering 1, 180–188 (2024).

[20] Hwang, C.L., Yoon, K.: Multiple Attribute Decision Making: Methods and Applications. Springer, Berlin, Heidelberg (1981).

[21] Opricovic, S., Tzeng, G.H.: Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research 156(2), 445–455 (2004)