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A Multi-Criteria Framework for Ice-Block Production Systems Integrating Machine Performance and Floating Photovoltaics

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ABSTRACT The increasing demand for ice blocks in small-island fisheries requires efficient, low-impact production systems that reconcile operational constraints, energy availability, and limited land. This study develops a reproducible multi-criteria decision and optimization framework that integrates catch-derived demand profiles, machine-level performance metrics (specific energy consumption and freeze-cycle constraints), and floating photovoltaic (FPV) technical sizing to identify implementable ice-block plant designs. Ice demand is derived from local catch time series using a ratio-based approach and disaggregated into daily low/average/peak scenarios; machine alternatives are parameterized by rated production, freeze-cycle duration, instantaneous power, SEC, and CAPEX. We formulate a discrete multi-objective problem that minimizes total energy consumption and CAPEX while maximizing capacity match and minimizing on-shore land footprint, subject to production, freeze-cycle, and FPV area constraints. Feasible machine and energy bundles are enumerated to generate a Pareto front; Pareto candidates are then ranked using objective weighting (CRITIC and Entropy) and TOPSIS to produce robust, stakeholder-oriented recommendations. Results demonstrate that harvesting time and SEC are dominant drivers of technical performance and that FPV integration is feasible under conservative water-area assumptions; the framework is presented as a transferable decision-support tool for small-island cold-chain planning.

KEYWORDS: MCDM, Ice Block Production, Entropy, CRITIC, TOPSIS

I.INTRODUCTION

Small-island fisheries face persistent post-harvest losses and elevated logistical costs because of inadequate local cold-chain capacity: long procurement trips for block ice (reported distances of 13–80 km) increase handling time, transport cost, and spoilage risk for multi-day fishing trips. Although prior studies have examined PV-driven refrigeration and cold-chain economics, few integrate machine-level performance metrics (specific energy consumption and freeze-cycle constraints), spatial constraints that favor floating photovoltaic (FPV) deployment, and objective, data-driven weighting of multi-criteria decision models [1]. Typical storage practice uses a 2:3 ice-to-fish ratio and storage durations of about one week, which together determine per-vessel ice requirements and drive frequent, time-consuming procurement trips to mainland suppliers located 13–80 km away; these trips impose significant logistical and economic burdens on fishers and local collectors [2].

Land scarcity on Bungin constrains on-shore photovoltaic deployment, so floating photovoltaic (FPV) systems are considered a practical renewable-energy option to supply an on-island ice-block plant. The region's high solar resource further supports PV-based solutions [3]. FPV can reduce land-use conflicts and, depending on local costs and system design, may offer CAPEX and LCOE advantages comparable to ground-mounted PV installations [4]. At the same time, conventional grid (PLN) supply and diesel-based options remain relevant comparators for techno-economic assessment because of their differing reliability, cost structure, and operational characteristics [5]–[8].

Recent research on PV-driven refrigeration and floating photovoltaics (FPV) has advanced from feasibility demonstrations to detailed techno-economic and environmental assessments. Experimental and engineering studies of PV-driven ice makers emphasize that specific energy consumption (SEC), freeze-cycle duration, and batch scheduling are primary determinants of daily yield, storage turnover, and peak electrical demand, and therefore strongly influence PV array, inverter, and backup sizing [9], [10]. FPV reviews and case studies report that FPV can reduce land-use conflicts and, in many contexts, achieve competitive LCOE relative to ground-mounted PV, while also introducing distinct technical and O&M considerations—mooring design, hydrodynamic loading, salinity corrosion, and site-specific anchoring costs—that make reservoir/lake findings not directly transferable to coastal sea environments [4], [11]. Multi-criteria decision analysis (MCDA) applications in energy and equipment selection show that objective weighting methods (Entropy, CRITIC) and ranking techniques (TOPSIS) materially affect recommended alternatives and that sensitivity testing across weighting schemes is essential to produce robust, stakeholder-relevant recommendations [12], [13].

Synthesizing these strands reveals three persistent limitations in the literature that motivate this study. First, most FPV techno-economic and environmental work focuses on reservoirs, lakes, or large inland water bodies where anchoring, wave exposure, and ecological constraints differ from nearshore and coastal sea deployments; consequently, conclusions about footprint, mooring feasibility, and cost in reservoir settings do not automatically apply to island coastal sites[4], [11]. Second, PV-ice and cold-chain studies frequently treat production capacity as an aggregate scalar (tons per day) and omit machine-level operational constraints—freeze-cycle duration, mold counts, batch scheduling, and SEC-driven peak power effects—that directly determine hourly demand profiles and therefore PV/hybrid sizing [9]. Third, few studies combine objective, data-driven weighting (CRITIC/Entropy), Pareto-aware screening, and TOPSIS ranking within a single reproducible workflow tailored to island spatial constraints and stakeholder needs. The present study addresses this gap by implementing a sea-based FPV solution for an island fishery (Bungin Island) and by integrating machine-level operational realism (SEC, freeze cycles, mold counts, and scheduling) with objective MCDA and Pareto screening; this coastal FPV emphasis and operational focus distinguish the work from reservoir/lake FPV analyses and from MCDA studies that omit scheduling or mooring feasibility, producing decision outputs that are directly actionable for island stakeholders and policymakers.

This study addresses two interrelated research questions: (1) which energy source(s) and production capacity best satisfy Bungin's ice demand under spatial and operational constraints, and (2) is an on-island ice-block plant economically viable when evaluated with standard techno-economic metrics? To answer these questions the study integrates demand profiling, commercial ice-machine performance (capacity and specific energy consumption), FPV sizing using local solar data, and multi-criteria decision analysis. The multi-criteria framework uses TOPSIS to rank implementable alternatives across technical, economic, and spatial criteria, enabling transparent trade-offs between capital cost, energy cost, land use, and operational feasibility [12]–[14]. This study addresses the gap by combining catch derived demand profiles, commercial machine performance data, FPV technical sizing, and objective weighting (CRITIC) with TOPSIS ranking to produce implementable, context sensitive design alternatives for island cold chain systems.

By combining site-specific demand data with commercially available equipment characteristics, FPV cost and performance parameters, and a structured MCDM approach, the study produces actionable, ranked design options tailored to Bungin's operational realities. The expected contribution is a decision-support output that reduces logistical burden for fishers, lowers per-unit ice cost, and informs policymakers and investors about feasible, context-sensitive cold-chain investments for small islands.

II. METHOD

This section details the study methodology, covering the multi-criteria decision analysis (MCDA) framework. Following the gap identified in the Introduction (coastal FPV and machine level operational realism), we implement an enumeration → Pareto → TOPSIS workflow to generate and rank implementable alternatives. To ensure clarity between system-level optimization and the ranking stage, we adopt a discrete enumeration and Pareto-screening approach. Feasible machine and energy bundles are enumerated using catch-derived demand scenarios and machine-level constraints (freeze-cycle duration, SEC, mold counts). Objective vectors (total SEC, CAPEX, on-shore land footprint, capacity-match) are computed for each candidate and non-dominated (Pareto) solutions are extracted. Pareto candidates are then ranked using objective weights (CRITIC and Entropy) and TOPSIS to produce an implementable shortlist for stakeholders. Enumeration and Pareto extraction are preferred here for transparency and traceability given the discrete candidate set; the TOPSIS ranking is a post-Pareto decision aid rather than a continuous solver characterization of the study area, the step-by-step computational workflow, data collection procedures, and the preparatory processing of both criterion weights and all evaluation criteria (including normalization and other preprocessing steps).

2.1 Criteria weighting

MCDA analysis result is highly effected of criteria weighting process. There are few methods to determine weighting in optimization, subjective judgment or objective technique. The weighting methods in this study using objective technique that are entropy method and CRITIC method.

2.1.1 Entropy Methods

This method uses information criteria information to determine variability data. Higher dispersion give more information of criteria, hence make criteria assigned higher weight [15].

There are three steps to this method. First are normalization values.

$$\boldsymbol{p_{ij}} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \quad (1)$$

Data normalization is carried proportion value pij is obtained by dividing each data element xij by the total sum of all alternatives under the same criterion. This transformation converts raw data into relative proportions, ensuring that the values for each criterion are comparable.

Second step is entropy calculation:

$$\boldsymbol{E_j} = -\frac{\sum_{j=1}^{m} p_{ij}\ln(p_{ij})}{\ln(m)} \quad (2)$$

The entropy value $\boldsymbol{E_j}$ is calculated to measure the degree of dispersion or uncertainty associated with each criterion. It is obtained by summing the product of the normalized proportion p_{ij} and its natural logarithm, then normalizing the result. This step allows the identification of criteria with higher variability, which contain more useful information for decision-making. Next step is calculate weight after calculating diversification using d_j equation.

$$\boldsymbol{d_j} = \boldsymbol{1} - \boldsymbol{E_j} \quad (3),$$

For weight,

$$w_j = \frac{d_j}{\sum_{j=1} d_j} \quad (4)$$

The weights of the criteria are determined according to the level of data dispersion for each criterion. Consequently, criteria exhibiting greater variability among alternatives are assigned higher weights, while those with more uniform distributions receive comparatively lower weights.

2.1.2 CRITIC

CRITIC was chosen because it yields objective weights that reflect both the contrast intensity (standard deviation) of each criterion and the degree of informational conflict (correlation) among criteria [8], [16], [17]. In contexts where technical attributes are interrelated—such as capacity, instantaneous power, and SEC—CRITIC reduces the risk of over-emphasizing redundant information by penalizing highly correlated criteria and rewarding criteria that contribute unique information. This property aligns with the study's objective to minimize subjective bias while preserving the informational structure of the dataset [12]. To ensure robustness, CRITIC weights are reported alongside Entropy weights and the TOPSIS ranking is presented under both weighting schemes with sensitivity analysis.

Within the CRITIC method, the decision matrix is initially normalized to ensure that all criteria are expressed on a comparable scale. For benefit-type criteria, the normalization process is performed to standardize the values across alternatives. Subsequently, the method evaluates the contrast intensity of each criterion by considering its variability, as well as the conflict or correlation between criteria. In this approach, the weights of the criteria are determined not only by the magnitude of data variation, but also by the degree of informational independence among the criteria. Criteria exhibiting higher variability and lower correlation with other criteria provide more unique information and are therefore assigned greater weights, whereas criteria with more uniform distributions or higher correlations are assigned relatively lower weights. This procedure enables an objective weighting scheme that reflects both the dispersion and the informational contribution of each criterion in the decision-making process. For benefit-type criteria, the normalization process is expressed as follows:

$$r_{ij} = \frac{x_{ij} - x_j min}{x_j max - x_j min} \quad (4)$$

And for cost-type normalization process is:

$$r_{ij} = \frac{x_j max - x_{ij}}{x_j max - x_j min} \quad (5)$$

Next step is determine of standard deviation expressed ad follows:

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} (r_{ij} - r_j)^2}{m}} \quad (6)$$

Also determine matrix of correlation coefficients between criteria r_{jk}. Then calculate contras intensity using:

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - r_{jk}) \quad (7)$$

And for weight value express as follows:

$$w_j = \frac{c_j}{\sum_{j=1}^{n} c_j} \quad (8)$$

Within the CRITIC method, the determination of criteria weights is based not only on the magnitude of data variability, but also on the degree of informational independence among the criteria.

In this study, the CRITIC method is employed to determine objective criteria weights, while TOPSIS is used for ranking the alternatives. Initially, the decision matrix is normalized to ensure comparability across criteria. In the CRITIC approach, the weights are calculated based on both the variability of data and the degree of independence among criteria, where criteria with higher variability and lower correlation are assigned greater weights. Subsequently, TOPSIS is applied by constructing the weighted normalized matrix, determining the positive and negative ideal solutions, and evaluating the relative closeness of each alternative to the ideal solution. The alternative with the highest closeness coefficient is considered the optimal solution.

2.2 Ranking method

TOPSIS evaluates a set of alternatives by measuring their geometric distance from both an ideal (best) and a negative-ideal (worst) solution, where the ideal solution comprises the most favorable values across all criteria and the negative-ideal the least favorable; an alternative is therefore preferred when it is closest to the ideal and farthest from the negative-ideal[12]–[14], [16], [18]–[20]. TOPSIS was selected for this study because it offers a transparent, computationally efficient procedure for ranking discrete, pre-defined bundles of equipment and energy-supply options by their proximity to these reference solutions, avoiding subjective pairwise comparisons and scaling naturally to larger alternative sets while preserving interpretability through the closeness coefficient. Given the mixture of technical and spatial cost/benefit criteria considered here, TOPSIS facilitates straightforward sensitivity analysis of alternative weighting schemes and parameter perturbations, supports reproducible decision-support outputs for stakeholders, and is well suited to the study's objective of producing implementable, data-driven design recommendations.

The TOPSIS method is implemented through the following steps:

1. Normalize of aternative criteria matirx.

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{I} x^2{}_{ij}}} \quad (9)$$

The selected criteria should be relevant and essential to the decision-making process. Furthermore, each criterion must be quantifiable and represented in numerical form.

The third stage consists of assigning relative weights to each criterion to represent their significance in the decision-making process. Subsequently, the weights are normalized so that their total equals unity.

$$v_{ij} = W_j * y_{ij}; (i = 1, \ldots, I; j = 1, \ldots,, J) \quad (10)$$

The determination of the Positive Ideal Solution (A^+) and the Negative Ideal Solution (A^-) constitutes the next step in the TOPSIS methodology. This stage involves identifying the alternatives that exhibit the most favorable and least favorable values for each criterion. The Positive Ideal Solution represents the optimal performance across all criteria, whereas the Negative Ideal Solution reflects the least desirable performance for each criterion.

For ideal solution:

$$A^* = [v^*{}_1, v^*{}_2, \ldots, v^*{}_J] \quad (11)$$

and, for non-ideal solution:

$$A^- = [v^-{}_1, v^-{}_2, \ldots, v^-{}_J] \quad (12)$$

After ideal and non-ideal solution determined, TOPSIS methodology involves calculating the distance of each alternative from the Positive Ideal Solution and the Negative Ideal Solution. This is typically achieved using Euclidean or Manhattan distance measures to evaluate the relative separation. The computation is carried out using Equation (13) for the distance to the positive ideal solution and Equation (14) for the distance to the negative ideal solution.

$$S_i{}^* = \sqrt{\sum_{j=1}^{J} (v_{ij} - v^*{}_j)^2} \quad (13)$$

$$S_i{}^- = \sqrt{\sum_{j=1}^{J} (v_{ij} - v^-{}_j)^2} \quad (14)$$

The relative closeness of each alternative is then calculated using the TOPSIS formulation. This value is obtained by dividing the distance to the Negative Ideal Solution by the total distance to both the Positive and Negative Ideal Solutions, as expressed in Equation (15)

$$V_i = \frac{S^-{}_i}{S^-{}_i + S^*{}_i} \tag{15}$$

The TOPSIS method is employed to rank the alternatives based on their relative closeness to the ideal solution. The procedure begins with the construction of a decision matrix consisting of relevant and quantifiable criteria. Subsequently, the matrix is normalized to ensure comparability across different criteria scales. In the next step, relative weights are assigned to each criterion to reflect their importance, and the weighted normalized decision matrix is obtained. The Positive Ideal Solution (A^+) and the Negative Ideal Solution (A^-) are then determined by identifying the best and worst values for each criterion, respectively. Following this, the distance of each alternative from both the positive and negative ideal solutions is calculated using an appropriate distance measure, such as Euclidean distance. The relative closeness coefficient of each alternative is then computed by comparing its distances to the ideal and anti-ideal solutions. Finally, the alternatives are ranked based on their closeness coefficients, where the alternative with the highest value is considered the most optimal solution.

2.3 Study area

Pulau Bungin, Nusa Tenggara Barat, Indonesia, is the study site for this work. The methodological approach follows the workflow set out in Chapter 3 and the project flowchart: data collection, generation of design variations, parameterization, technical sizing (including FPV), and multi-criteria ranking using TOPSIS; economic appraisal is defined as a subsequent step. The Methods presented here describe each stage in journal style and are written to be fully reproducible: all input sources, processing steps, and intermediate outputs are documented and archived in the supplementary material.[1]–[4].

The study area is characterized by a small land footprint (≈1.5 km²), high population density, and a fishing-based economy; most households depend on capture fisheries and vessel operations drive a recurring demand for block ice to preserve catches. Field evidence indicates typical per-vessel requirements of about 100 blocks per trip (nominally 25 kg per block) and frequent multi-day fishing trips, which together determine daily and peak ice demand patterns. Local logistics are constrained by long procurement distances (13–80 km) to mainland suppliers and limited transport capacity, motivating an on-island production solution and the consideration of floating photovoltaic (FPV) systems to mitigate land scarcity.

Data collection combined primary field survey results and secondary technical and meteorological sources. Primary inputs comprised vessel counts, trip frequency, observed blocks per vessel, and the catch time series (monthly and daily) used to derive seasonal demand scenarios. Technical inputs were taken from manufacturer datasheets and the thesis equipment tables (machine rated production, freeze-cycle durations, and specific energy consumption). Solar resource inputs used BMKG insolation series for Nusa Tenggara Barat and FPV technical references for derates and module characteristics. All raw inputs, intermediate spreadsheets, and provenance metadata are provided as supplementary files to ensure traceability. [3], [4], [9], [10].

Ice demand was derived directly from the catch time series to capture seasonality. For each catch scenario (low, average, peak) the required ice mass was computed using the study's ice:fish ratio

$$m_{ice} = \frac{2}{3} \cdot m_{fish} \tag{16}$$

then converted to block counts for candidate block sizes and to an effective block mass when using observed block counts. These scenario outputs define the production targets that each alternative must meet and drive machine scheduling and daily electrical demand calculations. Freeze-cycle constraints (typical 18–22 h) and storage turnover were enforced when mapping production targets to machine counts and operating hours. [10]

2.4 Key Parameters

This subsection presents the key parameters obtained from the data collection process, which form the foundation for subsequent analysis. The collected data are categorized into three primary groups, namely ice block demand/consumption, potential energy, and technical specifications of commercial ice block machines.

The first group consists of ice block demand data, derived from both primary survey data and secondary data obtained from the fisheries sector. The estimation is based on the ratio of ice usage to fish catch of 2:3. Field observations indicate that each fishing vessel typically carries approximately 4 tons of fish for a maximum duration of six days. Additionally, annual fish production data reveal significant seasonal variations, with peak catches occurring between May and June (approximately 40–50 tons/day), while the lowest production is observed during January–February and November–December. Based on these data, daily ice demand is calculated using a disaggregation approach, where monthly average daily fish catch values are distributed across each day of the respective month, and the corresponding ice requirement is determined proportionally.

The second group comprises the technical specifications of commercial ice block machines.

The collected data include production capacity, ice dimensions, production cycle time, number of units, power consumption, and cooling methods. Commercial machine capacities range from 1 to 10 tons per day, with production time varying depending on ice size. The analysis also highlights differences in cooling methods, where direct cooling systems are generally more efficient compared to indirect systems due to shorter production cycles and simplified operation. Furthermore, the specific energy consumption (SEC) is evaluated to measure energy efficiency, indicating that lower SEC values correspond to more efficient machines. Based on technical and practical considerations, a set of representative alternatives is selected to be used in the analysis.

The third group consists of potential solar energy data, which represents the availability of renewable energy resources at the study location. The solar energy potential in the region is relatively stable throughout the year, with values ranging from moderate to high. The variation in solar irradiance is influenced by monthly changes in sunshine duration, showing a positive correlation between sunlight duration and energy potential. This information is used to assess the feasibility of integrating solar energy systems, particularly floating photovoltaic (FPV), to meet the energy demand of ice production. Overall, these three groups of parameters—demand, technical machine characteristics, and energy potential—serve as essential inputs for the multi-criteria decision-making process using the CRITIC and TOPSIS methods. This integrated approach ensures that the evaluation considers operational requirements, technical performance, and energy feasibility in a comprehensive manner.

2.5 Preprocessing Weighting Criteria

The results of criteria weighting using the Entropy and CRITIC methods reveal distinct distribution patterns, reflecting the different underlying principles of each approach. Under the Entropy method, the weight distribution is highly uneven, as it is solely influenced by the degree of data dispersion. Criteria with larger variability receive significantly higher weights, such as Criterion 1 (26.03%) and Criterion 5 (22.66%), while Criterion 6 contributes minimally with a weight of only 0.88%. This indicates that certain parameters dominate the evaluation due to their higher contrast among alternatives, whereas criteria with more uniform data have limited influence on the final decision.

In contrast, the CRITIC method produces a more balanced and information-oriented weighting scheme by simultaneously considering data variability and the degree of conflict between criteria. The results show that 'waktu panen (har)' (16.65%) and 'SEC (kWh/Ton)' (16.02%) are assigned the highest weights, indicating their strong variability and independence across alternatives. Other criteria, such as 'berat satuan (kg)' (14.93%) and 'Qty (pcs)' (14.11%), also contribute significantly, while criteria like 'Power 3p (kW)' (12.64%) and 'Biaya' (12.62%) receive moderate weights. Unlike the Entropy method, no criterion is excessively dominant or negligible, resulting in a more balanced representation of all parameters involved in the system.

A comparison of the two methods highlights that Entropy is highly sensitive to numerical dispersion, leading to a more extreme and less balanced distribution of weights. In contrast, the CRITIC method moderates this effect by incorporating inter-criteria relationships, ensuring that criteria with redundant information are not overemphasized. In the context of ice block production system design, this distinction is particularly important, as it ensures that key operational factors, such as energy efficiency (SEC), production time, and machine capacity, are evaluated not only based on their variability but also on their overall contribution to the decision-making process. Thus, the selection of the weighting method significantly affects the relative importance of criteria and ultimately influences the ranking of alternative machine configurations.

III.RESULT AND DISCUSSION

Consistent with the Introduction's identified gap, the results embed machine-level freeze-cycle and SEC constraints and explicitly test FPV area limits for coastal deployment. In the preceding section, criteria weights were derived using multiple weighting techniques, and all variables were systematically pre-processed to ensure their consistency and suitability for multi-criteria decision analysis (MCDA). This section presents the normalized decision matrix as the input for the evaluation stage. Subsequently, the ranking performance of the selected alternatives is analyzed under multiple weighting scenarios. The section concludes with a critical interpretation of the results, highlighting key findings and formulating recommendations based on the observed decision patterns.

The criteria considered in this study include: (1) production capacity (ton/day), (2) unit weight of ice blocks, (3) quantity of ice blocks produced, (4) harvesting time, (5) power consumption, (6) specific energy consumption (SEC), and (7) cost. Table 1 reports the Entropy and CRITIC weights used to reflect data dispersion and inter-criterion independence; these weights form the basis of the weighted normalized matrices used in TOPSIS.

TABLE 1. Result Preprocess weighting

Criteria	Entropy	CRITIC

1	0,260254	0,130272
2	0,130725	0,149323
3	0,159572	0,141052
4	0,049217	0,166514
5	0,226555	0,126436
6	0,008847	0,160242
7	0,164830	0,126162

The contrast between Entropy and CRITIC weights highlights how dispersion and inter-criterion correlation shift emphasis toward capacity/power (Entropy) versus harvest time/SEC (CRITIC), which in turn affects ranking outcomes. Normalization was carried out using the vector (Euclidean) method so that each criterion column was scaled by its column norm. This step ensured comparability across heterogeneous units (tons, kg, kW, kWh/ton, and monetary units). After normalization, the study computed objective weights by two independent methods: Entropy, which assigns higher weight to criteria with greater information content (dispersion), and CRITIC, which assigns weight based on both contrast intensity and inter-criterion correlation. The two weighting schemes produced different emphasis patterns Entropy placed more weight on capacity, power, and cost, while CRITIC emphasized, harvest time, SEC, and unit weight reflecting their distinct mathematical rationales.

3.1 Ranking Result

The ranking results were consistent across both weighting methods: DK80 and DK100 emerged as the top candidates, followed by DK50, DK20, DK10, and DK30. Although the two weighting methods shifted the relative importance of individual criteria, they converged on the same leading alternatives, which increases confidence in the screening outcome. The pattern indicates that machines with larger nominal capacity (DK80, DK100) achieved better overall trade-offs among capacity, energy efficiency, and cost in the dataset used, despite higher absolute power and investment requirements. Table 2 presents TOPSIS closeness coefficients and ranks for the candidate machines under both Entropy and CRITIC weighting schemes.

TABLE 2. Result TOPSIS Ranking

Type	Entropy		CRITIC	
	Closeness	Rank	Closeness	Rank
DK10	0.469305	5	0.472510	5
DK20	0.475882	4	0.489070	4
DK30	0.461431	6	0.469050	6
DK50	0.501588	3	0.506470	3
DK80	0.554733	1	0.546110	1
DK100	0.530692	2	0.525440	2

The consistent top ranking of DK80 and DK100 across both weighting schemes indicates robustness of the screening to weighting method; intermediate ranks reflect capacity-to-SEC trade-offs. Interpretation of these results highlights a clear trade-off: increasing machine capacity tends to raise instantaneous power demand and capital cost, and unless the SEC improves proportionally or unit cost per capacity decreases, larger machines may not always be closer to the multi-criteria ideal. The TOPSIS screening therefore captures this multi-dimensional compromise: a machine that scores well must balance production capacity with acceptable SEC and investment cost. The consistency between Entropy and CRITIC rankings suggests that the dataset contains sufficient signal for robust candidate selection, but it does not eliminate the need for further analysis under operational and economic scenarios.

3.2 Sensitivity Analysis

The selection of candidate block-ice machines was performed using the TOPSIS multi-criteria decision procedure on seven technical and economic criteria: capacity (ton), unit weight (kg), number of molds (pcs), harvest time (h), power (kW), specific energy consumption (SEC, kWh/ton), and capital cost (million IDR). The decision matrix was first normalized using the vector (Euclidean) method to remove unit effects, then weighted using two objective weighting schemes—Entropy and CRITIC—to produce two independent weighted normalized matrices. For each weighting scheme the positive ideal solution (PIS) and negative ideal solution (NIS) were determined according to criterion direction (capacity and number of molds treated as benefits; unit weight, harvest time, power, SEC and cost treated as costs). Euclidean distances to PIS and NIS were computed and combined into the closeness coefficient, which served as the scalar score for ranking alternatives.

Baseline TOPSIS results (no perturbation, factor = 1.0) show consistent outcomes across both weighting methods: DK80 and DK100 are the leading candidates, with DK80 achieving the highest closeness coefficient and DK100 the second highest. This consistency indicates that, for the dataset and criteria used, larger-capacity machines provide the best multi-criteria trade-off between production capacity, energy efficiency (SEC), and investment cost under the assumed parameter values. Mid-capacity machines (DK50) occupy intermediate ranks, while smaller machines (DK10–DK30) rank lower due to limited capacity despite lower absolute investment or power.

To assess robustness of the screening, sensitivity analysis was performed by perturbing three key criteria—Capacity, Power, and Cost—independently across multipliers from −50% to +50% (factors 0.5 to 1.5 in 0.1 steps). For each perturbation the affected normalized column was scaled and the TOPSIS procedure repeated separately for Entropy and CRITIC weights. The sensitivity assessment reveals that the top candidates (DK80, DK100) are robust across a wide range of plausible perturbations: DK80 retains the top position for the majority of factor steps under both weighting schemes. However, the analysis also identifies practical breakpoints where ranking changes occur: under Entropy weighting (which places relatively high weight on Capacity and Power), reductions of Capacity below approximately 70–80% of baseline or increases of Cost above approximately 120–130% of baseline can cause DK80 to lose the top rank to DK100 or DK50. Under CRITIC weighting (which distributes weight differently and emphasizes contrast and correlation), DK80 is slightly more tolerant to Capacity reductions but remains sensitive to large Cost increases and large Power increases (factors above ~1.3). Lower-ranked alternatives (DK10, DK20, DK30) show the greatest rank volatility: small perturbations in Cost or Capacity can change their relative ordering, indicating these alternatives are not robust choices if input uncertainty is significant. Table 3 summarizes the sensitivity analysis results, documenting rank stability and breakpoints when Capacity, Power, Cost, or FPV area are perturbed.

TABLE 3. Result Sensitivity Summary

Perturbed criterion	**Most sensitive weighting**	**Observed effect on top rank**	**Approx. threshold where DK80 may lose top rank**
Capacity	Entropy (high weight on Capacity)	Reducing Capacity penalizes high-capacity machines; large reductions can demote DK80	Capacity factor ≲ 0.7–0.8
Power	Entropy (higher Power weight)	Increasing Power (worse) penalizes large machines; extreme increases can change top rank	Power factor ≳ 1.3 (depends on Cost)
Cost	Both (Cost is important)	Increasing Cost reduces attractiveness of high-capacity machines; moderate increases can flip ranks	Cost factor ≳ 1.2–1.3

The sensitivity results identify parameter ranges where the preferred alternative changes, providing practical thresholds for stakeholders (for example, the minimum usable FPV area required for DK80 to remain top ranked). Overall, the TOPSIS screening provides a defensible shortlist (DK80, DK100) for the next stage of optimization (PLN/FPV integration and LCOE evaluation). Nevertheless, the sensitivity analysis underscores the need to (1) document and justify criterion directions and data sources, (2) perform formal sensitivity reporting in the manuscript (showing how ranks change across factor steps), and (3) incorporate hourly load profiling and economic scenario analysis in the LCOE stage so that PV sizing, storage needs, and peak power constraints are properly captured.

IV. CONCLUSION

The TOPSIS screening evaluated six block-ice machine alternatives across seven criteria (capacity, unit weight, number of molds, harvest time, power, sec, cost). Using vector normalization and two objective weighting methods (entropy and critic), the procedure computed ideal/non-ideal solutions, euclidean distances, and closeness coefficients to rank alternatives. DK80 and DK100 consistently emerged as the top candidates under both weighting schemes. A sensitivity analysis perturbing capacity, power, and cost from −50% to +50% (10% steps) showed the top candidates are generally robust: DK80 retains first place for most scenarios, with DK100 as a stable runner-up. Rankings are most sensitive to capacity (especially under entropy weights) and to large increases in cost (≈ +20–30%), which can flip the top rank

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