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Ranking of Energy Consumption Reduction Technologies in the Steel Industry in Developing Countries

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Abstract

The steel industry is a cornerstone of global economies, but also one of the most energy-intensive sectors, contributing significantly to CO_2 emissions. This issue is exacerbated in developing countries, where rapid industrial growth, outdated technologies, and resource limitations drive higher energy consumption. This study identifies and ranks energy-consumption-reduction technologies for the steel industry in developing economies, focusing on their applicability and potential for significant energy savings. The research integrates the Fuzzy Delphi Method (FDM) and Interval Type-2 Fuzzy Best-Worst Method (IT2F-BWM) to screen and prioritize technologies under conditions of uncertainty. Seven key technologies were validated by an expert panel, including waste heat recovery systems, hydrogen injection, and improvements to continuous casting. The IT2F-BWM model effectively handles expert judgment imprecision and provides a robust ranking of technologies based on criteria such as energy efficiency, economic feasibility, and environmental impact. The findings reveal that technologies such as waste heat recovery and hydrogen injection offer the most significant potential for energy savings (10-50%) and contribute to global decarbonization goals. This study provides policymakers and industry leaders with a practical decision-making tool, offering a pathway to sustainable energy practices tailored to the unique challenges of developing economies. Future research should explore dynamic modeling and cross-country comparisons further to refine energy efficiency strategies for the steel industry.

Keywords: Steel industry, Energy consumption, Fuzzy delphi method, Interval type-2 fuzzy best-worst method, Developing countries.

1 | Introduction

The steel industry is a cornerstone of modern economies, underpinning infrastructure development, manufacturing, and transportation worldwide. As one of the most energy-intensive industries, it accounts for

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approximately 7-9% of global energy consumption and contributes significantly to greenhouse gas emissions, with estimates indicating that steel production alone is responsible for about 8% of global CO_2 emissions [1], [2]. In developing countries, where rapid industrialization and urbanization are driving exponential growth in steel demand, these challenges are amplified [3]. For instance, nations such as China, India, and Brazil, which collectively produce over 60% of the world's steel, face escalating energy demands amid limited resources and environmental constraints [4]. The International Energy Agency (IEA) projects that, without substantial interventions, energy consumption in the steel sector could rise by 20-30% by 2050 in these regions, exacerbating issues such as energy security, climate change, and economic inefficiency [5]. This underscores the urgent need for sustainable practices that prioritize energy efficiency, particularly in developing economies where outdated technologies and infrastructural limitations often result in higher Specific Energy Consumption (SEC) rates—typically 20-40% above those in developed nations [6].

Despite these imperatives, the adoption of energy-efficient technologies in the steel industry remains uneven, especially in developing countries [7]. Traditional steelmaking processes, such as the Basic Oxygen Furnace (BOF) and Electric Arc Furnace (EAF) routes, are inherently energy-intensive, with primary production requiring 20-25 GJ per ton of crude steel [8]. The literature highlights a range of technologies aimed at mitigating this, including waste heat recovery systems, advanced process controls, scrap recycling enhancements, and alternative fuels such as hydrogen injection [8], [9]. Studies have explored these in contexts such as energy auditing and lifecycle assessments, revealing potential reductions in energy use of 10-50% depending on implementation [10]. However, much of the existing research focuses on developed economies, with limited attention to the unique socio-economic, regulatory, and technological barriers in developing countries, such as capital constraints, skill gaps, and supply chain vulnerabilities [11]. This gap is evident in reviews that emphasize technological feasibility but overlook context-specific prioritization, often relying on deterministic methods that fail to account for uncertainties inherent in emerging markets [11], [12].

To address these shortcomings, this study employs a systematic approach to identify, screen, and rank energy-consumption-reduction technologies tailored to the steel industry in developing countries. Drawing on a comprehensive literature review, we first compile a portfolio of relevant technologies encompassing areas such as process optimization (e.g., continuous casting improvements), material efficiency (e.g., thin-slab casting), and renewable integration (e.g., biomass co-firing). These are then screened using the Fuzzy Delphi Method (FDM), which incorporates expert opinions under uncertainty to refine the list to the most viable options. Finally, the fuzzy best-worst method (IT2F-BWM) is applied for ranking, providing a robust multi-criteria decision-making framework that handles vagueness in judgments more effectively than traditional analytic hierarchy process (AHP) variants.

The novelty of this work lies in its integration of fuzzy logic into both screening and ranking phases, offering a nuanced decision-support tool specifically for developing countries. Unlike prior studies that provide generic rankings or ignore epistemic uncertainties, this approach yields context-sensitive insights, enabling stakeholders to prioritize technologies that balance economic feasibility, environmental impact, and technological readiness in resource-constrained settings. By bridging methodological gaps in multi-criteria decision-making for energy efficiency, this research contributes to sustainable industrial transitions aligned with global agendas, such as the United Nations Sustainable Development Goals (SDGs).

The research questions guiding this investigation are as follows:

I. What are the key energy consumption reduction technologies identified through the literature review that apply to the steel industry in developing countries?

II. How do the screened technologies rank in terms of priority using the IT2F-BWM, and what implications does this ranking hold for policy and implementation in developing economies?

This paper is structured as follows: Section 2 reviews the literature on energy-efficient technologies in steelmaking; Section 3 details the methodology, including the fuzzy Delphi and IT2F-BWM methods; Section

4 presents the results and analysis; Section 5 discusses implications and limitations; and concludes with recommendations for future research.

2 | Literature Review

This section provides a comprehensive review of the existing literature on energy consumption in the steel industry, with a focus on developing countries. It is structured into five subsections: an overview of the steel industry in developing countries; energy consumption patterns and challenges; barriers to the adoption of energy efficiency; multi-criteria decision-making methods for technology ranking; and identification of key energy-reduction technologies.

2.1 | Overview of the Steel Industry in Developing Countries

The steel industry plays a pivotal role in the economic development of emerging nations, serving as a key driver of infrastructure, manufacturing, and employment. In developing countries, steel production has seen rapid expansion, with China, India, and Brazil accounting for over 60% of global output in recent years [1]. This growth is fueled by urbanization, population increases, and industrial policies aimed at self-sufficiency [13]. However, the sector's reliance on energy-intensive processes poses sustainability challenges, particularly in regions with limited access to advanced technologies and renewable energy sources [2]. Recent studies show that while developed economies have transitioned to more efficient EAF routes, developing countries predominantly use BOF methods, which are less efficient but better suited to available raw materials such as iron ore [14]. The OECD Steel Outlook 2025 emphasizes the need for policy interventions to balance economic growth with environmental sustainability in these contexts [6]. Overall, the literature underscores the dual opportunity and challenge: leveraging steel for development while mitigating its environmental footprint [13].

2.2 | Energy Consumption Patterns and Challenges in Steel Production

The intricate patterns of energy consumption in steel production are deeply rooted in the fundamental processes that define the industry, particularly ironmaking, steelmaking, and rolling. Ironmaking, often conducted in blast furnaces, relies heavily on chemical reactions to reduce iron ore into molten iron. This step demands intense thermal energy to sustain high temperatures and facilitate the necessary metallurgical transformations. This is compounded in steelmaking, where processes like the BOF or EAF convert raw materials into liquid steel through oxidation or melting, further amplifying energy needs due to the inherent inefficiencies in heat transfer and material handling. Rolling, the final shaping phase, adds another layer by requiring mechanical energy to deform hot steel into usable forms, often involving repeated heating to maintain malleability. At the core of these patterns is a profound dependence on fossil fuels such as coal for both energy and as a reducing agent, alongside electricity for powering furnaces and machinery, which creates a systemic vulnerability to resource availability and environmental impacts [15], [16].

In developing countries, these consumption patterns are exacerbated by structural factors that perpetuate inefficiency. Unlike in advanced economies, where modern technologies enable optimized energy flows, many facilities in emerging markets operate with legacy equipment that lacks advanced controls, resulting in excessive heat loss, suboptimal process integration, and prolonged production cycles. This is particularly evident in the dominance of primary production routes, which start from raw ores and consume vast amounts of energy in extraction and initial processing, compared with secondary routes that recycle scrap and inherently require less input. The reliance on outdated infrastructure not only inflates operational costs but also hinders the adoption of cleaner alternatives, trapping industries in a cycle of high energy intensity driven by limited access to capital for upgrades and a workforce that may lack specialized training in efficient practices [17].

The challenges embedded in these patterns extend beyond technical limitations to encompass economic and regulatory dimensions. Fluctuating energy prices, influenced by global market volatilities and geopolitical tensions, pose a constant threat to profitability, forcing producers to navigate unpredictable costs that can disrupt long-term planning. Supply chain disruptions, whether from raw material shortages or logistical bottlenecks, further complicate energy management, as inconsistent inputs lead to irregular operations and wasted resources. Increasing regulatory pressures for decarbonization add another layer of complexity, as governments in developing regions grapple with balancing industrial growth against international commitments to reduce emissions, often imposing standards that require transformative shifts without adequate support mechanisms. This interplay creates a paradox: while energy demand growth in emerging economies has shown signs of moderation in recent years due to efficiency gains and economic shifts, the absence of proactive interventions risks amplifying future pressures as population-driven demand escalates [18–20].

Moreover, the linkage between energy consumption and CO_2 emissions underscores a broader environmental challenge: heavy reliance on fossil fuels in developing contexts not only contributes to global climate change but also perpetuates local pollution and resource depletion. This dependency fosters a vicious cycle, as efforts to scale production for economic development inadvertently heighten vulnerability to climate-related disruptions. Addressing these entrenched patterns demands targeted innovations that rethink the entire value chain —from integrating renewable energy sources to fostering circular economies that prioritize recycling and waste minimization —while ensuring solutions are adaptable to the socio-economic realities of developing nations [21], [22].

2.3 | Barriers to Energy Efficiency Adoption

In developing countries, the adoption of energy efficiency technologies in the steel industry is significantly hindered by a complex array of barriers. Economic constraints are among the most pressing challenges, with the high upfront costs of energy-efficient technologies and limited access to financing being key obstacles. This is especially problematic for small and medium-sized enterprises (SMEs), which often lack the financial resources to invest in advanced energy-saving solutions. Additionally, technological barriers further exacerbate the situation. The absence of a sufficiently skilled workforce, combined with inadequate infrastructure for integrating modern technologies, makes the transition to energy efficiency more difficult. The incompatibility of new technologies with existing equipment and systems also poses a significant challenge for many steel producers in developing nations [23], [24].

Regulatory and policy-related issues add another layer of complexity. In many cases, there is a lack of consistent, robust policy frameworks to support green investments, leaving industries without clear incentives to adopt energy-efficient practices. Furthermore, socio-cultural factors contribute to the slow adoption of these technologies. Resistance to change within companies, coupled with low awareness of the long-term economic and environmental benefits of energy efficiency, often delays decision-making. These challenges are compounded by broader geopolitical and supply chain vulnerabilities, especially pronounced in regions such as Sub-Saharan Africa and Southeast Asia, where external factors, such as political instability or fluctuating market conditions, further impede progress toward energy efficiency goals [25].

While these barriers result in significant energy inefficiencies, they also present opportunities for tailored solutions. Overcoming these challenges requires a comprehensive approach that addresses both the technical and non-technical aspects of energy efficiency adoption. Collaboration between governments, international organizations, and the private sector is crucial, as is the need for capacity-building programs to foster the development of local expertise and infrastructure. Only through coordinated efforts can developing countries overcome the barriers to energy efficiency in the steel industry and make meaningful progress toward more sustainable, cost-effective practices.

2.4 | Identification of Energy-Reduction Technologies in the Steel Industry

The literature reveals a broad spectrum of innovative technologies designed to reduce energy consumption in the steel industry, with a particular focus on the unique challenges and opportunities within developing countries. These technologies encompass a variety of approaches, including process optimization, material efficiency, and the integration of alternative energy sources. A central theme in this body of research is the potential for these technologies to not only reduce energy use but also enhance overall sustainability in resource-constrained environments. Among the most promising solutions are waste heat recovery systems, which capture and reuse thermal energy from exhaust gases, thereby significantly improving energy efficiency. Additionally, integrating hydrogen injection into blast furnaces as a substitute for carbon-based reductants offers a pathway to decarbonize steel production processes, aligning with global sustainability goals [26].

Further innovations include the application of advanced process controls powered by artificial intelligence (AI) and the Internet of Things (IoT), enabling real-time monitoring and optimization of production parameters and enhancing energy performance. In parallel, improvements in scrap recycling have been shown to increase the efficiency of EAFs, a vital process in steel production. Renewable energy integration, such as biomass co-firing, provides a means to reduce reliance on fossil fuels and further mitigate the environmental impact of steel production. Collectively, these technologies form comprehensive portfolios tailored to the needs of developing countries, emphasizing their feasibility and adaptability in environments where resources and infrastructure may be limited. The implementation of such technologies, however, requires careful consideration of local conditions and the unique challenges faced by steel producers in these regions [27].

To synthesize this, *Table 1* presents a compilation of prominent energy-reduction technologies, including descriptions, potential savings, and supporting references.

Table 1. Energy reduction technologies

Technology	Description	Potential Energy Savings	References
Waste heat recovery systems	Capture and reutilize heat from flue gases and cooling processes using organic Rankine cycles or preheaters.	10-30%	[9], [28–30]
Hydrogen injection	Inject hydrogen into blast furnaces as a reductant to minimize coke usage and CO_2 emissions.	20-40%	[30–32]
Continuous casting improvements	Enhance casting efficiency through near-net-shape casting, reducing the need for reheating.	15-25%	[33–35]
Thin-slab casting	Produce thinner slabs directly from liquid steel, minimizing energy in rolling mills.	20-35%	[36], [37]
Biomass Co-firing	Co-inject biomass with coal in furnaces to partially replace fossil fuels.	10-20%	[38–40]
Advanced process controls	Implement AI-driven controls for optimizing furnace operations and energy flows.	5-15%	[41], [42]
Scrap recycling enhancements	Improve scrap preheating and sorting to increase EAF efficiency.	15-30%	[43], [44]

This table draws from recent reviews and serves as the foundation for the screening and ranking in subsequent sections.

3 | Methodology

3.1 | Research Context

This study employs a mixed-methods approach to identify, screen, and rank energy-consumption reduction technologies in the steel industry, with a particular focus on developing countries, including Iran. In the qualitative phase, a Systematic Literature Review (SLR) is utilized to compile a comprehensive set of energy-saving technologies applicable to steel production in resource-constrained settings. This involves analyzing global and region-specific studies to ensure relevance to developing economies. In the quantitative phase, the FDM is applied, with an expert panel screening the identified technologies for suitability to the Iranian steel industry. During this process, some technologies may be excluded, while others may be added based on expert consensus and contextual factors. To rank the screened technologies under uncertainty, the Interval Type-2 Fuzzy Best-Worst Method (IT2-FBWM) is employed, providing a robust multi-criteria decision-making framework that effectively handles vagueness and imprecision in expert judgments. The detailed methodology is outlined below.

3.2 | Fuzzy Delphi Method

The Delphi method seeks to establish expert agreement on a particular subject by conducting several rounds of anonymous surveys, gathering insights from a chosen panel of professionals who possess expertise and experience in a specific domain. Nevertheless, the conventional Delphi approach faces challenges such as uncertainty and a time-intensive process [45].

To address these challenges, the FDM was created by combining fuzzy theory with the traditional Delphi approach. As a collaborative decision-making tool, the FDM emphasizes anonymity, consensus-building, controlled feedback, and the synthesis of participants' responses using linguistic preferences, making it highly effective for predicting outcomes [46].

The process for applying the FDM involves the following steps [47]:

Step 1. Perform a literature review to pinpoint and gather pertinent criteria for the research issue.

Step 2. Experts assess the selected criteria through a fuzzy Delphi questionnaire to evaluate their significance. Linguistic terms (as presented in Table 2) are employed to articulate the importance of each criterion. Triangular fuzzy numbers (TFNs) are chosen for their simplicity and prevalent use in research. A triangular fuzzy number F=(l,m,u) comprises three components: the lower bound l, denoting the smallest possible value; the upper bound u, representing the largest possible value; and the most probable value m.

Table 2. Triangular fuzzy numbers of the 5-degree Likert scale.

Fuzzy Number			Linguistic Terms
l	m	u	
0	0	0.25	VL
0	0.25	0.5	L
0.25	0.5	0.75	M
0.5	0.75	1	H
0.75	1	1	VH

Step 3. The definitive set of criteria is established by comparing each criterion's weight against a predetermined threshold. The weight for each criterion is computed using the equations provided below:

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \text{ for } i = 1 \dots n;\ j = 1 \dots m, \tag{1}$$

$$\tilde{\tau}_j = (l_j, m_j, u_j) = \left(\min\{l_{ij}\}, \left(\prod_{i=1}^{n} m_{ij} \right)^{\frac{1}{n}}, \max\{u_{ij}\} \right). \tag{2}$$

Where i represents the expert, n is the number of experts, j is the criterion, and m is the total number of criteria. $\tilde{a}$ represents the fuzzy value assigned to each criterion by an expert, and $\tilde{\tau}$ is the aggregated fuzzy value for each criterion.

$$\text{crisp value} = \frac{l + m + u}{3}. \tag{3}$$

If the defuzzified value surpasses the established threshold (e.g., 0.7), the criterion is retained; otherwise, it is excluded. The threshold value may be set using different approaches, depending on expert agreement and the study's requirements.

3.3. Interval Type-2 fuzzy BWM (IT2F-BWM)

Interval type-2 fuzzy numbers build upon type-1 and type-2 fuzzy logic, offering an enhanced approach to modeling uncertainty in intricate decision-making scenarios. These fuzzy numbers are instrumental when the degree of membership is itself uncertain. Nonetheless, there is also a requirement to decrease computational complexity relative to complete type-2 fuzzy sets [48].

In type-1 fuzzy logic, every value is assigned a precise membership degree within the range [0,1]. In contrast, in type-2 fuzzy sets, the uncertainty in the membership function leads to each value having a secondary membership function. This characteristic enhances decision-making under uncertainty. However, the high computational complexity of full type-2 fuzzy sets restricts their broad adoption. To address this issue, interval type-2 fuzzy numbers were developed, where the secondary membership function is assigned a constant value, thereby defining a range of membership degree values for each element [49].

A key benefit of employing interval type-2 fuzzy numbers is their capacity to capture uncertainty in pairwise comparisons and qualitative evaluations more precisely. This characteristic is particularly valuable in multi-criteria decision-making approaches where linguistic data and expert insights are central. By adopting this method, human judgments can be represented with greater accuracy, leading to more dependable outcomes [50].

In the fuzzy best-worst method, linguistic scales are commonly employed to compare inherently uncertain criteria. Utilizing interval type-2 fuzzy sets within BWM facilitates a more precise representation of ambiguity in expert opinions, especially when there are notable differences in perspectives.

The following steps outline the structured process of IT2F-BWM [51]:

Step 1. Selecting the best and worst criteria

Specialists determine the most significant (best) and least significant (worst) criteria from the chosen set.

Table 3. FOU data linguistic terms.

	U				L			Centroids	M
EI	1.0000	1.000	1.000	1.000	1.000	1.000	1.000	1.0000	1.0000
VI	1.0000	1.000	1.718	2.617	1.000	1.073	1.927	1.3105	1.6489
MI	1.4308	2.350	2.800	3.397	2.517	2.694	3.083	2.2339	2.9247
MP	2.1515	3.000	3.850	4.811	3.355	3.537	3.828	2.8388	4.1499
SI	3.3101	4.250	5.050	6.011	4.414	4.890	5.028	4.0868	5.2602
SP	4.6893	5.500	6.200	6.949	5.638	5.889	6.062	5.3207	6.3536
VS	5.9686	6.750	7.100	8.231	6.717	6.889	7.104	6.5486	7.4660
VVS	7.0136	7.650	8.000	8.707	7.517	7.813	8.083	7.5781	8.0816
EX	7.0253	8.862	9.000	9.000	8.868	8.991	9.000	7.9099	8.9506

Step 2. Pairwise comparisons using interval Type-2 fuzzy numbers

Experts provide linguistic evaluations to compare the best criterion against all other criteria and all criteria against the worst criterion using interval type-2 fuzzy numbers.

The obtained IT2F best-to-others (IT2FBO) and IT2F others-to-worst (IT2FOW) vectors are:

$$\tilde{A}_B = (\tilde{A}_{B1}, \tilde{A}_{B2}, \dots, \tilde{A}_{Bn}), \tag{4}$$

$$\tilde{A}_W = (\tilde{A}_{W1}, \tilde{A}_{W2}, \dots, \tilde{A}_{Wn}). \tag{5}$$

Clearly, $\tilde{A}_{BB} = \tilde{A}_{WW} = [(1,1,1,1),(1,1,1)]$.

The definition of a consistent IT2F preference (IT2FP) is as follows:

The IT2FP $\widetilde{A_{jk}}$ is consistent if

$$A_{\widetilde{Best},J} \times \tilde{A}_{jk} = A_{\widetilde{Best},k}, \tilde{A_{lk}} \times A_k, \tilde{W}orst = \tilde{A_{jW}}, j, k \in N. \tag{6}$$

Step 3. Constructing the IT2F-BWM model

The obtained fuzzy comparisons are used to formulate a set of optimization equations to determine the optimal weight vector.

$$\min\max\{|\tilde{w}_B/\tilde{w}_W = \bar{A}_{Bj}|, |\bar{w}_j/\bar{w}_W = \bar{A}_{jw}|\},$$

s.t.

$$\begin{cases} \sum_{j=1}^{n} C(\tilde{w}_j) = 1 \\ w_{j1}^U \leq w_{j1}^L, w_{j3}^L \leq w_{j4}^U \\ w_{j1}^L \leq w_{j1}^L \leq w_{j3}^L \\ w_{j1}^U \leq w_{j2}^U \leq w_{j3}^U \leq w_{j4}^U \\ w_{j1}^U \geq 0, j = 1,2,\dots,n, \end{cases}$$

where

$\bar{w}_B = [(\bar{w}_{B1}^U, \bar{w}_{B2}^U, \bar{w}_{B3}^U, \bar{w}_{B4}^U), (\bar{w}_{B1}^L, \bar{w}_{B2}^L, \bar{w}_{B3}^L)]$, $\bar{w}_j = [(\bar{w}_{J1}^U, \bar{w}_{J2}^U, \bar{w}_{J3}^U, \bar{w}_{J4}^U), (\bar{w}_{J1}^L, \bar{w}_{J2}^L, \bar{w}_{J3}^L)$, $\bar{w}_w[(\bar{w}_{W1}^U, \bar{w}_{W2}^U, \bar{w}_{W3}^U, \bar{w}_{W4}^U), (\bar{w}_{W1}^L, \bar{w}_{W2}^L, \bar{w}_{W3}^L)]$, $\bar{A}_{B.J} = [(\bar{w}_{B.J1}^U, \bar{w}_{B.J2}^U, \bar{w}_{B.J3}^U, \bar{w}_{B.J4}^U), (\bar{w}_{B.J1}^L, \bar{w}_{B.J2}^L, \bar{w}_{B.J3}^L)]$, $\bar{A}_{J.W}[(\bar{w}_{J.W1}^U, \bar{w}_{J.W2}^U, \bar{w}_{J.W3}^U, \bar{w}_{J.W4}^U), (\bar{w}_{J.W1}^L, \bar{w}_{J.W2}^L, \bar{w}_{J.W3}^L)]$.

To avoid obtaining multiple optimal solutions from the model, one can minimize the maximum absolute gaps between $\left|\frac{\bar{w}_B}{\bar{w}_j} \times \bar{A}_{Bj}\right|$ and $\left|\frac{\bar{w}_j}{\bar{w}_w} \times \bar{A}_{jw}\right|$. To solve the model under the assumption that the maximum absolute gap is $\bar{\delta}^* = [(\delta^*, \delta^*, \delta^*, \delta^*), (\delta^*, \delta^*, \delta^*)$, the model can be transformed through the following programming model:

s.t.

$$\begin{cases} |w_{B1}^U - w_{J1}^U w_{BJ,1}^U| \leq \delta, |w_{B2}^U - w_{J2}^U w_{BJ,2}^U| \leq \delta, |w_{B3}^U - w_{J3}^U w_{BJ,3}^U| \leq \delta, \\ |w_{B4}^U - w_{J4}^U w_{BJ,4}^U| \leq \delta, |w_{B1}^L - w_{J1}^L w_{BJ,1}^L| \leq \delta, |w_{B2}^L - w_{J2}^L w_{BJ,2}^L| \leq \delta, \\ |w_{J3}^U - w_{W3}^U w_{JW,3}^U| \leq \delta, |w_{J4}^U - w_{W1}^U w_{JW,4}^U| \leq \delta, |w_{J1}^L - w_{W1}^L w_{JW,1}^L| \leq \delta, \\ |w_{J2}^L - w_{W2}^L w_{JW,2}^L| \leq \delta, |w_{J3}^L - w_{W3}^L w_{JW,3}^L| \leq \delta, \sum_{j=1}^{n} C(\tilde{w}_j) = 1, \\ w_{j1}^U \leq w_{j1}^L, w_{j3}^L \leq w_{j4}^U, w_{j1}^U \leq w_{j2}^U \leq w_{j3}^U \leq w_{j4}^U, w_{j1}^U \geq 0, j = 1,2,\dots,n. \end{cases}$$

Step 4. Solving the optimization model

The objective function minimizes the maximum deviation between the pairwise comparisons and the calculated weights, ensuring consistency in expert judgments.

Step 5. Defuzzification and normalization

The final interval type-2 fuzzy weights are defuzzified and normalized to obtain crisp weights for decision-making.

Step 6. Consistency check

The consistency of expert judgments is evaluated to ensure reliable weight calculations. The CR inspects the degree of consistency and the reliability of the obtained weights through:

$$\mathrm{CR} = \delta^*/\mathrm{CI}. \tag{7}$$

The value of CR ranges from 0 to 1, where a CR approaching 0 signifies higher consistency, while a CR closer to 1 indicates lower consistency. [51].

Table 4. Consistency index for the IT2F-BWM.

LTs	EI	WI	MI	MP	SI	SP	VS	WS	EX
Centroids	1.000	1.7751	3.3551	4.3403	5.7189	6.5494	7.3902	8.3475	8.4302
CI	0	0.1882	0.7537	1.3038	2.0756	2.8840	3.7304	4.3412	4.7937

4 | Findings

In this study, the Fuzzy Delphi questionnaire was meticulously designed. According to scholarly references, implementing the FDM requires a minimum of 5 experts, with an optimal range of 5 to 20 participants; however, using a larger pool is advisable when additional experts are available 48].In this study, the questionnaire was distributed to 12 experts specializing in energy efficiency technologies and the steel industry, and their responses were systematically collected. The Fuzzy Delphi process was conducted over three rounds, after which it was halted, as the difference in the defuzzified values of the criteria between the two stages was less than 0.2, indicating sufficient convergence [52]. With a threshold of 0.7, 7 of the 7 proposed technologies were validated by the experts.

In addition to these technologies, "Smart Energy Management Systems with Predictive Capabilities" was also proposed. However, due to factors such as the target country's technology readiness, implementation costs, and the need for advanced digital infrastructure, the experts rejected this technology. In developing countries, where technological and infrastructural limitations may exist, challenges for implementing these systems are present. However, if feasible, this technology could significantly reduce energy consumption and improve productivity.

Table 5. Expert Panel Information.

No	Gender	Degree	Specialization	Work Experience (Years)
1	Male	PhD	Energy efficiency technologies, the steel industry	12
2	Female	MSc	Energy efficiency, steel production	10
3	Male	PhD	Steel industry, process optimization	15
4	Female	MSc	Energy management, industrial engineering	8
5	Male	PhD	Environmental engineering, energy efficiency	13
6	Female	MSc	Energy systems, steel industry	9
7	Male	PhD	Energy efficiency, renewable energy	14
8	Female	MSc	Industrial energy, steel production	11
9	Male	MSc	Steel manufacturing, energy efficiency	10
10	Male	MSc	Energy technology, sustainable steel production	16
11	Male	PhD	Steel industry, energy optimization	12
12	Male	MSc	Energy systems, carbon footprint reduction	14

Table 6. FDM results.

Technology	Symbol	L	M	U	Defuzzification	Acceptance
Waste heat recovery systems	T1	0.25	0.900	1	0.762	Accepted
Hydrogen injection	T2	0.25	0.858	1	0.741	Accepted
Continuous casting improvements	T3	0.5	0.909	1	0.829	Accepted
Thin-Slab Casting	T4	0.5	0.887	1	0.819	Accepted
Biomass Co-Firing	T5	0.25	0.837	1	0.731	Accepted
Advanced process controls	T6	0.25	0.829	1	0.727	Accepted
Scrap recycling enhancements	T7	0.25	0.870	1	0.747	Accepted

Using the opinions of experts who held PhD degrees and solving the resulting models using the Best-Worst Fuzzy Type-2 method, the weight intervals for all technologies, along with the consistency ratio, were obtained and are shown in *Table 7*.

Table 7. Optimal weights of technologies calculated through the IT2F-BWM.

Technology	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Final Weight	Rank
T1	0.213	0.323	0.206	0.212	0.209	0.231	2
T2	0.369	0.323	0.356	0.372	0.356	0.357	1
T3	0.116	0.098	0.112	0.115	0.114	0.111	3
T4	0.080	0.068	0.112	0.080	0.074	0.082	5
T5	0.037	0.031	0.035	0.036	0.043	0.036	7
T6	0.093	0.078	0.090	0.090	0.088	0.089	4
T7	0.093	0.078	0.090	0.092	0.114	0.093	6
k	0.128	0.108	0.123	0.122	0.095	0.095	
CR	0.034	0.029	0.033	0.028	0.026	0.026	

5 | Conclusion

The findings of this study provide a robust framework for prioritizing energy consumption reduction technologies in the steel industry of developing countries, with a specific focus on Iran. By integrating the FDM and the Interval Type-2 Fuzzy Best-Worst Method (IT2F-BWM), this research addresses critical gaps in the literature by offering a context-sensitive, uncertainty-aware approach to technology prioritization. The validated portfolio of seven energy-efficient technologies, as confirmed through the FDM process, balances technological feasibility, economic viability, and environmental impact, tailored to the resource-constrained settings of developing economies.

The Fuzzy Delphi process, conducted over three rounds with a panel of 12 experts, ensured rigorous screening of technologies. The convergence of expert opinions, with defuzzified values stabilizing within a 0.2 margin, underscores the reliability of the selected technologies. Notably, the exclusion of "Smart Energy Management Systems with Predictive Capabilities" highlights a critical insight: while advanced digital technologies hold transformative potential, their adoption in developing countries is often hindered by infrastructural limitations, high implementation costs, and insufficient technological readiness. This finding aligns with prior studies [23], [24], which emphasize economic and technological barriers as key impediments to energy efficiency adoption in emerging markets. However, it also suggests an opportunity for future investments in digital infrastructure to unlock the potential of such systems, particularly as developing economies progress toward Industry 4.0.

The IT2F-BWM results, as presented in Table 8, provide a nuanced ranking of the seven validated technologies based on their weighted importance. The use of interval type-2 fuzzy sets in the BWM framework effectively captures the epistemic uncertainty inherent in expert judgments, thereby offering a methodological advancement over traditional deterministic approaches such as the Analytic Hierarchy Process (AHP) [11], [12]. The consistency ratio (CR) values, ranging from 0 to 1, indicate high reliability in the derived weights, reinforcing the robustness of the ranking process. Technologies such as waste heat recovery systems and hydrogen injection in blast furnaces emerged as high-priority options, reflecting their potential for significant energy savings (10-50% as noted in [10]) and alignment with global decarbonization goals [26]. These findings are particularly relevant for developing countries, where the dominance of energy-intensive BOF routes necessitates scalable, cost-effective solutions.

From a policy perspective, the ranking offers actionable insights for stakeholders in developing economies. For instance, waste heat recovery systems, which capture and reuse thermal energy from exhaust gases, present a relatively low-cost, high-impact solution that can be integrated into existing infrastructure with minimal disruption. This is critical in contexts like Iran, where capital constraints and outdated equipment are prevalent [17]. Similarly, hydrogen injection, while requiring greater initial investment, aligns with long-term sustainability objectives, such as the United Nations Sustainable Development Goals (SDGs), by reducing reliance on fossil fuels. However, its implementation demands supportive policies, including subsidies for research and development and international collaborations to access cutting-edge technologies [25].

The study also reveals trade-offs in technology adoption. For example, while advanced process controls powered by AI and IoT offer real-time optimization, their deployment is challenged by the need for skilled labor and robust digital infrastructure [27]. In contrast, material efficiency technologies like thin-slab casting require less technological sophistication but may face supply chain vulnerabilities in developing countries [11]. These trade-offs underscore the importance of context-specific prioritization, as generic solutions often fail to account for local constraints such as fluctuating energy prices or regulatory inconsistencies [18], [19]. By employing fuzzy logic, this study mitigates such limitations, offering a decision-support tool that is both flexible and precise.

Despite its contributions, this research has limitations. The focus on Iran as a case study, while providing depth, may limit generalizability to other developing countries with different industrial structures or policy environments. Additionally, the exclusion of emerging technologies like Carbon Capture and Storage (CCS) due to cost and readiness barriers suggests a need for future research to explore their long-term viability as infrastructure improves. The reliance on a 12-expert panel, while sufficient for FDM [48], could be expanded to include diverse stakeholders, such as policymakers and industry practitioners, to enhance the robustness of the findings.

The implications of this study extend beyond academia to inform practical decision-making. For policymakers, the ranked technologies provide a roadmap for targeted investments and incentives, such as tax breaks for waste heat recovery or grants for hydrogen-based innovations. For industry leaders, the findings highlight the need for capacity-building programs to address skill gaps and foster technology adoption. Internationally, the methodology can serve as a blueprint for other developing nations seeking to balance industrial growth with environmental sustainability. Future research should explore dynamic modeling to account for evolving technological and economic conditions, as well as cross-country comparisons to identify best practices in energy efficiency adoption.

In conclusion, this study advances the discourse on energy efficiency in the steel industry by offering a systematic, uncertainty-aware approach to technology prioritization. The integration of FDM and IT2F-BWM not only addresses methodological gaps but also provides a practical tool for stakeholders in developing countries. By aligning technological solutions with local constraints and global sustainability goals, this research contributes to the broader agenda of sustainable industrial development.

Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this manuscript.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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