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ORIGINAL RESEARCH

A multi-criteria decision support model for adopting energy efficiency technologies in the iron and steel industry

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Abstract
Promoting energy efficiency in iron and steel production provides opportunities for mitigating environmental impacts from this energy-intensive industry. Energy efficiency technologies differ in investment costs, fuel-saving potentials, and environmental performance. Hence the decision-making of the adoption strategy needs to prioritize technological combinations concerning these multi-dimensional objectives. To address this problem, this study proposes a hybrid multi-criteria decision-support model for adopting energy efficiency technologies in the iron and steel industry. The modeling framework integrates a linear programming model that determines the optimal technology adoption rates based on the techno-economic, energy, and environmental performance details and an interactive multi-criteria model analysis tool for diverse modeling environments. A real case study was performed in which a total number of 56 energy efficiency technologies were investigated against various criteria concerning economics, energy, and environmental performances. The results examine the tradeoffs and synergies were examined with regard to seven criteria. A balanced solution shows that a total investment of 13.4 billion USD could save 2.51 Exajoule fuel consumption, cut 67.4 million tons (Mton) CO_2 emissions, and reduce air pollution of 1.5 Mton SO_2, 1.41 Mton NOx, and 0.86 Mton PM, respectively. The case study demonstrates the effectiveness and applicability of the proposed multi-criteria decision-making support framework.

Keywords Multi-criteria decision analysis · Energy efficiency · Technology adoption · Iron and steel production · Air pollution

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1 Introduction

Sustainable development increasingly calls for multi-dimensional decision-making in green supply chain management. Firms are gradually compared in a wide-ranging fields perspective, e.g., the environment, economy, corporate, social, or technological development (Zopounidis et al., 2020). In this context, multi-criteria decision analysis (MCDA) has been widely applied to studying environmental sustainability in an increasing number of areas, such as construction, manufacturing, supply chain and logistics, tourism, and policy planning (Colapinto et al., 2020). Multi-criteria assessing and rating energy-related technologies is of practical significance in pursuit of sustainable development and mitigating climate change (Kumar et al., 2017). Some latest examples include energy system planning (Marinakis et al., 2017; Saraswat & Digalwar, 2021), energy technology selection (Alao et al., 2020), renewable energy site selection (Xu et al., 2020), renewable energy investment decision-making (Garcia-Bernabeu et al., 2016), etc. Typical indicators taken into account include social, environmental, economic, technology and resources criteria (Ghenai et al., 2020; Mukhamet et al., 2021; Vishnupriyan & Manoharan, 2018). It is noteworthy that different assessment methods have also been wide applied to technology evalution, e.g., life-cycle assessment (LCA) that focuses on evaluating the environmental impacts of a product through its full life cycle or cost–benefit analysis (CBA) that compares the estimated costs and benefits associated with the targeted technological options. Each method has its own characteritics and emphasis, and in many cases, a set of methods could be used in a combinative way (Campos-Guzmán et al., 2019; Miraj et al., 2021).

Iron and steel production is one of the most energy-intensive industrial sectors. The economic impacts of the environmental regulations on the iron and steel sectors are increasingly significant, and the investment strategies of mitigation technologies become highly crucial for decision-makers of producers (Riccardi et al., 2015). Wang et al. built a many-objective optimization model to plan the application of the four types of decision variables: process equipment, cleaner production technologies, end-of-pipe treatment technologies, and synergic technologies for China's iron and steel industry (Wang et al., 2019). Adopting energy-efficient technologies is viewed as a cost-effective measure not only to reduce energy use and greenhouse gas emissions but also to curb emissions of the pollutants associated with energy consumption (Chowdhury et al., 2021; Qian et al., 2021; Zhang et al., 2014, 2019). Therefore, the strategy to balance the objectives between economics and environmental benefits is essential in the relevant decision-making processes for policymakers, investors, and other stakeholders. This decision-making necessitates a hybrid multi-criteria model analysis (MCMA) approach that allows for measuring the co-benefits and tradeoffs of investing in energy-efficient technologies in the iron and steel industry from various angles.

A large number of energy efficiency technologies are available for iron and steel production. Such technologies are associated with diverse capital investments, operational costs, and environmental impacts such as emissions of CO_2 and other air pollutants. Many studies have explored the driving forces of the rapid growth of energy use, the potential of pollutant emissions reduction, and the energy efficiency improvement potential for this industry (Hasanbeigi et al., 2013; Zhang et al., 2014). The selection of technological options is a complex decision problem because the impacts go beyond the perpetual dilemma of economic growth and environmental benefits. Notably, investments into such technologies often entail enormous capital costs, which may hinder decisions to adopt such technologies, despite the government's series of supporting policies. In this context, decision-making regarding energy-efficient technology adoption requires modelling the relations between the technology adoption rates, a metric representing the magnitude of technologies adopted in the production process, and the consequences measured in economic and environmental terms (An et al., 2018).

Some recent studies further demonstrate its potential in industrial sectors. For instance, (Yu et al., 2017) developed a multi-objective mixed-integer non-linear programming model for an investment decision-making problem of energy savings and emissions reduction in the coal-mining industry. (Marinakis et al., 2017) evaluated alternative scenarios for the sustainable energy action plan in local energy planning by implementing a multiple-criteria decision support framework. (Parkinson et al., 2018) presented a multi-criteria framework for assessing integrated water-energy system transformation pathways with consideration of their climate impacts. Despite the advantages of the MCMA methodology and associated tools to effectively support decision-making, especially in situations involving economic and environmental issues, MCMA has not been applied yet in China's iron and steel sector.

This study aims to analyze strategies for adopting energy-efficient technologies in this important industry confronting multi-faceted challenges by developing a multi-criteria analytical framework. A decision support model is developed and integrated into the MCMA methodology. The effectiveness of the analytical framework is demonstrated by collecting and applying actual data regarding techno-economics, energy, and environmental performances for a variety of commercially available technologies at different production stages of the industry. Although this study focuses on China's iron and steel industry, the described approach might be interesting for researchers dealing with technologies' environmental and economic impacts in other industrial and policy-making practices.

This paper is structured as follows. After this introduction, Sect. 2 describes the problem background, i.e., the availability, characteristics, and adoption status of energy-efficient technologies in China's iron and steel production, and specifies the system boundary in this study. Section 3 details the proposed decision support modeling framework, which consists of two interlinked components: (1) a mathematical programming model of relations between decisions (adoption rates of technologies) and the consequences of their implementation represented by several criteria corresponding to economic and environmental impacts, and (2) an MCMA methodology and the corresponding software environment for the model analysis. Section 4 presents the results for the considered criteria with different priorities on the adoption strategies of energy efficiency technologies by computing Pareto-efficient solutions of the above problem. Section 5 concludes and discusses the possible application area of this modeling approach.

2 Problem background and system boundary

2.1 Challenges of further development of the iron and steel industry

China's iron and steel industry has undergone unprecedented development since 2001, particularly in production volume and energy efficiency. The production volume of crude steel increased more than six-fold from 152 to 995 million tons (Mton) between 2001 and 2019 (China National Bureau of Statistics, 2021; The Editorial Board of China Steel Yearbook, 2021; World Steel Association, 2021). In 2019, this industry consumed approximately 16% of China's total energy (China National Bureau of Statistics, 2021). It emitted 17% of the total of SO_2, 23% of the total NOx, and 12% of the total particulate matter (PM), respectively

(China National Bureau of Statistics, 2020). Additional information regarding the historical development is provided in the Supporting Material (SM).

Thanks to the government's efforts in alleviating air pollution, remarkable improvements have been achieved in phasing out small-scale and inferior technologies. For example, the air pollution emission standard has been upgraded several times. A wide range of energy-efficient and pollutant-control technologies, such as dry quenching, dry dust removal, and sintering desulfurization, have been popularized, resulting in a decline in energy use and pollutant emissions per unit steel production. Despite these achievements, there is much room for further improvements in energy efficiency. Unit energy use in China's iron and steel industry is still significantly higher relative to the world's advanced level. Adopting energy efficiency technologies requires enormous investments and brings about co-benefits of air pollution reduction, which reduces the investment in pollutant-control technologies. Additionally, capital investment in energy efficiency technologies can save fuel costs in the long run. The actual investment decision-making process should take into account all of these factors.

2.2 Iron and steel production and system boundary

Iron and steel production has been undergoing improvement in energy efficiency in each production stage. This study builds upon the already researched technology combinations of energy efficiency measures at the industrial level, which entails an explicit definition of the system boundary regarding technologies and the corresponding processes. Figure 1 shows a schematic flowchart of steel manufacturing composed of seven key processes, to which the relevant energy efficiency technologies can be applied.

In general, there are four main processes in iron and steel production: raw material processing, iron making, steel making, and post-processing. The bold solid lines in the flowchart show the dominant technologies utilized in production flow in China's iron and steel industry, while the dashed lines represent the alternative technologies accounting for only small shares. Raw material processing involves either sintering or a pellet-making process, depending on the feedstock type utilized for smelting and converting iron ore into either sinter or pellet,

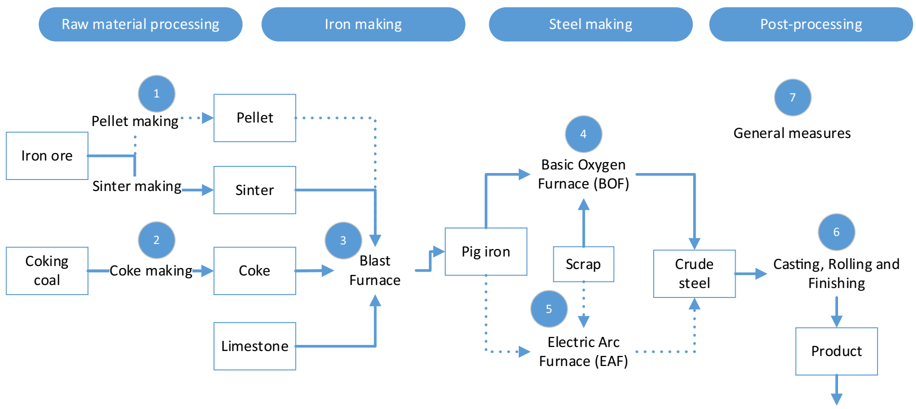

Fig. 1 Schematic flowchart of iron and steel production and the seven key energy-intensive processes

respectively. In parallel, coke is produced from a coke-making process. These types of feedstock, along with limestone, are sent to a blast furnace, where pig iron is produced, referred to as an iron-making process. For the subsequent steel-making process, 90% of capacities in China are running on the so-called basic oxygen furnaces (BOFs), while only a small share of installations use electric arc furnaces (EAFs). This structure is distinguished from those in industrialized economies, where more advanced EAFs are dominant, and scrap serves as the main feedstock. The last post-processing stage involves casting, rolling, and finishing (CRF) to transform crude steel to different final steel products. As this step consumes much less energy relative to the preceding three, these three processes are normally treated in a combined way.

2.3 Energy-efficient technology options

Seven key energy-intensive processes are identified along with the production flow shown in Fig. 2. There are various technological options for each process that can be either added or renovated to improve energy efficiency and mitigate climate/environmental impacts. Besides, some general measures, such as upgrading energy monitoring and management systems, can also be considered. Table 1 lists the numbers of the selected technologies for each process. All the relevant data, including fuel-saving potential, techno-economics, and environmental benefits, are collected.

The data needed for calculations of technological parameters of the model specified in Sect. 3.1, such as energy-saving potential, capital cost, variable cost, lifetime, and payback period, are collected from the previous research (Zhang et al., 2014). Emission reductions of CO_2, SO_2, NOx, and PM are calculated according to the method recommended by the China Ministry of Environmental Protection (2017). Emission factors for the calculations are obtained from the (MEP) and the model of Greenhouse Gas and Air pollution Interactions and Synergies (GAINS) developed by the International Institute for Applied Systems Analysis (Amann et al., 2011). Selected attributes and key parameters of the considered technologies can be found in Tables S1 and S2 in the SM.

The decision-making problem is to find the optimal combinations of these technologies, represented as adoption rates, of energy efficiency technologies in the iron and steel industry under a variety of objectives. For this analysis, seven crucial criteria are taken into account, namely, investment, financial benefits, energy saving, CO_2 emission reduction and three indicators of air pollutants reduction.

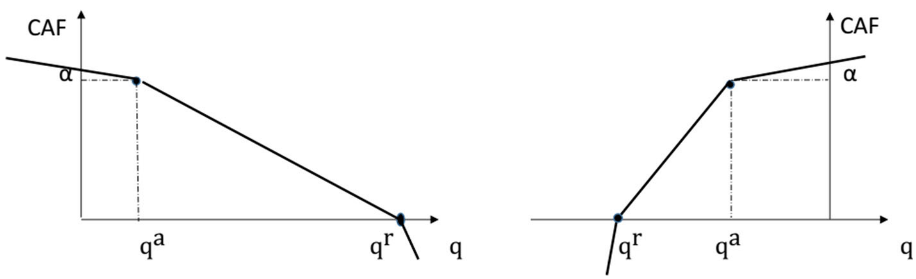

Fig. 2 Criterion achievement functions. For minimized (left) and maximized (right) criteria, respectively

Table 1 Technological options for each process in iron and steel production

Process no.	Process name	Number of technologies
1	Sinter/pellet making	8
2	Coke making	5
3	Iron-making	12
4	Steel-making, BOF	5
5	Steel-making, EAF	8
6	CRF	15
7	General measures	3

3 Analytical framework

3.1 Model specification and implementation

The mathematical programming model in this study is dedicated to making the decisions of the optimal adoption rates of energy efficiency technologies in the iron and steel industry under a variety of objectives, such as investment costs, financial benefits, fuel-saving, and emissions reduction. The model is composed of a minimum set of variables and constraints that adequately represent the relations between the decisions and the consequences of their implementations.

3.1.1 Sets of indices

The model uses several indices organized into the corresponding sets. The adopted notation associates set with their elements by using the same letter, i.e., upper-case for sets and lower-case for indices. For example, let set I be composed of indices i, and vector $\boldsymbol{x}$ represent either a variable or a relation/constraint or a parameter; then, x_i, $i \in I$ denotes i-th element of $\boldsymbol{x}$, i.e., $\boldsymbol{x} = \{x_i\}, i \in I$.

The model involves the following sets and the corresponding indices:

- Industrial processes, $i \in I$, are defined in Table 1.
- Technologies of each process, $j \in J_i$, defined in Table 1.
- Types of emissions $p \in P$, $P = \{CO_2,\ SO_2,\ NOx,\ PM\}$; climate change impact represented by the CO_2, and air pollution impact by the three air pollutants.
- Fuels,$e \in E$, $E = \{\text{coal},\ \text{electricity}\}$.

3.1.2 Decision variables

Technology adoption rate refers to the percentage of the installed capacity of one technology in the market, which measures the magnitude of one technology adopted in the production process. The model decides to which degree the energy efficiency technologies shall be adopted in iron and steel production. Therefore, the decision variables, adoption rates, are denoted by $ar = \left\{ar_{ij}, j \in J_i, i \in I\right\}$. The standard convention is used, i.e., values of 0 and 1 denote no implementation and full technology adoption, respectively. Moreover, some of the considered technologies have already been implemented. In such a situation, the remaining technology adoption rate is lower than 1. Therefore, the decision variables ar have to conform to:

$$0 \leq ar_{ij} \leq 1 - araj_{ij}, \quad \forall j \in J_i, i \in I \tag{1}$$

where the model parameter $0 \leq araj_{ij} \leq 1$ denotes the rate of the already implemented i-th technology in j-th process.

3.1.3 Parameters

The model parameters are defined below:

$araj_{ij}$ The adoption rate for technology already installed;
cap_{ij} Unit capital cost of technology j in process i, unit: \$/ton;
act_{ij} Activity level (or output) of process i, unit: ton/yr;
tc_{ij} Total cost for technology j in process i, unit: \$/ton:

$$tc_{ij} = cap_{ij} + \sum_{t=0}^{T_{ij}} df_t \left(fom_{ijt} + vom_{ijt} - \sum_{f \in F} ues_{ijf} \cdot pr_{ft} \right) \tag{2}$$

where T_{ij}—lifetime of technology j in process i, unit: years; df_t—discount factor in year t; fom_{ijt} – fixed operational and maintenance (O and M) cost of technology j in—process i in year t, unit: \$/ton; vom_{ijt}—variable operational and maintenance (O and M) cost of technology j in process i in year t, unit: \$/ton; pr_{ft}—price of fuel f in year t, unit: \$/GJ, it is estimated as a constant value according to historical prices. ues_{ijf}—energy saving of fuel f by technology j in process i, unit: GJ/ton; uc_{ijp}—emission reduction rate, unit: ton/ton.

3.1.4 Outcome variables

The model outcome variables (for short, called outcomes) measure the consequences of implementing the decisions. The application of outcomes in the model analysis is discussed in Sect. 3.2, here we present their interpretations and specifications.

We consider seven outcomes measuring economic, climate, and environmental consequences of the corresponding decisions on technology adoption rates ar_{ij}. Each of the following specifications involves decisions ar_{ij} and several parameters.

*Investments (in \$)*total capital costs required to implement

$$inv = \sum_{i \in I} \sum_{j \in J_i} cap_{ij} \cdot act_{ij} \cdot ar_{ij} \tag{3}$$

Benefits (in \$) total financial benefits from the technology implementations

$$ben = -\sum_{i \in I} \sum_{j \in J_i} tc_{ij} \cdot act_{ij} \cdot ar_{ij} \tag{4}$$

Note this model deals with financial benefits. Due to energy efficiency technology preselected for the analysis, the savings are greater than the costs, i.e., $tc_{ij} < 0$. The benefits defined by Eq. (3) are equal to the absolute value of costs, which are negative.

Fuel savings (in GJ [Gigajoule]) the amount of saved fuels

$$fsave = \sum_{f \in F} \sum_{i \in I} \sum_{j \in J_i} ues_{ijf} \cdot act_{ij} \cdot ar_{ij} \tag{5}$$

Pollution reductions (in tons) decreases of pollutant emissions, compared with the base case, i.e., without the considered energy-efficient technologies

$$er_p = -\sum_{i \in I} \sum_{j \in J_i} uc_{ijp} \cdot act_{ij} \cdot ar_{ij} \quad \forall p \in P = \{CO_2, SO_2, NOx, PM\} \tag{6}$$

The outcome variables are measured over the whole lifetime of technology implementation. The *inv* outcome is conflicting with all other outcomes, i.e., decreasing investments results in worsening the other outcomes; note that different worsening patterns may correspond to a given/computed investments. The other six outcomes are in synergy, i.e., improving one of them also improves others (although not necessarily all of them).

3.1.5 Model implementation

The specified model has been implemented in GAMS 27.1 (the General Algebraic Modeling System), a high-level modeling system for mathematical optimization (GAMS Development Corp., 2021). The model instance has been generated in the standard GAMS language; it can, therefore, be used and modified with the standard GAMS software.

3.2 Multi-criteria model analysis

The mathematical programming model defined by Eqs. (1)–(6), is further on referred to as the core model in this section. In terms of mathematical programming, the core model is a Linear Programming model with continuous variables, and it properly represents the decision problem that has infinitely many feasible solutions, i.e., combinations of values of decision variables conforming to Eq. (1). The solutions are considered in two inter-dependent spaces, the decision space (values of technology adoption rates $\boldsymbol{ar}$) and the outcome space, i.e., values measuring the resulting consequences in terms of seven outcome variables defined by Eqs. (2)–(6). MCMA supports the selection of the best (optimal) solution (in terms of seven outcomes, further on denoted by $\mathbf{q}$).

The remaining part of this section explains the multi-criteria analysis methodology and the software tool applied to the study. First, the three basic concepts exploited in the approach are summarized: (1) preferences amongst the criteria $\mathbf{q} \in \mathbf{R}^n$, (2) set of Pareto-efficient solutions, and (3) representation of preferences for the selection of a Pareto solution. Then we discuss the achievement satisfaction function that defines the scalar optimization objective parametrized by the user preferences. Next, we outline the structure of the MPP generated for finding the Pareto-efficient solution and conclude the MCMA presentation with the outline of the functionality of the MCMA modular tool.

We conclude this overview with comments on the outcome variables and their subset selected as criteria $\mathbf{q}$ for each analysis. This distinction is essential for the design and implementation of the MCMA tool. However, in this paper, we often use the corresponding terms interchangeably. Another simplification is by using the terms outcomes and criteria for values of the corresponding variables whenever the context allows.

3.2.1 Preferences

Any MCMA approach builds on the classical efficiency concept that can be summarized in plain language as follows. An outcome is efficient if: (1) it is attainable, i.e., a corresponding model's decisions exist, and (2) there is no other attainable outcome that dominates it.

For outlining the dominance concept, as well as enabling a consistent treatment of the considered model criteria, let vector $\mathbf{q}$ be composed of values of n criteria, each criterion either minimized or maximized:

$$\mathbf{q} = \{q_i\}, \quad i \in I, \; I = \{1, \ldots, n\} \tag{7}$$

Consider two such vectors $\mathbf{q}^1 \neq \mathbf{q}^2$. Outcome $\mathbf{q}^1$ dominates $\mathbf{q}^2$, if each component q_i^1 is at least as good as the corresponding q_i^2 outcome, i.e., $q_i^1 \leq q_i^2$ and $q_i^1 \geq q_i^2$ for minimized and for maximized criteria, respectively. Such dominance relation is denoted by $\mathbf{q}^1 \succ \mathbf{q}^2$ (equivalently by $\mathbf{q}^2 \prec \mathbf{q}^1$). Note that the Pareto outcomes are objectively incomparable, i.e., if $\mathbf{q}^1 \in Q_P$ and $\mathbf{q}^2 \in Q_P$ and $\mathbf{q}^1 \neq \mathbf{q}^2$, then $\mathbf{q}^1 \sim \mathbf{q}^2$, where $\sim$ denotes indifference.

The set of all efficient solutions is Pareto set and denoted by Q_P. Various synonyms are often used for Q_P, including Pareto-efficient, non-dominated, and Pareto-optimal. Although Pareto solutions are objectively incomparable, the model user typically has subjective preferences for tradeoffs between values of the corresponding criteria.

The Pareto set Q_P is unknown; therefore, the preferences are specified ex-ante, i.e., represent the desired outcomes. The preferences should be represented in a user-understandable way and then mapped into a parametrization of a scalar optimization objective. The solution of the Mathematical Programming Problem (MPP) representing the multi-criteria optimization combined with the core model provides the Pareto solution $\mathbf{q}$ and the corresponding decision variables ar. The preference representation challenge is to assure that such a solution best fits the specified preferences.

For the preference representation, we apply the established Aspiration-Reservation methodology (for short, called here the AR approach), in which the user specifies for each criterion two values:

- q_i^a—aspiration: the desired i-th criterion value the user wants to achieve, and
- q_i^r—reservation: the worst i-th criterion value the user considers still acceptable.

The AR approach provides the user with full control of navigating the entire Q_P by interactive preference specification in a natural (in quantities having obvious meaning for those knowing the modeled problem), easy (requiring neither mathematical skills nor preparatory computations), and transparent way (obvious interpretation of relations between the specified preferences and the resulting solutions). Moreover, the A and R values have to conform to only one unquestionable condition: $A \succ R$, which is assured by the user interface.

3.2.2 Achievement scalarizing function

The Pareto solution matching the specified aspiration A and reservation R values requires optimization of the corresponding MPP, which in turn requires a scalar optimization objective representing the degree of satisfaction from the computed Pareto solution. We define such objective through two functions:

- Criterion Achievement Function (CAF), which scalarizes achievements of criteria, typically specified in diverse units and magnitudes, in order to map individual achievements into a common performance measure, and
- Achievement Satisfaction Function (ASF), which aggregates individual criteria performances into the scalar measure of overall achievement satisfaction degree.

The CAF concept has been proposed long ago and is widely used (Makowski and Wierzbicki, 2003; Wierzbicki, 1980),. We summarize below only the main properties of the

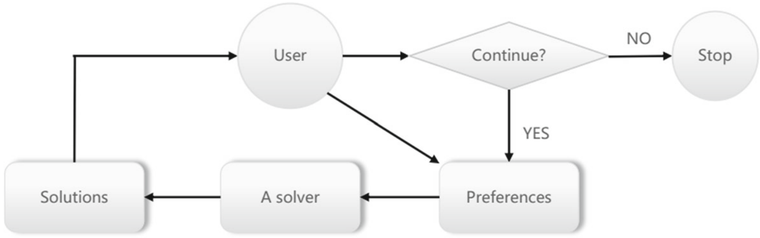

Fig. 3 Model analysis cycle

modified original CAF concept discussed in detail, e.g., in (Granat and Makowski, 2000). The CAF measures the performance of the corresponding criterion in terms of achievements. Following the common practice, CAFs are specified as Piece-Wise Linear (PWL) concave functions. CAFs are strictly increasing/decreasing for maximized/minimized criteria, respectively. Each CAF is parametrized by the corresponding aspiration q_i^a and reservation q_i^r values that define vertices of the 3-segment PWL as illustrated in Fig. 3.

The CAF for i-th criterion, denoted by $caf_i(q_i)$, is defined by:

$$caf_i(q_i) = PWL\left(q_i, q_i^r, q_i^a\right);\ caf_i\left(q_i^r\right) = 0,\ caf_i\left(q_i^a\right) = \alpha,\ i \in I \tag{8}$$

where α and slopes of the two outer segments are adaptively defined by the MCMA implementation for proper handling diverse magnitudes of criteria values. Thus, $caf_i(\cdot)$ represents i-th criterion performance in the measure common for all criteria. Moreover, the measure has an obvious interpretation in the achievement terms (degree of satisfaction) of reaching the aspiration (goal).

The ASF, denoted by $asf(\cdot)$, aggregates $caf_i(\cdot)$ into a single-criterion optimization objective. MCMA uses the established ASF definition, see, e.g., overview in (Makowski, 2009), methodological background in (Wierzbicki et al., 2000), and detailed discussion in (Granat and Makowski, 2000):

$$asf(\mathbf{caf}) = \min_{i \in I}(caf_i(\cdot)) + \frac{\in}{n} \cdot \sum_{i \in I} caf_i(\cdot) \tag{9}$$

where **caf** stands for the vector of $caf_i(\cdot)$, each defined by Eq. (8), $\in$, I, and n denote a small positive number, the set of criteria indices, and the number of all criteria, respectively. Maximization of the ASF defined by Eq. (9) provides a Pareto-efficient solution fitting best the AR values specified by the user.

The main role of the ASF defined by Eq. (9) is to aggregate the CAFs; this is achieved by the first term, i.e., min($caf_i(\cdot)$). This criteria aggregation method is motivated by the Rawlsian principle of justice interpreted as a preference for improving the situation (performance) of the weakest element (e.g., member of society or family). In the MCMA context, it means improving the achievement of the worst-performing criterion. This, in turn, implies that the ASF measures the overall achievement by the smallest value of all $caf_i(\cdot)$; in practice, usually, the smallest CAF values are equal for two criteria. The second term guarantees an $\in$-properly Pareto-efficient solution. A formal explanation of this concept is beyond the scope of this paper; it can be found, e.g., in (Wierzbicki et al., 2000). Informally, it means that small (in terms indirectly defined by the ϵ-value) deviations of criteria value may be ignored when Pareto-efficiency is determined. For instance, let $q_{benefits}^{nadir} = 0.56$, $q_{benefits}^{utopia} = 74.23$ in one decision-making iteration. The decision-maker needs to set a reservation value and an expectation value. As shown in Fig. S4 in the SM, the reservation and aspiration values are 37.4 and 55.81, respectively. The reservation and expectation values are then set as parameters in Eq. (8), which defines the CAF form. The subsequent Eq. (9) aggregates all the criteria and optimizes the calculated ASF to obtain the desired outcomes that meet the decision-maker's preferences.

3.2.3 Structure of the MCMA MPP

Computation of the Pareto-solutions of the core model that match the users' diverse preferences represented by Eq. (9) requires specification and solution of the corresponding MPP. While the ASF interpretation is intuitive and easy, its specification in terms of mathematical programming is not straightforward; therefore, the ASF is specified through an auxiliary linear programming (LP) model, further on called the multi-criteria (MC) sub-model. MCMA generates the MC sub-model for each AR specification and merges it with the core model representation to generate the required MPP. Next, the generated MPP is optimized with the same solver as used for the single-criterion optimization of the core model. Therefore, MCMA does not involve any modification of the core model.

The analyzed core models are developed and tested in diverse modeling environments and then provided to the tool in the GAMS format or in the structured collection of GAMS format files generated by the GAMS-based dedicated modeling environment described by Huppmann et al. (2019).

The MC sub-model defines small sets of own variables and relations for representing the ASF, as well as uses the core model variables representing criteria $\mathbf{q}$. The core model variables are, for this presentation, split into subsets according to their roles. For the sake of brevity, we present both merged models in the standard compact LP formulation that also covers the bound-type constraints. Therefore, the merged MC sub-model and core model takes the form:

$$\text{Maximize}\{asd = asf(caf)\} \tag{10}$$

subject to:

$$\underline{\mathbf{d}} \leq \mathbf{D} \cdot \begin{bmatrix} \mathbf{q} \\ asd \\ \mathbf{v} \end{bmatrix} \leq \overline{\mathbf{d}},\ \underline{\mathbf{b}} \leq \mathrm{A} \cdot \begin{bmatrix} \mathbf{q} \\ \mathbf{ar} \\ \mathbf{x} \end{bmatrix} \leq \overline{\mathbf{b}} \tag{11}$$

where variable asd represents the degree of satisfaction from reaching the aspirations A; the $asf(\cdot)$ is defined by Eq. (9); variables $\mathbf{q}$ represent the criteria; they are the only variables linking the MC-sub-model and the core model; auxiliary MC sub-model variables $\mathbf{v}$ are generated for defining the asd and for internal scaling of the criteria values; variables $\mathbf{ar}$ represent the decision variables of the core model; variables $\mathbf{x}$ represent the remaining variables of the core model; $\mathbf{D}, \underline{\mathbf{d}}, \overline{\mathbf{d}}$ are parameters of the MC sub-model; $\mathbf{A}, \underline{\mathbf{b}}, \overline{\mathbf{b}}$ are parameters of the core model.

Note that the MC sub-model only defines the objective function, i.e., it does not specify constraints on solutions of the core model. Therefore, the MPP (10)-(11) has the same set of feasible solutions as the core model. The numbers of rows and columns of the MC sub-model are small, usually between 15 and 50, depending on the criteria number and the needs of adaptive criteria scaling. Therefore, the computational requirements of the MCMA are, for large models, practically the same as of the single-criterion optimization. Finally, we note that the merged MPP solution contains values of all model variables, in particular, the decision variables **ar** and criteria **q**; Pareto-efficiency of the solution is guaranteed by the ASF properties. The LP optimization problem for the case presented in this paper is composed of 94 constraints and 81 variables.

3.2.4 Outline of the MCMA tool

Figure 4 illustrates a general view of the interactive process of multi-criteria analysis. In each iteration, the user specifies the AR values for each criterion, then the MPP described above is generated and solved, and the solution is added to the solution database. The user can select any already computed iteration as a basis for the specification of new AR values and see all solutions in the criteria space displayed as charts. The AR values for the next iteration can be specified in either graphical or numerical form. Annotated examples of solutions in the criteria and decision spaces are discussed in Sect. 4.

Before the interactive analysis starts, the MCMA tool automatically generates several values for computing the initial set of solutions that provides basic characteristics of Q_P. In particular, the so-called selfish (single-criterion for the selected criterion) optimization is run to compute the best value of each criterion. The point is called Utopia or Ideal because it is not attainable (best outcomes cannot be achieved for all outcomes simultaneously). Second, the Nadir point denoted by N, defined by the worst (within Q_P) values of each criterion. The values defining the U and N points also determine the corresponding ranges of outcomes' values in Q_P; for i-th criterion, these are equal to $\left|q_i^U - q_i^N\right|$. The role of Utopia and Nadir points is illustrated in Sect. 4.

The user goes through the analysis cycle shown in Fig. 4 through the following steps. First, the user interactively specifies preferences for criteria upon analysis of previously obtained results. Next, the computation of the corresponding MPP optimization task is performed

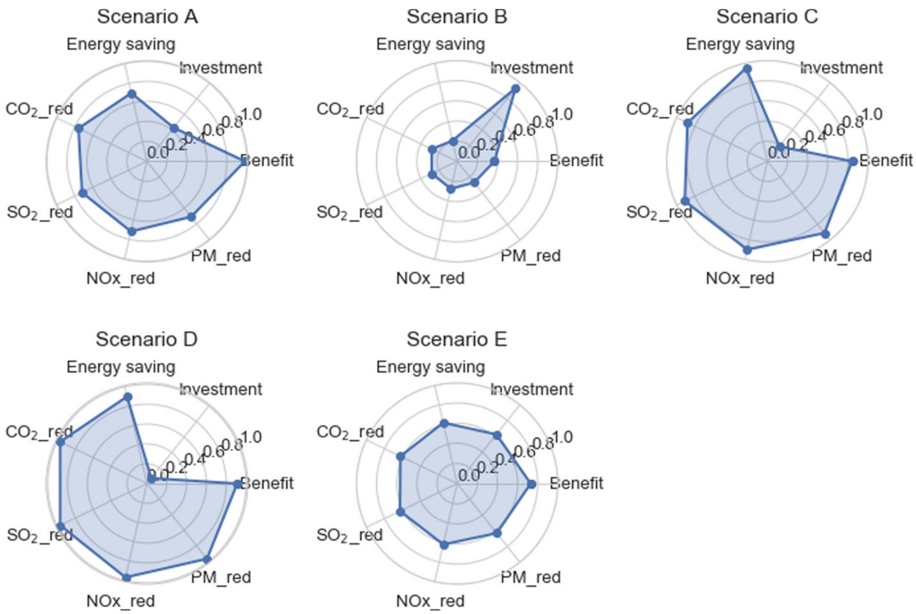

Fig. 4 Synergies and tradeoffs among the seven criteria in the five scenarios

without user involvement. The task solution (which fits best the specified preferences) is presented together with previously computed solutions in the criteria space as a chart. The solution fitness is evaluated by the user, who starts the next iteration by the preferences modification aiming at exploration of diverse tradeoffs between reachable efficient outcomes resulting from the corresponding decisions.

The MCMA tool supports its users in interactive model exploration by freeing them from formulating and managing the underlying modeling tasks. Thus, the users can focus on exploring tradeoffs between values of outcomes that are usually conflicting. However, the AR method also properly handles synergetic criteria (performance of both simultaneously either improves or worsens, although usually at different rates). An in-depth description of the modular tool architecture, as well as an illustration of the user interface to the interactive analysis, are provided in the SM. The description shows, in particular, the interactive specification of preferences in AR terms based on the presented characteristics of the previously obtained solution.

The MCMA applied to the presented research builds not only on the above-summarized methodology but also on numerous MCMA applications in diverse fields. The recent examples are presented in (Lehtveer et al., 2015; Parkinson et al., 2018).

4 Results and discussion

4.1 Discussion of results in the criteria space

The analysis results are first presented in the criteria space. Table 2 presents the criteria values of selected iterations, as well as the ranges of their values within the Pareto set. A more detailed discussion on the interactive analysis can be found in the SM. Criteria values are presented in the table as pairs composed of the actual criterion value and the percentage. The criteria percentage values represent the corresponding criterion achievements: therefore, 0% and 100% represent the Nadir and Utopia values, respectively. The percentages can be interpreted as a relative criterion optimality loss compared to the corresponding selfish (i.e., the criterion defines the objective function) optimization, and therefore, provides a good yardstick for assessing individual criteria performance.

The table is composed of three parts. The first (top) part provides the utopia and nadir values. Note that the ranges of criteria values are large (about two orders of magnitude), and thus call for comprehensive analysis of diverse Pareto-efficient solutions. The second part contains the results of the selfish optimization of each criterion, as well as the so-called neutral solution. The remaining part presents diverse iterations, sorted by increasing benefits.

In the remaining discussion of Table 2, solutions are identified by the #-character followed by the number (e.g., #8 stands for iteration number 8). The iterations #1 through #7 show the selfish optimization results. The optimized criterion reaches the corresponding utopia value at the expense of the poor performance of at least one other criterion. Selfish optimizations rarely provide acceptable tradeoffs but often offer a good basis for exploring solutions focused on the performance of the corresponding criterion. Note that the reductions of CO_2, SO_2, NOx, and PM emissions are calculated from energy-saving and their emission factors; therefore, the results of these four criteria are highly correlated with each other.

The neutral #08 solution is the last one with preferences generated automatically to attempt reaching a possibly balanced solution (in terms of performance relative to the Utopia-Nadir ranges). The results show that a total investment of 13.4 billion USD leads to saving energy

Table 2 Utopia, Nadir, and criteria values in selected iteration

	Benefit		Investment		Energy saving		CO_2 reduction		SO_2 reduction		NOx reduction		PM reduction	
	(10^9 USD)		(10^9 USD)		(EJ)		(10^6 ton)		(10^6 ton)		(10^6 ton)		(10^6 ton)	
Utopia	57.4	100%	0	100%	3.97	100%	108	100%	2.39	100%	2.24	100%	1.36	100%
Nadir	0.04	0	35.2	0	0.04	0	0.09	0	0.02	0	0.02	0	0.01	0
Iteration	Benefit		Investment		Energy saving		CO_2 reduction		SO_2 reduction		NOx reduction		PM reduction	
01	57.4	100.0%	32.2	8.5%	3.52	88.5%	100	92.6%	2.15	89.9%	2.02	90.1%	1.22	89.6%
02	0.41	0.6%	0	100.0%	0.04	0.0%	0.92	0.8%	0.02	0.0%	0.02	0.0%	0.01	0.0%
03	56.3	98.1%	35.2	0.0%	3.97	100.0%	108	100.0%	2.39	100.0%	2.24	100.0%	1.36	100.0%
04	56.3	98.1%	35.2	0.0%	3.97	100.0%	108	100.0%	2.39	100.0%	2.24	100.0%	1.36	100.0%
05	56.3	98.1%	35.2	0.0%	3.97	100.0%	108	100.0%	2.39	100.0%	2.24	100.0%	1.36	100.0%
06	56.3	98.1%	35.2	0.0%	3.97	100.0%	108	100.0%	2.39	100.0%	2.24	100.0%	1.36	100.0%
07	56.3	98.1%	35.2	0.0%	3.97	100.0%	108	100.0%	2.39	100.0%	2.24	100.0%	1.36	100.0%
08	40.7	70.9%	13.4	61.9%	2.51	62.8%	67.4	62.4%	1.5	62.4%	1.41	62.6%	0.86	63.0%
09	54.7	95.3%	27.9	20.7%	3.59	90.3%	98.7	91.4%	2.17	90.7%	2.03	90.5%	1.24	91.1%
10	51.6	89.9%	21.2	39.8%	3.16	79.4%	87.4	80.9%	1.91	79.7%	1.8	80.2%	1.09	80.0%
11	48.5	84.5%	20.9	40.6%	3.15	79.1%	85.9	79.5%	1.89	78.9%	1.78	79.3%	1.08	79.3%
12	45.8	79.8%	15.1	57.1%	2.65	66.4%	72.3	66.9%	1.59	66.2%	1.5	66.7%	0.91	66.7%
13	42	73.2%	13.3	62.2%	2.48	62.1%	67.6	62.6%	1.49	62.0%	1.4	62.2%	0.85	62.2%
14	40.4	70.4%	12.6	64.2%	2.41	60.3%	65.6	60.7%	1.45	60.3%	1.36	60.4%	0.83	60.7%
15	37.8	65.8%	11.4	67.6%	2.28	57.0%	62	57.4%	1.37	57.0%	1.29	57.2%	0.78	57.0%
16	35.1	61.1%	10.5	70.2%	2.18	54.5%	59.2	54.8%	1.31	54.4%	1.23	54.5%	0.75	54.8%

Table 2 (continued)

Iteration	Benefit		Investment		Energy saving		CO_2 reduction		SO_2 reduction		NOx reduction		PM reduction	
17	31.6	55.0%	8.12	76.9%	1.91	47.6%	52	48.1%	1.15	47.7%	1.08	47.7%	0.66	48.1%
18	27.6	48.0%	6.15	82.5%	1.68	41.7%	45.8	42.4%	1.01	41.8%	0.95	41.9%	0.58	42.2%
19	24.5	42.6%	3.83	89.1%	1.39	34.4%	37.9	35.0%	0.84	34.6%	0.79	34.7%	0.48	34.8%
20	21.2	36.9%	1.33	96.2%	0.84	20.4%	26	24.0%	0.53	21.5%	0.5	21.6%	0.3	21.5%
21	14.5	25.2%	0.08	99.8%	0.14	2.5%	9.22	8.5%	0.13	4.6%	0.12	4.5%	0.07	4.4%
22	9.53	16.5%	0	100.0%	0.09	1.3%	5.75	5.2%	0.09	3.0%	0.08	2.7%	0.04	2.2%

of 2.51 Exajoules (EJ), reducing 67.4 million tons (Mton) CO_2 emissions and air pollutant emissions of 1.5 Mton SO_2, 1.41 Mton NOx, and 0.86 Mton PM.

This setup is done by the MCMA solver by setting the criteria aspiration and reservation values equidistant from the corresponding Utopia and Nadir values, respectively. Generally, the neutral solution often serves as a basis for starting various branches of analysis; it provides another valuable yardstick for measuring the tradeoffs between improving the performance of selected criteria, which requires compromising the performance of other criteria.

Figure 5 presents, in graphical form, criteria tradeoffs for five selected iterations, referred to further on as Scenarios A-E. The criteria values are normalized between 0 and 1, each of these

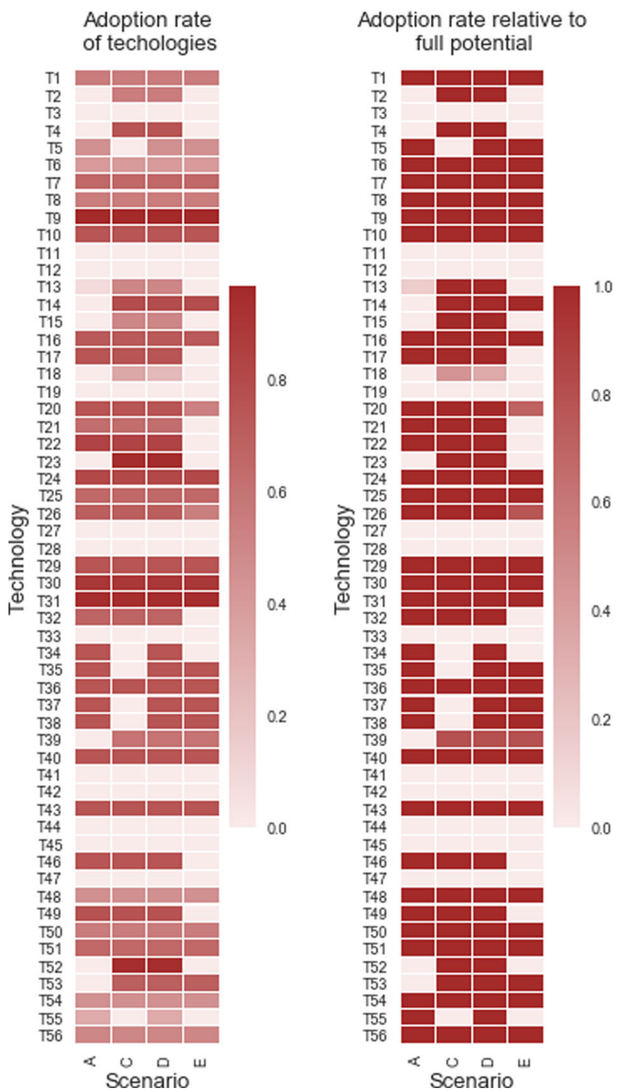

Fig. 5 Technological adoption under different scenarios

values corresponding to the worst and best criterion value within the Pareto set, respectively. For example, the score of 1 represents the minimum value of investment (resulting in the maximum values of pollution emission, respectively). One should note that theoretically, there are infinite Pareto optimal solutions, here we select five scenarios representing cases with regards to different preferences over the seven criteria, which are defined as below:

- *Scenario A* Scenario with near-largest benefits.
- *Scenario B* Scenario with near-lowest investments.
- *Scenario C* Scenario with near-largest energy savings.
- *Scenario D* Scenario with near-largest CO_2 emissions' reductions.
- *Scenario E* Balanced preferences (in terms of the value's ranges within the Pareto set) for all criteria goals.

Scenario A with the largest benefit also features very good performances of all other criteria but the minimized investment criterion, which attains the value close to its maximum value. In other words, the investment criterion is in conflict with all other (mutually synergetic) criteria. This observation is confirmed by Scenario B: minimizing investment leads to the highest score of 'investment performance' and the worst values of all other criteria.

Scenarios C and D have qualitatively similar results and also show the above-mentioned synergies. Both require maximum investments; however, the allocation of investments to technology adoption rates differs; therefore, also the performance of the maximized criteria also differs between these scenarios.

The balanced scenario E shows a similar relative performance of all criteria. From an analytical point of view (e.g., in terms of the relative criteria performance defined above), such a solution might be considered as being well-balanced. However, in actual decision-making, it is not necessarily the best choice because it might be rational to invest more money for achieving better values of benefits and the air quality. Therefore, such an analytical interpretation is typically not shared by all involved in the problem analysis.

In general, these five scenarios illustrate the need of investment necessary for increasing the total financial benefits and the air pollution emission reductions, as well as decreasing the energy use. However, the investments necessary for the full range adoption of energy-efficient technology might not be available. The MCMA supports the analysis of diverse tradeoffs between these conflicting criteria. The interactively generated iterations in the third part of Table 2 are the main part of such analysis. Due to the space consideration, we limit the discussion of the sample of the interactively generated iterations #9 through #22 to a small number of selected key issues. The iterations are sorted by decreasing benefits (which corresponds to the increasing investments). The benefits are either lower or higher than is the benefit of the neutral solution. Iterations with investment from 14.0 to 75.1% show diverse tradeoffs between the performance of the other criteria.

To evaluate the effects from parameter uncertainty, we assume the parameters follow uniform distributions; that is, for each technology, the key parameters range from 90 to 110% of their respective original values. We ran a total of nine scenarios, and each scenario represents a set of parameters sampled from the distributions under the assumption. The sampled parameters and the results for the nine scenarios are summarized and compared in Tables S3–S11 in the SM. We identified potential application rate $araj_{i,j}$ and energy saving $ues_{i,j,f}$ as the two most significant parameters influencing decision-making results.

4.2 Discussion of results in the decision space

The discussion of results in Sect. 4.1 focuses on the criteria values. The complementary discussion deals with the decisions that lead to these values, i.e., the corresponding technological choices determined by the adoption rates of the technology combination. Figure 5 summarizes the technology adoption rates for four scenarios. The left panel shows the absolute adoption rates of the technologies in each scenario. Note that Scenario B, which minimizes the total investment and thus leads to very small technology adoption rates, is excluded from this comparison. Among these technologies, T9, T24, T30, and T31 have the largest potential for adoption that can be realized at relatively small costs; thus, they are favored across all the scenarios.

There are two possible reasons for the low adoption of some technologies. First, it might be due to the high cost or low efficiency of the technologies, and second, it might be simply because these technologies have already been utilized extensively, and thus the potential left for further adoption is relatively small. To distinguish between these two cases, we calculate the relative adoption rates (the lower segment), measured as the rate between the incremental adoption in the future and the full potential adoption left in the base year of 2015. The two extreme situations, i.e., no utilization and full adoption, are represented by values 0 and 1, respectively.

The results indicate that some of the technological options are favored across all the scenarios. More specifically, either those technologies with the best energy-saving capability at a lower investment cost and small total cost, or the most cost-effective options would obviously become the first choices for all scenarios; for example, T1, T6-T10, T24-T25, T29-T31, T36, T48, T50, T51, T54, and T56. In contrast, there are also some technologies with the least cost–benefit performance that would never be selected in any scenario; these are T3, T11, T12, T19, T27, T28, T33, T41, T42, T44, T45, and T47. Some technologies in between are preferred over others in favorable scenarios. For example, T2, T4, and T23, with lower total costs and better energy-saving potential yet requiring higher investment, are adopted in Scenarios B and C but not in Scenarios A and D.

5 Conclusions

This study provides the decision-making support model for analyzing the adoption strategy of energy-efficient technologies in the iron and steel manufacturing processes. The model parameters are based on the techno-economic, energy, and environmental performance data collected for all relevant, commercially available technologies for iron and steel production. The key economic and environmental criteria of the technology adoption strategy are represented in this analytical framework, which supports the analysis of Pareto-efficient solutions with diverse tradeoffs between the simultaneously attainable goals for the criteria. The multiple-criteria model analysis is supported by the modular software tool, which enables the model integration for the interactive analysis.

The study results show that choices of technological combinations could vary significantly under different priorities for attainable goals. In this case, good performance in terms of energy-saving and pollutant emissions reduction go along with the total costs over the lifetime of implemented technologies. Diverse improvement levels of these criteria require different levels of capital investment in the short term. The decision support modeling framework developed by the reported study enables analysis of these conflicting objectives and computes the corresponding efficient adoption rates of energy-efficient technologies in the iron and steel industry. In particular, the four scenarios screen out the robust technology solutions that would consistently perform well at the higher benefit (lower negative costs), in addition to interior options with low energy saving potential but high investment requirements.

The applied MCMA methodology and the corresponding modular software tool provide an intuitive and transparent approach for the specification of user preferences for attainable criteria. The precomputed set of Pareto-efficient solutions provides initial information on the ranges of criteria values within the set of efficient solutions. MCMA provides a user-friendly interface for interactive analysis; therefore, users with diverse background knowledge can easily explore the whole set of Pareto solutions. After such a learning phase about diverse criteria tradeoffs, it is easy to focus on the Pareto-set regions corresponding to the user preferences.

The case study shows that the relevant strategy and policy design inherently entail consideration of diverse objectives and attainable goals, such as reducing energy use and restraining pollutant emissions, which usually compete with the required investments. This study provides a meaningful example for applying this concept to addressing this type of decision-making problem in real industrial and policy-making practice.

Technology adoption and investment problems require science-based support. Energy-intensive industrial sectors are of utmost significance for China to achieve its climate pledges (Lee et al., 2020; Ren et al., 2021; Zhang et al., 2020). The developed decision support framework can be easily adapted to the needs of other industrial sectors, in which economic and environmental impacts of possible investments in energy efficiency technologies adoptions should be examined. Moreover, the framework can readily be applied to the analysis of other efficiency dimensions such as material use. Nevertheless, it is noteworthy that the reported analytical approach might lead to infeasible solutions when applied to non-linear programming problems. Therefore, deepened research on the relevant theory and methods should be explored due to the complexity of the industrial system and the relevant decision-making problems.

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Appendix

Nomenclature

See Table 3.

Table 3 Description of variables and parameters

Symbol	Type	Description	Equation
ar_{ij}	Variable	The adoption rates of i-th technology in j-th process	(1), (3), (4), (5), (6)
inv	Variable	Total capital costs required to implement	(3)
ben	Variable	Total financial benefits from the technology implementations	(4)
$fsave$	Variable	Amount of saved fuels	(5)
er_p	Variable	Decreases of pollutant emissions, compared with the base case	(6)
$araj_{ij}$	Parameter	The adoption rate for technology already installed	(1)
cap_{ij}	Parameter	Unit capital cost of technology j in process i, unit: \$/ton	(2), (3)
act_{ij}	Parameter	Activity level (or output) of process i, unit: ton/yr	(3), (4), (5), (6)
tc_{ij}	Parameter	Total cost for technology j in process i, unit: \$/ton	(2), (4)
T_{ij}	Parameter	Lifetime of technology j in process i, unit: years	(2)
df_t	Parameter	Discount factor in year t	(2)
fom_{ijt}	Parameter	Fixed operational and maintenance (O&M) cost of technology j in—process i in year t, unit: \$/ton	(2)
vom_{ijt}	Parameter	Variable operational and maintenance (O&M) cost of technology j in process i in year t, unit: \$/ton	(2)
pr_{ft}	Parameter	Price of fuel f in year t, unit: \$/GJ, it is estimated as constant value according to historical prices	(2)
ues_{ijf}	Parameter	Energy saving of fuel f by technology j in process i, unit: GJ/ton	(2), (5)
uc_{ijp}	Parameter	Emission reduction rate, unit: ton/ton	(6)

Acronyms

MC	Multiple criteria
MCD	AMulti-criteria decision analysis
MCMA	Multi-criteria model analysis
BOF	Basic oxygen furnace
EAF	Electric arc furnace
CRF	Casting, rolling, and finishing
GAINS	Greenhouse gas and air pollution interactions and synergies
MPP	Mathematical Programming Problem
CAF	Criterion achievement function
ASF	Achievement satisfaction function
PWL	Piece-wise linear

LP	Linear programming
GAMS	General algebraic modeling system

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