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Optimizing the transition pathway of a steel plant towards hydrogen-based steelmaking

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Abstract

Direct reduction of iron ore using hydrogen is a promising alternative to traditional coke-based reduction that could greatly reduce CO_2 emissions from the steelmaking industry. In this alternative route, hydrogen and iron oxides react in a shaft furnace to produce direct reduced iron that is further processed in electric arc furnaces into liquid steel. The total process is greatly dependent on electricity, both for producing hydrogen and for operating the electric arc furnace. When considering a possible transformation of a traditional steel plant to hydrogen-based direct reduction, there are several open questions regarding appropriate configurations and dimensions of new units, scheduling of investments, integrated operation of old and new units, etc. Furthermore, the entire transformation process could span several decades, during which market conditions may change substantially. To help planning such a transition, this paper presents a steel plant optimization model that minimizes accumulated costs or emissions of investments and operation over a selected time horizon, during which new units can be constructed and old units possibly be decommissioned. The task is formulated as a mixed-integer quadratically constrained programming problem, with simplified regression models of blast furnaces and shaft furnaces based on more detailed models. Model performance is illustrated with an example case in which the possible transition of a steel plant with two blast furnaces that are expected to be decommissioned within the next twenty years is analyzed, demonstrating that the model is a flexible planning tool for comparing and assessing different future scenarios for decarbonizing the steel industry.

Keywords

steel production, optimization, process integration, hydrogen, transition model

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Introduction

With steel production being responsible for about 7% of anthropogenic CO_2 emissions,[1] there is a clear demand for decarbonization efforts in this industrial sector. About 70% of today's steel production is through the blast furnace-basic oxygen furnace (BF-BOF) route, in which most of the emissions are due to the use of coke and coal for the reduction of iron oxides. A promising alternative route is based on reduction of the iron oxides in solid state in shaft furnaces using hydrogen (referred to in this paper as the H_2DR route). The hydrogen in turn could be produced via electrolysis using low-carbon or carbon-free electricity, hence potentially reducing the emissions of this route to a fraction of those of the BF-BOF route.[2]

The potential of the H_2DR route has previously been studied by comparing it with the BF-BOF route[3] and with direct reduction using natural gas.[2] While the route presents great potential for reduced emissions from steel production, its performance and feasibility depend on the costs and carbon intensities of the available electricity. As a large consumer of electricity, a hydrogen-based steel industry would place large requirements on the wider energy system.[4] Despite the challenges in implementation, hydrogen-based steel production is considered an essential part of the decarbonization of steel industry, playing an important role in limiting global warming.[5]

Different projects regarding the decarbonization of steel production are currently underway, with, e.g., the HYBRIT project in Sweden,[6] H2Stahl in Germany,[7] and new installations in Gijón in Spain[8] implementing hydrogen direct reduction with the ambition to produce fossil-free steel. Lopez et al.[9] highlight the need to consider different

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options for the green steel supply chain apart from integrated production at one site, with the possibility for importing DRI produced at locations with lower H_2 production costs for further processing in electric arc furnaces.

This paper presents a novel modelling approach for optimizing investments and operation at a steel plant subjected to a transition to hydrogen-based steelmaking. In the approach, the steel plant is studied for a given time horizon divided into subperiods, for which changes in the plant setup and material and energy flows are allowed, with the goal of optimizing the overall performance over the time horizon. A similar approach has earlier successfully been applied to study the evolution of regional energy systems towards carbon neutrality.[10] The model can be used for analyzing different possible configurations at different stages of a transition and to evaluate possibilities given different external circumstances and constraints. Section 2 gives a brief overview of the underlying mathematical model, Section 3 presents some example cases demonstrating the model functionality, while the fourth and final section concludes the paper with a discussion also proposing future steps in model development.

Approach and models

Steel plant models

The overall system consists of simplified models of the main unit processes in the steel plant in steady state interacting with each other and the external world through flows of materials and energy from/to the system. A schematic of the system is shown in Figure 1: units included in the model are blast furnaces (BF), hot stoves (HS), coke plants (CP), air separation units (ASU), basic oxygen furnaces (BOF), rolling mills (RM), combined heat and power plants (CHP), pellet plants (PP), electrolyzers (EL), shaft furnaces (SF) and electric arc furnaces (EAF). Continuous variables in the model are flows of materials, gas, heat, steam and electricity, while binary and integer variables represent decisions and logical relations.

Since mixed integer nonlinear programming (MINLP) problems easily become burdensome to solve, the level of detail and mathematical simplicity have to be balanced in the unit models. Most of the unit models are written as linear models relating unit material outputs to required material and energy inputs, but for more complex units (e.g., blast and shaft furnaces) surrogate regression models were developed. Therefore, models developed earlier by the research group of blast furnaces and hot stoves,[11,12] and a one-dimensional DR shaft furnace model proposed by Shao et al.[13] were applied to generate a large number of feasible operation points, and these were subsequently used in developing the surrogate models. In- and output variables for this regression are listed in Table 1 for the BF and DR shaft furnace model. Note that these are in- and output variables to the regression models, not the variables of the physical units. Most relations between regression in- and outputs are linear, but some require quadratic relations to achieve sufficient accuracy. Quadratic constraints were also required in the EAF model to describe the relations between the ratio of DRI to scrap in the charge as input and electricity use as well as furnace yield as output.

In the present model formulation, the BF is charged with burden that can consist of coke, lime, pellets, scrap and DRI, while pulverized coal is injected in the (possibly) oxygen-enriched hot blast. The DR furnace feed gas is assumed to be pure hydrogen.[6] EAFs can be charged with any combination of scrap or DRI, but the ratios affect the yield and electricity demand of the furnaces. Blast furnace gases can be utilized in the hot stoves, CHP and coke plant, coke oven gas can be utilized in the CHP and post-processing units (reheating furnace, cutting operation, etc.), while BOF gas can be utilized in the CHP.

Optimization problem formulation

To evaluate investment options and operational conditions over a long-term time horizon an MINLP model minimizing accumulated costs or emissions was formulated. A detailed description of the base model is provided in Haikarainen et al..[14] The principal idea is to use a generalized optimization model for analyzing the entire time horizon, from initial conditions through intermediate steps to an end state, rather than to optimize a final configuration without considering how reach it from the present state. This approach is expected to give rise to solutions that more realistically reflect the forthcoming gradual green transition in the steel industry.

The considered time horizon is divided into a set of time steps, each representing a predetermined number of years of operation with the system configuration featured in that step, as exemplified in Figure 2. At the beginning of each subperiod, new investments can be realized and old units can be phased out, but the plant layout and flows remain constant within the subperiod. Further, parameters are defined for each subperiod, so, e.g., evolution of prices or technology efficiencies can be considered over the whole time horizon.

The overall goal is to minimize accumulated costs or emissions for the entire time horizon, so the system impacts during the entire transition phase are considered. For the cost optimization, the objective function is the sum of investment costs and operational costs for each time step

$$\min C = \sum C_{\text{inv},t} + C_{\text{oper},t} \qquad \forall t \in T \tag{1}$$

where investment costs are the sum of accumulated investment costs for each new system unit and operational costs relate to how the system is functioning in each time step to ensure required steel production rates. The costs are projected back to the initial day by considering the discount rate. As an example, investment costs for a pellet plant (PP) for a time step t can be written as

$$C_{\text{inv,PP,t}} = a \times n_{\text{ap}} \times c_{\text{inv,PP},t} \times S_{\text{PP},t} \tag{2}$$

where a is an annuity factor calculated based on discount

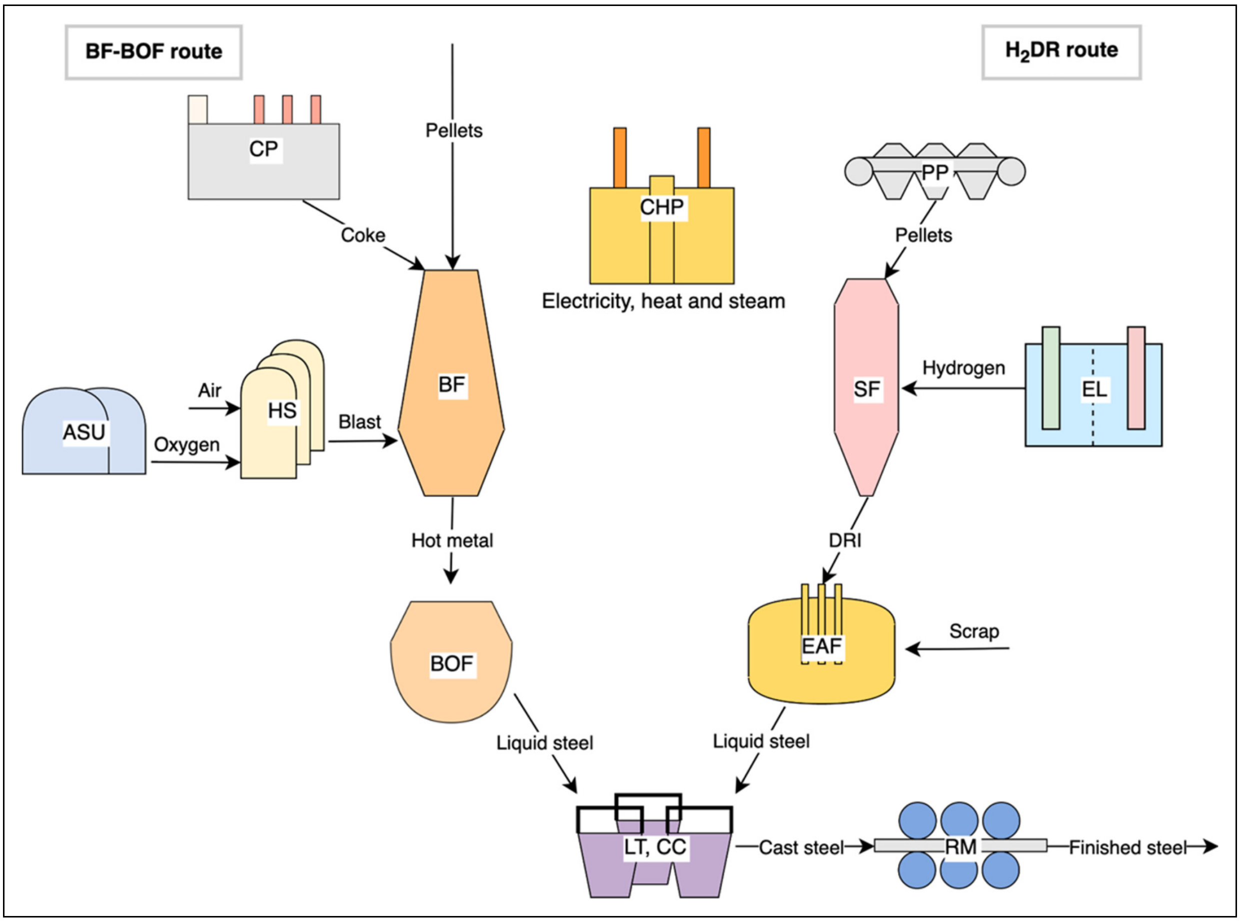

Figure 1. Schematic of the main units in the BF-BOF and H_2DR routes in the model. Additional connections between the units include flows of process gases, energy and recycled steel scrap, etc. Abbreviations: ASU – Air separation unit, BF – blast furnace, BOF – Basic oxygen furnace, CHP – Combined heat and power plant, CP – Coke plant, EAF – Electric arc furnace, EL – Electrolyzer, HS – Hot stoves, LT, CC – Ladle treatment and continuous casting, PP – Pellet plant, RM – Rolling mill, SF – Shaft furnace.

Table 1. In- and output variables in the regression models.

Input variables	Output variables
BF model	
Hot metal output	Coke input
Pulverized coal input	Pellet input
Blast oxygen rate	Lime input
Blast temperature	Blast input
DRI input	Slag output
	Top gas temperature
	Top gas composition
	Top gas volume
	Flame temperature
SF model	
Pellet input	DRI output
Hydrogen input	Metallization degree
Furnace diameter	Top gas temperature
Pellet iron content	Top gas hydrogen content
Gas injection temperature	Gas injection pressure

rate and expected lifetime, n_{ap} is the number of years each time step represents, $c_{\mathrm{inv,PP},t}$ is a capacity-dependent cost coefficient and $S_{\mathrm{PP},t}$ is the plant capacity. Different units may have additional factors affecting how the costs are treated in the model.[14]

Operational costs in each time step can be written as

$$\begin{aligned} C_{\mathrm{oper,t}} = n_{\mathrm{ap}}(&C_{\mathrm{pel},t} + C_{\mathrm{coal},t} + C_{\mathrm{coke},t} + C_{\mathrm{lime},t} + C_{\mathrm{scrap},t} \\ &+ C_{\mathrm{pc},t} + C_{\mathrm{ng},t} + C_{\mathrm{O_2},t} + C_{\mathrm{el},t} + C_{\mathrm{H_2recyc},t} \\ &+ C_{\mathrm{oper,EAF},t} + C_{\mathrm{CO_2},t} - C_{\mathrm{sell},t}) \end{aligned} \tag{3}$$

where $C_{\mathrm{pel},t}$, $C_{\mathrm{coal},t}$, $C_{\mathrm{coke},t}$, $C_{\mathrm{lime},t}$, $C_{\mathrm{scrap},t}$, $C_{\mathrm{pc},t}$, $C_{\mathrm{ng},t}$ and $C_{\mathrm{O_2},t}$ are the costs of imported pellets, coal, coke, limestone, scrap, pulverized coal, natural gas and oxygen, $C_{\mathrm{el},t}$ is the cost of grid electricity used, $C_{\mathrm{H_2recyc},t}$ is a cost on hydrogen recycling in shaft furnaces, $C_{\mathrm{oper,EAF},t}$ represents costs of EAF operation, and $C_{\mathrm{CO_2},t}$ is costs placed on direct CO_2 emissions from the steelworks. $C_{\mathrm{sell},t}$ is optional credits for exported streams (electricity, slag, etc.).

Finally, model constraints comprise the unit models, describing relations between different material and energy flows with, e.g., mass and energy balances as well as logical constraints related to unit operations, as described by Haikarainen et al.[14]

Taken together, the system model constitutes a mixed-integer quadratically constrained programming problem that was implemented in Python using the

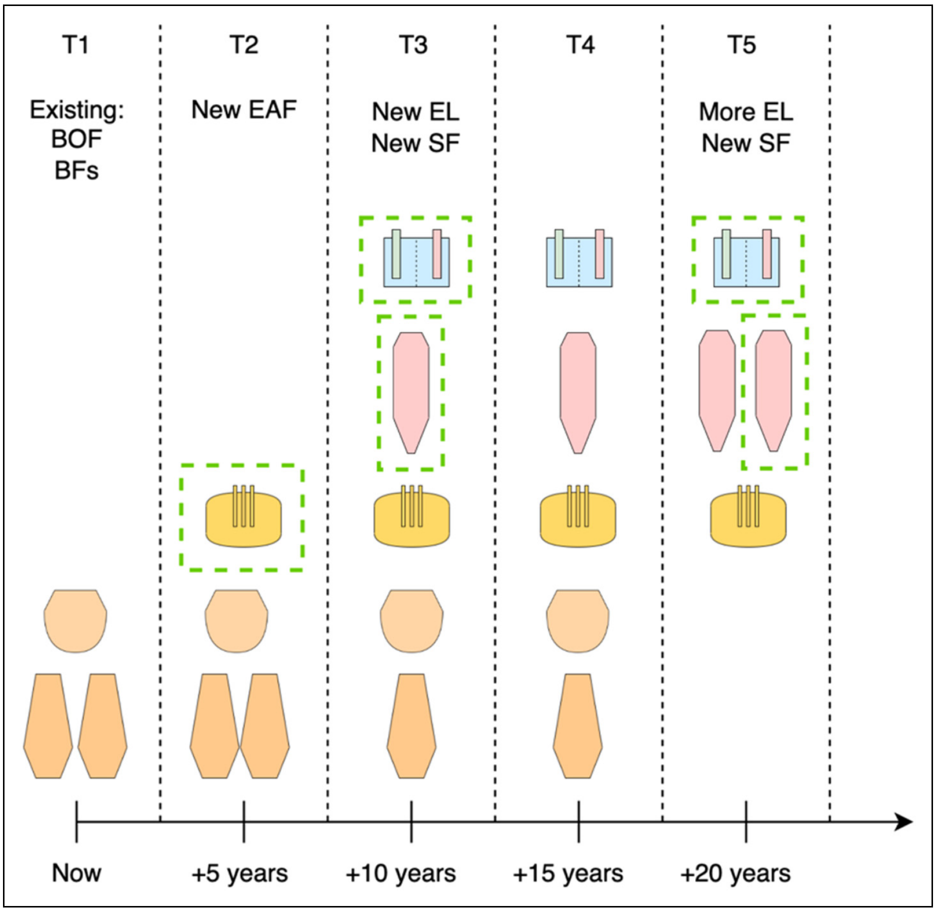

Figure 2. Schematic of the division of the time horizon into time periods. Abbreviations: BF – blast furnace, BOF – basic oxygen furnace, SF – shaft furnace, EL – electrolyzer.

Pyomo framework[15] and solved using Gurobi 10.0.[16] With the time horizon divided into five time periods, most problem instances were solved within seconds or minutes on a regular laptop computer. More time periods frequently resulted in calculation times counted in hours, so the example cases in the next section were all solved with a time horizon of 25 years divided into five-year periods.

Example cases

In this section the functionality of the proposed modelling and optimization approach is presented through some example cases. The initial configuration in these cases features a conventional integrated steel plant with two blast furnaces, each with a maximum capacity of 160 t_{hm}/h (3840 t_{hm}/d), one requiring relining after 10 years and the other after 20 years. New investment options are up to three DR furnaces and up to three EAFs, each with capacity options 150 t/h, 200 t/h or 250 t/h, as well as electrolysis units and a pellet plant with maximum capacities as continuous variables. The output of rolled steel was fixed at 260 t/h in the present study.

Costs of investments and raw materials were assembled from the literature and online sources, with parameter values based on the values used in Ref..[14] Naturally, estimates of future prices are highly uncertain and need to be treated with caution. The model can easily be adapted to different cost structures representing different regions and circumstances by changing the parameter values and including system units. Since one alternative steel production route is an EAF operated on steel scrap, the prices and availability of scrap are of crucial importance. In the present model examples, scrap prices are assumed to increase with increasing imports. Starting from 220 €/t, the price increases by 30 €/t for every additional 20 t/h of imported scrap up until 490 €/t. This price dynamic restricts scrap imports without setting explicit limits.

Another parameter greatly affecting the results is the cost of CO_2 permits. Data from the past ten years shows that EU carbon pricing has increased from about 6 €/t_{CO2} in 2013 to around 100 €/t_{CO2} in 2023.[17] In the present model examples, carbon prices were initially set to 20 €/t_{CO2}, and increased by 40 €/t_{CO2} every five years, i.e., at each time step. This serves as an example of how the estimated evolution of prices will affect the optimal transition. Naturally, such projections are highly uncertain, and a thorough sensitivity analysis should be performed to assess different scenarios.

Cost minimization

The transition was optimized with respect to overall costs with the above initial and parameter settings but for different fixed values of the price of electricity, yielding optimal transition scenarios. Figure 3 shows how operational costs vary throughout the time horizon in the optimal solutions for electricity prices in the range 20–70 €/MWh. Each case starts with identical plant setup with the specified initial configuration, and the operation costs are almost identical as electricity demands are covered by the internal CHP plant. In successive time steps, the investment paths are highly dependent on the electricity prices, with higher prices leading to continued blast furnace use coupled with EAF use, where scrap is introduced to address the increasing specific costs of CO_2 emissions. By contrast, lower electricity prices lead to increasing use of hydrogen reduction in DR furnaces. The increasing trend seen in the cost curves is due to the increase in carbon permit prices as time proceeds.

In all these solutions, investment in an EAF happens immediately in the second time period, while investments in DR furnaces and electrolyzers occur in time period 4 with 50 €/MWh, time period 3 with 30–40 €/MWh and time period 2 with 20 €/MWh, as indicated by circles in the figure. With electricity prices above 50 €/MWh the solutions did not include electrolyzers or shaft furnaces when minimizing costs. These results can be compared with those of Vogl et al.,[3] who calculated that the H_2DR route becomes cost competitive with integrated steel plants at electricity prices around 40 €/MWh with carbon permit prices of 34–68 €/t_{CO2}. In the present model, if the carbon permits are fixed at, e.g., 50 €/t_{CO2}, solving with electricity prices of 40 €/MWh or higher results in configurations with one EAF producing about 100 t/h from steel scrap and the rest coming from the BF-BOF route, while electricity prices of 30 €/MWh result in shaft furnace and electrolyzer investments in the third time period. On the other hand, fixing carbon permits at a very high level, e.g., at 200 €/MWh, leads to solutions favoring EAFs charged with steel scrap from the second time period onward with electricity prices at 30 €/MWh or above, while still cheaper electricity warrants investments in the H_2DR route in the second time period.

These total accumulated costs can be compared with costs when only utilizing the BF-BOF route throughout the time horizon. For 70 €/MWh the total cost reduction is about 13%, while for 20 €/MWh, the reduction is almost 27%, since the H_2DR route can make use of the cheaper electricity. The primary reason why this route becomes economically beneficial is the growing costs of the CO_2 emission permits, which drive the system towards decarbonization. Figure 4 shows a breakdown of the total costs for the 25-year period under different electricity prices. It should be noted that the investment costs in the figure only reflect costs relevant to the decisions in the model, and they exclude any investments that are required at the steelworks related to parts that are static in the model configurations. With higher electricity prices, the solutions favor continued blast furnace use combined with EAF and increased scrap use, which means that costs of scrap, pellets and emissions make up a large portion of the total costs. With cheaper electricity, the solutions adopt the H_2DR route, with costs shifting towards iron ore for the internal pellet plant, electricity and higher investment costs, but scrap costs are also a significant part of the total. Although the electricity price is low (e.g., 20 €/MWh), the electricity use is so considerable that the total electricity costs exceed 17% of the total accumulated costs.

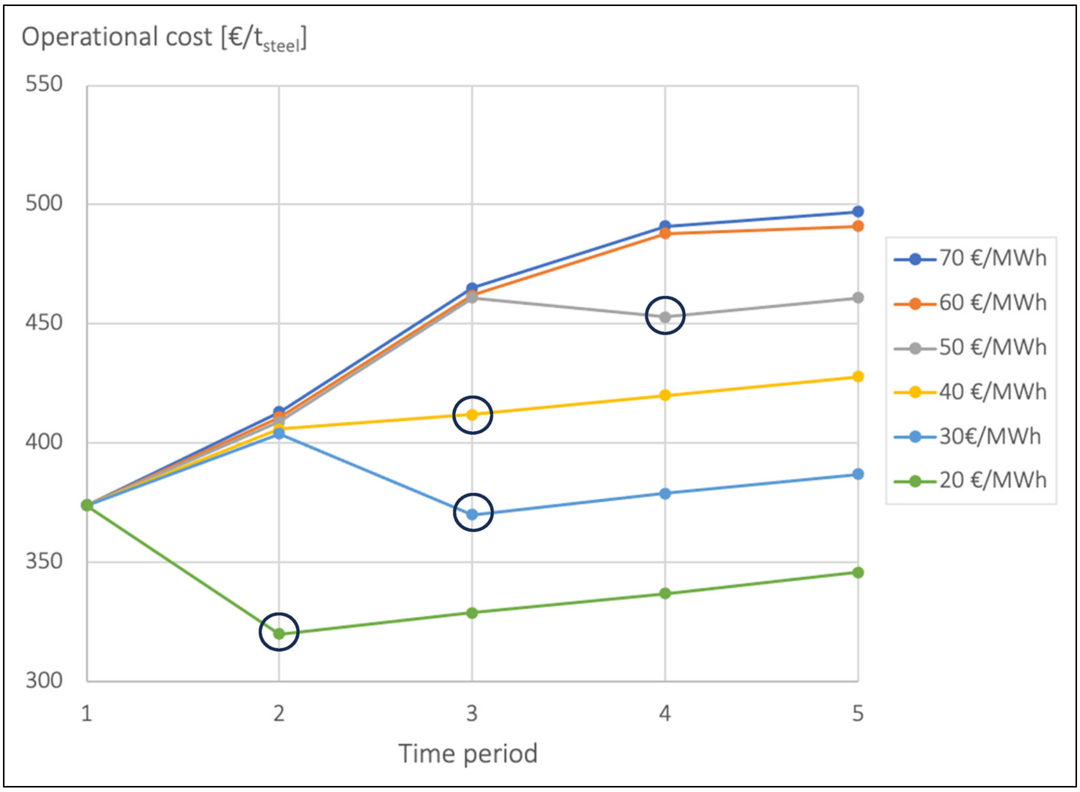

Figure 3. Evolution of operational costs in the time periods for scenarios optimized under different electricity prices. Circles indicate the period when direct reduction and electrolysis units were introduced.

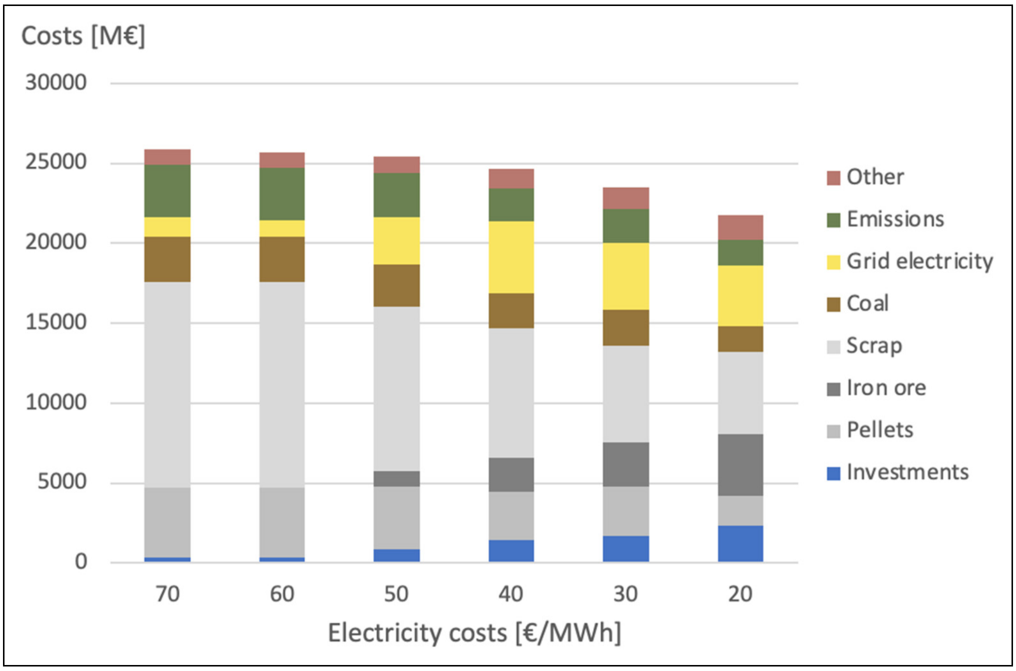

Figure 4. Breakdown of total accumulated costs in the cost-minimized optimal solutions with different electricity prices.

The total emissions for the above solutions were also compared under different grid emissions intensities (GEI). When minimizing costs, the GEI values do not affect the solutions as there is no additional cost placed on upstream emissions in the objective function. Figure 5 compares the specific emissions of producing steel in the different time steps for the solutions with electricity price 70 €/MWh and 30 €/MWh, with three different GEI values, where the initial configuration in the first time period has specific emissions of about 1.9 t_{CO2}/t_{steel}. In the base case (solid lines), GEI was 0.089 t_{CO2}/MWh, reflecting emissions from Finnish grid electricity in 2018–2022.[18] The dashed curves show the specific emissions for GEI = 0.25 t_{CO2}/MWh, which is close to an average value in the European Union in 2022,[19] and with zero emissions (dotted lines) from grid electricity.

Complementing the specific emissions in Figure 5, total accumulated emissions in the solutions can be compared with only using the BF-BOF route: with 70 €/MWh, the differences between GEI values are quite small since the optimal plants do not incorporate electrolysis units. The reduction in total accumulated emissions compared to BF-BOF amounts to around 40% in these cases. For an electricity price of 30 €/MWh, GEI makes a larger difference: in the base case the reduction in total accumulated emissions is 44%, in the EU average case is 23%, and with zero grid emissions 56%. In testing with higher GEI values (not shown here), the model indicates that a threshold of GE ≈ 0.3 t_{CO2}/MWh when emissions from the H_2DR route equals those from the BF-BOF route. As a comparison, Rechberger et al.[2] calculated that direct reduction with hydrogen has lower emissions than with natural gas if GEI is below 0.12 t_{CO2}/MWh. If known, effects of possible expected rates of reductions in GEI can be considered in the optimization.

Emission minimization

The strategy can also be changed to minimizing the total accumulated emissions, but minimizing emissions alone may yield solutions that are economically infeasible. In an illustration of the concept, and to provide a meaningful comparison with the results of the cost minimization, the emissions were minimized subject to a constraint on total costs relative to the minimized costs in the previous model solutions. Figure 6 shows how the accumulated emissions vary in solutions with different electricity prices when minimizing emissions (with GEI = 0.089 t_{CO2}/MWh), limiting total costs at to be maximally 2%, 5% or 10% higher than for the case with minimized costs. Emissions reductions reached compared to the cost-optimal solutions are listed in Table 2. Especially with the higher electricity prices, the achievable emissions reductions are considerable, e.g., 20% emissions reduction with a 2% increase in costs with an electricity price 70 €/MWh. Thus, the difference in costs between adopting new technologies and continuing with the BF-BOF route is relatively small in the cases studied. With the lower electricity prices, the potential reductions are smaller, as the direct reduction technologies are already utilized in the cost-optimal solutions. With available estimates on how much more the market is willing to pay for steel with less environmental impact, the solutions presented can be used to assess the economic feasibility of the decarbonization.

Discussion and future prospects

The modelling approach presented in this article illustrates how mathematical optimization can aid the planning of technological transitions. Steel production involves a complex network of intertwined processes, so a complete steelworks model necessarily involves coarse simplifications. Nevertheless, even simplified models can give

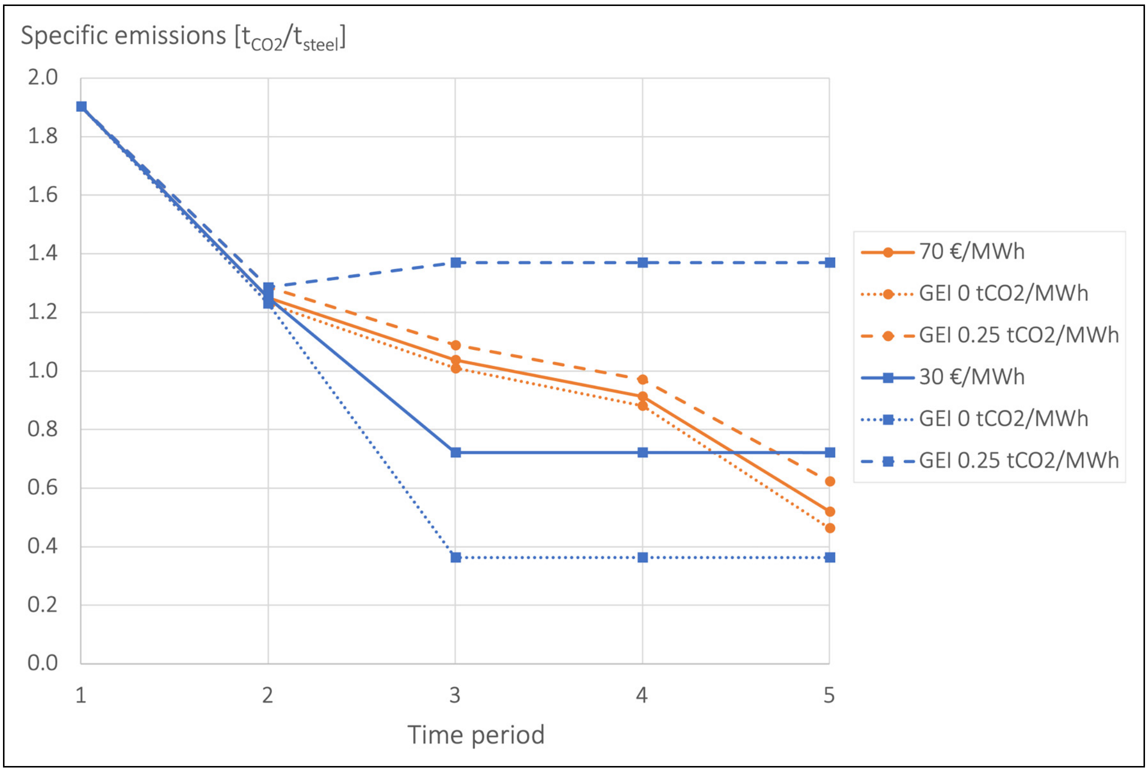

Figure 5. Evolution of specific emissions for producing steel in model solutions with different grid emission intensities.

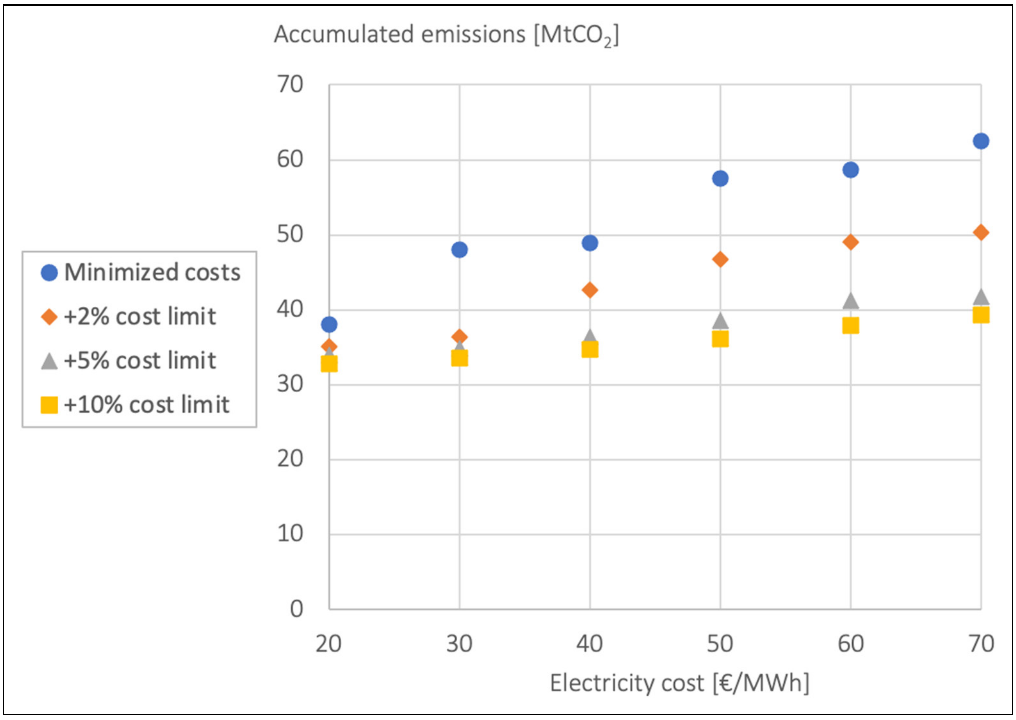

Figure 6. Minimized total accumulated emissions with different limits on total costs.

indications of challenges and possibilities regarding steel plant configurations and operational schemes.

The example cases indicate how prices of electricity and carbon permits affect model solutions and give hints on how the H_2DR route compares with the BF-BOF route. Low grid emission intensities are crucial when determining the benefits of the H_2DR route in terms of emissions reductions and the model can account for estimated changes in future GEI values as well as changes in other key parameters. Results indicate that with grid emissions at present average European levels a change to hydrogen/electricity-based steelmaking may only lead to modest reductions in CO_2 emissions, so concurrent efforts in reducing emissions from electricity generation are essential.

Table 2. Changes in CO_2 emissions comparing solutions with cost-constrained minimized emissions and solutions with minimized costs.

Electricity price [€/MWh]	Total emissions with minimum costs [Mt CO_2]	Costs limit		
		+2%	+5%	+10%
70	62.5	CO_2: −20%	−33%	−37%
60	58.7	−16%	−30%	−35%
50	57.5	−19%	−33%	−37%
40	48.9	−13%	−26%	−29%
30	48.1	−24%	−27%	−30%
20	38.1	−8%	−11%	−14%

Examples also showed how considerable reductions in emissions could be reached with relatively small increases in total costs when considering solutions beyond the cost-optimal solutions.

The calculation efficiency of the demonstrated model allows for more thorough scenario analyses with large sets of various parameter combinations to find robust solutions. The calculation efficiency depends on the number of time steps included, so the length and resolution of the time horizon are restricted. Another possible future model development that depends on efficient calculation involves the addition of system dynamics in contrast to the present steady-state formulation. The individual unit models should also be improved, especially the EAF and shaft furnace models, to allow for more diverse and more realistic operational considerations. Diversifying the shaft furnace input gas mixture could allow interesting options for utilizing process gases in transition phases.

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