Integrating life cycle analysis into system dynamics: the case of steel in Europe

Julian T. M. Pinto1,2,3*, Harald U. Sverdrup1,2 and Arnaud Diemer1,3

Abstract
Background: Steel is an important material in modern economies but responsible, nevertheless, for substantial environmental impacts throughout its supply chain. During the last couple of decades, this industry has addressed its impacts more incisively with the support of modelling and assessment tools.

Methodology: This article used the European steel industry as a case study to explore the potential benefits of integrating life cycle analysis (LCA) into system dynamics (SD) under the scopes of circular economy and industrial ecology. The goal was to explore if this integration could not only reproduce results generated separately by LCA and SD, but also to provide additional support for decision- and policy-making on the biophysical aspects of long-term materials sourcing. Unlike previous studies focused on methodological exchanges between the two, the entire LCA methodology was brought into the SD modelling environment, following ILCD and ISO guidelines and standards.

Results: The results indicated that integrating LCA into SD is feasible and capable of contributing to both in different levels, supporting discussions on raw material scarcity and self-sufficiency, and resource ownership retention.

Conclusion: Given continued effort is put into supporting the use of environmental impact indicators, this approach has potential to interest policy-makers and industrial decision-makers alike.

Keywords: Steel, Europe, System dynamics, Life cycle assessment, Industrial ecology, Circular economy

Background
Steel is the most commonly used alloy of iron and has historically been one of the most essential materials worldwide. It is present in most aspects of everyday life, from infrastructure to transport, from canned food to electronics (WS 2012a, b, 2017b, c; Beddows 2014). Steel’s cycle through environment and society originates in the ores mined from mountains and underground reserves and most commonly meets its end inside long life service structures or as recyclable scrap (Warrian 2012; Vaclav 2016).

The Second World War was a turning point for steel-making due to the substantial changes it caused to the geopolitical environment. By the end of the conflict, the European demand for steel decreased significantly, all the while Chinese and Indian steelmakers became competitive. As decision-making became more complex, European steelmakers once focused only on scale and costs to supply the war effort then faced new challenges: over-capacity, the alloy specialization requirements of the private sector, and the growing attention given by society and governments to environmental impacts (Vaclav 2016; WS 2017b; Nuss and Blengini 2018).

Adequately supporting and informing decision-makers rose even further in the list of priorities as the roles and importance of technology critical elements (TCEs) and critical raw material (CRMs) present in steel became more evident. Thus, this industrial sector was among the first to the benefit from the efforts of managerial scientists, engineers and academics as the development of new concepts, tools and methods gained traction, notably after the 1960s (van Berkel et al. 1997; Baas and Boons 2004).

From that period onward, European steelmakers have increased their strategic outreach towards environmental
goals, improving their supply chain management to encompass both end-of-life and circularity solutions (D’Costa 1999; Material Economics 2018). Today, steel in Europe is recycled at a 70% rate and most of its byproducts can be reused in other industries (Yellishetty et al. 2012; WS 2017a).

In comparison to the 1980s, the average manufacture now uses 50% less energy, helping vehicles become more fuel efficient with stronger and lighter steel alloys. Steel today can even be environmentally competitive enough to front plastics and aluminum products (Warrian 2012; WS 2013; Vaclav 2016; Material Economics 2018).

Renowned worldwide after the success of the Kalundborg Industrial Park, Industrial Ecology (IE)—one of the drivers of the aforementioned environmental progress—studies, organizes and models industrial activities and their interactions with the environment by approaching them organically. It seeks to accrue benefits from transitioning linear-or open-loop operations—in which outputs end up in sinks—toward closed-loop operations—in which outputs can become inputs (Erkman 1997; Ehrenfeld 1997, 2004; Nielsen 2007; Taddeo 2016; Prosman et al. 2017).

To do so, IE encompasses approaches to multiple aspects of industrial operations, namely (a) material and energy flows—known as industrial metabolism, (b) technological change, (c) eco-design, (d) life-cycle planning, (e) dematerialization, (f) decarbonization, (g) corporate responsibility and stewardship, and (h) industrial parks—also known as industrial symbiosis (Chevalier 1995; Cohen-Rosenthal 2004; Gibbs and Deutz 2007; Despeisse et al. 2012; Leigh and Xiaohong 2015).

Circular economy (CE) complements IE by approaching materials from two perspectives: biological nutrients—which should eventually reintegrate the biosphere without causing any harm, and technical nutrients—which circulate in the economy (Pearce and Turner 1989; Seager and Theis 2002; Korhonen 2004; EMF 2012, 2013, 2014b; Liao et al. 2012; Tükker 2015; Geissdoerfer et al. 2017).

CE suggests that all economic activities should be performed focusing on (a) the use of wastes as inputs, (b) the adoption of renewable and clean energy sources, (c) the accurate biophysical costs of their extraction, transformation, use and reinsertion into either economy or biosphere, and (d) outputs designed from the beginning so as to facilitate collection, recycling, refurbishing, reuse, redistribution, maintenance and sharing throughout their lifespan (Park et al. 2010; EMF 2014a, 2015a, 2016, 2017; Haas et al. 2015). Due to the commoditization of its products and of its raw materials, the steel industry traditionally pays close attention to factors and productive variables that can affect price and competitiveness just as much as quality. With this in mind, for decades, this industry has been using putting in place environmentally-friendly practices such as recycling and by-product reuse even before Circular Economy and Industrial Ecology became widespread concepts or part of policy-driven efforts (EC 2013b; WS 2016).

In Europe, most policies regarding environmental impacts came into force or were revised close to the turn of the century. Notably examples are the Environmental Assessment Directive 2011/92/EU (EP 2011), the Industrial Emissions Directive 2010/78/EU (EP 2010), the Air Quality Directive 2008/50/EC (EP 2008a), the Water Framework Directive 2000/60/EC (EP 2000), the Packaging Waste Directive 94/62/EC (EP 1994), the Waste and Hazardous Waste Framework Directive 2008/98/EC (EP 2008b), and the Landfill Directive 99/31/EC (EU 1999).

Although these documents address how industries should manage, control and report their undesired or potentially hazardous outputs, minimal attention was given to input alternatives, resource efficiency or circular behaviors. Moreover, no particular or direct attention was given to the steel supply chain (EP 1999, 2000a, 2008a, b, 2010, 2011), with the exception of the Extracting and Mining Waste Directive 2006/21/EC (EP 2006).

In 2012 the European Union and its member states committed to the application of a Circular Economy Package as new driver for its economic model, boosting a transition to resource-efficient practices that eventually lead to a regenerative progress toward nature (Zhijun and Nailing 2007; UNEP 2011; EC 2012; Su et al. 2013; Kahle and Gurel-Atay 2014; EMF 2015b; Gregson et al. 2015). Soon after, the European Commission conceived an action plan focused on the European steel industry, which summarized the situation of the European steel industry as of 2012 and brought to light the difficulties faced by the sector in terms of prices, competitiveness, trading and energy (EC 2013b).

To deal with these obstacles while furthering environmental progress on resource efficiency and climate, the action plan highlighted the need for developing secondary metals markets in order to boost the production of steel from scrap (EC 2013b; EUROFER 2015). From that point on, the European Commission and the European Council created multiple policy-supporting documents, the most noteworthy being the Best Available Techniques (BAT) for Iron and Steel Production (EC 2013a). Along Directive 2006/21/EC and the BAT for the Ferrous Metals Processing Industry (EC 2001). These documents proposed operational techniques capable of directly addressing certain environmental impacts and, when possible and pertinent, suggested potential circular integrations.
Still, the previously mentioned policies and most of their supporting documents either addressed steel indirectly through other sectors or approached different stakeholders/process of the steel supply chain separately (EUROFER 2015). Even alongside the BAT documents, these policies have been deemed insufficient to address climate and resource efficiency issues. Therefore, in order to stop this counterintuitive obstruction of circularity, more attention should be given to end-of-life steel, energy sourcing and systemic/holistic approaches (EC 2013b, 2014; Diener and Tillman 2016; Dunant et al. 2018; EUROFER 2015).

In an attempt to provide the European steel industry with additional support for decision- and policy-making, this article explored the potential benefits on integrating two methodologies used in the context of IE and CE: life cycle assessment (LCA) and system dynamics (SD) (Lewandowski 2016; Pomponi and Moncaster 2017; Winans et al. 2017).

Unlike previous studies, in which LCA and SD models ran in parallel and exchanged intermediary outputs or data exogenous to each other (Yao et al. 2018; Stasiopoulos et al. 2011), the present article brought the entire LCA methodology, in its attributional form, into the SD modelling environment. By doing so, the authors expected to maximize the amount of endogenous dynamics at play.

In the interest of identifying possible barriers or constraints to the integration, available literature was investigated and both LCA and the SD methodology were subjected to SWOT analyses—a strategic assessment technique used to identify the strengths, weaknesses, opportunities and threats faced by a given object of study (USDA 2008). Furthermore, it was deemed important to ensure that both LCA and SD would operate properly despite the integration, task achieved by comparing the results to those in existing literature generated by LCA and SD separately.

**LCA and its uses in the European steel industry**

As a tool, LCA is used for the accounting of series of static inventory inputs and outputs of the processes that exist in the life cycle of an object of study. These values are then scaled in accordance to a functional unit and characterized into sets of environmental impact indicators. This allows for a clearer understanding of the environmental performance of a series of processes throughout an item’s life cycle and enables detailed analyses and comparisons with similar goods (Palazzo and Geyer 2019; Tietenberg and Lewis 2004; ISO 2006; Ekvall et al. 2016; Koffler et al. 2014).

LCA has gained ground over the years due to its quantitative diagnostic applications, helping companies identify improvement opportunities in their supply chains (Hunt and Franklin 1996; Sonnenmann et al. 2004). By individually analyzing the environmental impacts and environmental performance of each stage of a product’s life cycle, LCA enables product designers and decision-makers to better visualize the ramifications of inserting a product into the market (Ferreira 2004). This then allows for the revision and correction of a product’s characteristics or of a supply chain’s operation in order to reduce potential harm to the environment (Daddi et al. 2017).

The life cycle of steel, summarized in Fig. 1, begins with at least one of two main raw materials: iron ore or steel scrap. Iron ore is mined from Hematite (Fe₂O₃, ~ 70% Fe content), Magnetite (Fe₃O₄, ~ 72% Fe content), Limonite (2Fe₂O₃ + 3H₂O, ~ 59% Fe content), Goethite (Fe₂O₃ + H₂O ~ 63% Fe content) or Siderite (FeCO₃, ~ 48% Fe content) (Stubbles 2017; Jones 2017; Kozak and Dzierzawski 2017).

Steel scrap, on the other hand, often has over 95% Fe content and, once given the appropriate triage and treatment, goes straight into steelmaking after its collection from manufacturing processes, recycling centers, junkyards or even landfills (Warrian 2012; WS 2012b; Beddows 2014; Stahl 2017).

Steel can leave the manufacturing stage in many forms and with many different chemical and mechanical characteristics, depending on the application to which it was designed (Beddows 2014; Stahl 2017). Once it goes into the use stage, it will be stored, reused and remanufactured until losses in quality demand its recycling (WS 2012b; Vaclav 2016). Throughout this entire sequence of stages, however, energy is consumed, byproducts are created and environmental impacts are generated, all of which can be accounted by LCA.

By following the guidelines of ISO 14040:2006 and using Simapro as a modelling platform to analyze data from EcoInvent, Burchart-Korol (2013) developed the LCA of the Polish steel industry. In the study, the functional unit was set to one tonne of cast steel produced within Polish cradle-to-gate boundaries, resulting in CO₂eq emissions measurements according to IPCC and CED criteria, as well as in ReCiPe Midpoint indicators for 17 different categories of environmental impacts per main productive process. Not only were the authors capable of identifying the human health and environmental risks posed by the raw materials as well as the energy demand of each productive process, but also to suggest changes in energy sourcing that could allow for the Electric Arc Furnace (EAF) method to be less emission-intensive (Burchart-Korol 2013).

A similar study was performed in the Turkish steel industry, in which 14 IMPACT2002 + Midpoint indicators were used instead of ReCiPe’s 17, focusing on five
different steel products: billet, slab, hot rolled wire rod, hot rolled coil (Olmez et al. 2015). The main contributions of this study were (a) identifying hot rolled products as the most environmentally hazardous due to their intensive emission of inorganic particles—thus requiring efficient dust collection methods, and (b) highlighting the significant Global Warming Potential of this industry as a whole due to its high consumption of fossil fuels (Olmez et al. 2015).

Another similar example of LCA pertinent to the discussion at hand took place in Italy, additionally considering emissions from logistics while focusing on a functional unit of 1 million tons of steel slab (Renzulli et al. 2016). Unlike previous studies, this one suggested the regional reuse of BOF and BF slag for agriculture or infrastructure purposes as a mean to help reduce the overall environmental impact of the production process, while also suggesting a partnership with nearby power plants in order to improve energy efficiency (Renzulli et al. 2016).

Based on literature and practice just as much as on the examples above, Table 1 summarizes the analysis of strengths, weaknesses, opportunities and threats (SWOT) executed by the authors of this article.

It is from understanding and experiencing some of the limitations above as well as the limited availability of literature on LCA for European steel that the authors of this article considered also exploring how SD can support decision-making in the steel industry.

**SD and its uses in the steel industry**

While LCA is capable of giving scholars and decision-makers a very insightful snapshot of a supply chain, SD can, in turn, transform that snapshot into a film. Decision-makers gain, thus, the means to analyze a supply chain as it progresses through the effects of multiple

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Fig. 1 Steel’s life cycle as per the circular economy framework (adapted from EMF 2017)
feedbacks and loops of which visibility, relevance or scale could only become evident with the passage of time or with their simultaneous interactions (Forrester 1962; Booth and Meadows 1995).

SD is a methodology for studying complex nonlinear behavior within systems, often used for simulating new potential behaviors by adding, removing or changing variables, triggers and delays (Sterman 2000; Ogata 2003). To do so, it deconstructs a system into smaller—often binary—interactions. It then analyzes their behavior not only independently but also as part of the whole, which then generate balancing or reinforcing loops that help determine the system's overall behavior (Ruth and Hann 2012).

Instead of pushing data through series of stocks and flows—as LCA commonly does, SD lets the ensemble of interactions between each correlated pair of variables define the behavior of the system (Ogata 2003; Ruth and Hann 2012). This approach allows for very small-scale problem-solving just as much as it allows for the analysis of large-scale interactions. SD often encompasses market dynamics and relies on endogenous data to create projections and trends, more easily representing circular behaviors when compared to other methodologies (Sterman 2000; Ruth and Hann 2012).

SD derived from the school of Systems Thinking of the 1950s and 60s, which intended to support and improve productive decision-making (Forrester 1962; Booth and Meadows 1995). Its application begins on the definition of a clear question, then proceeds to conceptualize the system where the problem is located. During this step, its components, the causal relations and the feedbacks therein are mapped, generating a causal loop diagram (CLD) (Forrester 1969; Coyle 1997; Haraldson 2004; Morgan 2012; Capra and Luisi 2014).

Next, the CLD is converted into a Flow Chart (FC), a diagram which allows for data and variable inputs, task usually performed in a modelling software such as Stella or Vensim (Morgan 2012; Ruth and Hann 2012). Having built a model that represents the system at hand and having added pertinent data to it, results and analyses can be derived from the simulation of scenarios (Randers 1980; Karnopp and Rosenberg 1975; Sterman 2000; Ogata 2003). Regarding the steel industry, and especially in Europe, not many studies and publications have yet made use of SD. Below, the authors present examples of SD studies on steel performed by researchers in China, Iran, Sweden and the United Kingdom.

The first study consisted of a macro-level analysis of the sintering process, one of the raw material preparation steps commonly used in the iron making stage. Both CLDs and FCs were created, resulting in a SD model capable of replicating the known behavior of sintering operations in the Anshan Iron and Steel Corporation (AISC) (Liu et al. 2015). The model was then used to run a multi-variable simulation comparing the AISC’s operation to the Shouqin Corporation’s operation, pointing to the latter as capable of delivering sinter with better compacted ness and higher iron content to the Chinese market (Liu et al. 2015).

The next study focused on reducing the consumption of natural gas and oil in Iranian national steelmaking by simulating the energy requirements through 20 years of subsidies, exports and consumption (Ansari and Seifi
A macroeconomic SD model was created to test the aforementioned variables simultaneously and in face of price variations, resulting in up to 33% reductions in fossil fuel consumption depending on the mix of subsidy reforms, recycling stimuli and EAF deployment scenarios (Ansari and Seifi 2012).

Next, researchers studied how SD can support decision-makers in identifying the main obstacles for extending a product’s lifespan so as to comprise multiple life cycles (Asif et al. 2015). Global and North American data on steel was used to build a simplified global SD model in which resource scarcity and steel consumption were defined as the main drivers (Asif et al. 2015). As a result, the researchers suggested that enterprises and nations should attempt to keep scarce or non-renewable resources within their supply chains for as long as possible during multiple life cycles in order to accrue the most economic and environmental advantage possible (Asif et al. 2015).

The last study brought to the reader’s attention was one of the earliest concerning the steel industry using SD as a methodology. In it, the researchers attempted to create a model capable of reproducing the effects of bottlenecks, breakdowns and other operational constraints in steel-making supply chains which adopt Minimum Reasonable Inventory (MRI) as a business strategy (Hafeez et al. 1996). After simulating different operational scenarios, the main outcome of the study was a set of strategies to achieve MRI for each individual stock unit according to system-wide operational risks, instead of altogether uniformly, which would tend to require either operational risk insurances or higher levels of working capital binding (Hafeez et al. 1996).

As previously performed for LCA, Table 2 summarizes the SWOT analysis of SD considering the examples above as well as other relevant literature. After having finished SWOT analyses for both LCA and SD, the authors identified multiple points of divergence but also of convergence. Most importantly, however, is that in situations where one flounders, the other often excels, thus pointing to the potential benefits of a combined approach.

**Methodology**

Bringing LCA and SD together is a relatively recent idea as of the development of this article, with earliest attempts dating back to 2011. In the scientific studies published so far, systems thinking was used to pursue the same results generated by either LCA (Onat et al. 2016; Halog and Manik 2011; Yao et al. 2018; Stasinopoulos et al. 2011) or Material Flow Analysis (MFA) (Sprecher et al. 2015).

In some of their attempts, previous academics ran both methodologies in parallel and used them as interchangeable sources of endogenous data to each other (e.g. Yao et al. 2018; Stasinopoulos et al. 2011). In other attempts, series of results originated in MFA or LCA were then used in a SD model, simulating a circular environment for the retrieval of dynamic behaviors (e.g. Sprecher et al. 2015; Onat et al. 2016; Halog and Manik 2011). Plevin et al. (2014) and Palazzo and Geyer (2019) also tested different variations of LCA—attributional or consequential, respectively—in order to bring systemic attributes into their LCA results and discussions.

In all cases, authors were capable of broadening and deepening the understanding of the systems under study and their efforts brought significant advancements to the discussion of how approaching LCA and MFA with a SD mindset can be productive and insightful (Onat et al. 2017; Palazzo and Geyer 2019).

Nevertheless, answering questions regarding sustainability’s triple bottom line or regarding

Table 2 SWOT analysis of system dynamics. [Sources: Forrester (1962), Booth and Meadows (1995), Coyle (1997), Hafeez et al. (1996), Ogata (2003), Haraldson (2004), Ansari and Seifi (2012), Capra and Luisi (2014), Asif et al. (2015), Liu et al. (2015), Kunc (2017)]

| Strengths | Weaknesses |
|-----------|------------|
| Focus on circularity, causality and the effects of variables over time | Strategic analyses often do not suffice for effective decision-making |
| Strong for strategic analyses and problem-solving | Visualization of stakeholder involvement is highly dependent on how the model is built |
| Flexible modelling environment facilitates the use subjective or abstract variables if necessary | Levels of error and uncertainty are harder to determine |
| Multiple independent objects of study can be subject of analysis simultaneously | Aggregation can hide or ignore important variables if not done carefully |
| Model structure is easy to adapt and change if necessary | Model structure might not be objectively represent the actual series of processes and flows of the system under study |
| Can be used for modelling market dynamics | Limited support for using indicators |

| Opportunities | Threats |
|---------------|---------|
| Can be of great use for communication purposes | Scarc expertise |
| Can foster the development of multidisciplinary studies | Analyses can become over-simplistic |
| Can generate endogenous trends and projections | Vulnerable to data reliability |
different environmental nexi with larger scopes and boundaries still faced two main methodological dilemmas: data aggregation levels had to be altered—often upwards and towards simplification; and data output formats had to be adapted—often seeking the lowest common complexity denominator.

Although none of these modifications were inherently negative, they interfered with each individual methodology enough to justify this article’s different approach: one focused on maximizing endogenous feedback and minimizing data aggregation issues or format adjustments. Having learned from the aforementioned experiments and from the authors’ previous experiences, this article tries something different: to bring the entire LCA methodology into the SD modelling environment.

It is to say that, in addition to using SD to broaden and deepen the achievements of LCA, we have attempted to create a win–win environment in which LCA can provide its own contributions to SD as well. To delve into the details of this endeavor, this section is divided in three parts, namely (a) research design—in which the authors introduce question, case-study and the methodological steps; (b) model description—in which the model itself and its development are explained; and (c) parameterizing and operation—where details regarding data inputs, variable control and operational behaviors are presented.

**Research design**

Considering that neither SD nor LCA were originally devised to work with each other, as well as the limited number of available attempts of their integration until now, the primary concern was to properly envision where, when and how LCA and SD could supplant each other’s weaknesses while maintaining their own strengths. With that in mind, a methodological question took priority over the originally conceived one, resulting in the following:

1. Can the integration of LCA into SD reproduce the results or behaviors previously observed in studies that used LCA or SD separately?
2. What potential benefits derive from this integration toward decision-making on the biophysical aspects of long-term materials sourcing?

Keeping in mind the frameworks and concepts of both IE and CE, the main expected result of the study was achieving a favorable answer to the first question, which would hypothetically indicate that the integration was realized adequately and to the extent of not interfering with either SD’s or LCA’s correct implementation. The quantitative criteria for answering both questions, keeping in mind the case study at hand, focused on (a) emissions, (b) biophysical depletion of iron ore, (c) steel scrap generation and consumption, (d) liquid steel output from production, (e) iron circularity, and (f) steel input into the economy, as derived from literature already presented thus far or to be introduced further in this section.

For qualitatively answering them, the SWOT analyses based the search for the following patterns: SD’s broader and more flexible modelling approach contributing to LCA’s (a) circularity, (b) long-term perspective, and (c) the macro analysis potential; while LCA’s objective and empirical representation of an operation improves SD’s (d) stakeholder involvement identification, (e) analysis reliability, and (f) applied/practical usefulness across managerial levels.

The case study used for testing this integration was the European steel industry, chosen by the authors due to (a) its current transition towards more environmentally-oriented decision-making; (b) its importance for the European economy, security and sovereignty; (c) its global contextual concerns regarding the rise of international competitors, and; (d) to the policy limitations regarding its environmental aspects. Therefore, as boundary, the study took into account the EU28 zone, represented by the supply chains of the steelmakers members of the WorldSteel Association that operate within it, which account for 84% of the entire European steel industry.

In order to adequately represent this industrial activity and give focus to the biophysical transformations that take place throughout the supply chain while keeping in mind European average steel production behavior, the study was conducted using the following methodological steps: (1) business process mapping (BPM), carried out with the support of the BizAgi software and aimed at identifying all the core processes of steelmaking in Europe; (2) causal loop diagraming (CLD), made with the support of the OmniGraffle tool so as to represent the steelmaking supply chain in a systematic and holistic manner; (3) flow charting (FC), within the SD modelling environment of the Stella Architect software (ISEE Systems 2016); (4) data collection and scenario building; (5) model parameterizing and testing; and (6) simulation runs and analyses.

Iron was defined as the driving chemical element of steelmaking, while steel scrap and iron ore were defined as the key raw materials. Nevertheless, connections to all other chemical elements and raw materials involved in steelmaking were included, as summarized in Fig. 2.

Furthermore, two different levels of aggregation were adopted: cradle-to-gate processes were disaggregated down to chemical level, while gate-to-cradle processes were aggregated to product level. This choice was made in order to give decision-making granularity for the steelmakers without over encumbering macro-level analyses.
that could affect policy-making on end-of-life and circularity services.

In order to obtain the desired alloys, the material needs of the furnaces were used to define the amounts of raw materials pulled from their respective sources. This *pulling* behavior is present in the system until liquid steel becomes an intermediary output, point in which the system then *pushes* materials through the subsequent processes so as to reproduce the continuous casting operation. Additionally, attention was given to the feedbacks that *close the loop* (e.g. recycling, repair, refurbishment), so as to enable the system to operate under the definitions of CE and IE.

**Model description**

In total, twenty modules were created, one for each chemical element involved in the steel supply chain (e.g. iron, carbon, nickel, chromium, zinc, oxygen), all of which used a functional unit (FU) of 1 ton of steel and were built to be structurally identical. Specific flows and stocks were introduced whenever necessary so as to properly represent the typical behaviors of each chemical element throughout the supply chain.

Within each module, the production processes and the stocks of steelmaking were approached modularly and established as individual LCA-based units, capable of being displaced, rearranged or replicated with minimal interference in the overall structure of the model. This allowed for the user interface to be less polluted then traditional SD models and should enable this model to be easily adapted to the reality of different stakeholders in the future, as exemplified in Fig. 3.

The productive processes were grouped into macro-processes based on their most common occurrence in the European steel industry, namely: (a) EAF and (b) BFBOF—each encompassing sintering, pelletizing, degassing, alloying, desiliconization, desulfurization, homogenization or dephosphorization, whenever applicable; (c) casting—which encompassed all shape, heat and surface treatments; (d) metallurgy—which encompassed all forming and metalworking processes; (e) economic sectors—divided in construction, automotive, other transportation, tools and machinery, appliances and electronics, and heavy mechanical equipment, as per WorldSteel Association standards; (f) recycling—which fed back into the stock of scrap used as input for “a” and “b”; (g) repair/refurbishment—which fed back into each economic sector according to their share in its demand; and (h) losses and landfills—which configured a process-based sink.

It is important to note, however, that (1) due to the lack of available disaggregated data, emissions from mining, casting and metallurgy were attributed to the EAF and the BFBOF macro-processes accordingly and proportionally; (2) dust and particulate matter generation were incorporated into the mass of emissions; (3) no disaggregated emission data was found for end-of-life and circularity solutions; (4) energy flows were considered only in the form of amount of fossil fuels consumed and not in the form of heat or electricity (directly by BFBOF and indirectly from generation for EAF); and (6) no pricing, costing or speculative variables were included in this attempt—variables these which will be addressed in a subsequent publication.

Finally, a control panel was created in order to facilitate the visualization and management of data inputs and variable control, as well as for the easier identification of issues. It allowed for the (a) adjustment of variables that affect all 20 modules, (b) monitoring of stocks, flows and outputs of the supply chain, and (c) follow-up on operational losses. Moreover, different levels of granularity were made possible for analysis merely by switching on and off the tracking of individual chemical elements.

**Parameterizing and operation**

Table 3 summarizes the data inputs used in the study, all of which encompassed the interval between 2001 and 2014, and were verified for cohesion, coherence and reliability based on the criteria of the ILCD Handbook (EC 2010) and of ISO14044:2006 (ISO 2006), however, in its current state, it presented itself as a less consolidated and less disseminated methodology, with available applications focused mainly in the construction sector.
operational requirements; and (c) steel scrap down cycling over time due to alloying quality loss during repeated service lives.

Finally, all circularity and end-of-life behaviors were set to respond in a business-as-usual pattern, with no direct or indirect stimulus of any kind, evolving only in proportion to the demands of the elements present in steel scrap.

**Results and discussion**

After running the model, the authors proceeded to verify if the integration could reproduce results of studies that used SD and LCA separately. In what regarded SD, the results were favorable and all features of SD remained functional.

As the biophysical depletion of recoverable high-grade iron ore reserves takes place, as seen in Fig. 4, BFBOF production would be forced to migrate to inferior grades of iron ores by 2051. Moreover, its availability would become critical circa 2054, i.e. 53 years after the initial data point of 2001. These results very much reproduced those of Sverdrup and Ragnarsdottir (2014), in which such a condition would take place around the year 2050. Having analyzed and reproduced the means by which their results were achieved, the authors identified that the 4-years difference occurred due to two main factors: Sverdrup and Ragnarsdottir (2014) used (a) longer data series and (b) considered the aggregate demand for all steel types.
Table 3  Summary of data inputs

| Type                        | Variable                                                                 | Unit             | Sources                                                                                                                                 |
|-----------------------------|--------------------------------------------------------------------------|------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| EAF inputs                  | Scrap, oxygen, natural gas, coal, limestone, dolomite, water, ore        | kg/kg of steel   | Shamsuddin (2016), WS (2012a, b, 2017a, b, c), EU (2011), Madias (2013), Cullen et al. (2012), Yellishetty et al. (2011a, b), EUROFER (2017a), EUROSTAT (2009, 2018b), Seetharaman (2013) |
| BFBOF inputs                | Ore, hot blast, scrap, water, limestone, coke, dolomite                  | kg/kg of steel   |                                                                                                                                          |
| Typical chemical compositions of the inputs | Scrap, ore, coke, natural gas, coal, dolomite, limestone, hot blast | %                | MINDAT (2017), Webmineral (2017)                                                                                                      |
| Typical compositions of steel alloys, as outputs | UNS S30400, UNS S31600, UNS S43000, UNS S17400, UNS S32205, UNS S40900 | %                | Bringas (2004)                                                                                                                          |
| Typical slag composition ranges | EAF slag, BF slag, BOF slag                                            | %                | Yildirim and Prezzi (2011), Adegoloye et al. (2016), EUROSLAG (2017)                                                                  |
| Typical composition ranges of emissions to the atmosphere | EAF emissions, BF emissions, BOF emissions | %                | Ferreira and Leite (2015), Ramirez-Santos et al. (2018), Uribe-Soto et al. (2017), Schubert and Gottschling (2011), Seetharaman (2013) |
| Stocks in use               | Automotive, construction, tools + machinery, appliances + electronics, heavy mechanical equipment, other transportation | tons             | Pauliuk et al. (2013), EC (2017)                                                                                                       |
| Participation of economic sectors in steel demand |                                                                 | %                | WS (2017b), EUROSTAT (2009, 2018b)                                                                                                   |
| Typical lifespan of steel per economic sector (as delays) |                                                                 | years            | Cooper et al. (2014), EUROSTAT (2009, 2018b), EC (2017)                                                                         |
| Recycling/refurbishment rate per economic sector |                                                                 | %                | NFDC (2012), EUROSTAT (2018a), Björkman and Samuelsen (2014), BIR (2017), Panasiyk et al. (2016), EUROFER (2017a), Eckelman et al. (2014), Terörde (2006) |
| Repair/reuse rate per economic sector |                                                                 | %                | NFDC (2012), EUROSTAT (2018a), Dindarian and Gibson (2011), Truttmann and Rechberger (2006), Bovea et al. (2016), Kissling et al. (2013), RREUSE (2012), Eckelman et al. (2014) |
| Distribution and end-of-life losses |                                                                 | %                | Pauliuk et al. (2017), Johnson et al. (2008)                                                                                          |
| Typical cooling water reuse and recycling rates | EAF cooling water, BFBOF cooling water | %                | WS (2015a, b), WSSTP (2013), Burchart-Korol and Kruczek (2015)                                                                         |
When analyzed alongside Fig. 5, the decrease in iron ore consumption associated with its loss in iron content had a direct effect on the input of steel into the economy, despite a strong trend of increasing steel scrap generation until around 2060. This happened due to a delayed transition from BFBOF towards EAF, limiting the amount of steel delivered to the economy even with BFBOF eventually operating at maximum capacity during phase-out, corroborating the conclusions of Asif et al. (2015).

As high-grade iron ore becomes scarcer, higher priority should be given to retaining the resources and materials originated from it within a same supply chain, in order to accrue as much environmental and economic benefits from them as possible. The same logic applies to all of the TCEs and CRMs involved in the production of different steel alloys, notably nickel, niobium, titanium, vanadium and molybdenum. To do so in the EU28 while keeping in mind CE would require stakeholders within a supply chain to work on improving and integrating their operations, also an argument brought up by Asif et al. (2015) and Nuss and Blengini (2018).

**Table 4** Summary of parameters used to test and run the model

| Parameter                                | Value     | Unit      | Sources                                                                 |
|------------------------------------------|-----------|-----------|-------------------------------------------------------------------------|
| EAF tap-to-tap time*                     | 0.8       | Hours     | Shamsuddin (2016), WS (2012a, b, 2017b, c), EU (2011), Madiax (2013), Cul- |
|                                          |           |           | len et al. (2012), Yellishetty et al. (2011a, b), EUROFER (2017a), Seethara- |
|                                          |           |           | man (2013)                                                              |
| EAF furnace capacity                      | 100.000,00| kg        |                                                                         |
| BFBOF cycle capacity                      | 42.000,00 | kg/batch  |                                                                         |
| BFBOF productivity*                      | 7         | Batches/h |                                                                         |
| Share of EAF production in the EU28      | 39.70     | %         | WS (2017b)                                                              |
| Share of BFBOF production in the EU28    | 60.30     | %         |                                                                         |
| Worldwide recoverable high-grade iron ore| 82 billion| Tons      | Sverdrup and Ragnarsdottir (2014), UNCTAD (2017)                         |
| Worldwide recoverable low-grade iron ore | 92 billion| Tons      |                                                                         |
| Worldwide recoverable very-low-grade iron ore | 166 billion | Tons |                                                                         |

* As both delay and yield factor

**Fig. 4** High-grade iron ore depletion
Figure 5 also points to iron circularity being hardly affected, phenomenon replicated to other elements until biophysical exhaustion, and consequent of a balancing effect in which (a) even though more steel scrap is generated, more of it is consumed, and (b) no additional stimulus is being given to increasing circularity other than by responding to the demand for scrap and the elements within it. If a transition from BFBOF to EAF production occurs as is, steel’s presence in the EU28 economy would be forced to go through a decline not only due to availability restrictions on other alloying elements, but due to iron itself—argument also previously brought forward by Ansari and Seifi (2012) and Sverdrup and Ragnarsdottir (2014).

Figure 6 reinforces this notion, in which by maintaining the status quo, EAF will not be able to cover for the liquid steel output reduction of BFBOF steelmaking: even by using more scrap and less ore, the depletion of ore itself would slow down. One of the main drawbacks of such a situation is the undesired and indirect stimuli potentially given to the market for developing materials alternative to steel, which could add competition detrimental to steelmakers’ margins (Asif et al. 2015). Nevertheless, the integrated model allowed for easier analysis of individual chemical elements, as exemplified in Table 5.

Next, regarding LCA, the results were also favorable, but one of its features could not be reproduced. As an example, obtaining the average CO₂ eq emissions of 837.41 kg/FU from EAF steelmaking and 2255.39 kg/FU from BFBOF steelmaking was possible as they derived directly from the model’s mass balances—results consistent with those of Burchart-Korol (2013). Due to the need for modeling each individual characterization criteria for each potential indicator, however, it was not possible to determine the impacts of these emissions on specific environmental compartments—as per ReCiPe characterization criteria, for example.

The same occurred for slag generation: while the average results of 459.84 kg/FU from the BFBOF and 121.17 kg/FU from the EAF aligned with those from Renzulli et al. (2016), determining specific impact indicators was, notwithstanding, unachievable at this point. In the cases of both slag and emissions, nevertheless, the integrated model allowed for easier analysis of individual chemical elements, as exemplified in Table 5.

The results and analyses derived from the integrated model answered favorably the first question, indicating that the integration did not interfere with the results of either LCA or SD. The use of indicators, however, one of LCA’s features—was rendered impractical. After identifying the flows within the system during the inventory phase of LCA, most LCA softwares provide a solid platform for the characterization of each flow into an impact
indicator category. SD, on the other hand, requires each indicator and its characterization factors to be modeled individually, offering no support for the allocation of the flows into impact categories, point in which more extensive research and development would be necessary.

In order to answer the second question, the authors referred back to the criteria listed in “Research design” section. Criterion ‘a’ was perceived by the authors as considerably improved, with the addition of a more detailed understanding of the dynamics of steel in the economy outside of the steelmakers’ gates.

Criterion ‘b’, on the other hand, saw SD give LCA a substantial boost in terms of how many years of steelmaking operation could be simulated or projected using only endogenous data feedback. Whether calculating annually for a period of 200 years—as performed in this study—or even down to hourly calculations for a certain period of interest, SD’s delay and feedback mechanics allowed LCA to have a better grasp on how the gate-to-cradle dynamics loop back into its mostly cradle-to-gate approach.

The contribution to the improvement of LCA’s macro analysis potential, as per criterion ‘c’, derived mostly from the possibility to track many different elements while concurrently simulating changes in more than one variable at a time throughout the entire supply chain, as exemplified in Fig. 7. Moreover, not only did stocks and flows help influence the system’s overall behavior, but so did

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**Table 5 Summary of observed slag and emission compositions**

| Emissions | Slag | Comments |
|-----------|------|----------|
| BFOF      | EAF  |          |
| CO        | 39.1%| 62.7%    | From partial oxidation in the furnaces |
| CO₂       | 20.8%| 3.1%     | From the combustion of fossil fuels |
| N         | 3.4% | 30.8%    | Mostly in the form of oxides (NOₓ) |
| H         | 32.6%| 3.3%     | Either as CH₄ or as H₂ |
| H₂O       | 4.0% |          | Byproduct |
| Ca        | –    | 28.5%    | 30.6% As part of CaO and CaS |
| O         | –    | 36.3%    | 32.8% Present in all oxides |
| Si        | –    | 11.4%    | 7.3% As part of SiO₂ |
| Mg        | –    | 4.5%     | 3.8% As part of MgO |
| Al        | –    | 3.9%     | 2.3% As part of Al₂O₃ |
| Cr        | *    | 11.8%    | 1.1% Free ion or as part of Cr₂O₃ |
| Mn        | *    | 1.5%     | 3.3% As part of MnO |
| Fe        | *    | 0.4%     | 17.6% As part of FeO and Fe₂O₃ |
| P         | –    | 0.4%     | 0.8% As part of P₂O₅ |
| S         | –    | 1.0%     | 0.2% Free ion or as part of CaS |
| Zn        | *    | 0.3%     | 0.2% Free ion or as part of ZnO |
| Ti        | –    | –        | –          |

*Trace amounts, less than 0.1% altogether

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**Fig. 6 Steel output and the sources of iron (tons)**

![Graph showing steel output and sources of iron](image-url)
both feedbacks and delays, features characteristic of SD that broadened LCA’s range of analysis.

With respect to criterion ‘d’, bringing LCA into SD did in fact allow for more precisely and objectively visualizing and accounting the stocks and flows of materials through and within the involved stakeholders, notably after steel leaves the industry and cycles through the economy and through end-of-life and circularity services.

The collection and input of case-specific data following the LCA guidelines of ILCD and ISO improved the reliability and especially the granularity of the SD analyses—as per criterion ‘e’—, which were better supported by objective and empirical results such as those exemplified in Table 5.

For these reasons, the practical usefulness of the results across managerial levels-criterion ‘f’—was also perceived as improved, which could allow for different decision-makers to use the same model for variables that ranged from chemical composition all the way to ore scarcity and demand planning. In all cases, nevertheless, further improvements to its managerial applicability could be achieved by linking such a model to real-time operational data inputs.

The authors understand that verifying the feasibility and the potential benefits of integrating SD and LCA very much depends on how the integration itself is performed and, considering the methodological steps and the modelling approach used in this study, the integration was deemed not only feasible, but also capable of better supporting stakeholders that would previously only consider SD or LCA, adding to their individual strengths.

With this in mind, it is important to note that LCA seemed to contribute more for the improvement of SD than the other way around. It is to say that, overall, the distinctive diagnostic and process efficiency features of LCA emerged much more tangibly as a result of the integration process than SD’s problem-solving orientation.

For professionals or academics used to LCA applications, the current obstacles for working with indicators might configure enough of a barrier to avoid either a transition or an integration into SD. Future improvements on
this integration could potentially solve such issues and favor its adoption. Nevertheless, the aforementioned strategic gains should suffice to attract attention to the discussion and to entice interested agents to further investigate gate-to-cradle dynamics and their feedbacks into production.

For SD scholars, however, the benefits of integrating LCA expertise into SD modelling were substantial. Enhancing the reliability, the granularity and the stakeholder visibility in the results can compensate for many of the weaknesses identified in the SWOT analysis of standard SD applications, notably helping to mitigate the threat of over-simplistic analyses. SD practitioners and policy-makers could take advantage of this approach to better subside their analyses, adding to the levels of objectivity and representativeness of their studies, especially when process efficiency is a key decision factor.

Additionally, particularly from cradle-to-gate, the integrated model was very reminiscent of what IE calls Industrial Metabolism. Certain similarities to other IE tools such as Material Flow Analysis (MFA) and its dynamic form (dMFA) became evident as well, especially regarding the visibility of flows and stocks. Also, due to the characteristics of the European steel industry, the model posed as another good example of how CE envisions end-of-life processes as suppliers to the earlier stages of the supply chain. Further studies would need to be done, however, in order to add more renewable energy sources into the operation, as well as to better manage how some chemical elements rejoin the biosphere.

Finally, the authors believe that if data in more disaggregated levels were available, even better results would have been achieved. This could lead to significantly better analyses of individual processes such as sintering, pelletizing, mining, forming, metalworking and recycling, especially regarding emissions and the use of energy directly in the form of heat and electricity.

Conclusions and recommendations
This study based itself on SWOT analyses of relevant SD and LCA studies on steel as well as on business process mapping to subside the creation of a model that integrated LCA into SD. The model was built in ISEE Stella Architect using the European steel industry as a case study while following ISO and ILCD standards. As the main result, the integration was deemed feasible and beneficial for both SD and LCA in different levels. Table 6 summarizes the results for both the quantitative and qualitative criteria used in evaluating the performance of the integrated model.

By allowing the simulation of longer periods of time, the testing of multiple simultaneously changing variables, endogenous feedbacks, and a clear visualization of gate-to-cradle dynamics, SD added strategic value to LCA. This could potentially interest industrial decision-makers who would like to broaden the understanding of their operations as their goods and products integrate the economy as well as when they leave it.

The benefits that LCA brought to SD were more substantial and revolved around increased granularity, reliability, stakeholder involvement and applicability of the

| Table 6 Summary of quantitative and qualitative results |
|--------------------------------------------------------|
| **Quantitative** | **Reproduced LCA?** | **Reproduced SD?** | **Qualitative** | **Integration evaluation** |
| **Criterion** | **LCA?** | **SD?** | **Criterion** | **Integration evaluation** |
| Emissions | Yes | – | SD improves LCA’s circularity analyses | Considerable/minor improvement: more detailed gate-to-cradle dynamics |
| Biophysical depletion of iron ore | – | Yes | SD improves LCA’s long-term perspective | Substantial/major improvement: allows for full timespan flexibility |
| Steel scrap generation and consumption | Yes | Yes | SD improves LCA’s macro analyses potential | Substantial/major improvement: allows for the tracking of multiple elements while multiple variables are interacting or changing simultaneously; not only OFAT |
| Liquid steel output | Yes | Yes | LCA improves SD’s stakeholder involvement identification | Substantial/major improvement: more precise depiction of flows, stocks and roles as per LCA requirements |
| Iron circularity | – | Yes | LCA improves SD’s analysis reliability | Substantial/major improvement: increased reliability and granularity due to data disaggregation and objectivity |
| Steel input into economy | Yes | Yes | LCA improves SD’s applicability across managerial levels | Considerable/minor improvement: analyses can range from operational to strategic levels, but depend on how the model is built |
results on different managerial levels, factors that could attract policy-makers in need of a deeper understanding of a specific supply chain.

No interferences to the application of SD were identified while reproducing the results of previous studies. The replicability of LCA results from previous studies suffered no interferences either; however, it could not benefit from the use of indicators derived from ReCiPe’s characterization criteria, for example. Further research on how to better integrate LCA indicators into a SD modeling environment is required in order to improve the integration. Moreover, even when integrated into SD, LCA still calls for complex or disaggregated data to be as effective as possible.

Henceforward, the authors recommend further investigation into the integration of LCA and SD. However well aligned it already was to the concepts and frameworks of both IE and CE, more attention to environmental impact indicators, renewable energy sources and to the reintroduction of substances into the biosphere is desirable.

By giving the model pertinent market data, setting other TCEs or CRMs present in the supply chain as key drivers instead of iron, and by using an industrial case study, researchers should be able to make even more progress towards the implementation of a joint LCA + SD mindset across academia, management and government.

Finally, based on the potential brought forward by the results of this study, the authors will extend the exploration of this methodological integration and its application to the European steel industry. Planned developments include: (a) testing the benefits that different supply chain integration strategies focused on closed loop operations could bring to biophysical circularity; (b) examining the potential effects of different end-of-life and secondary market development policies on supply- and demand-side dynamics; as well as (c) verifying which biophysical dynamics have the most relevant interactions with steel trade and its futures market.

**Highlights**

- Compiles relevant SD and LCA studies on steel and presents SWOT analyses of both SD and LCA;
- Introduces a model integrating LCA into SD and studies its application in the European steel industry;
- Integration of SD and LCA is deemed feasible and beneficial for both methodologies in different levels;
- Corroborates discussions on raw material scarcity, transition towards EAF steelmaking and resource ownership retention.

**Abbreviations**

LCA: life cycle assessment; SD: system dynamics; TCE: technology critical elements; CRM: critical raw material; IE: industrial ecology; CE: circular economy; BAT: best available techniques; ISO: International Standardization Organization; IPCC: International Panel on Climate Change; EAF: electric arc furnace; BFBOF: blast furnace and basic oxygen furnace; SWOT: strengths, weaknesses, opportunities and threats; OFAT: one-factor-at-a-time; CLD: causal loop diagraph; FC: flow chart; MRI: minimum reasonable inventory; MFA: material flow analysis; BPM: business process mapping; FU: functional unit; ILCD: International Life Cycle Database and Guidelines; PEF: product environmental footprint; UNS: unified numbering system.

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**Authors’ contributions**

Due to the nature of the study, all authors were involved in all steps of development. All authors read and approved the final manuscript.

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**Author details**

1 European Commission’s Horizon 2020 Programme, Marie Skłodowska Curie Fellowship Actions in Excellent Research, AdaptEcon II Project, Clermont-Ferrand, France. 2 Department of Industrial Engineering, University of Iceland, Reykjavik, Iceland. 3 Centre d’Études et de Recherches sur le Développement International (CERDI), Université Clermont-Auvergne, 26 Avenue Léon Blum, 63000 Clermont-Ferrand, France.

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