Digital Twins for Decision Support: An example of Regional Transforming Steel Industries

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Abstract. Decision-makers in transformation processes face complexities introduced by evolving regulatory landscapes and market dynamics. This study delves into the use of Agent-Based Models (ABMs), Multi-Agent Systems (MAS), and Digital Twins (DTs) to support strategic planning through the simulation of intricate interactions and dynamics. Our research specifically focuses on the application of MAS and DTs to the steel industry's shift from coal-based to hydrogen-based processes, with a strong emphasis on sustainability. By analyzing literature, case studies, and theoretical frameworks, we provide insights for modelers on leveraging these technologies for industrial transformation. We present a conceptual framework designed to address complex decision-making challenges and propose a corresponding architecture. We identify potential benefits of ABMs, MAS, DT in steel industry transformation and illustrate how these tools can become particularly valuable for understanding market dynamics, enhancing stakeholder engagement, and incorporating non-monetary factors into decision-making.

Keywords: Decision Support · Multiagent System · Digital Twin · Industrial Transformation · Hydrogen Economy · Sustainable Industry

1 Introduction

Decision Support Systems (DSS) are valuable tools for aiding decision-making processes, but they often fall short in capturing dynamic interactions among stakeholders and systemic impacts of technological and policy shifts. There is a gap in current DSS applications and literature regarding dynamic stakeholder interactions and the systemic impacts of technological and policy changes. Our work aims to provide better guidance for modelers in creating sophisticated, comprehensive DSS to effectively address complexities.

DSS enhanced with Agent-Based Models (ABMs) and Digital Twins (DTs) provide an integrative and multidisciplinary approach to strategic planning and decision-making. ABMs can simulate complex interactions and dynamic strategies [3] within regulatory frameworks and markets. DT technology, integrated with ABMs, creates digital replicas of real entities, enhancing the DSS. This integration enables the simulation of complex interactions and scenario analysis, providing critical insights for informed decision-making.

To illustrate the application of DSS powered by ABM and DT, we examine the steel industry, which is particularly interesting due to its complex transformation toward carbon-neutral production. The steel industry, crucial for economic development, incurs substantial environmental costs [22, 37]. Emerging EU regulations such as the Carbon Border Adjustment Mechanism (CBAM) [48] aim to reduce pollution and promote greener steel production. Essentially, climate change regulations necessitate a shift to hydrogen-based methods, requiring sustained innovation among stakeholders [2]. Integrating new processes demands extensive infrastructure changes and involves local industry and political stakeholders, complicated by unequal power dynamics [43]. Therefore, decision-makers must navigate a complex landscape with long-term outlooks, collaborations, and evolving regulations. This complexity requires advanced DSS.

We define key requirements for our use case. The model must represent *dynamic stakeholder interactions*, emphasizing partnerships. It should support *strategic decision scenarios* like investment choices and hydrogen production collaborations. The DSS must *evaluate the viability of operations*, comparing sustainability and profitability. It should *examine impacts of different hydrogen sources*. The process must *integrate frameworks, data, and expert insights*. The system should *analyze market competitiveness* and include *sustainability and environmental metrics* to guide CO2-neutral production and evaluate carbon footprints, aligning with industry goals and regulations. These requirements are essential for the DSS to support decision-making in CO2-neutral production transitions.

Our research question is: *What are key challenges and opportunities for using ABMs and DTs in decision-making to support the industrial transition to CO2-neutral production?* and this question guides our investigation into the potential of DSS powered by ABM and DT to offer a dynamic and interactive approach to decision support. In Section 2 we outline the innovative use of MAS and DT. In Section 3 we critically assess existing literature and methodologies, identifying gaps and aligning our work with the latest advances in DSS. In Section 4 we propose an architecture of a general model designed to handle and analyze the complex scenarios encountered in decision support for our use case. Finally, in Section 5 we discuss our findings and suggest future research directions. Our analysis shows the benefits of DSS powered by ABM and DT in understanding market dynamics, enhancing stakeholder engagement, and incorporating non-monetary factors into decision-making. Our literature review and proposed framework serve as resources for modelers dealing with complex industry transitions. Though our conceptual framework is use case-specific, focusing on the steel industry's transition to CO2-neutral production, it demonstrates how to approach the transformation complexity, providing modelers with insights on using ABMs, MAS, and DTs to develop effective DSS for industry challenges.

2 ABMs and Digital Twins For Decision Support

In the current data-driven industrial landscape, DSS have emerged as crucial tools for strategic decision-making by incorporating various technologies to analyze data, identify trends, and provide actionable insights to enable informed decision-making [34]. The progression of DSS from static databases to real-time, multidimensional analysis mirrors the escalating complexity in decision-making. Yet, even contemporary DSS grounded in big data analytics [25] are limited by historical data, lacking the capability to dynamically adjust to new information or predict the outcomes of new strategies. The opacity of AI-driven machine learning algorithms challenges their transparency and interpretability, affecting user trust and their fit for strategic use. Common DSS technologies fall short in supporting the complex decisions [33] needed for transforming steel production [16]. Effective DSS require technologies that transcend reliance on historical data [9] and are user-friendly [1]. For that purpose, ABMs with DTs representing the stakeholders offer a valuable expansion to classic DSS by offering predictive analytics through what-if scenarios, overcoming historical data constraints.

Generally, ABMs comprise autonomous agents pursuing goals in coordination or cooperation. Their interactions in dynamic environments allows to explore how individual traits influence micro-level decisions and how macro-level behaviors emerge from interactions [3]. The next step is to model complex agent interactions using digital replicas of physical and abstract entities, providing tailored decision support. In the absence of a unified definition of DTs and the distinction from other technologies [42], we define DTs as digital replicas of both physical and abstract entities, where agents—each with specific resources, goals, and actions—can operate either autonomously or under the control of real-world stakeholders.

3 Approaches to Simulating Transforming Energy Markets using ABM, MAS and DTs

To better understand opportunities for using ABMs and DTs in decision-making to support the transition to low-carbon steel production, we begin by examining how ABMs have been effectively utilized to simulate sustainable transformations in the energy market. We then shift to essential challenges that ABMs must address to effectively manage complex simulation tasks. Subsequently, we introduce relevant studies that explore the application of DTs for DSS. Publications were chosen based on their accessibility, up-to-date content, and relevance to the core themes discussed in this paper. This overview aims to provide a comprehensive snapshot of the significant opportunities for leveraging ABMs and DTs, setting the stage for decision support in steel production transformation.

Agent-Based Modeling for Energy Market Transformation
Markets are shaped by the interactions among its participants, leading to emergent networks of cooperation and competition in daily operations and long-term

transformations alike. ABMs are an appropriate tool to explore the costs and benefits of such strategies [46] under conditions of distrust and uncertainty [17] as well as interdependencies across the supply chain [35]. By employing appropriate modelling procedures, such as data dependency diagrams for participatory modeling [35], ABMs can facilitate understanding market dynamics and the complex interplay of consumer behavior, policy impacts, infrastructure and cooperative strategies that drive market transformation [23].

Unsurprisingly, ABMs are increasingly used to explore various aspects of evolving markets, such as policy, consumption and innovation diffusion [19]. Despite the positive trend, ABMs (and simulations in general) are still considered a specialized niche approach in the field of sustainable transformation research [26] with many questions from older studies still unaddressed in literature [31].

Such under-utilization could stem from the complexity of changing markets. The diversity of participants and the range of planning horizons for technology choices present significant challenges for modeling [47], leading to a neglect of crucial mechanisms such as mutual influences on major decisions [5].

Additionally, there is often limited practical application of models beyond generating one-time policy recommendations. These challenges are not inherent faults of ABMs as a technology - but rather underscore the importance of stakeholder involvement to enhance ABMs' efficacy as decision support tools. Without stakeholder involvement, it is impossible to fully address the complexities required for accurate modeling.

Challenges in Modelling for Decision Support

Stakeholder engagement is crucial for the modeling of transforming markets. Policies, communication and relations between stakeholders are vital components of decision processes, which are shaped by power dynamics between participants [18]. Thus, DSS must foster an environment that promotes extensive communication among stakeholders, ensuring decisions are informed by collective insights and discussions [8]. This approach enhances the system's relevance and applicability.

Naturally, this requires models that accurately reflect the complexity of multiple perspectives [21]. Referring back to the use case of the steel industry, studies have already demonstrated the benefits of user-centric approaches featuring surveys and expert interviews throughout the research process [32, 24]. Such a user-oriented approach ensures the credibility of models and helps the continuous validation. Yet, false outputs may lead to misinformation and unintended negative consequences [39]. In this regard, DTs can further support the credibility of an ABM by providing contextualized information for decision-makers [11]. Issues such as unreliable information and unintended consequences are known in the context of ABMs, yet ABMs are recognised as beneficial regardless and should not be discarded in this context either [30].

When using DSS, it is important to consider wider implications beyond immediate economic impact. To achieve sustainability, decision-making must go beyond just addressing profitability and include a broad range of non-monetary considerations. A shift from shareholder value towards strategically incorporating ethical practices, engaging stakeholders, and enhancing sustainability reporting has been demonstrated to improve corporate performance and competitiveness [41, 10]. Following this trend, effective modeling for DSS requires the integration of ecological, societal, technical, and political dimensions which are represented as tangible components in the ABM, following novel comprehensive methods for firm evaluation [14]. Additionally, with respect to different civil stakeholders involved in regional transformation, topics such as employment and local value creation are major aspects due to the significance of industry as local employer [13, 29].

Finally, it is essential in decision support modeling to establish clear practical guidelines on developing ABM within DSS. Detailed taxonomies of agent characteristics and life-cycles for building agent-based DSS provide these guidelines, illustrating how intelligent agents can enhance decision-making by utilizing the inherent features of MAS [6]. This method highlights ABM's capacity to facilitate collaborative problem-solving within DSS. To ensure that simulations are accessible to various stakeholder groups, models should be integrated into a DSS that offers intuitive usability. This approach is exemplified by the simulation-supported crisis management dashboards developed during the pandemic, which included architectural guidelines for designing user-friendly simulation dashboard [38].

Designing, implementing, and introducing a DSS using ABMs is complex, but documented benefits indicate significant potential for further application in other areas. By fostering dialogue among stakeholders, ensuring the careful validation and presentation of information, decision-making processes can become more nuanced and effective.

Advancing Decision Support with Digital Twin Technology

By creating digital replicas of stakeholders, encompassing their capabilities, assets, and other pivotal traits, DTs offer a nuanced understanding of each stakeholder's potential actions and outcomes and empower personalized support. Existing shift towards inclusive policy-making emphasizes DTs' role in facilitating stakeholder engagement, enabling stakeholders to experiment with policy outcomes in a virtual environment, making decision-making collaborative and feedback-rich [44]. A review of 75 studies highlights the growing use of DTs across sectors, emphasizing their potential to simulate real-time decision outcomes [12]. Practical implementations of DTs [45, 28] underline the versatility of DTs in management decision-making, demonstrating how DTs, through real-time data visualization and scenario simulation, enhance strategic planning and operational management. The adaptability of DTs offers a blueprint for integrating them into day-to-day processes and strategic decision-making [27]. A multi-layered DT model using agent-based modeling (ABM) investigates complex systems and sustainable decision-making, providing a template for exploring intervention strategies in complex systems [36].

The advancements in DT, as discussed in the literature, open new avenues for decision-making grounded in accuracy, inclusivity, and sustainability. By offering a detailed replication of systems and stakeholder traits, DTs allow for a nuanced exploration of potential decisions and their impacts across various domains.

4 Bringing it all together

To improve decision-making in transforming markets, we recommend incorporating diverse interdisciplinary research insights into a cohesive framework. Figure 1 illustrates a proposed model designed to handle and analyze the complex scenarios encountered in decision support for our use case. Our framework is structured around four principal components: Data, Coordinator, Modeling and DSS.

The *Data* component plays an important role in this architecture, facilitating the flow of information between independent components, akin to the technical architecture proposed by [38]. This component serves as an intermediary, managing communications between the central coordinator and individual data storages. It enables the dynamic use of various database systems, tailored to the specific sources and types of data available. This flexibility enhances the system's ability to effectively leverage diverse data structures and storage technologies.

Essential to our overall decision support tool is the *Central Coordinator*, a component which facilitates communication with other system components via APIs. The concept is based on the data-science engine driven generator-analyst component proposed in [38], and expanded upon beyond analysis functionalities. The primary function of central coordinator is to initialize simulation models with stakeholder-specific data, thereby creating a DT on which simulation experiments are conducted and assessed. This setup enables the DSS to provide a graphical, interactive user interface, allowing stakeholders to manage simulation experiments and analyze results effectively.

The *Modeling* component has a complex structure. The simulation API serves as a vital link between the coordinator and a model repository, where each of

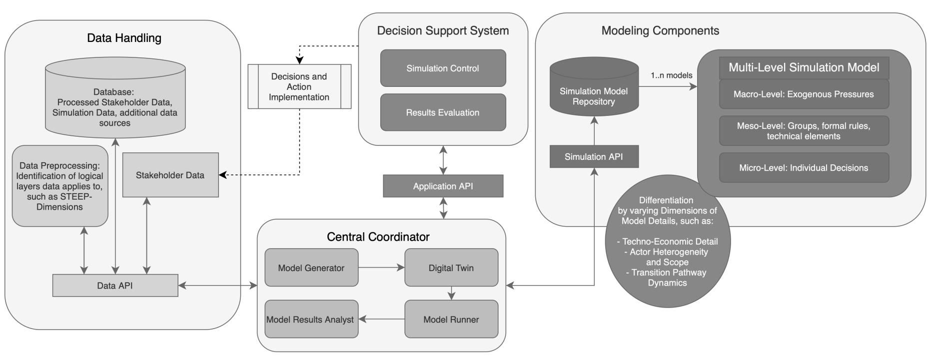

Fig. 1. Suggested Architecture

the n models addresses specific layers defined during the preprocessing of stakeholder data. These different layers of decisions underscore the necessity for diverse models. A method to differentiate and classify these models involves using the three dimensions of socio-technical energy transition (STET) models, which include the level of techno-economic detail, the scope and heterogeneity of actors, and transition pathway dynamics [29]. Moreover, conceptualizing DTs in layers can significantly enhance the focus when addressing specific queries [36]. We recommend establishing distinct logical layers and determining the extent to which stakeholder and other data influence these layers. We suggest that the selection of layers for a DSS, particularly for the context of transforming markets, should be guided by the sociological, technological, economical, environmental and political (STEEP) dimensions [40], and potentially extending to include further (e.g. legal) dimensions. The choice of layers should depend on the priorities, scope, and available resources of the specific scenario being modeled. The primary advantage of defining logical layers lies in facilitating the categorization of model purposes. This categorization not only aligns with the characteristics of STET models in terms of content but also helps in identifying the types of questions the models are designed to answer. This structured approach enhances the efficacy and relevance of the simulation models in our decision support framework. Each layer within the framework is represented by a specific model; for example, there is a distinct model dedicated to the economic layer. These models incorporate further levels of complexity, adhering to the three-tier structure [19], encompassing Macro-, Meso-, and Microlevels. Different models are needed for each layer because a single model can become unwieldy [4]. Not all of these models need to be agent-based; for instance, a macro model can be an economic equilibrium model using differential equations. Specialized models serve different purposes effectively. This approach allows for detailed representation and analysis of interactions within each layer. The Macrolevel addresses exogenous pressures that influence the system from a broader perspective. The Mesolevel focuses on groups, formal rules, and technical elements that mediate the impact of the Macro influences on individual behaviors and decisions represented at the Microlevel. This hierarchical setup allows the model to capture and simulate the complex interactions and dependencies across different scales, enhancing the model's ability to predict outcomes based on varying scenarios and interventions.

The *DSS* component is designed to enhance stakeholder interaction [46] and decision-making efficiency through a user-friendly platform [7, 38, 8]. This system features a graphical, interactive user interface that enables stakeholders to actively manage and control simulation experiments. The DSS also includes tools for comprehensive results evaluation: stakeholders can access analytical reports and visual representations of simulation outcomes, facilitating a deeper understanding of each scenario. This capability is crucial for evaluating the implications of various decision pathways and aids in formulating strategic responses to complex problems. By integrating these functionalities, the DSS serves as a critical analytical tool, empowering stakeholders to make informed decisions. This system bridges the gap between complex data processing and practical, actionable insights, marking a step forward in the usability and effectiveness of decision support technologies.

The proposed architectural framework can be adapted to fit our specific use case, such as a steel manufacturer and a local energy provider coordinating investments for the production of renewable energy, hydrogen and carbon-neutral steel with emphasis on local cooperation. Strategic decision-making is facilitated through the DSS component: relevant actors can actively engage with the simulation. This interactivity provides them the opportunity to probe various scenarios and assess the outcomes, which are vital for informed decision-making [8]. The opportunity to access the results of the simulation contributes to the user trust by ensuring transparency and interpretability of the results. Additionally, the multi-layer architecture can handle the complexities of evaluating scenarios that balance cost, sustainability, and supply chain reliability. On one hand, this architecture can help to better understand the impacts of EU environmental regulations by providing integrated visualization and forecasting capabilities. By segmenting these regulations into distinct economic, environmental, legal and other relevant dimensions within the framework, the system can thoroughly simulate the varied impacts. On the other hand, the implications of pricing adjustments, exploring new market opportunities, considering relocation options, and enhancing economic cooperation can be simulated at the economic layer. Thus, the multi-layer architecture helps ensuring a comprehensive evaluation that supports strategic planning and regulatory compliance. Finally, the modular design allows for various data handling methods and integration of diverse models, accommodating different scopes and time resolutions, thus the proposed architecture has the potential to leverage real-time capabilities [12, 28, 45] to improve the DSS for scenarios requiring operational analysis.

The reviewed literature and case studies provide valuable insights into the specificities of using ABMs, MAS, and DTs for developing DSS in complex scenarios, such as transforming steel production. These technologies are adept at modeling and simulating dynamic interactions among various stakeholders — producers, suppliers, and consumers —highlighting the critical role of partnerships in this transition [46, 17, 47]. They enable the development of scenarios for strategic decisions, such as investment choices or collaborations in hydrogen production, which are essential for navigating the shift to hydrogen-based processes [32, 20]. Furthermore, these systems can assess the systemic impacts of transitioning to different hydrogen sources, thereby understanding their broader implications on sustainability and market dynamics [13, 24, 15, 29, 11]. The integration of theoretical frameworks with empirical data and expert insights creates robust models that support complex decision-making processes [21]. This technologies can incorporate sustainability and environmental metrics [14] to guide CO2-neutral production and evaluate carbon footprints, aligning with industry goals and regulatory standards. This evidence underscores the transformative potential of ABMs, MAS, and DTs in enhancing the strategic capabilities of DSS to manage the complexities associated with industrial transformations.

5 Conclusions

This paper explored the use of ABMs, MAS, and DTs to support decision-making in the steel industry's transition from coal-based to hydrogen-based production. It emphasized the importance of these technologies in simulating complex interactions and dynamics to enhance strategic planning and sustainability. The research identified key challenges and opportunities in implementing these tools for industrial transformation, highlighting their utility in scenario analysis and stakeholder engagement.

The main findings demonstrate that ABMs and MAS are effective in visualizing dynamic interactions and market dynamics, while DTs help in creating accurate simulations of real-world processes to assist in strategic decision-making. By integrating these technologies, the paper presented a conceptual framework and architecture designed to tackle complex decision-making in areas such as the steel industry. This integrative approach is shown to be crucial for understanding and navigating the multifaceted challenges of sustainable industry practices and regulatory compliance.

Our literature and case study review, alongside the development of a generic model and the integration of accumulated knowledge, are designed to assist modelers in addressing complex use cases, such as transitioning steel industry. By synthesizing existing frameworks and introducing an advanced integrative model that combines ABMs, MAS, and DTs, we provide modelers with a possible tools and methodologies to develop sophisticated DSS. This structured approach helps modelers effectively manage the dynamic interactions and systemic impacts associated with complex use cases, such as those related to technological and policy shifts in the industry.

This study's main limitation is its theoretical approach to integrating technologies, which needs empirical validation in real settings. Future research should implement MAS and DT technologies in the steel industry to assess their real-world impact, considering regional and organizational specifics, regulatory differences, and economic conditions. Empirical studies will fill existing gaps and enhance understanding of digital technologies in sustainable transformation, potentially elevating MAS and DT technologies' role in strategic decision-making within and beyond the steel industry.

Acknowledgement. This work is funded by the German Federal Ministry for Education and Research (Bundesministerium für Bildung und Forschung) (BMBF, Grant No. 03SF0687C).

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