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A Combined Multi-Level Perspective and Agent-Based Modeling in Low-Carbon Transition Analysis

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Abstract: Low-carbon transitions are long-term complex processes that are driven by multiple factors. To provide a theoretical and practical framework of this process, we argue that the combination of the multi-level perspective (MLP) and agent-based modeling (ABM) enables us to reach a deeper and detailed analysis of low-carbon transitions. As an extensively applied theoretical form, MLP conceptualizes low-carbon transitions as a nonlinear process and allows a system to be analyzed and organized into multiple dimensions (landscape, regime, and niche). However, MLP cannot explain the many details of complex transitions, whereas ABM can estimate the influence of interacting behaviors in a complex system. Therefore, the main advantages of the combined approach for the analysis of low-carbon transition are verified: the MLP can contribute to the overall design of ABM, and ABM can provide a dynamic, continuous, and quantitative description of the MLP. To construct this combination framework, this paper offers a guiding principle that combines the two perspectives under a low-carbon transitional background to create an integrated strategy using three procedures: defining the common concepts, their interaction, and their combination. Through the proposed framework, the goal of this work was to reach a better understanding of social system evolution from the present high-carbon state to a low-carbon state under the pressure of ambitious climate goals, providing specific policy recommendations.

Keywords: low-carbon transition; agent-based modeling; multi-level perspective; complex system; sociotechnical approach; energy policy

1. Introduction

The concept of low-carbon transition refers to a significant evolving process of industrialization and urbanization. It is characterized by major changes in energy supply and demand systems. In recent years, this concept has become increasingly relevant to policymakers and academics [1–6] in response to the energy trilemma (i.e., security, equity, and sustainability) and issues associated with rapid economic growth, energy consumption, and environmental pressure (i.e., the energy–economy–environment trilemma) [7,8]. Low-carbon transition not only involves technological changes, but also major social changes, such as financial market fluctuations, policy intervention, and actors' behaviors. To describe and analyze the evolution of human society on such a vast scale, a sociotechnical approach called the multi-level perspective (MLP) was established [9,10].

However, society has been facing multiscale complexities during the low-carbon transition as a result of the effects of decentralization and information technology. For instance, accelerating or delaying transition processes have resulted from financialization, and capitalization of different kinds of energy with new technology like blockchain has led to an increasing degree of complexity in terms of the interactions of technological and social system components influenced by network and governance structures. Thus, research approaches are needed that can address the (increasing) complexity of confluent technical and social phenomena, diverse social actors, and nonlinearity, which is hard to solve using a single approach. Although the MLP is still useful for analyzing this transition, the multiscale representation essentially requires its combination with approaches for complex systems, such as agent-based modeling (ABM), to assess environmental changes as well as to provide specific policy recommendations based on the evolutionary properties.

Some recent studies [11–13] have discussed the methods used to integrate or bridge the gap between different analytical methods. The main achievement is the integration of sociotechnical- and modeling-based approaches. The former focuses on sociotechnical variables, such as participants and niche innovation, whereas the latter concentrates on niche innovation details and economic variables in a quantitative framework. However, previous studies relied too much on qualitative data from the MLP side, and only simple computational modeling approaches, such as the integrated assessment method (IAM) [11,12], were adopted as the counterpart in the integration. These integrated approaches also cannot fully reflect the multi-level scale and the interaction between different levels. For example, these methods mainly focus on the connection between the various approaches in different transition periods and cannot coherently or continuously describe the interaction between the levels, such as the MLP describes the emerged windows of the transition and bridges the IAM during the transition. By modeling agents individually, ABM, however, provides useful information about the behavior of the system as a whole through agent interactions. Microphonic modeling, as revealed by the ABM mindset, enables a natural and flexible description of a complex system of behavioral entities, which is promising for low-carbon transition analysis.

The effect of different strategies or environmental factors can be tested in the ABM. The behavior of agents in response to changes probably fundamentally changes the overall behavior of the system, which can be recognized as a kind of transition. Though in many domains ABM can provide realistic details for manageable levels [14], some issues remain related to its application. The first is that, as a modeling approach, it is designed to serve a specific purpose or to address a particular problem with just the right amount of detail and appropriate description. The results of ABM are only generalizable to the extent to which the model parameter space has been fully explored. This makes it difficult to abstract interdisciplinary and general social trends from separate ABM models and their results. The second is that ABM often involves 'soft factors' [15] and their interactions, both of which are difficult to quantify, calibrate, and sometimes justify. Even though an ABM looks comprehensible and reasonable at first glance, a systematic framework is still needed to help us evaluate it thoroughly. Are all relevant influences included? Are interactions between entities reasonable and can they capture emerging phenomena? Which parameter can be chosen as an indicator for the whole system? Does the transition actually occur? MLP does not directly provide these answers, but provides an analytical and heuristic framework to logically and orderly understand the model when a transition may happen. MLP can justify the complexity of real-world developments [9]. Under this framework, possible situations and agents involved can be listed. Changes in key parameters may indicate key nodes of the transition corresponding to MLP phases. MLP may help extract common characteristics of ABM models involving transitions.

Therefore, to reflect a multi-level scale with the interaction between levels in different transition stages in integrated approaches, we used the MLP combined with ABM to better interpret multiscale factors and provide reliable information for policymakers when forming policy strategies [9,10]. Previous studies often used ABM as a modeling approach to solve specific problems in reality [16,17]. However, limited interactions between the modeling approach and theoretical framework can be observed in this process. It is more likely that the ABM is applied in certain fields and the modeling results are explained by a certain theoretical framework. In this study, we sought to develop a coevolutionary framework with complementary views of the low-carbon transition and to provide a comprehensive method to investigate the related topics of present theoretical, practical and political interests. In other words, we tried to combine the quantitative multiscale analysis tool, ABM, with a qualitative method, MLP, to better understand social system evolution from the present high-carbon state to a low-carbon state under the pressure of ambitious climate goals [18]. We attempted to demonstrate that as a theoretical framework, MLP can guide the establishment and analysis of ABMs. Their common mindset can increase the comprehensiveness and logic of the model. The results of ABM can be explained and refined under MLP framework. The evolution pathways shown in ABM can extend and supplement the MLP framework. Policy suggestions from MLP can be tested using ABM and be further developed. As case studies in MLP can provide empirical validations for ABM, ABM also more qualitatively provides MLP suggestions. New proposals may be inspired by modeling and a perfect MLP framework. Active two-way feedback and strong correspondence compensate for some of the shortcomings of each approach, and the combination of ABM and MLP can provide a new and robust analytic framework for the low-carbon transition.

In the next section, we first review the analytical challenges of the low-carbon transition and introduce the two analytical approaches (i.e., the MLP and ABM) with their strengths and weaknesses. In Section 3, we propose and discuss the combination method by identifying the common concepts, interaction, and fusion between the two approaches. In Section 4, we provide an example of the application of the combined method. In Section 5, we discuss the structural verification and behavioral validation of the ABM considered in this paper to ensure its validity. The conclusion is given in Section 6.

2. Challenges and Analytical Approaches to Low-Carbon Transition

2.1. Low-Carbon Transition Challenges

Social transitions are difficult to model and have qualitative aspects as well [19].

The low-carbon transition is facing many challenges: (1) the multiscale and policy aspects of the low-carbon transition process, (2) the interactions between the emergence of stability and novelty in existing social systems, and (3) the complex views on managing social, economic, and technological change processes [12]. In addition, current economies have been largely reliant on a fossil-fuel based energy system. Low-carbon transitions require significant capital to be transformed from today's economy. A successful transition asks for close cooperation from the public and private sectors. Therefore, transformation into a low-carbon society will be slow and require intensive capital. We are also still in the early stage of this transition; therefore, a comprehensive assessment of new energy is necessary regarding its cleanness, cost–benefit analysis, and effect on greenhouse gas emissions. Moreover, cooperation among countries and stakeholders will be pivotal to leading the way. Long-term partnership and collaboration offer considerable opportunities to facilitate technological and system innovation, scaling up cooperation and increasing access to more capital.

The two types of low-carbon transition methods are qualitative and quantitative. These methods emphasize several major challenges in studying low-carbon transitions: (1) variable-scale transition processes and long-term transition processes, (2) the complex and unpredictable dynamics of innovation, and (3) the integrated management of low-carbon transition from various perspectives in an integrated way [12]. Qualitative instruments can only provide a conceptual explanation of and discussion on the transition, whereas the main drawback of quantitative methods is that they can only model the issues that can be transformed from mathematical considerations. Thus, these challenges have led to a discussion of how to demonstrate a more detailed qualitative framework and a verified interpretation of the quantitative model.

2.2. Agent-Based Modeling and Multi-Level Perspective

ABM and sociotechnical transition studies using the MLP have their own scientific theories and interpretations. In this section, we provide an overview of the two approaches and explain each approach for dealing with analysis challenges.

One of the analytical methods used to study transitions is the agent-based computational models and simulations. ABM is mainly based on modeling heterogeneous actors and various decision-making processes [15,20], and one of its main characteristics is that the model can generate self-organization patterns [9]. Using ABM, the modeler can estimate the influence of interacting behaviors described by simple rules [21].

The systems undergoing transitions to the low-carbon state are complex adaptive systems that include interactions that can lead to the emergence of new patterns and phenomena. In agent-based modeling, a system is modeled with a collection of autonomous agents. Each agent makes their own decisions based on a set of rules that allow complicated interactions between agents and agents with environments. ABM is naturally suitable for modeling complex systems in terms of a multiscale perspective, and ABM allows the researcher to carry out differential equations that are traditionally difficult, such as allowing the agent to learn and evolve, to explore nonlinear interactions, or to set richer behavioral actions [1]. Therefore, ABM is useful in sociotechnical systems research because it can reflect the interactions resulting from the evolution of technical factors and social actors in simulated systems [22].

ABM is a highly flexible approach that has the ability to change levels of description and aggregation [15]. Though it is not a modeling approach specially designed for transitions, ABM can still be used for analyzing transitions due to its ability to generate emergent phenomena from the bottom up. By observing an agent's response to changes in environment rules, certain parameters may be found to change aggressively before and after these changes as a result of agent interactions. With the definition of proper-order parameters, phase diagrams [1], time series plots [23], proportional charts [24], and other analysis tools can be used to study the timing and conditions for when a transition may occur. A system's phase diagram of the key variable is a powerful tool for studying the potential behaviors of a dynamic system over time. Phase diagrams not only reveal the possible existence of equilibrium but also all potential state trajectories starting from all feasible initial states [25]. Phase diagrams thus help to clarify which regions of a system's state are credibly reachable and further illustrate possible transition pathways between different states, which makes ABM a powerful tool for transition study.

The second method considers various social technology approaches. In social scientific transition research, various changes in diverse energy-related systems are conceptualized as sociotechnological processes. The MLP is a theoretical form that is extensively applied for studying low-carbon transitions [9,10]. The MLP recognizes that in multiple levels of analysis, a low-carbon transition can be interpreted as a nonlinear process that results from multiple endogenous and exogenous developments. The MLP is able to offset the dimensional structure and allows an energy system to be organized into multiple dimensions, where the interaction between the macro external landscape scale, the existing middle regime scale, and the micro technical niche scale is presented [26–28]. Furthermore, the MLP can present, as well as analyze, the interaction between the three levels, i.e., the micro, meso, and macro levels. [9]. First, the technology domain or innovation niches can offer various processes with competition and cooperation, as well as the space for building social networks that support innovations. Second, the social technology system or regime represents specific practices and conventions that often employ actors to create and reinforce specific technical systems. Third, the landscape evolves slowly and reflects the deeper structural relationships between broader social, political, and cultural elements. Finally, transition pathways are identified by interpreting the evolutionary interaction between technological factors and participant actions on the three distinct scales.

2.3. Advantages and Disadvantages

The ABM and MLP approaches concentrate on transition-related issues with unique perspectives, study frameworks, and methodologies. They reveal and emphasize different policy interventions, social interpretations, scales, and interactions. Here, we provide an overview of the important advantages and disadvantages of the two approaches from analytical, methodological, and policy perspectives [12,29,30]. Technology innovation systems (TISs), another approach to analyzing technology transitions, are discussed as a comparison with MLP. Similarly, ABM is compared with other modeling approaches to better illustrate its strengths and weaknesses. During such comparisons, we show that some strengths and weaknesses of ABM and MLP can complement each other. Therefore, a combination of these two approaches can partly compensate for their individual shortcomings and even transform disadvantages into advantages.

First, from an analytical point of view, the MLP can produce a fine-grained interpretation, but the analysis is primarily based on qualitative descriptions. In contrast to MLP, system performance assessments have been conducted at the system and the subsystem levels in TIS. The diffusion of the innovative technology or product under study and market rates, for example, are commonly used indicators for the overall performance of a technological system focused on the knowledge field or products [31]. A set of multiple indicators that cover generation, diffusion, and use of knowledge has also been designed for emerging innovation systems [32]. These assessments enable the evaluation and comparison between different innovation systems [33,34]. In MLP, new technologies and innovations emerge and develop in niches, which offer a special focus on certain contexts. Unfortunately, the concepts and tools used to investigate innovation dynamics at the niche level are less elaborated than those developed for TIS. Though some attempts have been made and certain processes have been proposed to analyze niche dynamics [35], the necessity and irreplaceability of these processes still lack solid support. Further research is needed to construct a wide-accepted assessment and definition for niche dynamics. For transitions with complex actors' activities and strategy making, which, may be the core driving force for niche evolution, the analytical power of MLP is still far from enough. Thus, a modeling approach can provide an option for complementing the qualitative assessments of MLP because quantitative modeling can provide parameters to observe. ABM can provide a more consistent analysis of complex systems and a more comprehensive analysis of multiple options. Different from equation-based modeling (EBM), which is a modeling approach that begins with a set of equations that express relationships among observables and evolve the system with the evaluation of these equations, ABM begins with individuals interacting with one another [14]. The observables are the outputs of the behaviors of each individual. From simple if-then judgement to nonlinear coupling such as neural networks, regardless of the form, decisions and behaviors must first be clearly defined. However, this could be highly difficult, especially when potentially irrational behavior, subjective choices, and complex psychology are involved. Therefore, it is limited in appropriately reflecting real problems because of their complexity [30]. Though for a system where the actors have a behavior of their own, ABM is a natural and easy method of describing the system. Fortunately, this microphonic modeling mindset corresponds with the niche-driven technology transition pathway in MLP. Representing the local level of innovation process, the niche concept may help to analyze and determine individual behavior in ABM.

Second, from a methodological perspective, for the MLP, the various actors and their behaviors or decisions are qualitatively considered, as are the social and technical factors and interactions at different times and levels, but this is mainly descriptive. The strength of MLP is that technology transitions can be explained by the interactions of stabilization of regime, the destabilization pressure of landscape, and the emergence of niche innovations [9]. Therefore, MLP leaves room for contingencies such as specific change or avalanche disruptions at the landscape level [10]. Compared with the relatively narrow perspective of TIS, which mainly regards the result of innovations as the consequence of the corresponding innovation system, more attention can be focused on the system's environment in MLP. This outward orientation of the MLP mindset naturally corresponds with the base-level rules of agents and higher-level set or "rules to change the rules" in the ABM mindset [36]. Structural commonalities allow for further combination of these two methods. MLP is thought to be less powerful when it comes to the roles and strategies played by different actors in such processes [37]. ABM performs better than EBM for cases where agents and their interactions are heterogenous, as the use of averages of critical systems variables over time and space in EBM cannot represent such heterogeneity [14]. Notably, research related to landscape interactions is still lacking. Although analysis of different transition typologies has provided significant contributions to understanding different niche–regime interactions [10,38], more extensive understanding of the dynamics between high-levels, namely, regime and landscape, is still unsatisfactory. ABM can quantitatively and economically represent system robustness through a formalized approach that focuses on system interactions. ABM can also mimic heterogeneous participants with strategic actions or decision-making capabilities during dynamic evolution. Though the dynamic mechanism depends on how we model, changes in variables in the process of system evolution, which are trackable, may provide some information about the follow-up dynamics. The emergent phenomena of such an evolution could be counterintuitive at times, which could further inspire the perfection of an MLP framework. ABM has its limitations too. The complexity of system behavior will perhaps make isolating cause and effect like a pure ABM model be difficult to test in reality. For example, extreme market policies tested in models can hardly be tried in reality. Therefore, data may be lacking for validation depending on the type of ABM, especially for prospective models [39]. Given the structural commonalities, a similar empirical study based on MLP may capture the common trends and assess the result of modeling. Studies on relevant cases can guide the determination of the initial values of the parameters.

Third, in terms of policy considerations, for the MLP, policy suggestions can reveal uncertainties while focusing on the overall strategy, and the forward-looking positioning of policy goals is limited. Through data input and settings of background implications, the initial state in the model is determined. However, with complex interactions, we cannot easily predict the ultimate results from initial information. ABM, however, is appropriate when the initial state is not a predictor of the future because the processes of growth and change are dynamic [14], which can inspire further extension of the policy suggestions in MLP. ABM can provide specific and simple policy suggestions on the basis of simulating the influence of policy choices on the pathways of a low-carbon transition, but it oversimplifies the decision-making of social policies. The robustness of a single run in ABM models is another problem. The only way to treat this problem is through multiple runs, systematically varying initial conditions or parameters to assess the robustness of results. However, with MLP, we may partially assess the result empirically and simplify the testing procedure to some extent.

In addition to the above comparison of the pros and cons of ABM and MLP in terms of analysis, methods, and policies, there are other comparisons, such as temporality and treatment of complexity [12]. For temporality, both methods can provide a long-term perspective (decades); for complexity treatment, modeling of a system is achieved through internally consistent parameters and decision-rules for ABM, and in-depth cases generate a rich understanding of sociotechnical dynamics and uncertainties for MLP.

3. Toward a Combined Analytical Framework

No single method can be applied to adequately cope with all analysis challenges. In this section, we offer a guiding principle that combines two perspectives under a low-carbon transitional background to create an integrated strategy using three procedures: defining the common concepts, their interaction, and their combination, as shown in Figure 1. An example of a low-carbon transition using this combination for analysis is outlined and verified in the following sections.

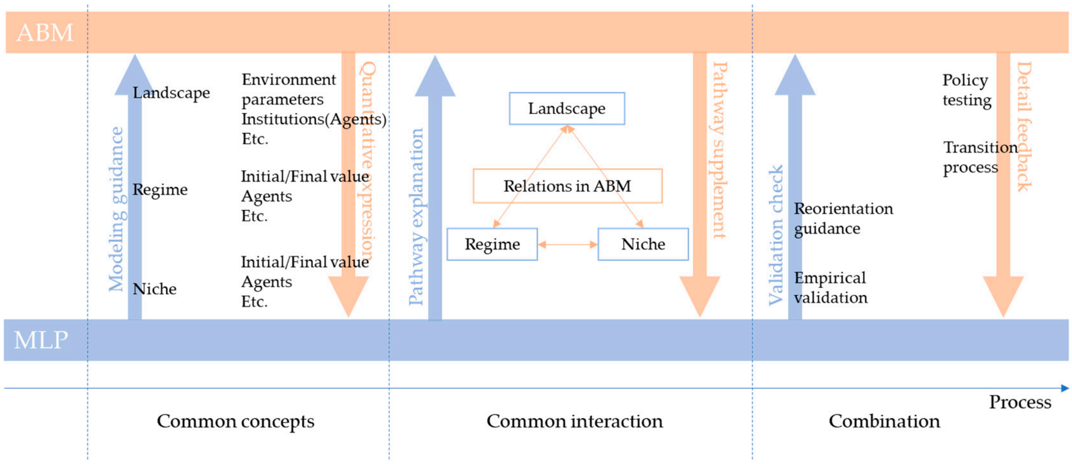

Figure 1. An overview of the combined framework.

First, we more specifically identify the paired elements in greater detail. We describe this step as defining a *common concept*. Second, two-way interactions with a feedback loop are required in the process of solving a transitional problem. We describe this step as an *interaction* that leads to active links between the two methods in the long term. Then, a series of interactions with feedback communication between the approaches is produced to highlight the political and practical determining factors. This interaction with feedback communication can be continuous or periodic and can be used to evaluate and identify the windows of opportunity shown in the cycles of regulation, political decision, and action. In the combined method, these windows can be both qualitatively and quantitatively investigated in terms of the evolutionary process among the niche, regime, and landscape. Third, two-way integration of ABM and the MLP is possible. We describe this step as *combination*, which involves establishing two-way links between the approaches around conceptual insight and detailed modeling with their feedback loops.

3.1. Common Concepts

In the process of combining ABM and MLP, the first step is to confirm the common concepts. These common concepts provide some space for conceptual interaction, which is considered important for both analytical approaches. The following sections elaborate upon these common concepts.

3.1.1. High-Carbon States

The first common concept is the interpretation of system evolution in the two analytical methods. The application of the concepts of *niche dynamics* and *system stability* (a regime of a system that maintains its robustness) is used to explain system evolution in both the analytical approaches.

- Niche dynamics and system stability can explain the interactions between participants or actors and social groups in MLP. The analysis of the MLP focuses on qualitative factors, such as distributed energy systems, energy networks, and evolution processes, that span multiple dimensions, such as the social, economic, technological, or political dimensions. This explains the emergence of niche innovation in that it competes with established degrees of the developmental trajectory.
- In ABM, the concepts of niche dynamics and system stability are applied to show the predicted rate of change in various quantitative indicators over time. ABM uses complexity theory to model the system through internally and externally consistent parameters and rules to investigate and explain the fundamental role of some key elements and their interaction in the low-carbon transition process. Different scenarios can be examined using various initial conditions and parameter settings that represent niche innovation and system conditions within their evolution. With landscape institutions and actors at the regime or niche levels modeled as agents, a specific

value in the initial or final stage can be used to determine the status of the system. Parameter settings are usually implications of landscape and regime environments.

3.1.2. Pathways of the Low-Carbon Transition

The second common concept is classifying the evolutionary process of the system into what is called a *pathway description*. Both methods are designed as practice- and policy-driven research tools used to describe the evolution of the system.

- The pathway description in the MLP concentrates on the interactions between different levels. By providing a comprehensive interpretation of sociotechnical complexity, the pathway description provides a method to describe a general pathway that reflects social phenomena and technical changes. The efficiency of policy selections and actions relies on a description based on an introduced strategy and patterns.
- For ABM, the pathway description is often designed using applied mathematics and parameterization based on complexity theory, and the scenario-based pathway description offers the chance to obtain specific interaction phenomena between different levels. With respect to policy concerns, first, policy actions are mainly analyzed through parameter settings and regulatory tools. Second, clear model-based transition recommendations for policy intervention choices can be provided. Third, a specific policy can be suggested on the basis of the phase diagram obtained from the ABM simulation by confirming key factors and actors as control parameters.

3.1.3. Low-Carbon States

The third common concept that is recognized through the two analytical methods explains the evolution of the system. The concepts of *system stability* and *dynamics* are applied in both analytical methods to explain system evolution.

- The concepts of system dynamics and stability in low-carbon states, used to interpret system stability and the impact of an existing regime that could explain a successful transition in interactions between actors and social groups, are applied in MLP. In addition, the analysis focuses on qualitative factors such as niche innovation in a low-carbon state, and the uncertainty of the future can be briefly interpreted through system evolution patterns.
- ABM applies the concepts of system stability and dynamics in low-carbon states so that various quantitative indicators reflect the expected rate of change over time. ABM can provide a detailed representation of system information such as niche innovation in low-carbon states and scenario simulations, therefore allowing system complexities in low-carbon states to be explored under specific constraints and policy actions as numerical instruments in models.

3.2. From Common Concepts to Conceptual Interaction

Interaction is described as a process that can reflect common concepts, system details, and transition goals so that a research strategy of interplay between the two analytical approaches can be established and iterations of such interactions can be produced. Therefore, to investigate low-carbon transitions, we can formulate an interactive research strategy between the two methods by adopting the commonly defined problem descriptions and frameworks that are used for communication between the approaches.

Given the common concepts of definition and perception, the MLP contains large amounts of information about the forces driving sociotechnical change, which can then be gathered into transition descriptions to generate a description of system evolution. ABM contains a causal relationship that connects or interacts with information on a multiscale level. Therefore, the conceptual interaction between the two approaches may adopt the MLP structure, which can inform ABM of the high-carbon status and the emergence and development of different low-carbon transition pathways and low-carbon states for a wide range of dynamics and interactions among different levels.

To ensure agreement between the two analytical approaches, we identified three typical low-carbon transition narratives (system state) that can be used as a combination of analyses between the two scientific methods.

The first system state (i.e., niche details with technological innovation in high-carbon states) explains sociotechnical system details and opportunities for various conditions of niche innovation to obtain a greater profit in the market in a high-carbon state. The narrative represents a clear and continuous transfer by a detailed regime and niche participants according to the policy intervention (e.g., energy, environmental and technological justice, transition justice, currency or monetary transition, economy and financial transition, different types of social and financial innovation, etc.).

The second system state (i.e., specific regime and niche changes with continuous sublevel dynamics in a low-carbon transition) discusses how to respond properly to the new environment, including the transfer of new social technology systems for an existing regime during a transition caused by breakthroughs in various niche innovations, which not only require technological changes, but also involve social factors. Each method provides a complementary type of interpretation, including system complexity assessment in terms of scales and temporalities by identifying policy interventions, exploring different transition patterns, and noting ongoing dynamics and interactions between the niche and the regime. Specific policy recommendations can be formulated by identifying key factors and actors as the controlling parameters in the phase diagram constructed from the ABM simulation.

The third system state (i.e., a low-carbon regime that describes and evolves with local and external system impacts in low-carbon states) describes how new niche innovations in low-carbon states should respond to new opportunities for obtaining more profit in the market from external system impacts. The narrative represents a continuous transfer by a detailed regime and niche actors in low-carbon states. Other more detailed elements (e.g., different types of energy in distributed energy systems, detailed technological innovations such as technology transfer between systems, and specific governance arrangements between systems) can be continuously evaluated under political actions with a regime change.

In short, three different stages of low-carbon transition (i.e., high-carbon state, transition pathways, and low-carbon state) with their main issues, such as niche innovation in a high-carbon state, regime and niche changes in transition pathways, and the emergence of a new regime in a low-carbon state, can be identified in three narratives.

3.3. Combination

These two methods can confirm the details of different levels with various niche innovations in high-carbon states and of the regime changes with continuous sublevel dynamics in low-carbon transitions. A framework for reflecting real-life sociotechnical details can be established in the MLP, whereas ABM can build a model with more detailed information and continuous dynamics in terms of scale and temporality under these transition narratives.

Both analytical approaches also benefit from identifying future regimes and their evolution with local and external system impacts in low-carbon states as part of one of these narratives. The combination of the approaches can explain the system situation of low-carbon states (i.e., qualitative MLP and quantitative ABM considerations) and how systems change over time under system complexity and external impacts. That is, the MLP qualitatively interprets new social phenomena and niche innovations to countermeasure potential policy ambitions in the existing states, whereas ABM uses specific tools or instruments to deal with policy ambitions and niche innovations by considering external impacts over time.

The conceptual combination space of these two methods is depicted in Figure 2, which shows the fundamental arrangement, sharing of a framework around high-carbon states (Phase 1, radical innovations emerge in niches; Phase 2, the innovation enters small market niches), transition pathways (Phase 3, the innovation breaks through), and low-carbon states (Phase 4, a new regime emerges) to obtain a normal form and model standard [40]. In different system states, a pathway's construction and communication of common analytical concepts can be continuously achieved using different methods. In Figure 2, the arrow indicates that an interaction may exist between different levels of MLP and ABM research. The full cycle of the different transition pathways can reflect the combination, where MLP can provide insight into niche momentum, regime strategic actors, and the landscape change. Variable settings in ABM can benefit from the structural guide from MLP. By addressing variables on different levels, expressions between the variables can be deliberated on one at a time. This process encourages the modeler to involve interactions among the three levels by building relationships between the variables at each level. ABM can produce a more robust model based on the combined contents and can then offer specific policy and practice recommendations. For example, the low-carbon transition can be realized by the combination of market adjustments that favor low-carbon energies and policy adjustments for low energy consumption (Pathway A). In contrast, with high energy consumption, transitions from high- to low-carbon states inevitably render a catastrophic depression (Pathways B and C) [1]. The different pathways also reveal the stylized conceptualization of continuous transition dynamics and evolution abstracted from past outcome data in the MLP and the specific explanation from ABM. These different pathways, some of which may even exceed our imagination, can be used as a supplement for the MLP framework. Policy strategies can be tested through ABM with the variation of environment parameters and the results can provide further guidance to policy suggestions offered by MLP.

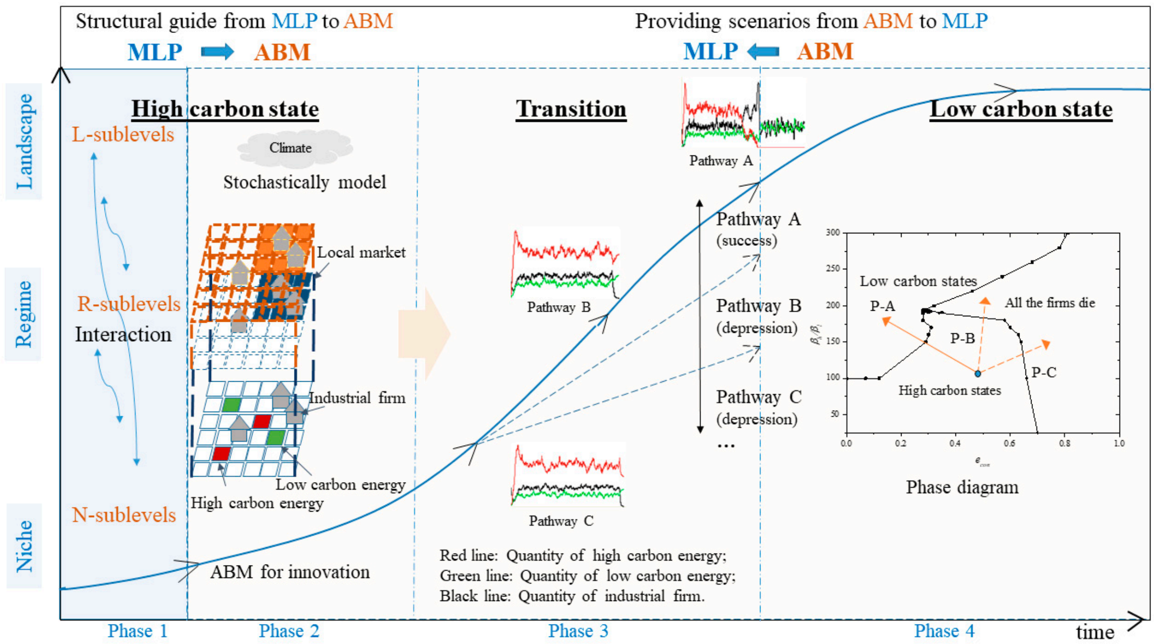

Figure 2. A schematic illustration of the combination of agent-based modeling (ABM) with a multi-level perspective (MLP).

3.4. Combination Flow of the Low-Carbon Transitions

This section illustrates how to combine the MLP and ABM frameworks, and provides a visual representation of the framework that clearly mobilizes various types of information when analyzing specific disciplinary and policy issues and when evaluating a constantly changing multi-level shift in transient strategy. Figure 3 displays a general schematic presentation of the two-way transfer between the methods in the interconnected analysis chain and illustrates how adjacent perspectives can be actively mobilized and communicated.

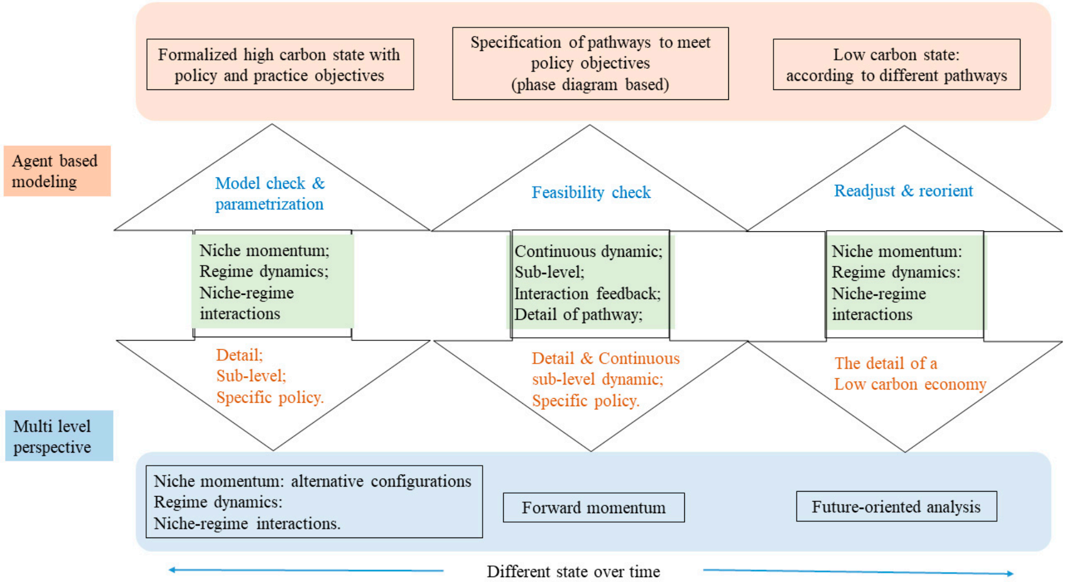

Figure 3. Schematic representation of the two-way combinations of the two approaches.

The combination is intended to orient and determine the specific practical area of the analysis in which confirmation and consensus proceed by detecting feasible windows of opportunity and by determining more system details, analytical scales, and temporalities. This can realize the transfer between practical data and the general model or indicator, and can direct and communicate the different estimation paradigms in a high- or low-carbon state, as well as the transition pathways.

By combining the approaches to analyze different stages of low-carbon transitions, we can further attain a more comprehensive assessment of the ever-changing and continuous multi-level dynamic transition strategies and further provide information for specific policy and practice suggestions. First, by analyzing duplicating patterns arising from the communication between specific measurable variations in terms of model checks and parametrization, policy intervention, and so forth, high-carbon states and current potential transition pathways can be evaluated through different approaches. Second, to conduct further collaborative studies, we can manipulate low-carbon transition pathways by maximizing the two-way transferability of conceptual orientation and model-based identification between the two methods. Forward momentum and predictable transition patterns can be interpreted and detected by communicating between and exploring the different methods to find distinct alternative pathways, given the various internal complexities and external impacts. Low-carbon transition pathways with specific policy recommendations can be easily formed by identifying key factors and actors as the controlling parameters in the phase diagram constructed from the ABM simulation. Finally, by analyzing internal and external impacts by considering the communication between specific measurable variations in terms of model readjustment or reorientation and political ambitions or intervention, low-carbon states and the potential beneficial interaction with external systems can be evaluated through different approaches.

4. Application of the Combined Approach

To operationalize this combined approach, we conducted reference-based case studies with ABM and simulation. For a given empirical domain (i.e., a distributed energy system) and narrative, combined methods can be applied to explain specific transition pathways and to evaluate different trajectories for different purposes (e.g., carbon emission mitigation ambitions). For high- and low-carbon states, a combined approach can help ABM to provide the specific policy performance and multi-level details in terms of technical, financial, or economic objectives to the MLP and can help the MLP to orient the parameterization and to check the model for ABM.

This section provides an example of the application of the combined approach. In the first step, a reference-based case study was selected: (1) a typical system, such as China; (2) an important economic domain (i.e., distributed energy system) for further study (see [39] for an overview), and (3) a quantitative model that can be consulted for the qualitative findings and results. In Liu, Y [41], an agent-based modeling approach was used to build an industry–energy ecosystem on the basis of the literature and field research. The two types of agents in this ecosystem are industrial firms and different types of energy (i.e., low- or high-carbon energy) with distinct energy capacities (i.e., 4 or 9), and two behaviors, which are the varying production of high- or low-carbon energy (i.e., 8% or 18%, respectively) and firms' life cycle (i.e., the purchase and consumption of energy resources, bankruptcy, and reproduction) in the model.

In the second step, to better understand the influence of social action or participant behavior on low-carbon decision-making, we designed the industry–energy ecosystem agent-based model to investigate the low-carbon transition [1]. This transforms the qualitative data sought in the MLP into the initial settings for the industry–energy ecosystem model, and we abstracted the local energy market with environmental market sensitivity to reflect the social emissions issue setting as a new parameter or variable (see [1] for an overview). We applied ever-increasing system pressures of carbon prices as market sensitivities to align the simulation scenarios to the domestic mitigation target of greenhouse gas emissions, which may be treated as a kind of policy pressure that can drive the system behavior toward a low-carbon transition [42,43]. With the pressure from the landscape (change in carbon price), niche innovations (low carbon firms and energy) break through the opportunity window and substitute the existing regime (from high- to low-carbon state). The ABM model was only built to investigate this transition pathway, which reflects the guidance from MLP to ABM. Finally, in the phase diagram constructed by the ABM simulation (see [1] for an overview), by identifying the key and influencing factors as control parameters, low-carbon transition paths and corresponding policies were easily obtained, according to different system conditions, that reorient and readjust as a feedback loop between the two methods, as recommended in practice. More specifically, in Wu, X. et al. [1], first, an agent-based model was adopted to simulate a distributed energy system coupled with localized energy markets to explore the relationship among some key factors (i.e., the roles of energy capacity, the energy consumption of firms, and economic regulations) and their combined effect on the low-carbon transition. Second, by scanning the parameter space of low- and high-carbon energy capacity (i.e., 8 or 18), energy consumption (i.e., 0.1–1), and market regulatory bias (i.e., 4–250) for exploiting the power of the present approach to policymaking, the model can construct phase diagrams in which three phases—catastrophic depression, a high-carbon economy, and a low-carbon economy—can be distinguished by the low-carbon penetration rate at equilibrium. The simulation results showed that a low-carbon transition can be facilitated by the combination of market adjustments that favor low-carbon energies (thus increasing environmental market sensitivity) and policy adjustments for low energy consumption (thus decreasing energy consumption). Third, from the obtained phase diagram, policy implications can be drawn regarding the regulation of localized energy markets for restricting the supply of high-carbon energy while cultivating the demand for low-carbon energy and improvements in energy saving, energy production efficiency, and storage capacity. The ABM results can be used to inspire forward-looking policy suggestions for MLP. In addition, a low-carbon state can be described by ABM, and because qualitative findings cannot be fully transformed into quantitative models, new parameterization and qualitative results may appear inconsistent.

The low carbon transition (LCT) model [1] introduced in the second step originated from a distributed energy system model proposed by Liu [41], and the model introduces a local-market price formation mechanism, which adds a correlation to the price and development rate of energy by its demand. The detailed schemes and features of LCT model are shown below.

Energy production: In each step, one unit of high-carbon energy or low-carbon energy can be generated on every local area unoccupied by any energy resources, with the probability r_h for high carbon energy and r_l for low carbon energy. The amounts of energy carried by one unit of high-carbon and low-carbon energy are defined as constants i_h and i_l, respectively.

Local energy market: Different from other similar distributed energy system models, in the LCT model, the price and development rate of high- (or low-) carbon energy fluctuate, caused by the ever-changing demand of high (or low) energy. Energy price is formulated by the local firm number:

$$p_{n,h} = \beta_h \rho_n^z, \tag{1}$$

$$p_{n,l} = \beta_l \rho_n^z, \tag{2}$$

where β_h and β_l are the coefficients describing the market sensitivity of high- and low-carbon energy, respectively. The local firm numbers ρ_n^z are counted in a neighboring area of 3×3 of the node. The demand of high- (or low-) carbon energy at time step t, $s_h(t)$ or $s_l(t)$, respectively, equals the sum of number of firms purchasing high- (or low-) carbon energy at every node n $\rho_{n,h}^{1\times1}(t)$ or $\rho_{n,l}^{1\times1}(t)$, respectively, as:

$$s_h(t) = \sum\nolimits_{n \in N} \rho_{n,h}^{1\times1}(t), \tag{3}$$

$$s_l(t) = \sum\nolimits_{n \in N} \rho_{n,l}^{1\times1}(t), \tag{4}$$

The development rates of high and low energy, $r_h(t)$ and $r_l(t)$, respectively, is determined by the demand at last time step t as:

$$r_h(t) = r_h(t=0)\log_b(1 + s_h(t)), \tag{5}$$

$$r_l(t) = r_l(t=0)\log_b(1 + s_l(t)), \tag{6}$$

Note that if no firm purchases a certain kind of energy at time n, there will be no development of such energy at time $n+1$, which means that when the demand of a kind of energy vanishes, production of this kind of energy will also stagnate from here on. Moreover, there is a critical value of the energy demand $(b-1)$ below which the supply r_h or r_l will continually shrink over time and be absorbed into null in a vicious cycle.

Firms' life cycle: In every time step n, all the firms in the simulation randomly walk to their neighboring node, dissipating an amount of energy e_{con} through consumption at the same time. If the firm is on the node covered by one kind of energy, it will purchase the energy at price $p_{n,h}$ (or $p_{n,l}$), gaining an effective energy $i_{n,h}^{eff}$ (or $i_{n,l}^{eff}$) as follows:

$$i_{n,h}^{eff} = i_h - c_h p_{n,h}, \tag{7}$$

$$i_{n,l}^{eff} = i_l - c_l p_{n,l}, \tag{8}$$

where i_h and i_l are the energy capacities of high- and low-carbon energy, respectively, as explained before. The firms' prosperity and decline are all fully determined by the energy obtained, E. If the firm does not have adequate energy ($E < 0$) to support its operation after the move, the firm will collapse due to energy shortages.

Finally, by tuning the control parameter, the model can produce phase diagrams in which three phases (catastrophic depression, a high-carbon economy, and a low-carbon economy) can be distinguished by the low-carbon penetration rate at equilibrium. The results obtain from ABM can feed back to MLP.

5. Agent-Based Model Verification and Validation

In the previous sections, the content and application of the combination were introduced. As one part of a combination, in this section, we verify the validity of the proposed agent-based model.

The rationality of the structure adopted in ABM models is responsible for the authenticity of their behavior. Both the MLP and ABM provide insights into the process of social transitions: the former provides a theoretical framework to locate different elements and the latter abstracts key factors of the transformation to particular parameters. Thus, the formulation and dynamics of an ABM model with good structural and behavioral validity should correspond well with the MLP framework for the same issue. This approach was applied to validate the ABM model of low-carbon transition [1] to test its validity. In this section, we mainly discuss the structural verification and behavioral validations of the ABM model.

5.1. Structural Verification

The assessment of structural verification focuses on (1) microscopically identifying the potential elements involved in the conceptual model and their internal connections, and (2) macroscopically determining how appropriately the model represents the relevant descriptive knowledge and phenomena of the initial problem [44]. The test of the model should establish whether the important concepts and structures in the low-carbon transition are included in the model to meet boundary adequacy. The assumptions and dynamic process adopted in the model should be consistent with real life to meet the requirements of structural verification [45].

First, we looked at the parameters in the model. In the MLP, landscape developments involve both slow-changing trends (i.e., energy price, economic growth, and infrastructures) and exogenous shocks (i.e., war, migration, and economic crisis). The landscape cannot be affected by niche actors or policymakers in the short term, and the urgency for rapid reductions in greenhouse gas emissions can be viewed as the consequence of landscape pressure [9]. Under this pressure, new technology for using clean and renewable resources is expected to improve performance of adjusting low carbon transition. In ABM, these factors are abstracted as a pair of parameters, β_h and β_l, which reflect the extent to which the public is willing to adopt low-carbon energy [46]. At the regime level, a stable and aligned set of rules forces the energy supply to move along a specific trajectory, and these shared and entrenched rules guide the participant's behavior [40]. For example, the government may set regulations to gain societal and business support for low-carbon energy, and the government can implement policies to enhance market opportunities [47]. Tax credits and subsidies are good choices to adjust the viability and market cost of different firms. As a result, a few niche actors share distinct energy resources in a relatively independent region, incurring additional costs for participants at the regime level, which form a localized energy market. In ABM, $s_h(t)$, $s_l(t)$, and $\rho_n^z(t)$ describe the number of participants in the localized market from different market perspectives. Another pair of variables, $i_{n,h}^{eff}(t)$ and $i_{n,l}^{eff}(t)$, reflect the viability expectations under this set of rules. In addition, traits of the market participants are represented by $E(t)$, e_{con}, and e_{sub}, which determine the vitality and fate of each firm. At the niche level, the expectations of niche actors contribute to building niche systems or market-like distributed energy systems as they build a constituency for fundamental change to fill specific market gaps [4,46]. For better development, niche actors need to gather more resources and share their expectations with more producers and users [48]. The amount and the efficiency of available low-carbon energy provide an integrated representation of a set of heterogeneous factors, such as technological development, civil consciousness, and political support. In the model, these factors are abstracted to two pairs of parameters: (1) i_h and i_l and (2) $r_h(t)$ and $r_l(t)$, respectively. The former focuses on how much the technological conditions are ready to support demand-side participants for a low-carbon society. We summarize the correspondence of these ABM parameters to the MLP in Table 1. The assumptions employed in ABM, which are also summarized in the same table, are in agreement with the MLP.

The dynamic equations formulated in ABM [1] can be regarded as the mathematical translation of the interactions among the three analytical levels of the MLP. Equations (1) and (2) indicate that the price of high-carbon (low-carbon) energy is proportional to the number of local firms, as the trading cost and development rate increase with the prosperity of the local market. The relation $\beta_h > \beta_l$ implies the assumption that the local market favors low- over high-carbon energies. As a result, the price of energy is the combined result of both the landscape context and the regime property, accurately reflecting the MLP interaction between the landscape and the regime. Equations (5) and (6) assume that the demand for energy, both of high and of low carbon, which is calculated as the sum of all purchased energy by relevant firms, as shown in Equations (3) and (4), has a separate positive feedback effect on its energy supply. This positive feedback reflects that large-scale and group development can accelerate the further development of niche innovations. To facilitate transitions, social acceptance and business support will be of considerable help [49]. Scaled industries and supply chains provide mature backup for firms and promote the alignment and functionalization of innovations. Thus, transitions gain momentum with multiple innovations linking together, acting in combination to reconfigure systems. The positive feedback shows the interaction between the regime and the niche. Finally, Equations (7) and (8) define the expression of the amount of effective energy obtained by a firm as the combination of the energy price and the amount of energy provided per unit. Depending on the energy that each firm can ultimately obtain, these two equations show how landscape trends, which are demonstrated by energy price and energy capacity driven by long-term technological innovation support, can affect niche actors. These relationships are shown in Figure 4.

Table 1. Structural comparison between the MLP and ABM.

MLP		ABM Model Parameters		ABM Model Assumptions
Landscape	Environmental pressure for carbon emission mitigation	β_h, β_l	β_h (β_l), carbon emission pressure for high-carbon (low-carbon) energy consumption	Environmental pressure impacts the regime level and market sensitivity coefficient for high (low)-carbon energy
	Technological development for emission reduction [9,10]		Long-term technical innovation supported for high (low) energy capacity	Technological development impacts the niche level, cultivating distributed energy systems, etc. [46]
Regime	Localized market, carbon tax, and subsidy policies [47]	$\beta_{h(l)}\rho_n^z$	Localized energy market	$\beta_h > \beta_l$: Low-carbon energy is thought to be less sensitive to market performance in distributed energy systems [50,51] $\rho_n^z(t)$: The local firm number represents the potential demand
		$s_h(t), s_l(t), i_{n,h}^{eff}(t), i_{n,l}^{eff}(t)$	Participant's market property	$s_h(t), s_l(t)$: Real demand (number of firms that purchase high-carbon (low-carbon) energy). $i_{n,h}^{eff}(t), i_{n,l}^{eff}(t)$: Effective high-carbon (low-carbon) energy capacity reflects the firm's real gains
		$e_{con}E(t)$	Participant's nature property	e_{con}: Energy consumption reflects the efficiency and life cost. $E(t)$: Amount of energy retained by a firm
Niche	Niche innovation and distributed energy system [46]	i_h, i_l	The amount of energy provided by one unit of high-carbon (low-carbon) energy	$i_h > i_l$ & $r_h(t) > r_l(t)$: Supply (at this time, high-carbon energy can perform with higher efficiency) [1]
		$r_h(t), r_l(t)$	Rate of high-carbon (low-carbon) energy development	

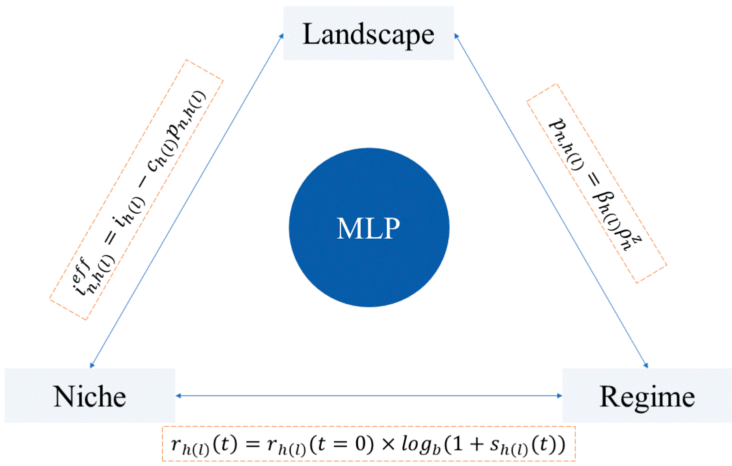

Figure 4. ABM structure corresponding to the MLP interactions.

Generally, in the MLP, the transition can be divided into different phases. The transition does not occur overnight. The steps from the niche to the regime level follow the trajectories of niche accumulation. In the ABM model, the transition was observed under different parameter settings. The results showed that higher market sensitivity, higher energy capacities, and low energy consumption can all contribute to an increase in the penetration rate of low-carbon energy [1]. This indicates that the success of a low-carbon transition involves several factors, including technological development and market adjustment. From the MLP perspective, to promote a certain transition, attention must be broadened to encompass combinations of multiple innovations and social systems, including consumer acceptance, business models, and sociopolitical drivers [47]. During the setting of variables and model assumptions, we followed the guidance from MLP to ensure that our model is organized and as comprehensive as possible.

The MLP specifies several transition pathways in response to different timings and natures of interactions [10]. According to the sequence of actors, the transition proceeds to different ends, such as the adjustment of existing rules, the substitution by new practices, or total erosion and collapse. The phase diagrams for Regimes 1 and 2 in Wu, X. et al. [1] qualitatively match these different pathways. The phase diagrams are divided into three phases: a high-carbon economy, a low-carbon economy, and a catastrophic depression. The high-carbon economy is a state that coexists with low-carbon energy, which is in line with the end in which the existing regime is adjusted. In a low-carbon economy state, there is no high-carbon energy, which represents the end in which total substitution is realized. The results also show that according to different initial conditions, a distinct sequence of parameter adjustments should be applied to promote low-carbon transition. As with the MLP method, different transition pathways also need different reactions from the three levels. ABM, in turn, provides quantitative support to the MLP.

5.2. Behavioral Validation

Behavioral validation aims to compare the model-generated behavior to that of a real system. During the construction of the baseline model, our model used a specific case: China's data obtained from available references or interviews about the real system [41]. Submodels were adopted in the LCT model, such as environmental sensitivity and feedback between supply and demand. The adopted submodels of the existing models can serve as structural validation for ABM, and Denmark can be used as one of representatives of the LCT model where the environmental sensitivity and feedback between supply and demand has been performed [1]. Therefore, we compared our simulation data with the real change that occurred in Denmark.

Through decades of effort, Denmark has combined its energy system with the localized energy market [52]. In addition, a carbon tax has been introduced to restrict high-carbon energy and promote low-carbon energy. The Danish carbon tax was gradually introduced as part of a larger program that includes energy and sulfur taxes and subsidies for green investments [53]. As early as 1992, Denmark issued a carbon dioxide tax. After years of development, the carbon tax has developed into an effective method for cutting greenhouse gas emissions; currently, according to the Denmark Council on Climate Change, Denmark is planning to sharply increase its carbon tax in the next 10 years [54]. The Danish standard carbon tax rate over time is shown in Figure 5 [54–56], demonstrating that the Danish carbon tax has increased overall.

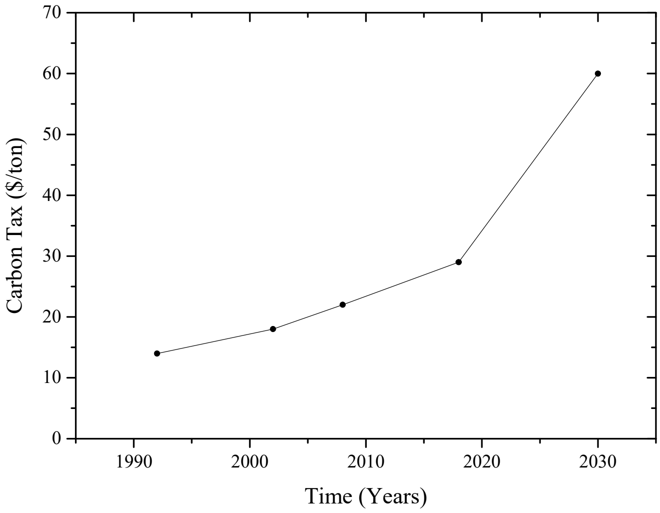

Figure 5. Denmark's carbon tax over time.

In our ABM model, we used the parameters β_h and β_l to reflect the carbon tax. The higher the $\frac{\beta_h}{\beta_l}$ ratio, the higher the carbon tax, because it measures the bias of market regulation on the two types. We set $i_h = 18$ and $i_l = 8$ in parallel with Regime 2 to ensure a possible transition pathway and to avoid catastrophic depression [1]. The other parameters were as follows: $e_{con} = 0.25$, $\beta_l = 0.1$, with all other parameters as default values. In the simulation, we gradually adjusted β_h/β_l from 100 to 140 and ran the program with an interval of 10 to show that the carbon tax was stably increasing. If we focus on the penetration rate of low-carbon energy in each stage, as shown in Figure 6, we can see a clear increase, which means that increases in the carbon tax under certain conditions are expected to accelerate the promotion of low-carbon energy.

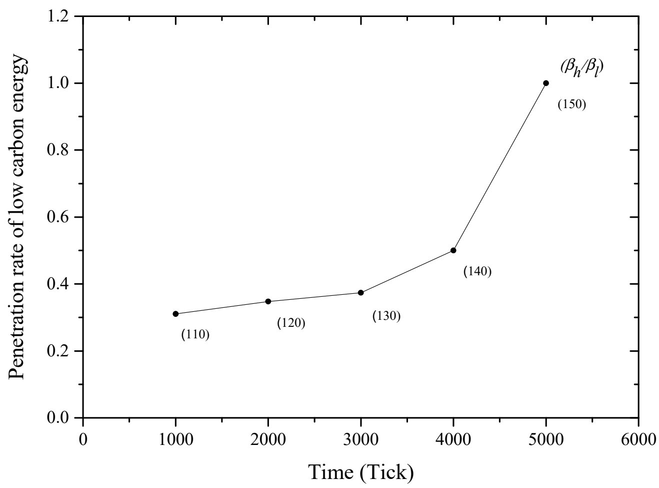

Figure 6. Low-carbon energy penetration rate of each stage in ABM.

In addition, Denmark's goal of being independent of fossil energy is becoming more practical in terms of the promotion of wind power and other renewable energies [57]. The high integration of wind energy, the widespread use of biomass, and the environmentally progressive energy tax system are contributing to Denmark's progress toward becoming green [58,59]. In 1990, almost 1 kg of carbon dioxide was emitted for every kilowatt hour (kWh) of electricity produced in Denmark; in 2012, less than 300 g was emitted [60]. To date, Denmark has reduced emissions by 38% compared to that in 1990 [54], and the Danish Council on Climate Change has stated that cutting emissions by 70% of the 1990 levels by 2030 is manageable. On its way toward the 2050 goal of 100% renewable energy, the Danish government has proposed a midterm goal of using renewable energy to cover at least half of the country's total energy consumption by 2030 [61]. The share of low-carbon energy in the final energy consumption in Denmark is shown in Figure 7 [61], which shows that the share of renewables is expected to increase steadily. Therefore, we conclude that the qualitatively verified study (gradually increasing the share of renewable energy and the system shift from high carbon state to low carbon state) provides the preliminary verification of the ABM.

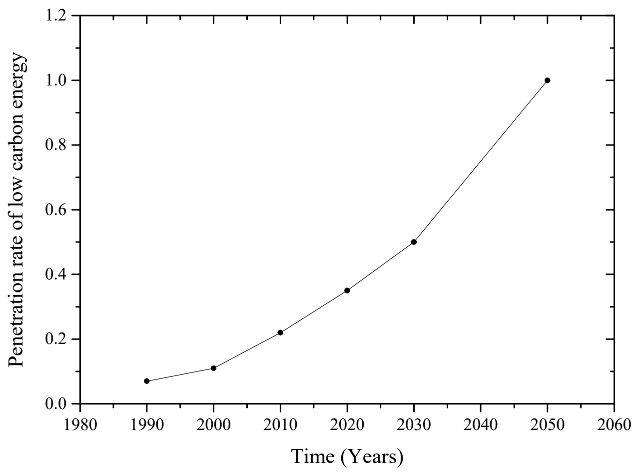

Figure 7. Denmark's low-carbon energy penetration rate over time.

6. Conclusions

Low-carbon transitions have received a significant amount of attention by researchers and organizations, and various theoretical frameworks have emerged that provided different insights into and facilitated studies on transitions. MLP, as one of these frameworks, is considered one possible approach to portray the development of the transition from the niche, regime, and landscape levels. However, the simplified conceptual MLP framework leaves room for debate on the dynamic and continuous changes in actual systems at different levels, whereas ABM shows its potential ability. By identifying low-carbon transition challenges and reviewing ABM and the MLP, we argue that when each approach is considered alone, reaching a full understanding of low-carbon transition and its associated challenges is difficult. In practice, the process evolves in the form of systematic complexity with properties of phenomenon emergence. Combining the two approaches leverages the advantages of comprehensive analysis, along with multiple levels and scales, to provide a more comprehensive assessment of possible pathways to low-carbon transitions. Therefore, this paper proposed the combination of quantitative and qualitative analytical approaches, namely ABM and the MLP, to perform a more comprehensive and flexible analysis of low-carbon transitions. This study shed light on the following points.

We presented and applied a theoretical framework that systematically draws qualitative insights combined with a quantitative approach for the interdisciplinary assessment of low-carbon transitions. We suggested that the MLP should be enhanced with insights from a complex system analysis, which is usually achieved through ABM and simulations. In addition, we provided the details of the combination by providing the common concepts, interaction, and combination for both methods in different transition states, namely, the high- and low-carbon states, and the transition pathways.

We also illustrated how this combined approach can work in practice by providing a case-based example and by performing an ABM verification and validation. Moreover, we showed that concrete policy recommendations can be inspired by identifying key factors and actors as the controlling parameters in the phase diagram from the ABM simulation, which can further develop the MLP.

The benefits of the combined approach for the analysis of low-carbon transition were verified because the MLP can contribute to the overall design of ABM, and ABM can provide a dynamic, continuous, and quantitative description of the MLP, including the dynamic interplay among the different levels.

We expect that this new combined framework can be applied to extensive and insightful research in the relevant areas of low-carbon transition.

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