Leveraging the Belief Desire Intention Framework for modeling the behavior of stakeholders in energy markets

Aliene van der Veen, Wester Coenraads, Pieter Verstraten
TNO
Den Haag, The Netherlands
{aliene.vanderveen, wester.coenraads, pieter.verstraten}@tno.nl

***Abstract*—The behavior of energy market participants depends on their needs, business strategy, and knowledge about the dynamics of markets and contracts. Considering these factors without decreasing the value of insights for decision-making is challenging and often neglected in energy system modeling. In this paper, we introduce and demonstrate BDEYE: a method for creating insights into energy system dynamics for industry decision-makers using agent-based modeling (ABM) and Agentic Reasoning Capture (ARC) using the Belief Desire Intention Framework. The demonstrations show that with BDEYE, we can provide insights into complex energy market dynamics while ensuring the transparency, explainability, and comprehensibility needed for decision-making on clean energy technology business strategies and policies.**

***Index Terms*—Power Purchase agreements; Contracts for Difference; hydrogen market; electricity market; agent-based modeling**

I. Introduction

Right-in-time investments in clean energy technologies are crucial for meeting climate goals while safeguarding the economic competitiveness of industries. Making decisions regarding investments including the utilization strategy for these future investments (e.g. amount of long-term contracted volume) requires industry to understand the dynamics of future energy markets. For policy makers, understanding the dynamics of industry decisions is needed for creating effective mechanisms to support the clean energy transition.

For understanding the dynamics of energy markets in transition energy market models made and operated by experts are often used: from system optimization models to agent-based models. Models like PyPSA are used to explore the optimal outcome under certain assumptions about functioning of the market. Agent-based models such as Amiris [1] and ASAM [2] are used to analyze how policy decisions influence the behavior of energy market participants [3].

Expert-driven models – where domain experts predetermine system behavior or scenarios – provide valuable insights. However, they face limitations in representing interactive multi-stakeholder dynamics in a comprehensible, transparent, and explainable way [4]. In recent projects, we addressed the challenge of capturing market dynamics arising from the interplay of multiple factors, including long-term contractual arrangements and cross-market interactions. A central difficulty lay in developing models that accurately represent market dynamics while remaining interpretable and useful to decision-makers. For example, validating assumptions about trading strategies for assets active in both the hydrogen and electricity markets —particularly through consultation with prospective participants in future energy markets— proved to be a non-trivial task. As companies continue to define their roles and business models within evolving energy systems, the strategic decisions of one actor influence the choices of others.

To overcome the challenge of balancing the usability (can stakeholders accomplish their goals with the results of the study) and usefulness (provide the insight in market dynamics stakeholders need) of our energy market modeling studies, we developed the method BDEYE. This method extends beyond existing models by integrating a *Belief Desire Intention (BDI) Framework* with EYE [14], an agent-based energy market model, enabling a logically structured bottom-up simulation of stakeholder behavior.

The bottom-up design of BDEYE enables full freedom to define behavior of stakeholders while the BDI Framework, serving here as an *Agentic Reasoning Capture (ARC) Framework*, ensures that the behavior of single agents as well as emergent multi-agent behavior can be well enough understood such that stakeholders can validate assumptions about their behavior in system context. As such, the feasibility of scenarios can be evaluated and explained.

The goal of this paper is to inform the energy market modeling community about the possibility and value of using ARC frameworks in combination with agent-based modeling. The demonstrated BDEYE method is a first implementation

This research was funded by the research program "MegaMind—Measuring, Gathering, Mining and Integrating Data for Self-management in the Edge of the Electricity System", (partly) financed by the Dutch Research Council (NWO) through the Perspectief program under number P19–25.

of this proposed approach. Other combinations of agent-based simulation models and ARC framework (e.g. Theory of Mind) can be applied in a similar way.

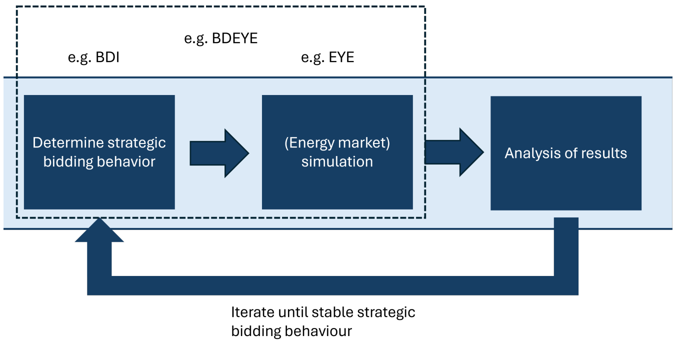

Fig. 1. BDEYE is a method that combines agent-based modeling of energy markets with agentic reasoning capture of trading strategies.

In Section 2, we introduce the BDEYE method and explain how it was developed through industry-driven use cases. In Section 3, we illustrate this development with the case of the 'hydrogen spot market.' In Section 4, we demonstrate the application of the BDEYE method for the quantitative evaluation of power purchase contract agreements. In Section 5, we give recommendations for the energy market research community and decision makers in the clean energy transition.

II. BDEYE

The BDEYE method applies the Belief-Desire-Intention (BDI) framework in the domain of EYE [14], a multi-energy market simulation model developed over the past seven years through an industry use case-driven process. The BDI framework is well-known in the multi-agent systems community for modeling the reasoning and decision-making processes of intelligent agents. It allows for a structured capture of the reasoning of market participants, leading to specific trading and contracting behaviors. EYE models this behavior to simulate market interactions, providing a dynamic representation of energy market outcomes. The simulation results are used to update the agentic reasoning models until a stable situation is found that makes sense from the stakeholders' perspective.

A. Exploring energy market dynamics with an agent-based model

EYE simulates prices on wholesale and local markets based on a scenario describing the parameters of the energy system and the bidding behavior of agents in the system. EYE also executes business rules, such as arising from long-term contractual agreements.

EYE creates bids produced by bidding agents by executing the bid logic for each agent. This bid logic can depend on the results of previous market clearings and contract rule executions. When all bids are collected, EYE executes the market clearing logic according to the selected market clearing mechanism (for example, a double-sided auction). The market clearing results are used to update the state of the bidding agents.

The system scenario input describes the state of the energy system in the Energy System Descriptive Language [5]. The bidding strategies input parameters describe how assets will bid into the market. EYE allows full freedom in defining the bidding logic in Python templates. From simple marginal price bidding to complex optimization logic with dependencies on forecasts and earlier market clearing results can be implemented.

EYE is designed for settings where a scenario is iteratively evaluated, preferably in close interaction with stakeholders. An initial scenario is based on the user's initial knowledge. Next, the user analyzes the results and updates the strategies as well as other scenario assumptions until he and the stakeholders he interacts with are convinced that the set of bidding strategies is stable: none of the players is expected to change their behavior in this scenario.

EYE gives the user full ability to change parameters and explore effects via a user interface. The level of flexibility and transparency allows EYE to be applied in workshops with stakeholders, where inputs and outputs can be discussed and changed on the fly.

B. Beliefs, Desires, and Intentions of energy market participants

The Belief-Desire-Intention (BDI) framework originates from philosophy and computer science and has been adopted in multi-agent systems for decision-making in dynamic environments [6], [7]. It is used to mimic the decision-making process of an agent based on:

- **Beliefs**: Information the agent perceives about the world, which can be updated as the environment changes.
- **Desires**: Objectives or goals that the agent wants to achieve.
- **Intentions**: Plans or actions the agent commits to executing to achieve its desires.

The BDEYE method combines the BDI framework with EYE to simulate the behavior of agents in an energy market environment. As such, it captures the following beliefs, desires, and intentions:

- **Beliefs in the Energy Market**: Beliefs represent an agent's knowledge of market conditions, including prices and demand forecasts, production capacities, and energy market regulations.
- **Desires in the Energy Market**: Desires correspond to the business objectives of agents, such as maximizing profit, minimizing risk, and achieving specific energy production quotas (e.g., for renewable energy).
- **Intentions in the Energy Market**: Intentions represent the commitments to specific strategies, such as bidding strategies in energy markets and long-term contracts for energy supply.

The user of the BDEYE method evaluates the assumptions about the Beliefs, Desires, and Intentions of individual agents in the system context on feasibility and stability. Partly, this analysis can be done offline, but EYE can also be used to evaluate whether a certain combination of strategies is feasible.

To create a comprehensible set of strategies, we mostly start with strategies that people are familiar with, such as marginal cost-based bidding strategies often assumed in system optimization models. Through conversations with industry (operators, investors), we enhance the scenario with real-world dynamics. By using the agentic reasoning structure, the real-world dynamics are captured in a transparent and comprehensible way. As the EYE results provide detailed insights into the bidding and clearing prices, the effects of bidding strategies on wholesale or local market prices are explainable.

III. Understanding the dynamics of a hydrogen spot market

An initial application of the BDEYE method has been demonstrated in the context of the HyXchange project, which simulates the nascent hydrogen market in the Netherlands [8]. The HyXchange project emerged from the need for a deeper understanding of the hydrogen system and the development of exchange services. In the project, the I-Elgas [9] optimization model and EYE were used together to support stakeholders in developing their understanding of the hydrogen markets and shaping the requirements of the hydrogen spot market.

One of the primary objectives was to simulate a hydrogen spot market to explore the dynamics of time-dependent variations in market volume and price. A key question was whether the hydrogen market would exhibit characteristics closer to the electricity market, with hourly price fluctuations, or the gas market, characterized by daily price changes. Understanding these dynamics is essential for establishing a robust blueprint for a hydrogen exchange.

First, the project examined the dynamics of an optimal dispatch based on the marginal cost of operation using the system optimization model I-Elgas [9]. This approach assumes a competitive market environment, which requires several conditions, such as a large number of buyers and sellers and unrestricted entry and exit. However, hydrogen spot markets are in their early stages and lack these characteristics. The current market features only a few large producers and a limited number of customers. Additionally, substantial barriers to market entry exist, including significant investment requirements, regulatory challenges, and limited access to infrastructure. As a result, market participants are likely to deviate from an optimized dispatch.

The BDEYE method was employed to account for the behavior of market participants in this environment, thereby providing more realistic simulations of emerging hydrogen market dynamics. This includes bidding behavior that is affected by long-term contracts and the results of and expectations about electricity markets.

Through interviews and work sessions, the Beliefs, Desires, and Intentions of hydrogen market participants were collected. Targeted interviews were conducted with specific market participants, such as hydrogen consumers and green hydrogen producers. These insights were used to capture the behavior of specific classes of market participants expected to be present in the Dutch hydrogen market. Collaborative work sessions involving multiple market parties facilitated discussions on how the decisions of one participant might influence others. EYE simulation results were discussed in these sessions, and the Beliefs, Desires, and Intentions were updated until the participants agreed that a stable, comprehensible mix of strategy sets was found.

The BDEYE method led to the development of strategy sets that represent the assets and corresponding bidding behaviors of hydrogen market participants. Examples of these strategy sets include:

- **Marginal Cost Bidding**: Assets in this strategy set bid their marginal cost or opportunity cost (based on marginal cost price taking in other markets) on a hydrogen spot market.
- **Integrated SMR and Demand**: In this strategy set hydrogen demand is met by a Steam Methane Reformer (SMR) via co-ownership or a long-term contractual agreement.
- **Electrolyzer Integration**: In this strategy set electrolysers provide green hydrogen as long as they can, and an SMR offers flexibility to always meet hydrogen demand based on a long-term availability contract.

Industry parties participated in work sessions to select scenarios to evaluate. In each scenario, different mixes of strategy sets were assumed to be used by participants in the future hydrogen market. Two key uncertainties captured in these scenarios were the hydrogen system configuration and market integration. The hydrogen system configuration addresses the adoption of technologies such as ammonia crackers, while market integration concerns the extent to which current hydrogen production and demand will transition to a market-based system and how agents interact with electricity wholesale and balancing markets.

The simulations show that when all assets are present on a hydrogen spot market and bid based on marginal costs, production volumes vary on an hourly basis. The prices on the hydrogen spot market are less volatile than on the electricity spot market due to a stable demand profile and the wide availability of flexibility options such as storage, line pack, and ammonia crackers.

With the BDEYE method we found that not all parties will transition to a market-based system. Their Beliefs and Desires don't result in (full) participation. Most hydrogen is produced on-site, and producers have indicated that they will not make this hydrogen production available for the market in its initial stages. However, they will buy hydrogen from the market if it is cheaper than their own production. Furthermore, we observed that certain policies or business strategies may not incentivize electrolysers to (fully) participate in hydrogen and electricity spot markets. Evaluation of such developments is important for other stakeholders as the electricity market has a significant influence on the dynamics of the hydrogen market when electrolysers are active in spot markets.

If existing dedicated hydrogen production remains tied to on-site demand, private price and volume risks will remain limited. However, this comes at the expense of optimal system dispatch. As a result, transparency in hydrogen spot pricing will suffer. This lack of transparency undermines one of the core benefits of establishing an exchange.

IV. Demonstration long-term contracts

Another application of the BDEYE method has been demonstrated in the evaluation of Power Purchase Agreements (PPAs) and Contracts for Differences (CfDs) [12]. Such long-term contracts are essential instruments designed to stabilize revenue streams and reduce investment risk, thereby ensuring market stability and the uptake of renewable energy. The European Commission has highlighted the importance of PPAs and CfDs in the Electricity Market Design. Understanding the implications of these instruments on stakeholder behavior and market outcomes requires a robust analytical framework that extends beyond assumptions of optimal behavior.

A key question is how PPAs and CfDs alter participant behavior and, consequently, influence market interactions and stability [10], [11]. In the next section, we demonstrate how BDEYE can provide insights into the effect of long-term contracts on wholesale markets in the context of a full market context simulation.

A. *Simulating Power Purchase Agreements*

We evaluated the effect of PPAs in the 2 GW offshore wind farm tender Ijmuiden Ver [12]. The tender [13] requires the integration with a contracted demand whenever the offshore wind farm produces over 1 GW. This provided the foundation for the investigated scenarios:

1) **Base case**: The wind farm bids 100% of its capacity on the market, ignoring the tender criteria.
2) **PPA with existing demand (as-produced PPA (top))**: The wind farm engages in a PPA with already existing demand for any production exceeding 1 GW (thus adhering to the tender criteria).
3) **PPA with new demand (as-produced PPA (top))**: To adhere to the tender criteria, additional demand is created (e.g. by electrifying industrial processes) and the wind park and this new buyer arrange a Power Purchase Agreement (PPA) .

For the different cases, we developed the bidding strategies for the stakeholders engaged in these PPAs. The Beliefs and Desires of these parties is straightforward ('if I don't follow the agreement, I have to pay a penalty, so my Desires is to do exactly what I promised in the PPA') and so easy to translate into an Intention. For example, in the case of a PPA as-produced (top), the wind farm bids 1 GW of its produced electricity on the wholesale market at marginal cost (€0/MWh) and the remainder will be supplied via the PPA.

PPAs remove electricity production and (flexible) demand from the wholesale market compared to the base case. EYE was used to simulate this effect. Figure 2 shows price duration curves of the wholesale electricity market for each of the simulated scenarios. In some hours, the scenarios with a PPA (orange and green) have increased prices compared to the base scenario (blue). This is caused by the effective removal of production from the market, which can be interpreted as making the market less efficient.

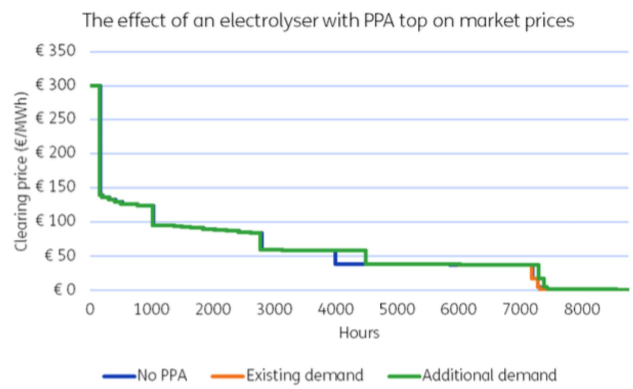

Fig. 2. Price duration curves of the wholesale electricity market for the investigated scenarios. The removal of production and demand caused by the PPA causes increased prices in some hours.

B. *Applying the BDEYE method to Contracts for Differences*

We also examined the effects of Contracts for Differences (CfDs) on energy market dynamics. CfDs provide stability for renewable producers by subsidizing their production when electricity market prices dip below an agreed strike price. A key question was how these CfDs influence participant behavior and, consequently, market interactions and stability.

In a CfD, an asset sells its electricity on the wholesale electricity market as usual. When the electricity price is below an agreed-upon strike price, the asset receives subsidies to make up the difference. This ensures that the asset will always receive at least the strike price for its sold electricity. Additionally, in a two-sided CfD, the asset pays back the subsidizer when electricity prices are higher than the strike price, as opposed to a one-sided CfD, where the asset keeps the excess revenue.

To implement CfDs in the EYE simulation, a BDI analysis was performed on renewable assets under a CfD. This analysis revealed that renewable assets are incentivized by the terms of the CfD to bid at the lowest possible price. The CfD ensures that the renewable asset receives at least the strike price (Belief) and they want to maximize their profit (Desire). To achieve this, they will have to maximize the amount of energy that they sell (Intention). The resulting bidding behavior is to bid the available capacity at the lowest market price (in our scenario set at -500 €/MWh). It is interesting to note that while one-sided and two-sided CfDs result in different costs and profits for the renewable asset and the subsidizing party, the BDI analysis showed that they result in the same bidding behavior and thus these different CfDs have similar effects on energy markets.

EYE was used to simulate a scenario where 50% of renewable producers (wind and PV) are covered by a CfD, and the other 50% of renewable producers use a marginal price bidding strategy.

Figure 3 highlights the effect of this configuration of strategies on the market for a single day. In hours 0:00-4:00 and 19:00-23:00 the total renewable production is insufficient to meet the demand, so the price is set by another production asset. In hours 5:00-8:00 and 14:00-18:00 the marginal cost bidding renewable producers set the market price at 0 €/MWh. For hours 9:00-13:00 the renewable producers which have a CfD can meet the demand and set the price at -500 €/MWh.

The next question is whether these bidding strategies are stable. As long as the contractual agreements stay the same, the strategies are stable, since the renewable assets have no reason to alter their bidding behavior. However, if the government alters the form of the CfDs, e.g. not providing subsidy for hours which have a negative price, this will bidding strategies will become more strategic.

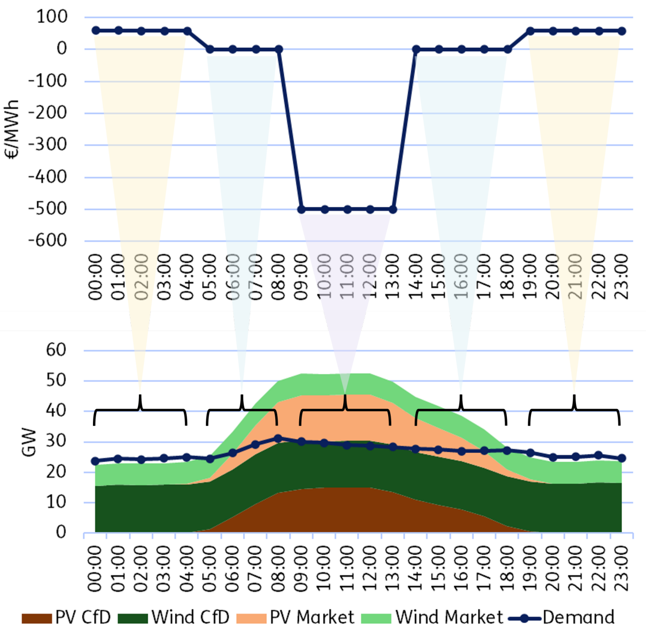

Fig. 3. Clearing prices (top) are determined by the assets supplying electricity (bottom). In the bottom graph, the renewable sources of electricity are stacked in order of bidding price.

C. *Overall findings on long-term contracts*

In both the evaluation of PPAs and CfDs, the BDEYE method was used to answer questions about how the behavior of specific assets influences overall market dynamics. Simulating PPAs provided a clear picture of how the market can become less efficient when more assets engage in PPAs. Applying the method to CfDs revealed that CfDs lead to significant differences in bidding behavior compared to PPAs, which in turn can result in drastically different market outcomes. Introducing CfDs should be done carefully to ensure that other market participants have the opportunity to adapt their business strategies.

V. Conclusions and Recommendations

Overall, this work highlights the value of applying Agentic Reasoning Capture (ARC) methods in combination with Agent-Based Modeling (ABM) for answering questions about benefits and risks of clean energy investments and operational business strategies. In this paper, we demonstrated BDEYE, a ARC+ABM energy market modelling method developed step-by-step through use case-driven innovation. We demonstrated that the BDEYE method can provide explainable and comprehensible insights into market dynamics caused by multi-market interactions and long-term contracts.

We recommend to consider agent-based models with ARC methods for questions that cannot be answered with enough certainty, clarity or trust by other models. We expect that other types of ARC Frameworks and ABM models can outperform BDEYE in both explainability and scalability. For future work, we recommend exploring the dynamics of future energy systems by training artificial agents with agentic reasoning capabilities in an online agent-based simulation to find stable and feasible scenarios of future energy market that can be understood from both a stakeholder and system perspective.

References

[1] Christoph Schimeczek, Kristina Nienhaus, Ulrich Frey, Evelyn Sperber, Seyedfarzad Sarfarazi, Felix Nitsch, Johannes Kochems & A. Achraf El Ghazi (2023). AMIRIS: Agent-based Market model for the Investigation of Renewable and Integrated energy Systems. Journal of Open Source Software
[2] Samuel Glismann, Ancillary Services Acquisition Model: Considering market interactions in policy design, Applied Energy, Volume 304, 2021.
[3] Frey, Ulrich J and Klein, Martin and Nienhaus, Kristina and Schimeczek, Christoph, Self-reinforcing electricity price dynamics under the variable market premium scheme, Energies, 2020.
[4] P. Verstraten and A.H. van der Weijde, "The Case for Simple Simulation: Stochastic Market Simulation to Assess Renewable Business Cases", July 2023.
[5] https://energytransition.gitbook.io/esdl
[6] M.E. Bratman, "Intention, Plans, and Practical Reason", 1987.
[7] A.S. Rao and M.P. Georgeff, "Modeling Rational Agents within a BDI-Architecture", 1991.
[8] B. den Ouden, S. Hers, J. Schellekens, S. Blom, P. Verstraten, A. van der Veen, T. Verboon, J. Wolda, and W. Coenraads, "Blueprinting the hydrogen market – hydrogen spot market simulation (H2SMS)", February 2024.
[9] B. Koirala, S. Hers, G. Morales-España, J. Sijm, M. Weeda, "Integrated electricity, hydrogen and methane system modelling framework: Application to the Dutch Infrastructure Outlook 2050", 2021.
[10] G. Zachmann, L. Hirth, C. Heussaff, I. Schlecht, J. Mühlenpfordt, A. Eicke, "The design of the European electricity market: Current proposals and ways ahead", September 2023.
[11] I. Schlecht, C. Maurer, L. Hirth, "Financial contracts for differences: The problems with conventional CfDs in electricity markets and how forward contracts can help solve them", 2024.
[12] P. Verstraten, M. Wevers and A. Raja, "The effects of PPAs on the electricity market", April 2024, https://repository.tno.nl/SingleDoc?find=UID%2007df5907-694b-41d5-8fbc-f0bbc584bfb2
[13] Permits for wind farms at IJmuiden Ver Alpha and Beta, https://english.rvo.nl/subsidies-financing/offshore-wind-energy/ijmuiden-ver
[14] https://www.esdl.nl/eye-energy-market-model/