HOW AI TOOLS CAN HELP DIAGNOSE MARKET DYNAMICS AND CURB MARKET POWER ABUSE AS THE NATION'S POWER SUPPLY TRANSITIONS TO RENEWABLE RESOURCES

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Synopsis: This study explores the intricate challenges arising from emerging technologies within the energy sector, particularly focusing on the critical juncture when the share of renewables overtakes fossil fuels and other sources in U.S. electricity generation. Using a newly available artificial intelligence (AI) tool, Long Short-Term Memory (LSTM) model, we conduct a comprehensive analysis of multiple regions, including the United States as a whole, to identify the critical threshold at which renewables constitute more than 50% of the energy mix. We delve into the far-reaching implications of this transition for energy regulations, which have traditionally been rooted in a fossil fuel-dominated paradigm. The integration of renewable energy with advanced battery storage technology has revolutionized the energy market, providing electricity sellers with enhanced control over capacity and market influence. These innovations have led to improved flexibility, grid stability, and greater renewable energy use. While this shift offers significant market opportunities, it also raises concerns about market power and the need for updated regulations. The new technology enables the storage of excess electricity during high production times for use during peak demand, highlighting potential market power challenges. Through an insightful case study, we demonstrate how adjustments in energy regulatory frameworks impact market power analysis outcomes. Moreover, we incorporate these empirically derived parameters into a novel AI-powered Agent-Based Model (ABM) designed for energy regulation frameworks. This dynamic model reveals the complex interplay between regulators and regulated companies, emphasizing the need to curtail excessive market power among sellers. Our research contributes to the growing body of literature on AI applications in energy regulatory frameworks, offering valuable policy options for updating existing regulations to accommodate emerging technologies.

This paper is structured into three sections. We will initiate by reviewing the background and then proceed to conduct our analysis, demonstrate AI's application, and explore the findings in subsequent sections. In Section I, we delve into

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the background of FERC's regulations, its methods, and our modeling. We begin by briefly introducing the Federal Energy Regulatory Commission (FERC) and its two pivotal programs – energy merger review and market-based rates (MBR). We provide insights into the evolution of regulations in the electricity market and the rapid growth of renewables. Subsequently, we introduce the Delivered Price Test (DPT), a foundational analytical tool for assessing market power in FERC's regulations. In addition, we examine two contrasting forecasting methodologies: traditional models and recently developed, more advanced AI models, specifically LSTM models and ABM. In our discussion, we highlight the superior accuracy and advanced capabilities of AI models, which have only become available in recent times, and explore their applications in regulatory contexts. In Section II, we embark on our analysis. We initiated the process by applying LSTM through Python coding to our renewables forecasting. We scrutinize the timeline at which the share of renewables is poised to surpass the share of fossil fuels and other sources in electricity generation in multiple regions, including the United States as a whole. Additionally, we analyze a specific case involving the DPT, presenting a novel sensitivity study within the realm of regulations. Our section culminates with the development of an ABM utilizing NetLogo codes powered by AI. In our simulation, we demonstrate the regulatory challenges posed by the rapid growth of renewables and the need to curtail excessive market power from power sellers. In our conclusion, we underscore that the share of renewable energy, boosted by emerging technologies, is expected to surpass the share of fossil fuels and other sources in U.S. electricity generation. We suggest shifting gradually from fossil fuel-based (nameplate capacity) calculations to renewable-based (sales or capacity-plus-battery) calculations as renewables continue their ascent towards dominance across the United States.

I. BACKGROUND FOR FERC'S REGULATIONS AND OUR RESEARCH METHODS AND MODELS

A. Introduction

The need to update regulations within the electricity industry is steadily growing in significance, particularly as renewables take center stage, gradually replacing traditional fossil fuels as the predominant source of electricity generation in the United States.[1]

The electricity market is a natural monopoly, meaning that it is very expensive to build and maintain an electricity grid, and it would be inefficient to have multiple grids competing in the same market. Regulations in the electricity market are designed to prevent natural monopolies from abusing their market power and to ensure that electricity prices are fair and reasonable, and that consumers have access to reliable electricity services. To avoid Enron-type energy crises, academic scholars, legal professionals, and federal and state antitrust officials are increasingly interested in understanding the market power implications of electricity market deregulation and energy mergers, as well as the importance of keeping regulation up to date.

At the federal level, three major agencies collectively shoulder the responsibility for overseeing the energy market: the Federal Trade Commission (FTC), the Department of Justice (DOJ), and FERC. These agencies all closely scrutinize energy mergers. The FTC and DOJ hold joint jurisdiction over merger review through the Hart-Scott-Rodino Antitrust Improvements Act of 1976 (HSR Act).[2] This legislation mandates companies to notify both the FTC and DOJ of specific

1. *See* U.S. ENERGY INFO. ADMIN., U.S. REGIONAL ELECTRICITY GENERATION, ELECTRIC POWER SECTOR, (2024) https://www.eia.gov/outlooks/steo/tables/pdf/7dtab.pdf. In 2022, about 4,243 billion kilowatthours (kWh) of electricity were generated at utility-scale electricity generation facilities in the United States. About 60% of this electricity generation was from fossil fuels—coal, natural gas, petroleum, and other gases. About 18% was from nuclear energy and others, and about 22% was from renewable energy sources. However, Northwest region is the first region in the United States where renewables surpassed half the region's electricity generation in 2022.

2. Hart-Scott-Rodino Antitrust Improvements Act of 1976, Pub. L. No. 94-435, 90 Stat. 1387 (codified as amended at 15 U.S.C. §§ 18a-18h).

mergers and acquisitions prior to their completion. Subsequently, the agencies evaluate the transaction and decide whether further investigation is warranted. If an investigation is initiated, the agencies may issue a request for more detailed information from the involved parties, including information concerning the transaction's competitive implications. While these agencies collaborate closely on merger review, the FTC primarily handles mergers within the electric utility sector, while the DOJ specializes in the oil and gas industry.

FERC, on the other hand, holds specific responsibilities and extensive expertise in the realm of energy and electricity regulation, enabling it to conduct sophisticated analyses for authorizing energy mergers.[3] Empowered by the Federal Power Act (FPA),[4] FERC oversees the wholesale electricity market to prevent the exploitation of market power by natural monopolies. Beyond energy mergers, FERC maintains its market-based rates (MBR) program through which it oversees the wholesale deregulated electricity market. FERC's regulations play a pivotal role in ensuring the fairness and reasonableness of electricity prices while guaranteeing consumers access to a reliable electricity service.

It is worth noting that the methodologies employed by the FTC and DOJ and FERC are not entirely identical. While FERC's approach hinges on structural analysis, examining market shares and Herfindahl-Hirschman Index (HHI) through the Delivered Price Test (DPT), the FTC and DOJ primarily rely on a behavioral approach to mergers.[5] The agencies focus on evaluating the potential and motivation for price hikes. Despite these disparities, nameplate capacity, adjusted by capacity factor, forms a crucial foundation for their horizontal market power analysis. The DOJ and FTC typically initiate their supply curve analysis using nameplate capacity, which denotes the maximum output a power plant can achieve under ideal conditions. FERC, on the other hand, consistently employs its screens and the more advanced DPT, both rooted in nameplate capacity, to assess electricity power seller applications within its merger and MBR programs. Nameplate or seasonal capacity serves as a metric to ascertain market share and gauge the overall energy capacity available within a specific market.[6]

However, the landscape of the energy industry has undergone a significant transformation in recent years, with renewable energy emerging as the fastest-growing source of energy in the United States. With the rapid development of emerging technologies, the capability of battery storage has surged, granting renewable energy sellers greater flexibility to expand their market share beyond their nameplate capacity during peak demand periods. Market power analysts now con-

3. *See* FERC, COMMISSION MEMBERS AND SENIOR STAFF, https://www.ferc.gov/commission-members-senior-staff/commission-members-and-senior-staff. As of October 2023, the staff of FERC is composed of over 1,200 employees. The staff includes about 200 engineers, 100 economists, lawyers, 150 attorneys, and 10 Administrative Law Judges, and other professionals.

4. Federal Power Act, 16 U.S.C. §§ 791a–828c *(*1976 & Supp. IV 1980).

5. Mark J. Niefer, *Explaining the Divide Between DOJ and FERC on Electric Power Merger Policy*, 33 ENERGY L. J. 505, 515 (2012).

6. Order No. 697, *Market-Based Rates for Wholesale Sales of Electric Energy, Capacity and Ancillary Services by Public Utilities*, 119 FERC ¶ 61,295 at P 343 (2007) (to be codified 18 C.F.R. pt. 35).

front novel challenges. The existing methods may underestimate the actual available energy, creating opportunities for sellers to manipulate their available capacity strategically at specific times and increase their market power.

The primary focus of this article is to examine FERC's market power analysis within its regulations amid the backdrop of this rapid growth in the renewable energy sector. It is noteworthy that FERC's current energy regulations, especially those related to market share calculations for antitrust purposes, remain grounded in fossil fuel energy, primarily utilizing capacity factor-based calculations, rather than accounting for the evolving landscape of renewable energy through sales-based or capacity-plus-battery-based calculations. This lack of updates by FERC to its market power analysis to reflect the increasing role of renewable power raises concerns that the current capacity de-rate standard may inaccurately reflect the available energy in the market. Recent examples highlight how the current de-rate standard for FERC's market power analysis can distort market share calculations, thereby posing a challenge to the foundations of FERC's regulations.

Given the challenges posed by the rapid growth of renewables, our study endeavors to identify the need for FERC to update its regulations, pinpoint the weaknesses in FERC's current market power analysis, explore potential solutions, and simulate the consequences of regulatory adjustments once renewables achieve dominance across the United States.

B. The Regulations of the US Energy Market and the Challenges

FERC was established in 1977 under the Department of Energy Organization Act, merging the Federal Power Commission and the Bureau of Accounts and Cost Finding from the Interstate Commerce Commission.[7] This restructuring signified a move towards a more consolidated and focused regulatory framework for overseeing the nation's energy markets.

Order No. 888 was a landmark decision by FERC that aimed to promote competition within the electricity market.[8] It relied on the existing 1935 Federal Power Act (FPA) to implement generic unbundling, requiring utilities to separate their generation, transmission, and distribution functions.[9] While Order No. 888 represented a significant step towards competition, FERC's regulatory approach has continued to evolve, adapting to various legislative changes, including the Energy Policy Act of 2005 (EPAct2005). While EPAct2005 did not universally require case-by-case rulings, it introduced additional factors for FERC to consider when determining the appropriate level of regulation for different market segments.[10]

7. FERC, ABOUT FERC, https://www.ferc.gov/about/what-ferc.

8. Order No. 888, *Promoting Wholesale Competition Through Open Access Non-Discriminatory Transmission Services by Public Utilities*, 75 FERC ¶ 61,080 at P 1 (1996).

9. *Control of Public Utility Holding Companies*, Pub. L. No. 74-333, 49 Stat. 838 (1935). The Federal Power Act, 16 U.S.C. §§ 791-828(c), passed in 1920 and amended in 1935 and 1986, created FERC as an independent regulatory agency that oversees the natural gas, oil, and electricity markets, regulates the transmission and sale of these energy resources (except for oil), provides licenses for non-federal hydroelectric plants, and addresses environmental matters arising in any of the areas above.

10. Energy Policy Act of 2005, Pub. L. No. 109-58, 119 Stat. 594, 718, 968 (2005).

Today, FERC stands as one of the United States' most influential energy regulators. Its decisions hold substantial sway over the wholesale electricity market and significantly impact the reliability and affordability of electricity for consumers.[11]

FERC, functioning as an independent agency, is charged with regulatory oversight over the provision of dependable and cost-effective energy service and the interstate infrastructure facilities that make that possible in the United States. FERC's core responsibilities encompass overseeing the reliability of the bulk power system, the vast interconnected network of power plants and transmission lines that deliver electricity nationwide. Additionally, FERC regulates the interstate wholesale electricity market, where generators sell power to utilities and other buyers, and oversees the interstate transmission of natural gas and oil.

FERC has been pivotal in promoting competition within wholesale electric markets. Market power analysis is a tool FERC employs to evaluate the potential for electricity companies to wield undue influence in the wholesale electricity market. This analysis is utilized in two main programs: the MBR program (section 205 of the Federal Power Act) and the merger review program (section 203 of the Federal Power Act). The premise here is that a seller's pricing practices are linked to its market power. Market power and manipulation can result in exorbitant prices causing harm to consumers, such as occurred during the Enron era abuses. It is FERC's duty to identify and mitigate market power to safeguard the public interest.

Under the MBR program, if a seller fails to pass certain preliminary indicative screens, FERC presumes that the seller possesses market power.[12] The seller can rebut this presumption by demonstrating the absence of market power through a more advanced method, the DPT. In the case of the Merger review program, FERC's market power analysis, including DPT, is employed to assess the potential impact of mergers and acquisitions on competition within the wholesale electricity market. FERC may approve such transactions if they are deemed "consistent with public interest."[13] However, if FERC finds that the merged or acquired entity could exert market power, it may require measures to counteract any anti-competitive effects, including divestitures, asset sales, or behavioral conditions.

To keep its regulations current, FERC has consistently issued orders aimed at fostering competition within wholesale electric markets. For instance, FERC mandated utilities to grant open access to their transmission lines, enabling generators to sell electricity nationwide.[14] FERC also established rules governing market pricing and dispatch, ensuring that wholesale electricity markets operate fairly

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11. FERC, WHAT FERC DOES, https://www.ferc.gov/what-ferc-does (last visited Mar. 3, 2024).

12. 119 FERC ¶ 61,295, at P 77.

13. Energy Policy Act of 2005, Pub. L. No. 109-58, § 1289, 119 Stat. 594, 982-3 (2005) (codified as amended 16 U.S.C. 824b (a)(4)).

14. Order No. 888-A, *Promoting Wholesale Competition Through Open Access Non-discriminatory Transmission Services by Public Utilities; Recovery of Stranded Costs by Public Utilities and Transmitting Utilities*, FERC STATS. & REGS. ¶ 61,220 (1997) (to be codified at 18 C.F.R. pt. 35).

and efficiently.[15] In recent years, FERC has implemented numerous enhancements to its regulations concerning affiliate and market power analysis.[16] These improvements streamline the process, reduce costs for sellers, and provide the Commission with the necessary data to protect consumers. This new guidance aids sellers in understanding the information required for their market power analyses and how to demonstrate a lack of market power.

Specific examples of recent improvements and new rules include:

In 2007, FERC issued Order No. 697,[17] introducing multiple improvements to the market power analysis process for sellers of electric energy, capacity, and ancillary services. These changes were designed to streamline the process, reduce costs for sellers, and equip FERC with the necessary information to safeguard consumers.

In 2019, FERC issued Order No. 860, which revamped the data collection process for MBR purposes. This order mandated all sellers holding MBR authorization to submit baseline filings to FERC's MBR relational database, streamlining the market power analysis process and simplifying the demonstration of the absence of market power.[18]

In 2021, FERC issued Order No. 881, introducing a new standard for transparency and transmission asset utilization. This order aimed to enhance the accuracy and transparency of transmission line ratings, ultimately promoting efficient power flow management, reducing congestion costs, and enhancing grid reliability.[19]

In 2023, FERC made a pivotal decision in *Evergy*, clarifying that the appointment of an investor's non-independent officer or director to the board of a public utility or public utility holding company constitutes a *per se* finding of control and affiliation.[20] These recent improvements and new rules related to affiliate and market power analysis have rendered FERC's regulations more efficient, effective, and equitable.

Notwithstanding these several regulatory changes, FERC has not updated its basic approach for market power analysis. Over 60% of the energy supply is derived from fossil sources such as crude oil, coal, and natural gas, and FERC's regulations have remained grounded in traditional fossil energy.[21] The heavy dependence on fossil fuels for electricity generation has led to growing concerns about climate degradation, resource depletion, energy security, and volatile fossil energy

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15. FERC, AN INTRODUCTORY GUIDE TO ELECTRICITY MARKETS REGULATED BY THE FEDERAL ENERGY REGULATORY COMMISSION, https://www.ferc.gov/introductory-guide-electricity-markets-regulated-federal-energy-regulatory-commission (last visited Mar. 3, 2024). This guide discusses the basics of wholesale electricity markets regulated by FERC and covers FERC's role in ensuring these markets operate fairly and efficiently.

16. *Evergy Kansas Central, Inc.*, 181 FERC ¶ 61,044 at PP 44-45 (2022).

17. FERC ¶ 61,295, at P 1 (2007).

18. *Data Collection for Analytics and Surveillance and Market-Based Rate Purposes*, 168 FERC ¶ 61,039 at PP 1-2 (2019).

19. *Managing Transmission Line Ratings*, 177 FERC ¶ 61,179 at PP 3-10 (2022).

20. 181 FERC ¶ 61,044, at PP 44-45.

21. *See generally* Angeliki N. Menegaki & Konstantinos P. Tsagarakis, *Rich enough to go renewable, but too early to leave fossil energy*?, 41 RENEWABLE & SUSTAINABLE ENERGY REVS. 1465, 1465-77 (2015).

prices. Motivated by these concerns, renewable (or clean) energy sources, including solar, wind, hydro, and biofuels, have gained unprecedented global attention as viable alternatives to fossil energy.[22]

In the United States, renewable energy has emerged as the fastest-growing energy source in recent years. In 2022, renewable energy accounted for 22% of total U.S. electricity generation, up from just 10% in 2000.[23] This growth has been propelled by various factors, including decreasing costs due to emerging renewable technology, increased government support, and rising public awareness of the environmental benefits of renewable energy. Over the past decade, the renewable sector has seen an annual growth rate of 5%, surpassing "the fossil fuel sector's growth rate of 1.7%."[24] To address the availability and reliability challenges associated with solar and wind energy, emerging technologies have played a pivotal role in reducing battery costs and expanded development of so-called "hybrid facilities," which combine multiple modes of electricity generation, often pairing renewable technologies like solar photovoltaics and wind turbines with storage systems or small fossil-fueled generators.[25]

In this evolving landscape, there is a dearth of studies that provide clear insights into when renewables will become the dominant energy source and when and in which regions of the nation the 50% renewable threshold will be exceeded. The attainment of the 50% renewable energy threshold signifies a pivotal transformation within the energy sector, bearing profound implications for the FERC's regulatory framework and its assessment of market power. This milestone, endorsed by both the administration [26] and the EIA[27], heralds several critical junctures. Primarily, the achievement of a 50% renewable energy mix marks the transition of renewable sources from a supplementary role to a predominant force in electricity generation. Such a shift fundamentally alters the dynamics of the market, potentially introducing new entities and redefining the hierarchy of established players. Furthermore, traditional FERC regulations, which are the focus of

22. *See generally* Imran Yousaf et al., *Green investments: A luxury good or a financial necessity?*, 105 ENERGY ECON. 105745 (2022).

23. See STATISTA, SHARE OF RENEWABLE SOURCES IN ELECTRICITY GENERATION IN THE U.S. 2000-2022 (Nov. 17, 2023), https://www.statista.com/statistics/183396/proportion-of-renewables-in-us-electricity-generation-since-2000/.

24. Jiahao Zhang et al., Does the connectedness among fossil energy returns matter for renewable energy stock returns? Fresh insights from the Cross-Quantilogram analysis, 88 INT'L REV. FIN. ANALYSIS 102659, 102659-60 (2023).

25. WIKIPEDIA, HYBRID POWER, https://en.wikipedia.org/wiki/Hybrid_power (last visited Mar. 4, 2024).

26. Nathan B. Galer et al., *BUY CLEAN: BIDEN'S EXECUTIVE ORDER ON CATALYZING CLEAN ENERGY THROUGH FEDERAL PROCUREMENT*, MAYER BROWN (Mar. 24, 2022), https://www.mayerbrown.com/en/insights/publications/2022/03/buy-clean-bidens-executive-order-on-catalyzing-clean-energy-through-federal-procurement ("In the Clean Energy EO, President Biden aims to align the federal government's energy procurement strategy with his administration's climate policy . . . . Purchase 50% carbon-free electricity on a 24/7 basis by 2030, with "24/7" meaning carbon-free electricity production that matches use "on an hourly basis and [is] produced within the same regional grid where energy is consumed."").

27. U.S. ENERGY INFO. ADMIN., EIA PROJECTS RENEWABLES SHARE OF U.S. ELECTRICITY GENERATION MIX WILL DOUBLE BY 2050 (Feb. 8, 2021), https://www.eia.gov/todayinenergy/detail.php?id=46676 ("By 2030, renewables will collectively surpass natural gas to be the predominant source of generation in the United States.").

subsequent sections, rely on metrics designed around fossil fuels, such as nameplate capacity and capacity factors. These measures may not accurately reflect the market influence of renewable energy entities, suggesting that surpassing the 50% renewable energy threshold necessitates a thorough reevaluation of FERC's regulatory approach and its mechanisms for analyzing market power.

Since the above reasons, answering 50% threshold questions holds profound implications for FERC's regulations, raising concerns about whether its existing regulations and market power analysis, grounded on metrics developed in an era when traditional fossil fuels were dominant, are suitable for an industry undergoing a transition toward renewable energy.

C. The DPT, a Core Analytical Tool for Market Power in FERC's regulations

As previously mentioned, the DPT is as a potent analytical tool within FERC's regulatory framework, crucial for identifying market power. FERC introduced the DPT in 1996 for section 203 filings in response to the "dramatic and continuing changes in the electric power industry."[28] This move aimed to ensure that future mergers align with the competitive objectives of the Energy Policy Act of 1992 (EPAct).[29] Subsequent developments in case law and policy statements have provided additional guidance but have not substantially altered the core DPT. On April 14, 2004, FERC took a significant step by incorporating indicative screens and the DPT into section 205 filings (MBR program).[30] Sellers who fail the indicative screens have the option to conduct the DPT.

In an attempt to consider the adoption of the Department of Justice's 2010 Horizontal Merger Guidelines (DOJ 2010 Guidelines),[31] FERC issued a Notice of Inquiry on March 17, 2011. On February 16, 2012, FERC decided against adopting the DOJ 2010 Guidelines, reaffirming its existing policies for horizontal market power analyses in both the merger and MBR contexts.[32] FERC noted that while its existing methodology might not perfectly capture market conditions in every scenario, the DPT remained a suitable method for identifying suppliers in a market. FERC further noted that it's a well-established test in the electric industry, flexible enough to consider fact-specific evidence of competitive harm.[33]

The DPT operates as a "hypothetical monopolist" model, striving to answer the question: "If a seller were to raise prices by a small but significant amount, typically around five percent, are there enough suppliers capable of supplying the

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28. Order No. 592, *Inquiry Concerning the Commission's Merger Policy Under the Federal Power Act: Policy Statement*, 61 Fed. Reg. 68,595 (1996); Merger Policy Statement, FERC STATS. & REGS. ¶ 31,044 at 30,110-111 (1996).

29. Merger Policy Statement, *supra* note 28, at ¶ 31,044.

30. *AEP Power Marketing, Inc.*, 107 FERC ¶ 61,018 at PP 1, 70 (2004), *order on reh'g,* 108 FERC ¶ 61,026 (2004).

31. Notice of Inquiry, *Analysis of Horizontal Market Power under the Federal Power Act*, FERC STATS. & REGS. ¶ 35,571, 76 Fed. Reg. 16,394, 16,394 (2011).

32. *Order Reaffirming Commission Policy and Terminating Proceeding*, 138 FERC ¶ 61,109 at P 34 (2012).

33. *Id.* at P 59.

study area to counter this hypothetical price increase?"[34] According to FERC, its primary function is to define the extent or size of the relevant geographic market by identifying potential suppliers, accounting for transmission availability and pricing, and evaluating the impact of a transaction on market concentration.[35]

The DPT is an economic model that combines generation costs and availability with a transmission model, usually referred to as the Simultaneous Transmission Import Limit study. This model estimates the available transmission capacity during seasonal peaks into a study area, often a balancing authority area. Various industry consultants use different application models, with the General Algebraic Modeling System being one of the most frequently employed software platforms. The General Algebraic Modeling System assists applicants in running the Competitive Analysis Screen model, aiding in the calculations required by Appendix A of FERC's Merger Policy Statement and Appendix F of the April 14 Order (Appendix F).

Within the General Algebraic Modeling System, the DPT algorithm analyzes each seller's available economic capacity (AEC) by minimizing the cost of each supplier at the destination market. This involves considering the supplier's generation portfolio, market price, transmission constraints, and native load obligations. The goal is to solve a linear programming model.[36]

FERC's guidance in Appendix F outlines the mechanics of the DPT, which involve the following five fundamental steps.

Step 1. Choosing a destination market and evaluating any market where the applicant does not pass the Pivotal Supplier or Market Share screen.

Step 2. Selecting the season and load level for analysis, typically including Super-Peak, Peak, and Off-Peak, for winter, shoulder and summer periods, and an extreme Summer Peak, for a total of ten season/load periods.

34. Gregory J. Werden, *The 1982 Merger Guidelines and The Ascent of The Hypothetical Monopolist Paradigm*, U.S. DEP'T OF JUSTICE (June 4, 2002), https://www.justice.gov/archives/atr/1982-merger-guidelines-and-ascent-hypothetical-monopolist-paradigm#:~:text=The%201982%20Merger%20Guidelines%20did,instrumental%20in%20its%20widespread%20adoption.

35. *See, e.g.,* Notice of Inquiry, *Analysis of Horizontal Market Power under the Federal Power Act*, FERC STATS. & REGS. ¶ 35,571 at P 2, 76 Fed. Reg. 16,394 (2011).

36. This linear programming model and equations are elaborated in Appendix I.

Table 1

SUMMER (June through August)	Super Peak 1 (S_SP1): Top 1 percent of peak load hours
	Super Peak 2 (S_SP2): Top 1-10 percent of peak load hours
	Peak (S_P): Remaining peak hours
	Off-peak (S_OP): All off-peak hours
WINTER (December through February)	Super Peak (W_SP): Top 10 percent of peak load hours
	Peak (W_P): Remaining peak hours
	Off-peak (W_OP): All off-peak hours
SHOULDER (September through November; March through May	Super Peak (SH_SP): Top 10 percent of peak load hours
	Peak (SH_P): Remaining peak hours
	Off-peak (SH_OP): All off-peak hours

Step 3. Determining the market price corresponding to each period, often using system lambda data as proxies.

Step 4. Identifying suppliers capable of selling into the destination market at a price within 5% of the market price, considering various factors, such as transmission availability and costs.

Step 5. Allocating transmission capacity, which is usually scarce, based on either an "economic" or "pro-rata" allocation method.

The DPT initiates its calculation based on nameplate capacity, calculates each supplier's economic capacity (EC) and available economic capacity (AEC), the remaining capacity after accounting for native load and contractual obligations in each season/load condition. This method has effectively served FERC in an environment where fossil fuels dominate. However, with the rise of renewable energy and advances in technology, the landscape is shifting. Renewable energy, coupled with enhanced battery storage capabilities, allows sellers to improve their market presence during peak periods. FERC, however, has not yet established updated standards specific to renewable energy resources.

Market power analysts within the MBR and merger programs now confront new challenges in assessing the presence and impact of renewable energy during critical periods. The key question currently facing regulators is whether this existing DPT methodology, designed for a fossil-fuel-dominant energy market, remains effective in an era where renewable energy supplies are poised to take the lead.

D. Forecasting Methods: Traditional Models and AI Models

Effective regulation revisions demand meticulous planning. Central to this process is the selection of a workable scientific method coupled with reliable forecasting upon which future regulations will be anchored. Renewable energy growth is expected to continue, spurred in part by the government's ambition to attain a net-zero emissions economy by 2050.[37] In pursuit of this objective, the administration has established a milestone to produce 50% of the nation's electricity from renewable sources by 2030.[38] Critical questions arise: is this goal feasible under current energy regulation and policy? Is there a need for supplementary policy or regulatory support? Addressing these inquiries requires a comprehensive quantitative analysis and accurate forecasting.

Forecasting, the process of predicting future events or trends based on historical data, is an invaluable tool for all organizations including federal regulatory agencies. Forecasting equips the regulatory bodies with the capability to make informed decisions. In the realm of forecasting, two primary methodologies hold sway: traditional models and AI models.[39] Traditional forecasting models, such as moving averages, exponential smoothing, and autoregressive integrated moving average models, leverage time series analysis to uncover patterns and trends within historical data. These patterns are then projected into the future to facilitate predictions.[40]

In the wake of recent advances in AI, LSTM models have emerged as some of the most robust and widely used in advanced AI modeling for time series forecasting. LSTM models belong to the category of recurrent neural networks, engineered to address long-term dependencies in sequential data. Stemming from their unique architecture, LSTM models are superior to conventional forecasting models such as autoregressive integrated moving average.

LSTM models are equipped with a distinct structure that includes three specialized gates: the input gate, forget gate, and output gate. These gates play a crucial role in managing the information flow within the network, making LSTMs particularly effective for tasks that require the understanding and retention of long-

37. WHITE HOUSE, FACT SHEET: PRESIDENT BIDEN SIGNS EXECUTIVE ORDER CATALYZING AMERICA'S CLEAN ENERGY ECONOMY THROUGH FEDERAL SUSTAINABILITY (Dec. 08, 2021), https://www.whitehouse.gov/briefing-room/statements-releases/2021/12/08/fact-sheet-president-biden-signs-executive-order-catalyzing-americas-clean-energy-economy-through-federal-sustainability/.

38. WHITE HOUSE, FACT SHEET: BIDEN-HARRIS ADMINISTRATION RACES TO DEPLOY CLEAN ENERGY THAT CREATES JOBS AND LOWERS COSTS (Jan. 12, 2022), https://www.whitehouse.gov/briefing-room/statements-releases/2022/01/12/fact-sheet-biden-harris-administration-races-to-deploy-clean-energy-that-creates-jobs-and-lowers-costs/.

39. Azzedine Boukerche et al., *Artificial Intelligence-based Vehicular Traffic Flow Prediction Methods for Supporting Intelligent Transportation Systems*, COMPUT. NETWORKS (Dec. 9, 2020), https://www.sciencedirect.com/science/article/pii/S1389128620311567?via%3Dihub.

40. FASTERCAPITAL, BRIEF OVERVIEW OF TRADITIONAL FORECASTING METHODS, https://fastercapital.com/topics/brief-overview-of-traditional-forecasting-methods.html (last visited Mar. 4, 2024).

term dependencies in data. The functionality of these gates is enhanced by the hyperbolic tangent (tanh) activation function, which helps in normalizing the values passing through the network, thereby preventing issues related to gradient vanishing or exploding.

LSTM models are like smart workers in an office who manage information. They have three "gates" or checkpoints: one for deciding what new information is important enough to keep, another for determining what old information to forget, and a third for deciding what information to use at the moment. These gates help the model remember and use important information from the past, which is great for tasks needing memory of previous events. The term "vanishing" refers to when details from the past start to fade away or get lost, which these gates help prevent by keeping the important stuff in focus.

The following illustrates how this works in electricity consumption. Imagine you are trying to predict how much electricity will be used in a city each day. You could look at the electricity usage over the past few days and guess based on that trend. This would be similar to what occurs under traditional forecasting models (such as under the autoregressive integrated moving average (ARIMA)). But suppose you have a method that can remember specific patterns from the past, like higher electricity usage on hot summer days due to air conditioning or lower usage during holidays when businesses are closed. That is essentially how LSTM models operate. LSTM models are advanced tools that excel in remembering important details over long periods and ignoring data points that are not relevant for purposes of the analysis. In effect, LSTM models provide a means of tracking significant electricity usage patterns and ignoring those deemed to be unhelpful for the desired analysis.

Since LSTM models feature three gates (input, forget, and output) for regulating the flow of information, all reinforced by the hyperbolic tangent (tanh) activation function, we can explain the three gates in the context of electricity usage prediction:

Input Gate: This is like a decision-maker who chooses which new information (like a sudden spike in electricity usage) is important enough to remember.

Forget Gate: This acts like a filter, removing outdated or irrelevant data (like old patterns of electricity usage that no longer apply).

Output Gate: This gate decides what information from the past and present should be used to predict the electricity usage for the next day.

The "hyperbolic tangent (tanh) activation function" works to keep these gates operating effectively. Think of it as a rule that operates so that the information utilized in the model remains balanced and useful.

In simpler terms, LSTM models are like having a highly efficient analysis system that remembers the right patterns and uses those insights to make better predictions about daily electricity usage, rather than just relying on recent trends (See APPENDIX II for a description of the process). Additionally, these models include two states, the cell state (long-term memory) and the hidden state (short-term memory), to efficiently grasp and exploit temporal dependencies in the data.[41]

LSTM models have demonstrated their superiority over traditional forecasting models in several key aspects:

- Ability to learn long-term dependencies: LSTM models are adept at identifying and capitalizing on long-term dependencies in the data, a significant advantage in forecasting future trends. Traditional forecasting models are often constrained to short-term predictions. "Dependencies" in this context means the relationships or connections between pieces of information across time.
- Resilience to noise and outliers: LSTM models exhibit greater robustness in the face of noisy data and outliers as compared to traditional forecasting models. This robustness is especially valuable when dealing with real-world data, which frequently contains noise and unexpected data points. In this context, "noise" refers to random or irrelevant information in the data that doesn't contribute to understanding the underlying patterns we are trying to analyze.

Versatility: LSTM models can be applied to forecast a wide spectrum of time-series data, including data marked by seasonal patterns and other non-stationary characteristics. Time-series data refers to information collected over time, where the sequence and timing of data points are crucial. Traditional forecasting models typically possess a narrower scope of applicability. In layman terms, LSTM models are like versatile tools for making predictions based on data collected over time, including data with repeating patterns like holiday sales spikes or changes that don't follow a set pattern. They are much more adaptable to different kinds of data changes than older prediction methods, making them useful for a broader range of forecasting tasks.

LSTM models are exceptionally well-suited for forecasting renewable energy shares. These models excel in uncovering long-term dependencies within data, a critical feature for forecasting renewable energy proportions in electricity generation, which are influenced by an array of factors subject to change over time, including technological advancements, government policies, and environmental regulations. LSTM models are also adept at handling noisy data and outliers, a key consideration for forecasting renewable energy shares, given the data's susceptibility to noise stemming from factors such as weather conditions and unexpected events.

Moreover, given that LSTM models require a significant volume of historical data for effective training, and access to such extensive data sets enhances the accuracy of forecasts, the abundance of national data spanning over twenty years, coupled with over ten years of regional data as well as thirty-four-year monthly

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41. Sima Siami-Namini et al., *A Comparison of ARIMA and LSTM in Forecasting Time Series*, 17 IEEE INT'L CONF. ON MACH. LEARNING & APPLICATIONS 1394, 1396-97 (Dec. 2018), https://ieeexplore.ieee.org/document/8614252 (explaining that in an LSTM model, the terms "cell state" and "hidden state" are used to describe two different ways the model remembers information, which helps it understand and use patterns in data over time).

sectional data, is a substantial asset. Our literature review further reinforces the potential benefits in using LSTM models. Studies conducted by several universities have demonstrated the superiority of LSTM models over traditional forecasting models for forecasting renewable energy shares and solar and wind power generation.[42]

E. Agent-Based Modeling (ABM) Simulation

With the recent advancements in emerging technology, computer models have gained prominence. Model simulations serve as invaluable tools for policy makers, regulators, and other stakeholders to understand complex systems and relationships and make informed decisions. A notable strength of simulation studies lies in their capacity to unveil the behavior of statistical methods, leveraging known "truths" from data generation processes, shedding light on methodological properties, such as bias.[43] Furthermore, conducting virtual experiments through simulation models is cost-effective and less time-consuming than real-world trials.

In recent years, ABM, a computer simulation model, has surged in popularity due to its ability to simulate complex systems. ABM involves individual agents with distinct rules and behaviors, fostering interactions within their environment, thereby generating emergent patterns at the system level. An "agent" is like a character in a video game. Each agent has its own set of rules and ways of behaving, which lets them interact with other agents and their surroundings. When all these agents act together, they create complex patterns or outcomes, similar to how individuals in a community contribute to the overall behavior of the group. Simultaneously, significant advancements in software testing have revolutionized complex system analysis by automating the discovery of security vulnerabilities.[44] We have summarized the most popular theoretical framework used in ABM in APPENDIX III.

One of the advantages of ABM is its ability to model the behavior of individual agents and their interactions in a dynamic way, capturing the complexity of real-world systems. This makes ABM a powerful tool for analyzing systems in which individual behavior is critical to the system's overall behavior. By modeling individual behavior and interactions, ABM can be used to study emergent properties of systems, such as pattern formation and cooperation. Additionally,

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42. Md. Iftekharul Alam Efat et al., *Deep-learning model using hybrid adaptive trend estimated series for modelling and forecasting sales*, ANNALS OF OPERATION RSCH. (July 1, 2022), https://link.springer.com/article/10.1007/s10479-022-04838-6#citeas; Janice Klaiber & Clemens Van Dinther, *Deep Learning for Variable Renewable Energy: A Systematic Review*, 56 ACM COMPUTING SURVS. 7-13 (Aug. 2023), https://doi.org/10.1145/3586006; Juan M. Lujano-Rojas et al., *Searching for Promisingly Trained Artificial Neural Networks*, 5 FORECASTING (Sept. 4, 2023), https://doi.org/10.3390/forecast5030031.

43. Tim P. Morris et al., *Using simulation studies to evaluate statistical methods*, STATS. IN MED. 2074 (Nov. 2, 2018), https://onlinelibrary.wiley.com/doi/full/10.1002/sim.8086.

44. Steven Manson et al., *Methodological Issues of Spatial Agent-Based Models*, J. OF ARTIFICIAL SOC'Y & SOC. SIMULATION (Jan. 31, 2020), https://www.jasss.org/23/1/3.html.

ABM's flexibility helps model designers and users manage the challenges that complexity poses for researchers and policymakers.[45]

A typical ABM has three elements: a set of agents with attributes and behaviors; the agents' environment, including who they interact with, how the consequences of those interactions are determined, and their resources, objects, and obstacles; and rules governing the agents' incentives, whether they can change their initial features based on the consequences of their neighbors' and their own previous actions, and other factors.[46]

To simulate agent behavior, modelers run the simulation in a sequence of discrete time steps, where each step represents the smallest unit of progress in the simulation. In each time step, the states of the agents and their neighborhoods are updated according to the specified rules. ABMs can model complex behaviors by simulating each agent separately. A problem that is difficult to describe at the group level can often be described individually at the level of the participating entities. With the help of a simulation, we can then model the group's behavior.[47]

Researchers have applied ABM to a wide range of topics in sociology, physics, and other fields to study complex social systems. For example, ABM has been used to study epidemiology, infectious diseases, climate change, social network formation, financial markets, firms, and consumer behavior.[48] In the energy sector, ABM has been applied to assess the economic impact of feed-in tariff policies promoting renewable energy investments.[49]

Despite its widespread use in other fields, ABM is nearly absent from legal literature. Only a few ABM models in the field have general relevance to theories about the need for and effects of regulation.[50] In fact, quantitative legal scholarship is currently dominated by the Law and Economics (L&E) approach, which relies on a more limited modeling framework, not simulation.

Our analysis of ABM suggests its possible application to regulation. ABM can be used to model the interactions between regulated agents. This is important

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45. Ross A. Hammond, *Considerations and best practices in agent-based modeling to inform policy*, NAT'L LIB. OF MED. (July 17, 2015), https://www.ncbi.nlm.nih.gov/books/NBK305917/.

46. Manson, *supra* note 44, at 2.

47. Christian Graf, *Overcoming Complexity with Agent-Based Models*, MEDIUM (Jan. 11, 2021), https://towardsdatascience.com/overcoming-complexity-with-agent-based-models5c4cca37cc61.

48. Stephen Eubank et al., *Modelling disease outbreaks in realistic urban social networks*, GALE ACAD. ONEFILE (May 13, 2004), https://go.gale.com/ps/i.do?id=GALE%7CA186370768&sid=googleScholar&v=2.1&it=r&linkaccess=abs&issn=00280836&p=AONE&sw=w&userGroupName=anon%7E8e734fe6&aty=open-web-entry; *see also* J. Doyne Farmer, *A simple model for the nonequilibrium dynamics and evolution of a financial market. International Journal of Theoretical and Applied Finance*, WORLD SCIENTIFIC (2000), https://www.worldscientific.com/doi/abs/10.1142/S0219024900000346.

49. Linda Ponta et al., *An agent-based Stock-Flow Consistent Model of the Sustainable Transition in the Energy Sector*, ECOLOGICAL ECON. (Mar. 2018), https://www.sciencedirect.com/science/article/abs/pii/S0921800916310138.

50. Sebastian Benthall & Katherine Strandburg, *Agent-Based Modeling as a Legal Theory Tool*, FRONTIERS (June 21, 2021), https://www.frontiersin.org/articles/10.3389/fphy.2021.666386/full.

because the behavior of one regulated agent can affect the behavior of other regulated agents. For example, if one regulated agent cheats and gets away with it, other regulated agents may be more likely to cheat as well.

In the context of an electricity wholesale market, "regulated agents" would refer to power sellers or electricity generating companies who must adhere to specific rules and guidelines set by a regulatory authority, such as FERC. For instance, consider various power sellers in an electricity wholesale market. These sellers are required to follow FERC regulations on how they conduct trades, adhere to behavior rules, and report their trade data to FERC. These regulations might include guidelines on fair pricing, ensuring reliability of supply, and transparency in their transactions.

If one power seller discovers a way to violate these rules without getting caught – for example, by manipulating market prices or not reporting certain transactions accurately – and if FERC does not penalize this seller, other power sellers in the market might notice this and consider engaging in similar behavior. This could lead to a broader issue of non-compliance within the market, affecting the overall integrity and efficiency of the electricity supply.

In this scenario, using ABM can be extremely valuable. ABM can simulate the interactions and decision-making processes of these regulated agents (the power sellers) within the confines of the regulatory framework set by FERC. By doing so, ABM can help in understanding how the actions of one power seller might influence the behavior of others, which is essential for maintaining a fair and efficient electricity market. To simulate the agents that aren't getting "caught" by the regulator, such as power sellers in the electricity market, without direct observational data on their illicit activities, one would rely on a combination of theoretical models, historical data, and observed patterns of market behavior. This approach involves constructing detailed simulations based on how agents are expected to behave within the regulatory framework and market conditions. By integrating these components, ABM allows for the construction of complex simulations that can mimic the decision-making processes and interactions of agents within the market. This methodology enables the exploration of potential outcomes and dynamics that may not be directly observable, providing regulators and policymakers with insights into how to effectively oversee and manage the market to ensure fairness and efficiency.

ABM is a relatively new tool in the field of regulation, but it has the potential to be used for a variety of tasks, including designing new regulatory policies, assessing the effectiveness of existing regulatory policies, studying the effects of different regulatory policies on different groups of people, and identifying potential unintended consequences of regulatory policies. ABM can help policymakers and regulators better understand the complex interactions between regulated agents and the potential consequences of different regulatory policies.

II. Analysis

A. Renewables Energy Forecasting: LSTM Model, Data, and Results

The background section has revealed that LSTM models offer advantages over traditional statistical models when it comes to forecasting. LSTM models exhibit the potential to enhance forecast accuracy, particularly in large datasets or for use in longer forecasting horizons.

Our LSTM discussed in this Article is designed to process sequential data, effectively capturing long-term dependencies.[51] Each LSTM cell receives inputs from both the current timestep and the previous timestep, including the input vector and the cell's hidden and cell states. This design allows our LSTM to retain and learn from the sequence of data, making it particularly adept at handling our tasks where the order and context of data points are crucial.

In this study, we explore the use of LSTM models for renewable energy forecasting. The core functionality of our LSTM lies in its unique structure of gates: the forget gate, input gate, and output gate. These gates regulate the flow of information, with the forget gate determining what to discard from the cell state, the input gate updating the cell state with new information, and the output gate deciding the next hidden state. This gated mechanism enables the LSTM to maintain relevant information over long sequences while discarding the irrelevant, enhancing its ability to learn from complex data sequences (more technical information is included in APPENDIX IV).

As previously discussed, LSTM models belong to the recurrent neural networks category. They were introduced as a solution to overcome the "vanishing gradient" problem commonly found in traditional recurrent neural networks. The 'vanishing gradient' problem is a tricky hurdle we come across when teaching certain kinds of neural networks. These networks are like complex systems used in machine learning where data moves through many layers of processing. In each layer, the network learns to recognize more and more complex features by fine-tuning its internal settings, a process we call "training." This is illustrated by the following.

Think of these settings as being adjusted based on a kind of feedback that tells the network how accurate its guesses are. This feedback acts like a guiding light, traveling back through the network and tweaking the settings at each layer. However, in the vanishing gradient problem, as this feedback moves back through numerous layers of the network, the feedback will diminish, similar to the way a whisper will become quieter and fade as it travels down a long corridor. Guiding feedback can likewise become too faint by the time it reaches early network layers, affecting these layers' ability to adjust properly. When this occurs, the network does not learn as effectively, particularly for patterns in the data that are related to earlier parts of the sequence.

To solve this problem, LSTM models were created. LSTM models are effectively a "smarter" system that keeps the feedback strong, even for long sequences of data. These models do this through a unique memory system that operates like a special notebook that is used to keep track of important things over time. As with such a notebook, the LSTM has various tools (gates) that help de-

51. "Effectively capturing long-term dependencies" refers to the LSTM's ability to remember and use information from both the recent and more distant past. In our plant example, this would be like remembering how much sunlight the plant got weeks ago, not just yesterday, and understanding how those factors a few weeks back are affecting its growth today.

cide what to remember and what to forget. With LSTMs, the network can remember important things for a long time, which helps it learn better, especially for patterns in the data that rely on understanding things from early in the sequence that would otherwise be lost.

We have built our LSTM model and developed codes for forecasting based on the above principles. The key components of an LSTM cell in our model, and steps for creating and executing the model, as well as results of AI metric measurements for a solar capacity forecasting and renewables share forecasting are summarized in Parts 1-3, Appendix IV.

Monthly data for U.S. solar capacities were sourced from the Information Administration (EIA)'s Table 10.6, titled "Solar electricity net generation," available in Total Energy Monthly Data - U.S. Energy Information Administration). This data spans from January 1989 to December 2022, incorporating a total of 396 observations. Our findings suggest a sustained growth in solar capacity throughout the forecast period. Figure 4 displays forecasted values, representing solar capacity predictions for future time periods based on our trained model. The upward trend in these values indicates an anticipated expansion of solar capacity in the future. However, as the forecast progresses, the growth rate appears to stabilize. This is evident from the relatively smaller differences between consecutive forecasted values in later periods compared to earlier ones. This stabilization implies that the rate of growth is likely to become more consistent and gradual, with reduced fluctuations in the future.

According to our LSTM forecasting models, solar power is projected to maintain a high growth rate, with an estimated increase from 0.258 billion kWh in January 2011 to 24.796 billion Kilowatt-hours (kWh) in July 2024, signifying a ninety-six-fold increase. Our final forecasted values derived from our forecasting model are presented in Figure 1.

Figure 1. Actual and Predicted Values for Solar Capacity Growth

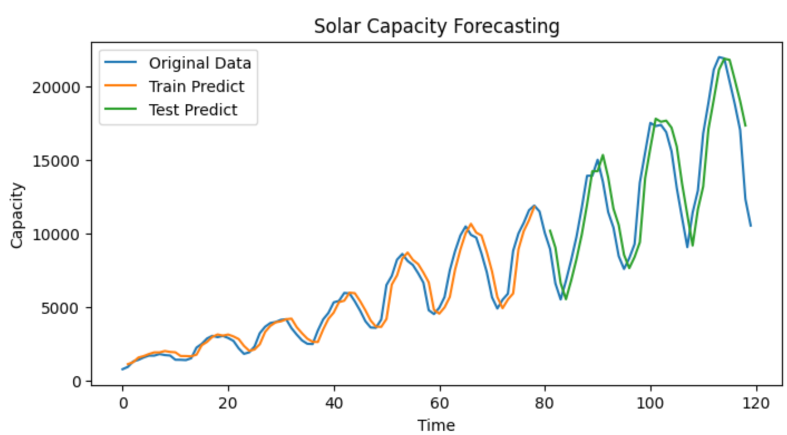

Figure 1: The model's predictions closely align with actual values for solar capacity growth.

Our LSTM forecasting model effectively uses past data and AI analysis to forecast solar capacity growth, closely matching actual figures. This suggests it not only projects trends forward but does so with a high degree of precision, supported by advanced data processing capabilities of AI.

Subsequently, we conducted renewables share forecasting. We sourced SPP and California regional, as well as U.S. national annual data from the EIA's Table 7d, titled "U.S. Regional Electricity Generation, Electric Power Sector," spanning from 2000 to 2022. For each item, we incorporated twenty-three observations in the model.

Our final forecasted values for renewable shares in electricity generation in California, SPP and USA derived from our forecasting model are presented in Figure 2.

Figure 2. The Future of Renewables: Forecasts for the Two Fastest Growing Regions and the Nation

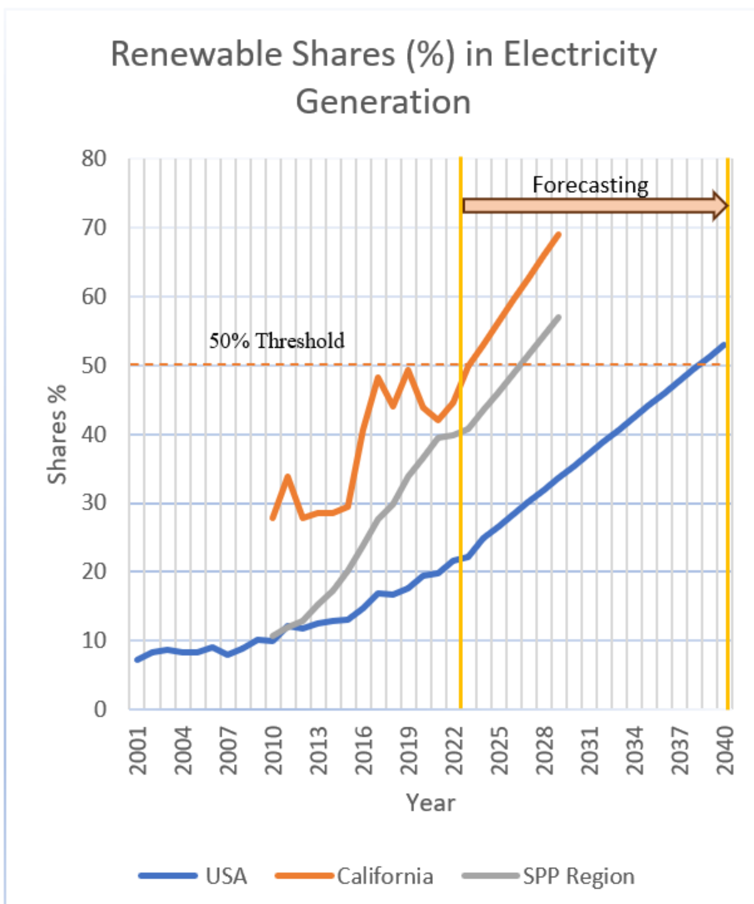

Figure 2: The model projects a robust continued increase in renewable shares, with the U.S. expected to surpass 50% by 2038, and even sooner in California and SPP regions.

The LSTM results, depicted in Figure 2, illustrate that renewable shares are projected to continue growing throughout the forecast period. The forecasted values exhibit an upward trend, signifying an ongoing increase in solar capacity. Nevertheless, the growth rate appears to stabilize as the forecasting progresses, with smaller variations between consecutive forecasted values in later periods compared to earlier ones. This stabilization implies that the rate of growth is likely to become more consistent and gradual in the future, with reduced fluctuations.

Our findings from the LSTM forecasting models indicate that renewable shares will continue to experience robust growth. We forecast the U.S. to surpass a 50% share in 2038 with California and the SPP region reaching this milestone as early as 2025 and 2026, respectively.

It is important to clarify that our LSTM model does not operate as a "crystal ball" forecasting tool. Instead, it's a scientifically sound AI model grounded in rigorous data analysis and advanced algorithmic design. By utilizing vast datasets and leveraging the latest advancements in machine learning, the model systematically analyzes patterns and trends in renewable energy generation and market movements. It's based on the principle that, while all models operate under certain assumptions and none can predict the future with absolute certainty, they can provide invaluable insights and guidance. Our LSTM model embodies this philosophy by offering a sophisticated yet practical tool for forecasting, grounded in the best available information and data. It represents the pinnacle of current scientific understanding and computational capabilities in the field of AI and renewable energy forecasting. As famously stated by statistician George Box, "All models are wrong, but some are useful." Our model falls into the category of being exceptionally useful, providing a solid foundation for making informed decisions and strategies in the renewable energy sector. It's a testament to the power of combining scientific knowledge with advanced technology to navigate the complexities of future energy trends.

B. DPT Case Study

As highlighted in the background section, the DPT is frequently employed in the MBR program and electricity energy merger cases. FERC allows the use of seasonal capacity factors to derate sellers' nameplate capacity in the DPT for market power analysis. For renewable resources like hydro and wind capacity, FERC's de-rate standard allows the use of capacity factors, permitting these resources to conduct an analysis based on historical capacity factors, including a five-year average capacity factor, along with a sensitivity test using the lowest capacity factor from the previous five years.[52] For new units lacking a history of

52. *Market-Based Rates for Wholesale Sales of Electric Energy, Capacity and Ancillary Services by Public Utilities*, 119 FERC 61,295 at P 344 (2007).

actual output, sellers can submit estimated capacity factors.[53] FERC reasons that using seasonal capacity ratings provides a more accurate reflection of seasonal real power capability, aligning with industry standards.[54]

In this section, we aim to address three important questions:

1. How will emerging technology impact capacity factors in electricity generation?

2. Could the flexibility provided by battery storage create opportunities for renewable companies to strategically adjust capacity factors and enhance market shares during peak demand times?

3. Will the growth of renewable energy challenge existing electricity regulations?

Recent developments, specifically the integration of renewables with battery storage technology, have transformed the energy landscape, offering new possibilities for electricity energy sellers to strategically modify capacity factors and increase their market influence. These changes have brought about several positive effects on the industry, such as enhanced flexibility, improved grid stability, and increased integration of renewable energy. These advancements enable energy sellers to adapt to the evolving energy landscape and capitalize on emerging market opportunities.[55] As the share of renewables in the energy mix increases, battery storage technology plays a crucial role in maintaining grid stability. Batteries act as a buffer for the grid, storing excess energy generated during peak production times from renewable sources like solar and wind, which can then be released during periods of high demand or low production. This not only ensures a consistent and reliable energy supply but also mitigates the variability and unpredictability associated with renewable energy sources. By smoothing out the fluctuations in energy production, batteries contribute significantly to the stability of the power grid, enabling a higher penetration of renewable energy sources and supporting the transition towards a more sustainable and resilient energy system.[56]

However, these developments have also raised concerns about market power in electric generation and the need for regulatory updates. Notably, new battery storage technologies allow power sellers to store excess electricity generated during periods of high production and discharge it during low generation or peak demand, when market power issues often arise. This technology provides opportunities for electricity sellers to strategically adjust capacity factors and enhance their market power during peak periods.[57]

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53. 107 FERC ¶ 61,018, at P 126; 108 FERC ¶ 61,026, at P 126.

54. 107 FERC ¶ 61,018, at P 126; 108 FERC ¶ 61,026, at P 129.

55. John E. Bistline, *Economic and Technical Challenges of Flexible Operations under Large-Scale Variable Renewable Deployment*, 64 ENERGY ECON. (2017), http://dx.doi.org/10.1016/j.eneco.2017.04.012.

56. ENERGY5, THE ROLE OF OFF-GRID BATTERY STORAGE IN ENSURING GRID STABILITY (Mar. 1, 2024), https://energy5.com/the-role-of-off-grid-battery-storage-in-ensuring-grid-stability.

57. H. Achour & A.G. Olabi, *Driving cycle developments and their impacts on energy consumption of transportation*, 112 J. OF CLEANER PROD. (2016), http://dx.doi.org/10.1016/j.jclepro.2015.08.007.

To demonstrate the transformative effects of recent advancements in renewable energy and battery storage, consider a renewable energy facility with a nameplate capacity of 100 megawatts (MW). Using traditional seasonal capacity factors under the DPT analysis, this facility's estimated capacity at peak times is around thirty-six MW.[58] This is a standard calculation based on current derating methods.

However, this scenario changes dramatically with the introduction of a fully charged battery system. With this addition, the facility's output capacity can surge to 115 MW during peak times, a figure that significantly exceeds the traditional thirty-six MW estimate. This 115 MW "boosted" output, made possible by the integration of battery storage, is what we call the Max Available Economic Capacity (MAEC).

To put this into perspective, the MAEC of 115 MW is 115% of the facility's nameplate capacity, a metric we term the Max Available Rate (MAR). This substantial increase in output capacity -- from the standard thirty-six MW to 115 MW -- illustrates the profound impact that modern battery storage technology can have on discrete renewable energy facilities, enhancing their capability to meet peak demand and altering their role and influence in the energy market.

Public information available through FERC filings indicates that the market power analysis, especially in the DPT, is becoming more complex with the growth of renewable energy and the flexibility of capacity factors. FERC is grappling with new challenges in analyzing the presence of renewable energy during key periods. The following hypothetical case based on actual FERC filings demonstrates how MAEC affects FERC's DPT analysis results.

X Electric Utility Power Company (Seller) filed indicative screens and DPT in its initial MBR authority application showing its new renewables facility with a 200 MW nameplate capacity in its small balancing authority area in the Northwest region. Its horizontal market power analysis, using calculated seasonal capacity factor consistent with FERC's existing method, suggests that while Seller doesn't pass the indicative screens, it passes the DPT with a market share just below the acceptable level of 20%.[59] Consequently, the seller concludes that it lacks horizontal market power in its balancing authority area and qualifies for MBR authority.

Given the inherent limitations in using seasonal capacity factors in a DPT analysis, particularly concerning hybrid facilities, we conduct a deeper evaluation to determine whether Seller is understating its capacity factors and the subsequent impact on market shares. Here is our analysis:

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58. Since FERC has not set updated standards in the DPT specifically for renewable energy resources, all sellers use availability/capacity factors based on the NERC Generating Availability Data System (GADS) to calculate the "average equivalent availability factor." which was routinely accepted by FERC in current fossil dominant environment under FERC regulations.

59. Here, we assume 20 percent is the only threshold for the analysis. Although FERC uses an on-balance approach to weigh all relevant factors, the market share threshold has the most important weight. *See* FERC, HORIZONTAL MARKET POWER (Feb. 18, 2022), https://www.ferc.gov/horizontal-market-power.

Seller X operates a renewable facility with a nameplate capacity of 200 MW. During Summer Super-Peak 1, Seller's delivery cost is $23 per MWh, and market prices are $200 per MWh. The seller's native load obligation is 43 MWs. Following FERC's current method, Seller X can derate 55% of its capacity during Summer Super-Peak 1, resulting in an economic capacity of 110 MW. After deducting the native load obligation, the AEC is 67 MWs, leading to a market share of 19%. However, if Seller X adopts the Max Availability Rates we propose, the results differ as shown in the following table.

Table 2. Seller X with Renewables Facility

		Market Share Comparison between Available Economic Capacity and Available Max Economic Capacity (MW)									
Supplier		**S_SP1**	**S_SP2**	**S_P**	**S_OP**	**W_SP**	**W_P**	**W_OP**	**SH_SP**	**SH_P**	**SH_OP**
EIA Total Capacity (MW)	(1)	200	200	200	200	200	200	200	200	200	200
FERC Current Availability Rates for Renewables (%)	(2)	55%	45%	36%	23%	30%	23%	5%	40%	30%	15%
Max Availability Rates for this Facility (%)	(3)	115%	100%	90%	33%	105%	35%	10%	20%	15%	5%
Delivery Cost ($/MWh)	(4)	23	23	23	23	21	21	23	20	20	25
Market Price ($/MWh)	(5)	200	130	38	31	29	24	22	38	28	26
Seller's Economic Capacity (EC)	(6) = (1)*(2)	110	90	72	46	60	46	10	80	60	30
Seller's Max Economic Capacity (MEC)	(7)	230	200	180	66	210	70	0	40	30	10
Load Obligation (MW	(8)	43	42	36	32	38	35	33	33	29	10
Seller's Available Economic Capacity (AEC)	(9) = (6)-(8)	67	48	36	14	22	11	-23	47	31	20
Seller's Max Available Economic Capacity (AMEC)	(10) = (1)*(3)	230	200	180	66	210	70	20	40	30	10
AEC Market Size	(11)	350	350	350	350	350	350	350	350	350	350
AMEC Market Size	(12)	500	500	500	500	500	500	500	500	500	500
AEC Market [60]Share (%)	(13)	19%	14%	10%	4%	6%	3%	0%	13%	9%	6%

60. 119 FERC ¶ 61,295, at P 112. Here, we use AEC not EC for our demonstration because the Commission explained in Order No. 697: "[I]n markets where utilities retain significant native load obligations, an analysis of available economic capacity may more accurately assess an individual seller's competitiveness, as well

	= (9)/(11)										
AMEC Market Share (%)	(14) = (10/(12)	46%	40%	36%	13%	42%	14%	4%	8%	6%	2%

Table 2 above vividly illustrates how emerging technologies empower energy sellers to increase their market share without breaching threshold of 20%. Under the AEC measure, Company X maintains market shares consistently below 20%. However, when employing the Max Available Economic Capacity (MAEC) measure, market shares exceed 20% in four specific season/load periods: Summer Super-Peak 1 (46%), Summer Super-Peak 2 (40%), Summer Super-Peak (36%), and Winter Super-Peak (42%).

This case demonstrates that the existing methods may not accurately represent the available energy in the market, allowing sellers to strategically adjust capacity factors and gain market power. The capacity to store and discharge electricity during peak periods provides energy sellers with enhanced market power, potentially enabling them to influence electricity prices and manipulate market conditions. Further, by withholding electricity supply during peak periods or releasing stored energy when prices peak, sellers with substantial battery storage capacity could exert market power and manipulate prices to their advantage.[61]

We recommend that as renewables increase towards becoming 50% of the energy mix, regulations should undergo systematic revision.[62] Regulations that determine market share based on nameplate capacity may no longer be suitable for renewable energy companies with significant intermittent generation capacity. As renewable energy's share in the grid expands, energy regulations must evolve to mirror the distinct characteristics of these sources. We emphasize the importance of adapting regulatory frameworks to evolving energy landscapes. Consequently, we advocate for a reevaluation of regulations to ensure alignment with the ongoing energy transition and the promotion of a level playing field for all energy sources.

We recognize that the specific 50% threshold for renewable energy penetration discussed above may vary depending on the region or market context.[63] The determination of the precise trigger point for regulatory revision should be based on a comprehensive evaluation, considering factors such as grid stability, technological advancements, and market dynamics. We believe it is reasonable at this

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as the overall competitiveness of a market, because available economic capacity recognizes the native load obligations of the sellers."

61. Tomaso Duso et al., *Abuse of Dominance and Antitrust Enforcement in the German Electricity Market*, 92 ENERGY ECON. 2-6 (2020), https://doi.org/10.1016/j.eneco.2020.104936.

62. *See* 18 CFR § 35.37 (2024). Regulations in this context encompass all FERC regulations related to measuring and mitigating market power within market-based rate programs and merger programs. This includes, but is not limited to, market power screen requirements, mitigation enforcement following a Delivered Price Test (DPT) failure, and regulations for Regional Transmission Organization (RTO) / Independent System Operator (ISO) market tariffs. Additionally, it covers aspects of market monitoring, supervision, and mitigation rules.

63. *See supra* Figure 2. As we forecasted on the last section, some regions such as Northwest, California and SPP reached and will reach threshold of 50 percent before the nation as a whole.

juncture for FERC to require sellers with substantial renewable hybrid facilities to conduct a sensitivity study using MAEC during this transition period or in regions where renewables have surpassed the national average. Simultaneously, FERC should proactively prepare for revisions in market power analysis as the threshold of 50% renewable energy penetration in the nation approaches, as indicated by our forecasting.

At the conclusion of this section, our case underscores the challenges encountered by FERC's market power analysts, affirmatively addressing the three questions posed at the beginning of this section**.**

C. ABM Simulation: Implications for Evolving Regulations and Customer Protection

In this section, we strive to measure or simulate the challenges to FERC's regulations using ABM simulation, which can be considered a deployment of artificial intelligence (AI), especially in the way AI mimics and predicts complex systems and behaviors. As mentioned before, we can think of an agent-based model as a virtual world, where each "agent" is like a character in a video game. These agents can represent anything -- people, animals, cars, power sellers, or regulators, etc. Each agent follows a set of rules or behaviors, which can be simple or complex. These agents present "intelligence" because they interact and make decisions. They can learn from their environment, react to changes, and even adapt their behavior over time. This is where the new AI techniques can be utilized.

AI techniques, like learning algorithms, can be used to make these agents smarter, allowing them to behave in ways that are more realistic or to discover patterns and solutions that might not have been programmed directly. In our ABM simulation, AI serves as the "brain" behind these agents, helping them to navigate and interact in their virtual world in a way that mimics real-life complexity and unpredictability. Our goal is to create an environment where renewables, enhanced by new technologies, steadily approach a dominant position and examine the impact this has on the regulatory landscape.

ABM, especially in its modern form integrated with artificial intelligence (AI), is a relatively new and powerful tool for understanding complex systems, such as energy markets. The novelty of ABM lies in its ability to simulate the interactions of multiple agents, each with their own set of behaviors and decision-making processes, in a dynamic environment. When combined with AI, this tool becomes even more potent, enabling the detection and analysis of intricate patterns and outcomes that might not be apparent through traditional methods.

In the context of the energy market, AI-enhanced ABM can be particularly insightful in understanding the implications of new technologies like battery storage. For instance, AI can analyze how the introduction of battery storage technology allows power sellers to store excess electricity during periods of high production. More importantly, AI can predict the impacts of releasing this stored power during periods of low generation or high demand. This is crucial for identifying when and how market power issues might arise, as these are the times when the ability to control supply can have the most significant impact on the market.

Furthermore, AI can uncover how battery technology provides opportunities for electricity sellers to strategically adjust their capacity factors. This means they can increase or decrease their electricity production based on market need and their own storage capabilities, potentially enhancing their market power during peak periods. By simulating these scenarios, AI-driven ABM provides valuable insights into how these technologies can be used, potentially manipulated, and regulated to ensure fair and efficient market operations. This capability marks a significant advancement in our ability to understand and manage complex market dynamics in the era of rapidly evolving energy technologies. In the section below, we present our ABM model's architecture.

1. Model Setting

The simulation takes place in a virtual electric wholesale market system for the simulation (see APPENDIX V). In this dynamic environment, we introduce resources, objects, and obstacles for three distinct agents: electricity regulators, New-Techs (NT) power sellers with increasing market power, and traditional power sellers who have the potential to transition to NT power sellers. These agents interact, move, and adapt based on a set of predefined rules, including incentives for movement, the capacity for agents to modify their initial characteristics (e.g., shifting from traditional power sellers to NT power sellers), and the influence of neighbors and past actions.

a. Agent Goals

Each agent operates with its own objectives: power sellers, whether traditional or NS, aim to maximize profits or minimize costs, while electricity regulators seek to safeguard the interests of customers and maintain the integrity of the market. Consequently, the behavior of power sellers is driven by economic incentives, considering costs and benefits, while electricity regulators prioritize public interests, ensuring just and reasonable prices.

b. Initial Conditions and Economic Effects

At the outset, most power sellers were traditional power sellers, and NT power sellers represent a relatively small portion of the market. Anticipating further cost reductions in battery storage due to technological advancements and increased government incentives and penalties for environmental pollution, we assume that economic incentives, --minimize costs, maximize profits, and avoid penalties -- will gradually influence the behavior of power sellers, prompting some traditional power sellers to transition to NT power sellers.

c. Agent Interaction and Neighborhood Effects

Within the model setting, the behavior of power seller agents is first guided by their own economic interests but then influenced by other power seller agents in the same market. Agents establish connections with all immediate neighbors and generate a surplus if they are NT power sellers. This surplus enhances the resources of both theirs and their neighbors.

2. ABM Simulation

From the simulation, we observe a growing number of NT power sellers and a diminishing number of traditional power sellers with each iteration. Over time, traditional power sellers are mostly replaced by NT power sellers.

a. Control Variables

Several control variables are incorporated into the simulation, including the acceleration of new technology adoption, increased subsidies for renewables, adjustments in the cost of environmental pollution penalties, modifications to FERC regulations, the likelihood of adopting the behaviors of neighbors who performed well in the previous turn, and the surplus generated by transitioning to NT power sellers.

To simulate the impact of emerging technology on electricity market regulations, we used a bottom-up modeling approach to incorporate the behavioral changes of three agents (electricity regulators, traditional power sellers, and NT power sellers) into the simulation. Drawing on the behavioral rules outlined for each agent (as derived from our theoretical analysis in the ABM theoretical framework in the background section and empirical study results from the LSTM model), we translated these insights into NetLogo code. Subsequently, we ran the model in NetLogo, making necessary adjustments to ensure the credibility of the simulation experiment. Our primary focus was to evaluate dynamic changes in the numbers of power sellers and regulators as renewable energy shares approach and then surpass 50% of the US generation market during the first ten periods. General system dynamics for simulation is elaborated in Appendix VI.

3. Analysis of Simulation Outcome

Once the model has been run for several rounds and the control variables have been adjusted to produce stable results, we can analyze how renewable growth supported by emerging technologies changes power sellers' behavior and how regulation can affect the outcomes. By plotting and monitoring the outcome data series, the simulation model allows us to observe how renewable development in an unchanged regulatory environment can yield different results from given initial conditions.

In the following two figures (Figure 3 and Figure 4), we can observe the compelling outcomes that emerge after running the model for numerous rounds and fine-tuning the control variables to achieve stable results. The simulation elucidates how new technologies contribute to the growth of NT power sellers and how regulations wield the power to influence these outcomes. By plotting and closely monitoring the data series generated by the simulation, we gain insights into the dynamics, system mechanisms, interrelationships, and alterations in agent numbers from their initial conditions.

Figure 3. Results of ABM Simulation: New Technologies' Impact on Numbers of Power Sellers and Regulators.

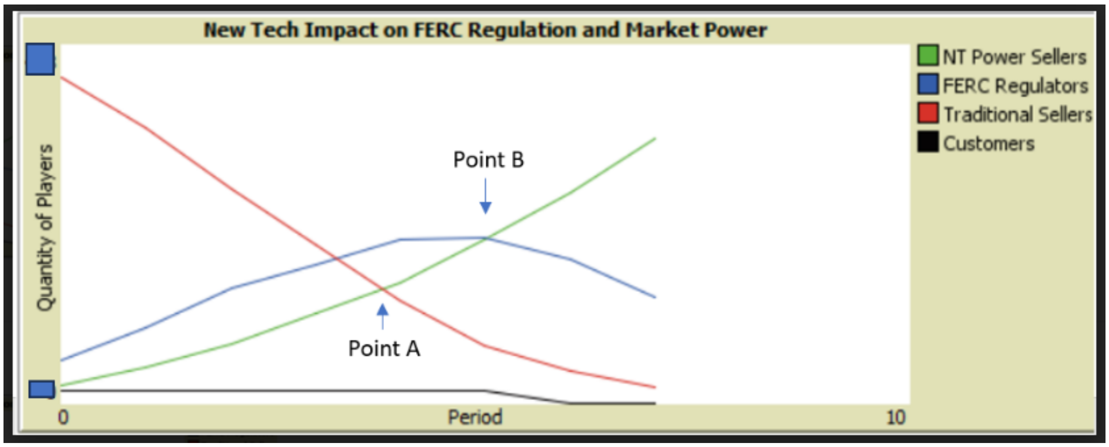


Figure 3 illustrates that the introduction of new technologies into the energy sector leads to an increase in the number of NT power sellers, while the number of traditional power sellers decreases.

Figure 3 shows our model's simulation of the evolution of the number of power sellers in the United States over ten periods,[64] starting in 2010 (green line). With the introduction of new technologies into the energy sector, their share began

64. The model period is a relative concept that can be defined as a specific timeframe, such as one or two calendar years.

to swell. Concurrently, the number of regulators (blue line),[65] encompassing various government resources, such as subsidies for renewables, increased along with renewables.[66]

As the model runs, we observe dynamic transformations: the number of NT power sellers (green line), with more flexibility and thus more market power in critical high-load times, accelerates, while the number of traditional power sellers dwindles (red line). Simultaneously, the number of regulators adjusts. Under the influence of economic factors and neighborhood effects, a growing number of traditional power sellers transition to NT power sellers, exerting mounting pressure on the regulatory framework.

Eventually, NT power sellers surpass traditional sellers at Point A, which is the critical threshold of our forecasting model where renewable share in electricity generation reaches 50%. After Point A, the strength of FERC's regulations starts to decline, although its existing regulations are still effective at protecting customers (blue line). However, as the strength of FERC's regulations further diminishes until a certain tipping point (Point B) where market power breaks regulatory boundaries, customers lose protection, and public interests are harmed.

Figure 4. Results of ABM Simulation: Regulation Gap

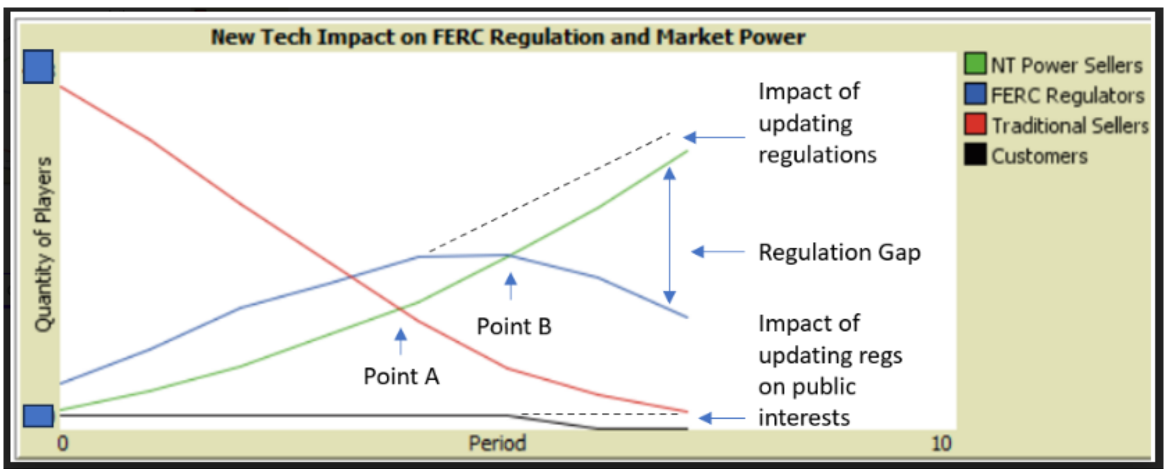


Figure 4 illustrates that the introduction of new technologies into the energy sector could lead to a regulation gap due to outdated regulations.

65. In this context, "regulators" refers to the extent and effectiveness of FERC's regulatory oversight over New-Techs (NT) power sellers. The term doesn't imply the actual count of commissioners. Instead, it's a measure of regulatory intensity. For instance, if the number of regulators increases in proportion to the number of NS power sellers, it suggests that regulation is keeping pace with the growing market, especially as we shift towards renewable energy sources. On the other hand, if there are fewer regulators compared to NS power sellers, it might signify that regulation and enforcement are falling behind, potentially leading to issues in market power abuse.

66. The customer line is an added line to the plot that mirrors regulation strength and is closely related to customer and public interests.

Figure 4 further elaborates our simulation results and policy options. Outdated regulations will open a regulation gap after Point B. However, if FERC updates its current market power analysis, such as by implementing the MAEC measure we suggested in the subsection under "Analysis," the regulations will be in a good position (see the dotted line about the green line) to mitigate possible market power originating from the side effect of emerging technologies development. The regulation gap will not occur. The dotted line about the dark blue line represents the impact of updating regulation on public interests, where customers are protected from market power. That is, regulatory agencies have measures in place to ensure fair competition and prevent power sellers from exploiting their dominant positions in a market.

The simulation offers forecasts regarding the dynamic relationship between power sellers and regulators. It underscores the pressing necessity for updated standards capable of accurately representing the available energy in the market and averting scenarios where sellers amass excessive market power. Moreover, it provides viable policy and regulatory options for FERC to revamp its regulations, thus ensuring customer protection during rapid technological advancement. The simulation demonstrates that without continuously updating its market power monitoring and analysis techniques, the regulatory strength of electricity regulation may diminish, allowing sellers to expand their market power influence in lockstep with technological growth. Once this dynamic reaches a critical juncture, market power may break free from regulatory constraints, potentially leading to adverse consequences for customers.

In summary, the simulation forecasts the dynamic interplay between electricity companies and regulators, showing the need for updated standards that reflect the evolving energy landscape and safeguard against excessive market power. The simulation also underscores the need for FERC to adapt its regulations to ensure customer protection in the face of rapid technological advancements.

III. CONCLUSION

This study establishes a framework for understanding and empirically analyzing the impact of new technologies on energy regulations and market power dynamics, forging a path for understanding and shaping the complex interplay between these forces. Additionally, this study explores the potential of AI models to forecast critical points for regulators and identifies policy tools and methodologies that can effectively analyze market power in a renewable-dominant landscape, mitigating regulatory gaps.

The research findings have significant implications for stakeholders in the energy market and for regulatory policies. First, the determination of the turning point at which renewables could surpass traditional fossil fuel power generation underscores the need for regulators and researchers to accelerate their efforts. Although a complete transition to renewables across the U.S. may take approximately 14 years, regional shifts may happen much sooner, with California and the SPP region expected to exceed the 50% renewable threshold as early as 2025 and 2026, respectively.

Second, the demonstration that an updated market power analysis can more accurately capture market dynamics emphasizes the profound influence of regulatory policies on protecting the public interest. We recommend a partial revision of current energy regulations soon, especially those pertaining to market share calculations for antitrust purposes. These suggested revisions should pivot from fossil fuel-based (specifically, nameplate capacity) calculations to include renewable energy, incorporating sales-based or capacity-plus-battery-based metrics. This revision should be implemented gradually as renewables continue their ascent towards dominance across the United States. These efforts aim to advance the field of government regulation theories and provide practical tools for regulators, particularly as regulatory scrutiny intensifies in evaluating merger cases and MBR authority.

While this study represents an initial foray into the application of AI models and the ABM in the realm of regulation, the ever-expanding influence of new technology and AI development will likely stimulate more extensive investigations in the future. Overall, the findings of this study carries far-reaching implications for the fields of market power analysis and energy regulatory policy, ultimately fostering the development of more AI applications in the energy sector and regulatory practices.

APPENDIX

APPENDIX I – THE DELIVERED PRICE TEST (DPT) EQUATIONS

Within GAMS, the DPT algorithm analyzes each seller's available economic capacity (AEC) by minimizing the cost of each supplier in the destination market. As we mentioned in Section 1, this involves considering the supplier's generation portfolio, market price, transmission constraints, and native load obligations. The goal is to solve a linear programming (LP) model with the following form:

Objective Function:

$$Mininimize\ Cost_s = \sum_{g=1}^{n} (Dispatch\ Cost + Transmission\ Cost)_g \times MW_g \qquad (1)$$

Where p is power seller, g is generating unit.

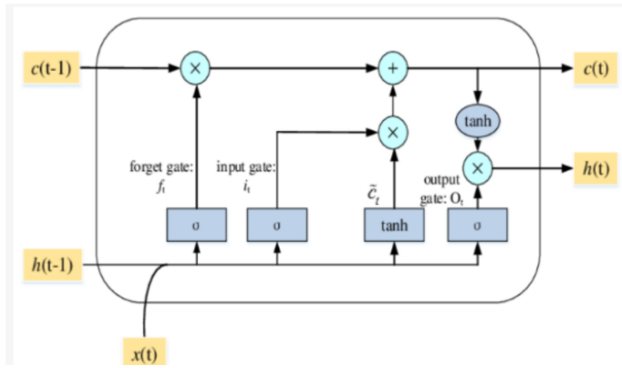
Subject to:

$$Delivery\ cost\ at\ destination\ \leq market\ price + 5\,\%, \qquad for\ all\ suppliers \qquad (2)$$
$$Supply\ < quantity\ (less\ native\ load), \qquad for\ each\ node \qquad (3)$$
$$Line\ flows\ < available\ linit, \quad for\ all\ interconnections\ (constrained\ network\ only) \qquad (4)$$

APPENDIX II - ARCHITECTURE OF LONG SHORT-TERM MEMORY (LSTM)

LSTM model's distinctive architecture can be summarized as "three gates, two states, and one function." See the following figure and explanation:

Appendix Figure 1. Architecture of a neuron in LSTM network[67]



Three gates: The input gate governs the amount of new information to be stored in the cell state, enabling the selective retention of relevant data. The forget gate decides which information to eliminate from the cell state, effectively filtering out obsolete or irrelevant data. The output gate determines the quantity of information to be extracted from the current cell state, facilitating the summarization of pertinent information for forecasting.

Two States: The cell state, known as the long-term memory, enables LSTM models to preserve information across different time steps, a vital component for capturing enduring dependencies in data, such as seasonal patterns. In contrast, the hidden state, often referred to as the short-term memory or the output of the LSTM model, encapsulates the current input and the preceding hidden state.

One Function: By harnessing the architecture of LSTM models, complete with their gates, states, and the tanh activation function, these models effectively apprehend and leverage temporal dependencies inherent in the data. LSTM models adeptly decode the intricate data patterns and dynamics, leading to heightened forecasting precision.[68]

APPENDIX III – AGENT-BASED MODEL (ABM)'S THEORETICAL FRAMEWORK

The most popular theoretical framework used in ABM is Gary Becker's rational choice theory.[69] Becker's theory posits that individuals make decisions based on a cost-benefit analysis, weighing the expected costs and benefits of different options in order to choose the one that maximizes their utility. Becker used the formula below to determine a potential offender's utility (*EYj*), which will affect his or her behavior:

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67. Daniela Durand et al., *An Analysis of the Energy Consumption Forecasting Problems in Smart Buildings using LTSM*, 14 SUSTAINABILITY 6 (Oct. 17, 2022), https://www.mdpi.com/2071-1050/14/20/13358.

68. Xianlin Ma Mengyao Hou et al., Enhancing Production Prediction in Shale Gas Reservoirs Using a Hybrid Gated Recurrent Unit and Multilayer Perceptron (GRU-MLP) Model, APPLIED SCI., (Aug. 2023).

69. Gary S. Becker, *Crime and Punishment: An Economic Approach*, 76 J. OF POL. ECON. 169 (1968), www.jstor.org/stable/1830482.

$$EY_j = p_j\left(Y_j - f_j\right) + (1 - p_j)(Y_j) \qquad (5)$$

Where p_j stands for the probability of being caught for the potential offender, f_j is the severity of the punishment, and Y_j is the benefit from successfully committing violations without being caught. An individual's utility is a function of the costs and benefits of violation; violation should rise in Y_j and fall for both p_j and f_j.

ABM predominantly relies on Gary Becker's rational choice theory, positing that individuals make decisions through cost-benefit analyses, aiming to maximize their utility by weighing the expected costs and benefits. This framework can be applied to regulation simulations, where regulated agents evaluate the benefits of non-compliance against the costs of detection and penalties, subsequently impacting their behavior.

For example, when regulations affect p_j, f_j, and Y_j, regulated agents' utility will be affected, and thus their behavior on regulation compliance will change.

APPENDIX IV – OUR LSTM'S COMPONENTS, CONSTRUCTION STEPS AND METRIC

This appendix is divided into three parts: first, an overview of the essential components of an LSTM cell; second, a detailed guide on the steps required to develop and run the model; and third, a description of the metrics used for evaluating the forecasting results.

Part 1. The Key Components of an LSTM cell in Our Model

1. Forget Gate: This gate determines the extent to which information from the previous cell state should be forgotten.

$$f_{(t)} = \sigma(Wf \times [h_{(t-1)},\ X_{(t)}] + bf) \qquad (6)$$

Here, W represents the weight matrices, b denotes the bias terms, σ represents the sigmoid activation function, and tanh is the hyperbolic tangent activation function. The LSTM cell involves several multiplications, additions, and activation function evaluations to update the cell state and hidden state at each timestep. Wf represents the weight matrix for the forget gate, $[h_{(t-1)}, X_{(t)}]$ denotes the concatenation of the previous hidden state $h_{(t-1)}$ and the current input $X_{(t)}$, and bf is the bias term.

2. Input Gate: Determines how much new information should be added to the cell state.

$$i_{(t)} = \sigma(Wi \times [h_{(t-1)},\ X_{(t)}] + bi) \qquad (7)$$

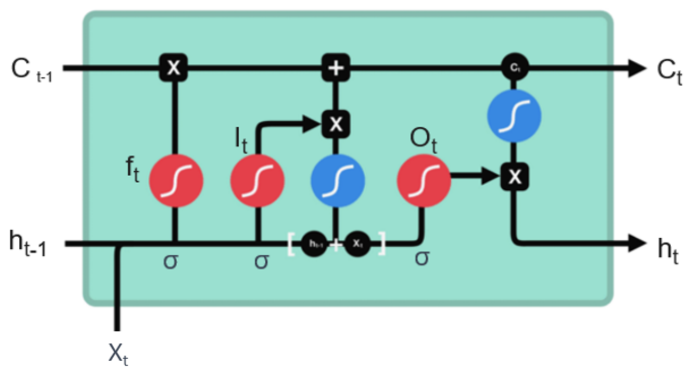
3.Update Cell State: Combines the information from the forget gate and the input gate to update the current cell state.

4.Output Gate: Determines the hidden state that will be passed to the next timestep.

$$o_{(t)} = \sigma(Wo \times [h_{(t-1)},\ X_{(t)}] + bo) \qquad (8)$$

Following Figure elaborates our model's structure:

Appendix Figure 2. LSTM's One Function, Two States, and Three Gates.



Appendix Figure 2 depicts the activation function (σ), previous cell state and new cell state (Ct-1 and Ct), and input gate, forget gate, and output gate (It, ft, and Ot).

$$C_t = f_t \times C_{t-1} + I_t \times c_t \qquad (9)$$

Where C_{t+1} previous cell state
f_t Forget gate output
I_t Input gate output
c_t candidate
C_t new cell state

In essence, each LSTM cell receives inputs, including the cell and hidden state from the previous timestep and the input vector from the current timestep. Subsequently, each LSTM cell generates a new cell state and a hidden state, which is utilized for processing in the next timestep. If the cell's output is required, such as for subsequent layers, it is represented by its hidden state.

Our model harnesses these gates and the memory cell to effectively capture long-term dependencies in sequential data while mitigating the vanishing gradient issue.

Part 2. Steps for Creating and Executing the Model

Here are the steps we've taken to create and execute an LSTM model that uses its own megawatts (MWs) and shares data to predict future MWs and shares:

- Data Preparation: We commence by gathering a dataset that encompasses historical MWs and shares values alongside their corresponding future MWs and shares values. Each sample within this dataset comprises a sequence of past MWs and shares values, coupled with the target future MWs and shares value.
- Data Preprocessing: In order to expedite the convergence of the LSTM model during training, we normalize the MWs and shares values to a consistent range, typically within zero and one.
- Sequence Generation: Input sequences for the LSTM model are generated. Each input sequence includes a window of past values, while the corresponding output sequence contains the future MWs and shares values.
- Dataset Splitting: The dataset is partitioned into training and testing sets. The training set is used to train the LSTM model, while the testing set is reserved for evaluating its performance.
- Model Architecture: We construct the LSTM model using a deep learning framework like TensorFlow or Keras. The model comprises LSTM layers, followed by one or more fully connected layers. The choice of the number of LSTM layers and the unit within each layer depends on the complexity of the problem, which we experiment with.
- Model Training: The LSTM model is trained with the training dataset. Throughout the training process, the model learns to recognize patterns and dependencies between past and future MWs and share values.
- Model Evaluation: After training, we evaluate the LSTM model's performance using the testing dataset. We calculate relevant performance metrics, such as mean squared error (MSE) or mean absolute error (MAE), to gauge the model's accuracy.
- Prediction: Subsequently, we deployed the trained LSTM model to make predictions for new MWs and share sequences. We supply the model with a window of past MWs and shares values, and it produces predictions for future MWs and shares values.
- Postprocessing: When we normalized the MWs and shares values during preprocessing, we undertake the necessary steps to convert the predicted values back to their original scale for meaningful interpretation.

- Model Refinement: In the event that the model's performance falls short of expectations, we experiment with various hyperparameters, model architectures, or explore advanced techniques such as attention mechanisms or hybrid models to improve its predictive capabilities.

Part 3. Metric for Forecasting Results

We initially conducted a solar capacity forecasting analysis. Solar energy was one of the fastest-growing renewable energy sources with a substantial drop in the cost of solar panels and the introduction of generous state and federal tax incentives.[70]

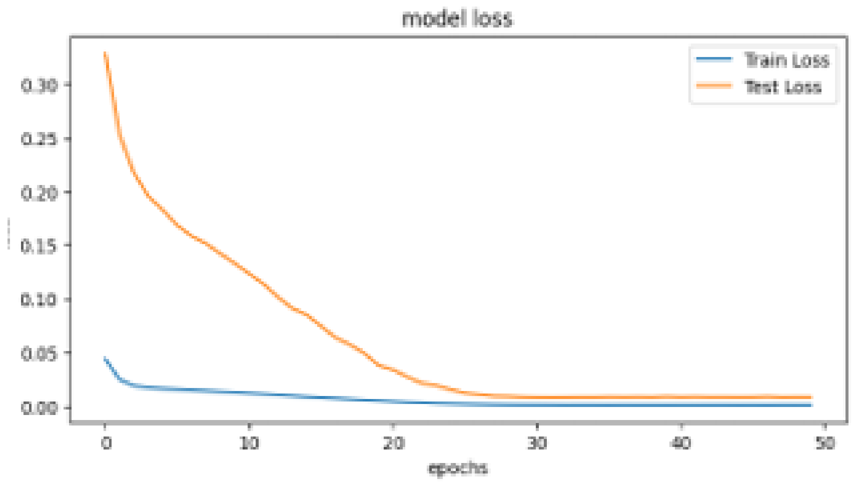
Monthly data for U.S. solar capacities were sourced from the EIA's Table 10.6, titled "Solar electricity net generation," available in Total Energy Monthly Data - U.S. Energy Information Administration (EIA). This data spans from January 1989 to December 2022, incorporating a total of 396 observations. Metric for Solar kWh forecasting in USA are shown in Appendix Table 1, and Appendix Figure 3.

Appendix Table 1. Metric for Solar kWh Forecasting in USA

	Train Score	Test Score
RMSE	0.75	1.95
MAE	0.54	1.67
R^2	0.93	0.81

70. *See* SOLAR ENERGY INDUS. ASS'N, SOLAR INDUSTRY RESEARCH DATA: SOLAR INDUSTRY GROWING AT A RECORD PACE ("48% of all new electric capacity added to the grid in 2023 has come from solar"); Elesia Fasching, *Wind, Solar, and Batteries Increasingly Account for More New U.S. Power Capacity Additions*, U.S. ENERGY INFO. ADMIN. (Mar. 6, 2023), https://www.eia.gov/todayinenergy/detail.php?id=55719 ("As of January 2023, 73.5 gigawatts (GW) of utility-scale solar capacity was operating in the United States, about 6% of the U.S. total . . . . Just over half of the new U.S. generating capacity expected in 2023 is solar power. If all of the planned capacity comes online this year as expected, it will be the most U.S. solar capacity added in a single year and the first year that more than half of U.S. capacity additions are solar.").

Appendix Figure 3. LSTM Training: Loss Function vs Iteration



Appendix Figure 3: The x-axis shows the number of iterations, and the y-axis shows the values of the loss function. At iteration 50, the loss function is equal to 0.0102386. Figure 3 shows that the loss function decreases over time, indicating that the model is improving.

Appendix Table 1 exhibits the root mean squared error (RMSE) values, the Mean Absolute Error (MAE), and the R-squared value.

Root Mean Square Error (RMSE) is a popular way to gauge how accurate a forecasting model is. Imagine a target on a dartboard, where the bullseye represents the actual values you're trying to predict. A train score of 0.75 RMSE means that, on average, the model's predictions within the training dataset are like darts landing 0.75 units away from the bullseye. The closer the darts (predictions) are to the bullseye (actual values), the better the model performs. So, in this scenario, a train score of 0.75 suggests the model is quite adept at hitting close to the mark, accurately capturing the patterns and trends in the training data.

Now, when it comes to the test score of 1.95 RMSE, think of it as the model trying to hit a new bullseye with different darts. This score measures the average difference between the actual and predicted values in the testing dataset, which comprises data the model hasn't seen before. A test score of 1.95 indicates that the model's predictions are, on average, about 1.95 units off target in this new set. This gives us a sense of how well the model can generalize its learning to unfamiliar data.

Mean Absolute Error (MAE) is another useful metric, akin to measuring the average distance of each dart from the bullseye, without considering the direction. With a test score of 1.67 MAE, we see that the model's predictions are generally quite close to the actual values, akin to most of the darts landing near the bullseye, showing the model's accuracy in predicting new data.

Finally, the R-squared value (R2), or the coefficient of determination, is a bit like understanding how much of the dart's path towards the bullseye can be explained by the way it was thrown. In this case, the model's R-squared value for the test data is 0.81. This means 81% of the variation in the target (or the dependent variable) is explained by the factors we're considering in our model (the independent variables). In other words, our model explains a significant portion of the changes in the data, indicating a strong fit to both the training and testing datasets.

The notation "Iteration 50, Loss = 0.0102386" reveals that the LSTM model underwent 50 iterations to optimize its parameters. The loss value of 0.0102386 denotes the final result of the loss function, which gauges the dissimilarity between the model's predictions and the actual values. A lower loss value signifies a more accurate fit of the model to the data.

Regarding renewables share forecasting, we sourced SPP and California regional, as well as U.S. national annual data from the EIA's Table 7d, titled "U.S. Regional Electricity Generation, Electric Power Sector," spanning from 2000 to 2022. For each item, we incorporated twenty-three observations in the model. LSTM model metric for renewable share in electricity generation in California, SPP and USA is presented in Appendix Table 2.

Appendix Table 2. LSTM Model Metric for Renewable Share in California, SPP and USA

	California		SPP		USA	
	Train Score	Test Score	Train Score	Test Score	Train Score	Test Score
RMSE	2.23	2.56	1.88	2.15	1.87	2.14
MAE	1.72	1.98	1.44	1.66	1.43	1.65
R^2	0.95	0.92	0.98	0.96	0.97	0.95

Note: Iteration 100 for each, Loss Values = Loss value: 1.86, 1.85, 1.87

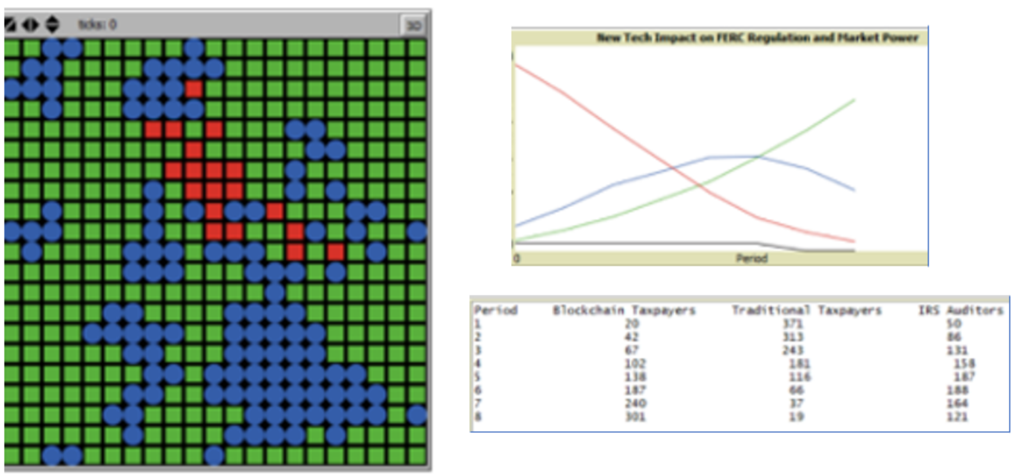
From Table Appendix 3, which provides the forecasting metrics for renewable share in California, SPP, and the U.S., we observe the following RMSE values: 2.23, 1.88, and 1.87 for the train scores, and 2.56, 2.15, and 2.14 for the test scores, respectively. Additionally, the MAE values for the train scores are 1.72, 1.44, and 1.41, and the MAE values for the test data are 1.98, 1.66, and 1.65. These values collectively indicate that, on average, the predicted values closely align with the actual values.

The R-squared (R^2) values for the train score are 0.95, 0.98, and 0.97, and for the test data are 0.92, 0.96, and 0.95, indicating that the change in past values in the model can explain 92%, 96%, and 95% of the variations in the forecasting values. R^2 of over 90% is generally considered quite good for a forecasting model.

APPENDIX V - ABM MODEL SETTING

The simulation is designed to unfold within a virtual 21x21 grid, which represents the electric wholesale market system. This means that the simulation is conducted on a grid consisting of twenty-one rows and twenty-one columns, which provide 441 individual cells for agents to operate within, and the specific dynamics of the simulation (see Appendix Figure 4). This grid serves as a dynamic playground where various elements come into play, mirroring the complexities of the real-world energy market. Within this environment, we introduce a variety of resources, objects, and obstacles that shape the interactions and strategies of three key types of agents: electricity regulators, innovative New-Techs (NS) power sellers who are gaining increasing influence in the market, and traditional power sellers who are at a crossroads, with the potential to evolve into NS power sellers.

Appendix Figure 4. Dynamic Environment of ABM Simulation



Period	Blockchain Taxpayers	Traditional Taxpayers	IRS Auditors
1	20	371	50
2	42	313	86
3	67	243	131
4	102	181	158
5	138	116	187
6	187	66	188
7	240	37	164
8	301	19	121

Appendix Figure 4 depicts a dynamic environment in the energy sector in a 21x21 virtual space where three distinct agents are represented by blue, red, and green colors. Data generated by the model can be visualized using plots and tables.

Each agent type operates under a unique set of behaviors and objectives. Electricity regulators work to maintain a balance and fair play in the market, overseeing activities and intervening when necessary. NS power sellers, equipped with advanced technologies and strategies, seek to expand their market share and influence, leveraging their innovative approaches. Traditional power sellers, meanwhile, face the decision of whether to continue with their established methods or transition to the more modern, potentially more profitable NS model.

The agents interact within the grid in complex ways. They move around, make decisions, and adapt their strategies based on a comprehensive set of predefined rules. These rules include incentives that drive their movement across the grid, such as market demands, regulatory changes, or technological advancements. Agents also have the capability to modify their initial characteristics. For example, a traditional power seller might adopt new technologies and strategies, transforming into an NS power seller. This reflects the real-world scenario where companies evolve to stay competitive and relevant.

Additionally, the agents' decisions and movements are influenced by their neighbors and past actions. This aspect of the simulation mimics the interconnected nature of the energy market, where the actions of one player can significantly impact others, and where historical data and trends play a crucial role in shaping future strategies.

Through this simulation, we aim to provide a detailed, interactive model of the electric wholesale market, offering insights into how different entities interact, compete, and evolve in response to changing technologies, regulations, and market dynamics. This model serves as a valuable tool for understanding the complexities and potential future scenarios of the energy market.

APPENDIX VI – NETLOGO'S GENERAL SYSTEM DYNAMIC

A general system dynamic for simulation can be summarized as below:

The NetLogo programming logic and general system dynamics follow the sequence below:[71]

1. System Setup:
   - Create a set of agents that will interact with each other and the environment.
   - Assign starting values to each agent - not at random
   - Define agent behavior - specify the rules that govern the agents' decision-making processes and interactions with other agents and the environment.
   - Model the environment, creating the setting in which agents operate and setting the rules that guide changes for each simulation run.
2. Define Variables:
   - Identify and select the variables relevant to the system being modeled, such as costs, benefits, resource availability, and subsidy conditions.
3. Develop Relationships:
   - Create mathematical or logical equations describing how changes in one variable impact others.
4. Run the Model:

* For each round:

- Apply the cost effect (or not).
- Apply the subsidize effect (or not).
- Apply the neighborhood effect (or not).

71. Eugene Y. Lee et. al., *Impact of Blockchain on Improving Taxpayers Compliance: Empirical Evidence from Panel Data Model and Agent-Based Simulation*, J. OF EMERGING TECHS. IN ACCT. 13-14 (2023), https://doi.org/10.2308/JETA-2022-046.

For each regulator agent:

- Distribute subsidies.
- Conduct inspections and impose penalties.

For each power seller agent:

- Process benefit payments.
- Adjust agent consumption.

* Next Round . . .

5. Test the Model:

- Execute the model, run it for a specified number of iterations, and analyze results to compare them with real-world observations or data.

6. Refine the Model:

- Modify agent behavior, environment, variables, or relationships to enhance the model's accuracy and validity.

7. Validate the Model:

- Compare the model's output with real-world data to ensure it accurately represents system behavior.

8. Use the Model:

- Utilize the model for predictions or test hypothetical scenarios by adjusting variables or introducing new rules to the system.

Leveraging reinforcement learning, the AI-driven NetLogo model optimizes agent behavior within the ABM by enabling learning through trial and error and reward maximization. This iterative process leads to increasingly affect agent behavior over time, demonstrating how new technology can influence the conduct of power sellers.