Modeling Renewable Energy Transitions as a Markov Decision Process

A Q-Learning approach to minimizing fossil-fuel reliance while meeting energy demands

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***Abstract*—There has been an encouraging global shift towards prioritization of renewables. However, renewable energy sources pose a complex decision-making challenge, especially when facing uncertain weather-dependent production and fluctuating demand. This paper presents a Markov Decision Process (MDP) model and a Q-learning approach to optimize renewable energy transitions, specifically focusing on wind power, while minimizing reliance on fossil fuels and ensuring energy demands are met. By representing state transitions as stochastic variations in wind speed and energy demands, our system captures both the inherent randomness in renewable output and the trade-offs in resource allocation. We employ Q-learning to derive an optimal policy that adaptively shifts the proportion of fossil-based generation in response to demand and weather conditions. The resulting policy aims to meet energy needs while reducing dependency on fossil fuels, offering a decision-making approach that supports cleaner, more resilient energy systems.**

***Index Terms*—Renewable energy, Markov Decision Process, Q-Learning, Wind power, Fossil fuels, Energy demand, Energiewende.**

I. High Level Overview

A. *Motivation*

This project started from an interest in Germany's *Energiewende* policy initiative in 2016 — a commitment to fully transition the country to renewable energy by the end of the year. Energiewende aimed to eliminate reliance on fossil fuels, largely through the building and use of solar and wind infrastructure [1]. Unfortunately, unprecedented weather patterns (less sun and wind than expected) meant that Germany was running a significant energy deficit, particularly in winter months. To meet demands, Germany was forced to reactivate old coal-fire plants it had shut down under the program [1]. The upfront emissions costs associated with reactivating old and inefficient coal plants are greater than the emissions costs of simply leaving coal plants running. Thus, Germany's overall emissions for the year actually *increased*, despite the rapid transition to renewable energy sources [1]. Energiewende highlights the complexity of energy transition plans, as well as the stochastic nature of weather patterns, and the inherent uncertainty of renewable energy production. This begs the question: "how can we minimize our reliance on fossil fuel energy while always meeting energy demands?"

B. *Goals*

This project aims to model our reliance on fossil fuels as a Markov Decision Process and optimize decisions using a Q-learning algorithm, ultimately minimizing fossil fuel usage while ensuring energy demands are met. We have chosen to focus specifically on wind power. At each state, we can choose either to increase or decrease our reliance on fossil fuels to meet energy demands. It is assumed that energy production from fossil fuels is both infinite in potential and guaranteed. That is, we can meet energy demands with probability 1 using only fossil fuels. However, since the energy production of renewables is uncertain, we cannot guarantee that renewables alone will always meet energy demands, as was the case for Germany in 2016. We also assume that the infrastructure for renewables remains constant, so the theoretical ceiling of production is entirely a function of weather patterns (specifically, wind).

While we are using wind power as a proxy for renewable energy in this project, this simplification is sufficient for our purposes. Wind energy shares the core challenges of other renewables (e.g. solar) in terms of variability and uncertainty due to weather patterns. Therefore, focusing on wind captures the essential dynamics of renewable energy production without loss of generality.

Our aim is to optimize the proportion of renewable to fossil fuel usage in the short term, seeking to minimize our reliance on fossil fuels while never failing to meet energy demands. Thus, there is a positive reward associated with decreasing fossil fuel usage while still meeting demands and a significant negative reward associated with failing to meet energy demands under any circumstance (Energiewende).

II. Data

We are using the Techno-Economic Summary and Index dataset from the National Renewable Energy Laboratory (NREL), derived from the WIND Toolkit. This dataset contains 126,693 wind sites across the continental United States, selected to represent existing and potential locations for wind energy development (see Fig. 1). Each site corresponds to a 2 km by 2 km grid cell and has a developable capacity of up to 16 MW [2]. We assume that each site represents a single wind turbine, allowing us to streamline the modeling process while maintaining the integrity of our analysis.

While the actual number of installed wind turbines in the United States is approximately 75,000 [3], this discrepancy arises because the dataset is designed to capture a potential build-out scenario for future wind energy development, not just existing infrastructure. The inclusion of additional potential sites ensures flexibility for modeling and simulation, allowing us to explore a wide range of renewable energy scenarios, including those with significantly higher wind energy penetration. This approach helps create a more robust and adaptable state space for our MDP.

Each row in the dataset contains the location of the wind plant along with a variety of other information, but we specifically care about `wind_speed` and `capacity_factor`, which are used in the formula to measure the power output in megawatts of the wind turbine (more on this in III-A). This allows us to construct our state space for our MDP. We have processed and cleaned the data for our needs. A visualization of the distribution of wind speeds across the continental United States is shown in Fig. 2.

Fig. 1. Map of Selected Sites [2]

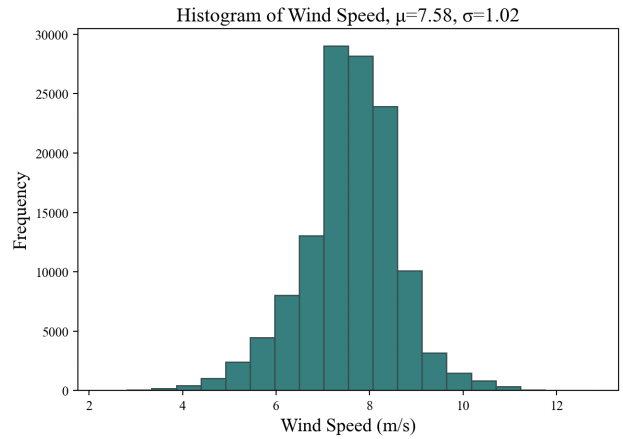

Fig. 2. Distribution of Wind Speeds from Dataset

III. MDP (Approach)

A. State Space

$$s_i = (\varphi_i, w_i, d_i)$$

where:

- $\varphi_i \stackrel{\text{def}}{=}$ Proportion of energy demand accounted for by fossil fuels at state i, where $0 \leq \varphi \leq 1$.
- $w_i \stackrel{\text{def}}{=}$ Wind speed at state i in m/s.
- $d_i \stackrel{\text{def}}{=}$ Energy demand in MW at state i

Additionally, we keep track of $O(w_i) \stackrel{\text{def}}{=}$ Power output of the wind turbine (MW). However, this depends only on w_i and is therefore not included in the state space because it is calculated deterministically when evaluating rewards or making transitions. The power output is derived using the formula [4]:

$$O(w_i) = 0.5 \cdot C_p \cdot \rho \cdot \pi \cdot R^2 \cdot w_i^3,$$

where:

- C_p: Capacity factor (mean C_p from dataset).
- ρ: Air density in kg/m^3, left constant at U.S average of 1.225 kg/m^3.
- R: Blade radius in meters (assumed constant at 66.9 meters, the average for newly installed wind turbines in the U.S.) [5].
- w_i: Wind speed in m/s.

State Space Discretization

Wind speed (w_i) and energy demand (d_i) are continuous variables. However, Q-Learning relies on revisiting states to update Q-values and propagate learning. When states are represented by continuous floating-point numbers, the probability of encountering the exact same state more than once is extremely low. This prevents meaningful learning because each state is effectively unique, making it impossible to update value estimates through repeated visits.

We address this issue by discretizing the continuous state spaces as follows:

- Wind Speed w is discretized into buckets of 1 m/s (e.g. wind speeds between 5.0 and 5.9 m/s are placed in the 5 m/s bucket).
- Energy demand d is discretized into four buckets defined as:
  - Low: Minimal energy demand.
  - Moderate: Average energy demand levels.
  - High: Above-average energy demand.
  - Very High: Peak energy demand scenarios.

B. *Action Space*

The action space is defined as:

$$a_i \in \{\varphi_{(+)}, \varphi_{(-)}, \varphi_0\}$$

where:

- $\varphi_{(+)} \stackrel{\text{def}}{=}$ increase the proportion of energy demand met by fossil fuels (φ_i) by a fixed increment $\Delta = 0.025$, capped at $\varphi_i = 1.0$. Through trial and error, we determined $\Delta = 0.025$ to offer fine-grained control over fossil fuel adjustments while maintaining a manageable state space for efficient learning and convergence.
- $\varphi_{(-)} \stackrel{\text{def}}{=}$ decrease φ_i by $\Delta = 0.025$, with a lower bound of φ_i.
- $\varphi_0 \stackrel{\text{def}}{=}$ leave φ_i unchanged.

Actions directly control the reliance on fossil fuels with the aim of reducing φ while ensuring energy demands are met.

C. *Transition Model*

1. Wind Speed Transition ($P(w'|w)$)

The next wind speed w' is modeled as a Gaussian distribution $P(w'|w) \sim \mathcal{N}\left(\mu'_w, \sigma_w^2\right)$ where:

μ'_w: Mean for the next wind speed. To ensure we balance realism in short-term wind speed transitions with long-term trends derived from historical data, we use exponential smoothing to compute $\mu'_w = \lambda \cdot w + (1-\lambda) \cdot \mu_w$ [6] where:

- w: Current wind speed.
- μ_w: Historical mean wind speed (computed from the dataset)
- $\lambda = \exp(-\alpha \cdot t)$: Weighting parameter that controls how strongly the transition depends on the current wind speed versus reverting to the historical mean. $\boldsymbol{\alpha}$ controls the rate of decay (reversion to mean) over time and $\boldsymbol{t}$ represents the time steps since the last wind speed update. Since our dataset is not a time series (each row is treated as an independent snapshot), we fix $\boldsymbol{t = 1}$, standardizing the transition dynamics to represent one simulation step. We choose $\boldsymbol{\alpha = 0.1}$ as a moderate decay rate to balance the influence of the current wind speed and the historical mean. Through trial and error, we saw the value 0.1 ensures a reasonable level of stochasticity in wind speed changes while still reflecting realistic trends over multiple steps.

σ_w^2: Variance of the wind speed. The variance σ_w^2 used in the wind speed transition is directly calculated from the sample variance of the wind speeds in the dataset:

$$\sigma_w^2 = \text{Var(wind speed)} = \frac{1}{n-1}\sum_{i=1}^{n}(w_i - \bar{w})^2,$$

with:

- w_i: Wind speed of the i-th wind turbine in the dataset.
- $\bar{w}$: Mean wind speed across all turbines in the dataset.
- n: Total number of observations in the dataset.

Putting everything together, the wind speed transition probability is:

$$P(w'|w) = \frac{1}{\sqrt{2\pi\sigma_w^2}} \exp\left(-\frac{(w' - [\lambda w + (1-\lambda)\mu_w])^2}{2\sigma_w^2}\right)$$

This Gaussian model makes sure that wind speed transitions are localized. If the current wind speed is $w = 10\,\text{m/s}$, and the distribution is $\mathcal{N}(10, \sigma_w^2)$, most next wind speeds w' will likely fall close to 10, with smaller probabilities for more distant values.

The weighted mean $\mu'_w = \lambda \cdot w + (1-\lambda) \cdot \mu_w$ combines the current wind speed w and the historical mean μ_w. This ensures short-term continuity (by incorporating w) while gradually reverting to the historical mean μ_w over time [6]. The parameter $\lambda = \exp(-\alpha \cdot t)$ determines how strongly the transition depends on w versus μ_w. Since t is set to 1 (due to the lack of time series data), λ simplifies to $\exp(-\alpha)$.

As described earlier, the variance σ_w^2 is calculated from the dataset as the sample variance of wind speeds, ensuring realistic fluctuations in modeled transitions.

2. Energy Demand Transition ($P(d'|d)$)

Since we do not have a dataset for energy demand, we model the next energy demand d' as a Gaussian distribution $P(d'|d) \sim \mathcal{N}(\mu'_d, \sigma_d^2)$, where the mean μ'_d is computed as:

$$\mu'_d = \lambda \cdot d + (1-\lambda) \cdot \mu_d,$$

where:

- d: Current energy demand, initialized as a constant value derived by dividing the real-time nationwide demand (e.g., $462,375$ MW as of 16:10 PT on December 7, 2024) by the number of rows in the dataset (126,693 wind sites) [7]. This ensures the model operates on a per-site basis ($462,375/126,693 = 3.65$ MW). While energy needs vary by region and wind power supplies only a fraction of the U.S. total, we make the simplifying assumption that dividing nationwide demand equally among all sites provides a reasonable approximation for per-site energy demand.
- μ_d: A chosen constant to represent the baseline mean energy demand, set to the same value calculated above (3.65 MW in the provided example) for consistency with the per-site demand approximation.
- $\lambda = \exp(-\alpha \cdot t)$: A decay factor controlling the weighting between the current demand d and the baseline μ_d. Since we lack explicit time series data, we set $t = 1$, and $\alpha = 0.1$ is chosen as a small decay constant.

The variance σ_d^2 is defined as a constant to introduce controlled variability around the mean energy demand. The U.S. Energy Information Administration estimates daily demand to vary by $10-20\%$ [7]. Therefore, in the case where real-time per-site demand is 3.65 MW, we compute $\sigma_d = 0.15 \times 3.65 = 0.55$ MW, which gives us an approximation for variance $\sigma_d^2 = 0.15 \times 3.65 = 0.3$ MW.

The energy demand transition probability is given by:

$$P(d'|d) = \frac{1}{\sqrt{2\pi\sigma_d^2}} \exp\left(-\frac{(d'-\mu'_d)^2}{2\sigma_d^2}\right)$$

This Gaussian model makes sure that energy demand transitions are localized around the current demand d, while allowing for some stochastic variability. Since we lack real-world demand data, the constants for μ_d and σ_d^2 were chosen to reflect plausible variability in energy demand. For instance, if the current demand is $3.65\,\text{MW}$ and $\sigma_d^2 = 100$, most next demands d' will fall between approximately $90\,\text{MW}$ and $110\,\text{MW}$, ensuring realistic but varied transitions.

3. Full Transition Probability

The transition probabilities for wind speed and demand are used to generate the next state (w', d') through sampling from their respective Gaussian distributions. These sampled values, along with the chosen action a, determine the updated state:

$$s' = (\varphi', w', d'),$$

where:

- φ': The updated proportion of energy met by fossil fuels, computed deterministically based on the action a (see Section III-B).
- w': The next wind speed, sampled from $P(w'|w)$.
- d': The next energy demand, sampled from $P(d'|d)$.

The power output $O(w')$ of the wind turbines is then computed deterministically from w' using:

$$O(w') = 0.5 \cdot C_p \cdot \rho \cdot \pi \cdot R^2 \cdot (w')^3,$$

where C_p, ρ, and R are constants as defined in Section III-A.

D. Reward Function

The reward function is designed to balance the competing objectives of minimizing reliance on fossil fuels (φ) and meeting energy demands (d). Reward is computed as follows:

$$R(s,a,s') = \begin{cases} 25(1-\varphi') - 5 + \delta_\text{s}, & \text{if } O(w') + \varphi' d' \geq d' \\ -100 + \delta_\text{s}, & \text{otherwise} \end{cases}$$

where:

- φ': Proportion of energy demand met by fossil fuels after transition.
- $O(w')$: Power output of wind turbines, computed from w'.
- d': Energy demand after transition.
- δ_s: A small reward (+1) for choosing "no change" action, incentivizing stability.

Demand Met Condition:

$$O(w') + \varphi' \cdot d' \geq d'$$

If the total energy supply meets or exceeds the demand, the agent is rewarded based on the proportion of renewable energy used. Here the term $25 \cdot (1-\varphi')$ encourages the reduction of fossil fuels, with a small constant penalty of -5 to ensure that cases where $\varphi = 1$ are discouraged.

Demand Unmet Condition: If the total energy supply does not meet the demand, a fixed penalty of -100

is applied (regardless of fossil fuel usage). This heavy penalty makes sure that failing to meet demand is strongly discouraged.

Stability Incentive: A reward of $+1$ is added for "no change" action to encourage stability in φ (when further changes are not beneficial)

Reward Structure Rationale:

- Minimize reliance on fossil fuels by rewarding reductions in φ.
- Strongly penalize unmet energy demands to ensure system reliability.
- Encourage stability in actions when appropriate to avoid unnecessary fluctuations in φ.

Essentially it seeks environmental and operational goals, guiding the agent toward an optimal policy for transitioning to renewable energy while also maintaining reliability.

E. Deriving the Optimal Policy using Q-Learning

We solve the MDP and derive the optimal policy via Q-learning. The action-value function $Q(s,a)$ represents the expected cumulative reward we obtain by taking action a in state s and then following the optimal policy. The optimal policy $\pi^*(s)$ is derived as [8]:

$$\pi^*(s) = \arg\max_a Q^*(s,a).$$

The Q-learning algorithm iteratively updates the Q-values based on observed transitions (s,a,r,s') using the update rule [8]:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right),$$

In the context of our renewable energy transition problem, the Q-learning algorithm iteratively updates $Q(s,a)$ and derives the optimal policy $\pi^*(s)$. We initialize the proportion of fossil fuels as $\varphi = 0.5$ to provide a balanced starting point, preventing early bias and allowing flexible adjustment during learning. As we iterate, we learn the best actions a to minimize φ while also ensuring demand is met ($O(w) + \varphi' \cdot d' \geq d'$), taking into account stochastic transitions in wind speed w and energy demand d to ultimately optimize a reward structure that balances environmental goals with meeting demand.

We implement an ϵ-greedy-exploration approach, where the agent chooses the current best-known action with probability $1-\epsilon$, but with probability ϵ it takes a random action instead [8]. This controlled randomness helps the agent to explore different portions of the state-action space rather than repeatedly selecting what appears momentarily to be the best action [8]. We chose a moderate $\epsilon = 0.3$ to encourage exploration, as the agent repeatedly became stuck in a cycle of suboptimal actions, never discovering new strategies – namely, never decreasing φ in favor of always meeting demand with fossil fuel usage. If the agent consistently hovers around high φ values because of the initial rewards, it may neglect the potentially more sustainable but unexplored actions at lower φ levels. By occasionally exploring less-traveled paths, the agent can uncover and prioritize long-term rewards that might be hidden behind initially uncertain actions, thus preventing it from simply oscillating near a suboptimal policy.

Q-learning was our chosen approach because it does not require explicit knowledge of the underlying probability distributions of the system. Instead, it learns optimal actions through trial-and-error interaction with the environment. This adaptability is crucial for energy systems, where perfect forecasting is essentially impossible. Over time, Q-learning refines the policy, ensuring that it can handle the stochastic nature of wind power and changing energy demands. Moreover, Q-learning's iterative updates and the ϵ-greedy exploration strategy allow the algorithm to continually improve as more state-action-reward transitions are observed, achieving a policy that is robust to uncertainty and variability.

Fig. 3 demonstrates the agent's exploration of different φ values over time. Each line represents the trajectory of updating φ an agent took in a given episode/iteration. Darker lines represent frequently traveled paths, while lighter lines represent infrequently traveled paths. The saw-tooth nature of the lines reflects the $\epsilon-$greedy search algorithm, where the agent deviates from the immediate optimal action with probability ϵ.

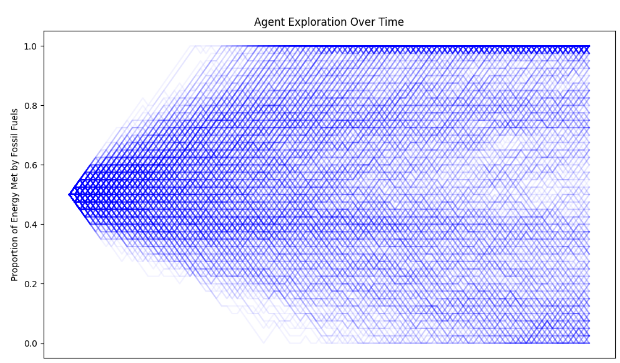

Fig. 3. Agent's Exploration of φ Over Time

IV. Results and Figures

1. Q-matrix: After discretizing states and running Q-learning, we are left with a Q matrix, which assigns a value to every state-action pair. Filtering for the action ”no-change,” where φ is left unchanged, gives a proof-of-concept of the Energiewende. As shown in Fig. 4, the three heatmaps display the Q-values for the action “no change” after 10, 100, and 10,000 learning episodes. Initially, the Q-values are near zero across all wind speeds and fossil fuel proportions (the agent has not yet learned meaningful patterns). Over time, the agent begins to associate negative Q-values (depicted in red) with maintaining the current proportion of fossil fuels when wind speeds are low (below 5 m/s). After 10,000 episodes, a clear pattern emerges, with significant negative rewards appearing when wind speeds are more than one standard deviation below average and fossil fuel reliance (φ) is low (below roughly 0.5). In these regions (shown as dark red areas on the heatmap) the agent recognizes that low wind speeds combined with low fossil fuel usage often lead to unmet energy demand, resulting in heavy penalties. Conversely, when wind speeds are higher, the Q-values remain neutral (blue) indicating that “no change” is a safer action. The Energiewende crisis falls somewhere within these dark red regions, where unexpectedly low renewable energy production led to an inability to meet demand.

Filtering for the action ”increase,” where φ is increased, we observe a similar story. In Fig. 5 (see page 7), the agent progressively learns to associate positive rewards with increasing fossil fuels when φ is small and renewables dominate and when wind speeds are low. The only instances where it is not particularly valuable to increase fossil fuel use (with φ roughly below 0.5) is when wind speeds are abnormally high. We also see that there is little room for error along the boundaries of positive and negative rewards, and that extreme rewards (either positive or negative) are generally of the same magnitude. This makes sense, as meeting energy demands is a binary event. Failing to meet energy demand is the same outcome regardless of the margin of failure.

2. Optimal Policy: Once we have established a Q-matrix, an optimal policy can be derived. This optimal policy matrix represents the actions for every possible state that yield the greatest cumulative reward. Because the optimal policy has three state dimensions and three possible actions per state, visualizing the entire policy is impractical. However, by fixing the demand to values at or near the average, we can visualize the policy for different combinations of φ (proportion of energy met by fossil fuels) and wind speed.

As an example, Fig. 6 (see page 7) shows the

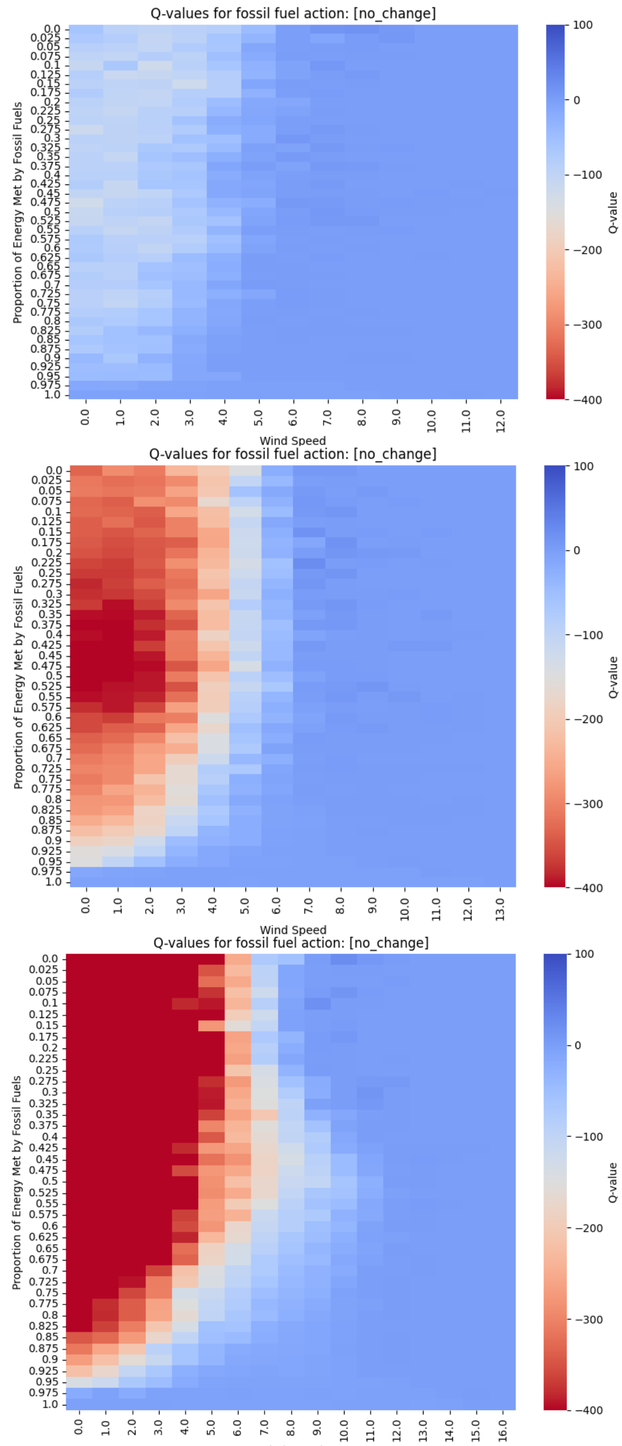

Fig. 4. Q-matrix after 10, 100, and 10000 learning episodes for action: ”no change”

optimal policy for demand values at or near average, where green represents an increase in renewable use (decrease in fossil fuels), yellow represents no change, and red represents an increase in fossil fuels (decrease in renewables). We see that, with particularly high wind speeds, it is almost always preferable to increase reliance on renewables.

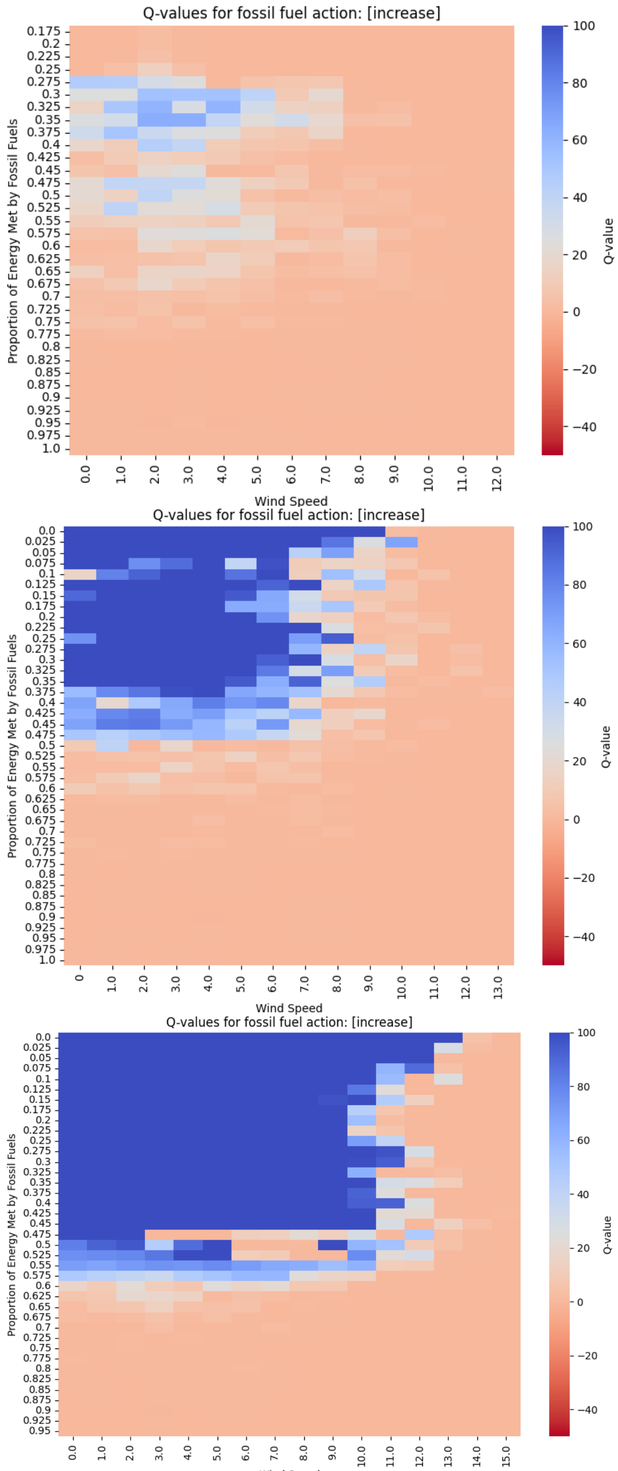

Fig. 5. Q-matrix After 10, 100, and 10000 learning episodes for action: ”increase”

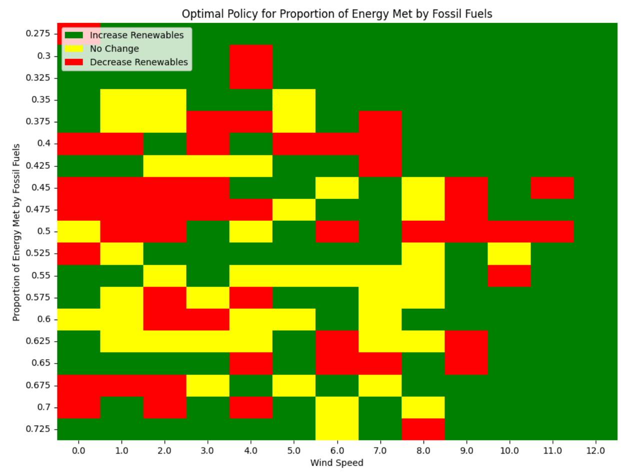

Fig. 6. Optimal Policy when Demand Near Mean

V. Discussion and Conclusion

While the assumptions of our model preclude this optimal policy from being used to predict or guide real-world energy policy, it serves an important demonstrative role in the intricacies of using a stochastic energy source like renewables. The results of this project demonstrate the capability of Q-learning within an MDP framework to optimize energy transitions under such conditions. The agent’s exploration, Q-matrix evolution, and the derived optimal policy provide key insights into how an agent can learn adaptive policies to minimize fossil fuel reliance while ensuring energy demands are consistently met.

We visualize the agent’s ϵ-greedy exploration of the proportion of energy met by fossil fuels (φ) over time in Fig. 3, and the Q-matrix for ”No Change” and ”Increase” reveal a clear pattern after 10,000 learning episodes. For ”No Change” (Fig. 4), the agent associates significant negative rewards with low wind speeds (below 5 m/s) and low fossil fuel reliance (below 0.5), with red regions reflecting the risk of unmet energy demand due to insufficient renewable output. At higher wind speeds, the agent then recognizes ”no change” as the safer option, reinforcing the need for adaptive decision-making in responding to wind variability. As for ”Increase” (Fig. 5), we observe positive rewards when wind speeds are low and φ is small. The agent must learn to manage energy transitions strategically to avoid penalties associated with fossil fuel use and unmet demand. As wind speeds approach higher values, increasing fossil fuel reliance offers little to no benefit. The derived optimal policy (Fig. 6) illustrates how the agent adjusts these actions based on the observed parameters, learning to rely on renewable output (lower φ) in response to favorable wind conditions (green regions) while opting to increase fossil fuels (higher φ) at lower wind speeds in order to mitigate the risk of unmet demand (red regions). Yellow regions provide the in-between scenario, where the agent has learned to maintain the current fossil fuel proportion (φ remains the same) as the safest choice.

Although the model relies on simplifications, it offers a valuable proof-of-concept for integrating stochastic factors into energy decision-making. Future work could enhance this framework by incorporating more granular data, regional variability, and real-time system constraints (such as grid capacity and storage limitations). The model can also be further extended to include multiple renewable sources (e.g., solar, hydro, and storage) and provide a more comprehensive representation of the energy systems at play.

Preventing the consequences of an Energiewende-like crisis requires mitigating the sharp boundaries in rewards. The balance of renewable energies and fossil fuels must be established in such a way that the stochasticity of renewables, even at its most extreme, does not prevent energy demands from being met. An increase in renewable infrastructure is the most direct and practical way to increase the tolerance of such a model and allow φ to approach 0. The derived optimal policy seeks to balance the trade-offs between minimizing fossil fuel reliance and meeting fluctuating energy demands. By incorporating stochastic transitions for wind speed and demand, the model captures the inherent uncertainty in renewable energy production. Our findings emphasize the importance of renewable infrastructure investments to mitigate stochastic variability and allow for more aggressive reductions in fossil fuel reliance.

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