Analysis of the Economic Agreements and Energy Management Systems for the Adoption of Rooftop Photovoltaic Microgrid Systems using Game-Theory and Fuzzy Q-Learning

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Abstract

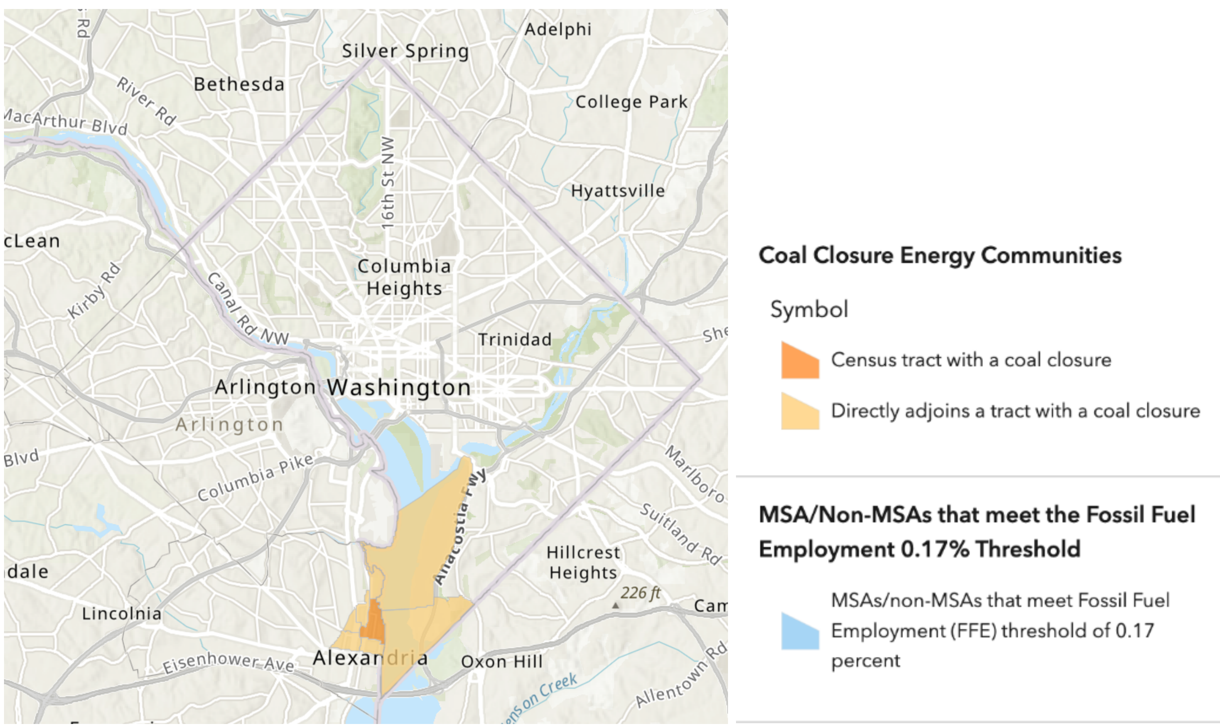
Many cities have formed policy goals to achieve clean energy by 2030, but the engineering and economic processes to do so remain unclear. The adoption of renewable energy through solar powered microgrids is a rising solution for cities. Microgrids operate near the end user and reduce transmission losses, transformation losses, and increase power reliability. Investing in local microgrid infrastructure reduces the congestion in the existing power grid. Building new power generation infrastructure and satisfying local consumer demand results in a complex economic and engineering game. Utility companies are dependent on third party solar developers to invest in power generation infrastructure and are limited to investing in only distribution infrastructure updates. Solar developers must find and lease land within the city to build solar power generation field sites. Once the infrastructure is in place, the microgrid is able to provide high quality power to its local community. The power provided to the local community is sold at a fixed price determined by the solar developer. The microgrid is integrated with the main grid to request and bid electricity at a price agreed upon by the utility company and solar developer. The microgrid should be able to act independently of other agents and maximize its rewards. This paper investigates the required economic agreements between: property developers and solar developers, and solar developers and utility companies. Furthermore, the control and operation of a 2 player microgrid system is proposed for the local community of Ward 6 - Washington, DC.

Keywords - microgrid, reinforcement learning, Q-learning, game theory, fuzzy logic, economic, control

1. Introduction

The District of Columbia has passed one of the most aggressive Renewable Energy standards in the country mandating that 100% of the District's energy comes from Tier 1 renewable energy sources by 2032 (DOEE, 2023). Furthermore, by 2041 at least 15% of the energy must come from solar energy generated within the District (DOEE, 2023). To incentivize the transition to clean energy, the District has proposed acts for electrifying transportation and updating building energy codes. Both acts increase the reliance of electricity compared to natural gas in the District. The transition to clean energy has not been well defined. The policies focus on goals rather than methods, so the engineering and economic transition plan remains unclear. This ambiguity has led to the District being unable to meet their goals. Several barriers are present primarily due to the high up-front infrastructure costs, high interconnection fees, and the influence of obsolete utility companies. The process of moving DC to all renewable energy by 2032 is a complex super game that hasn't been analyzed. It consists of a series of sequential and simultaneous games including the electrification of transportation, inter-agency vs tax payer politics, residential demand vs apartment management, and finally utility companies vs the District. A game theory analysis for solar energy generation within the District will provide insight into potential engineering and economic strategies that can facilitate the process of local power generation growth.

The Local Solar Expansion Act mandates that 15% of the District's energy comes from solar energy generated within the District (DOEE, 2023). Solar energy can be generated from ground installed panels or rooftop solar. Solar rooftop installation faces high infrastructure costs, while ground solar installation is limited due to the dense urban environment. The challenges for installing solar locally on buildings and ground areas is the distribution system hosting capacity, limited space, high costs, and financial customer barriers (DCPSC, 2023). Utility companies are not allowed to own solar infrastructure within DC but are still required to source a portion of their electricity from renewable energy sources. Utilities must purchase Renewable Energy Credits (RECs) or are faced with high compliance fees (DCPSC, 2023). Third party solar developers are able to develop field sites freely within the district but are dependent on utilities to buy RECs to recover high upfront costs. Furthermore, solar developers must enter into land lease agreements with high rise property developers in DC to procure land for field sites. Solar developers in DC do not receive any federal tax credit for solar development projects because no coal powered plants are present in the District.



<u>Figure 1: Fossil Fuel Energy Communities in DC eligible to receive Federal Tax Credits</u>

A game theoretic approach will be taken to design the economic process for building a solar power generation system for high rise properties in DC. The game starts by assuming that a solar developer will be self incentivized to obtain a rental agreement with a major property developer in DC. This assumption is rational because as shown in Figure 1, there is no dominant power generation company in the District. Electric power is distributed using Pepco from power generation plants in Baltimore (James, 2022). By establishing solar power generation sites, a set of local microgrids can be developed to support the local demand. If a self-motivated solar developer appears, they may dominate the local wholesale market and fix electricity prices, enabling them to recover upfront costs and become profitable. Additionally although solar developers receive no tax credits, property developers will receive credits and tax incentives for engaging in solar development projects. Both the property developer and solar developer benefit from collaborating on such an agreement.

Once a field site has been agreed upon and developed, the solar developer must then engage in another game to have the site approved and accepted by the utility company. The utility company holds influence in this game because the site must be approved to connect to the main grid. Without an interconnection the site is not as profitable. It is limited to selling only to the local building. If the site is rejected, the developer can engage the utility company in a power purchase agreement to expedite the interconnection process. A power purchase agreement guarantees selling the RECs to the utility company. The agreement also includes settling on a confidential strike price in the wholesale market, so that the utility company can purchase electricity at a very discounted rate (EPA, 2023). The success of the power purchase agreement depends on the utility company's need for RECs.

Finally each developed microgrid is able to act as an independent rational actor free to make its own decisions. Microgrids have the advantage of being more reliable because of its self dependence on its own power generation unit and its ability to directly serve a local demand without passing through a transmission network. Microgrids are also able to directly connect and disconnect to the main grid at various transmission points allowing them to serve local demand even if local power generation fails to meet the demand. Rather than using traditional control policies like PID or droop control, the application of multi-agent reinforcement learning for a 2 player microgrid system is investigated. The microgrid design assumes that interconnection to a larger grid has been approved, so the system is able to request and sell power. If the microgrid appears profitable, then the goal of the utility company and solar developer has been met.

2. Modeling the Problem: Economic Agreements and Energy Management System

A sequence of games is considered to develop a solar power generation field site. Each game explores a financial contract binding two parties together in a solar development project. Each player trades and holds real high-value assets for the full duration of the contract. It is assumed the assets are subject to increasing in value over time as both companies used for the model have high market caps. The last game exploring an energy management system can be described as both a distributed control and an economic game. Although in nature the energy management game is control based, its purpose is to maximize profit while maintaining self-dependence. The last microgrid game assumes that the prior financial contract games have resulted in successful contracts.

2.1. Modeling Economic Agreements as Evolutionary Games

The adoption of solar energy within DC can be modeled as a series of financial contracts or economic agreements between different parties. The two major financial contracts of interest are: rental agreements between solar developers and property developers, and power purchase agreements between solar developers and dominant utility companies. These contracts exist due to local operating restrictions placed on utility companies.

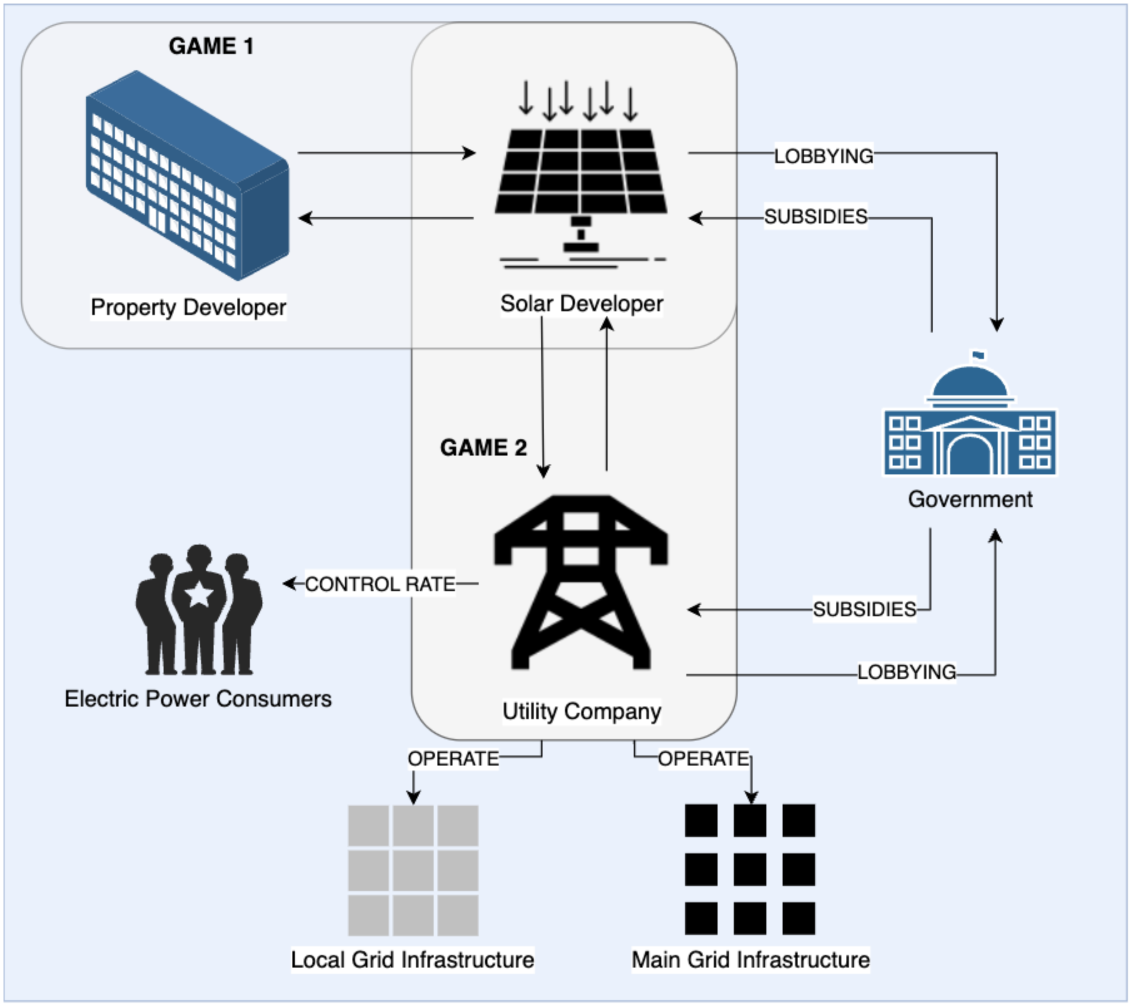


Figure 2: Supergame of all players in the Solar Power Development and Distribution Game

Utility companies are not allowed to develop power generation infrastructure within DC, but they are required to prove that a certain amount of power is generated from renewable resources. Therefore, utility companies are required to purchase Renewable Energy Credits (RECs) from solar developers (Marsh, 2023). Solar developers incur the upfront cost of installation, interconnection, and maintenance but are able to offset costs by selling RECs. Solar developers are dependent on utility companies accepting their field sites to connect to the main grid. Without an interconnection they are unable to freely sell the power generated on the wholesale market

Solar developers are able to freely develop solar power generation sites within the city and can pursue rental agreements with property developers to lease rooftop land for solar sites. Property developers are able to receive constant land rent while receiving green building credits if they engage in rental agreements. If a solar developer is able to procure enough agreements, they may emerge as a dominant energy market player in the district.

2.1.1. Relevant Equations:

These equations are referred to throughout the modeled payoff equations.

Land Appreciation Equation:

The land appreciation equation has been modeled as a continuously compounding interest value. The interest rate is dependent on the average increase of land value in the DC area. It is assumed to 2% increase for the industry standard $P_{standard}(t)$ while the real interest value fluctuates uniformly between 2% and 10% for $P_{real}(t)$. The land appreciation equations are used to express the dynamic value of land.

$$P(t) = P_0 e^{rt}$$

$$P_{standard}(t) = P_0 e^{0.02t}, \; P_0 = 8/3 \rightarrow \textit{Average rent/day/sq foot}$$

$$P_{real}(t) = P_0 e^{U(0.02,\, 0.1)t}$$

<u>Net Present Value Equation:</u>

The net present value equation represents the value of a company. The method provides a way to evaluate and compare capital projects and financial products like field development sites and solar panels. Cash flows referred to as R_t are capital gains from business operations. NPV is used to model the value of owning a high value asset of a public company. Similar to individual shareholders holding stock for x period of time, rental agreements bind each developer to hold a real asset for x amount of years.

To model the solar developer cash flows, the renewable energy company NextEra Energy is used. The discount rate for NextEra Energy is 0.0704. $NPV_{SolarDeveloper}(t)$ is calculated by valuing R_t as the cash inflow per share. The 2022 cash inflow from operations is used: $6 billion.

To model the property developer cash flows, a popular property developer in the DC area, AvalonBay Communities, is used. The discount rate for AvalonBay Communities is 0.0745. $NPV_{LandValue}(t)$ is calculated by valuing R_t as the cash inflow per share. The 2022 cash inflow from operations is used: $1.46 billion.

$$NPV(t) = \sum_{t=1}^{n\to\infty} \frac{R_t}{(1+r)^t} - R_0$$

$$NPV_{Solar\ Developer}(t) = \sum_{t=1}^{n\to\infty} \frac{R_t}{(1+0.0704)^t} - R_0, \; R_t = \text{6 billion in cash flow}$$

$$NPV_{Land\ Value}(t) = \sum_{t=1}^{n\to\infty} \frac{R_t}{(1+0.0745)^t} - R_0, \; R_t = \text{1.46 billion in cash flow}$$

<u>WholeSale and Local Electric Profit Equation:</u>

Upon entry to the wholesale market a solar developer approaches peak market value as it gains more control over the market. This process can be modeled as a logistic equation. Electric profit can range from 0 to peak market value. Peak market value P_{market} is the max profit a bid of 1 unit of energy can receive. If the energy must be discounted then the max profit is $P_{discount\text{-}market}$. Otherwise if the developer is limited to a local grid its max will be P_{local}. The max profits drive the separate equations of V(t).

$$V(t) = \frac{P_{market}}{1+e^{-k(t-t_0)}}, \; \textit{where } t_0 \textit{ is initial minimum profit}$$

$$V_{main}(t) = \frac{P_{market}}{1+e^{-k(t-t_0)}}, \; P_{market} = U(.087,\, .121)/kWh$$

$V_{discount-main}(t) = \frac{P_{discount-market}}{1+e^{-k(t-t_0)}}$, $P_{discount-market}$= 0.035/kWh

$V_{local}(t) = \frac{P_{local}}{1+e^{-k(t-t_0)}}$, P_{localt} = U(.05, .100)/kWh

Variable Benefits Equation:

Each player receives variable benefits from actively participating in agreements to develop and use solar power generation field sites. Buildings receive green building tax incentives and credits for green updates, installing rooftop solar, and energy storage devices. Commercial buildings can receive $2.50 to $5.00 per square feet in credit (Evans, 2023). Similarly solar developers can receive $300 to $400 for each MWh produced (EPA, 2023). They receive this when selling Renewable Energy Credits, which helps offset their upfront installation cost. Finally utility companies are required to purchase these Renewable Energy Credits to operate within the District or pay an alternative compliance fee (EPA, 2023). The fee for not meeting the REC requirement is $300/MWh (DCPSC, 2023). Utility companies are also able to settle on a non-public strike price with the developer allowing them to control the wholesale electric power market. The solar ppa strike price has reportedly fallen to an average $35/MWh (EPA, 2023), while the wholesale price for DC's regional trading hub Mid-Atlantic (PJM) ranged from $87/MWh to $121 MWh.

$B_{GreenBuilding}(t) = U(2.5,\ 5.0) * A_{Total\ Building}$

$B_{RECredits}(t) = 300 * E_{MWh}$

$B_{RECredits}(t) = U(50,\ 100) * E_{MWh}$

$P_{RECredits}(t) = U(300,\ 400) * E_{MWh}$

2.1.2. Rental Agreements between Solar Developers and Property Developers:

The rental agreement is modeled as a financial contract allowing the solar developer to develop a solar field site on high-rise buildings by renting rooftop space. Since there is no dominant solar developer in the DC area nor any dominant power generation company, a solar developer is incentivized to request a rental agreement with property developers. Property developers do not incur any upfront costs of installation and may receive Green Building tax credits by accepting a rental agreement. For the duration of the rental agreement both parties hold power over a high value asset.

However each party is entitled to valuing the asset they hold by a certain parameter. The parameter will range from $x \in [0,\ 1]$, where x = 0 means asset holds no value and x = 1 means asset holds market value.

Each parameter is from the perspective of each player:

- $\theta_{a\ solar} \in [0,\ 1]$ → The property developer's valuation of holding solar panel assets
- $\theta_{a\ land} \in [0,\ 1]$ → The property developer's valuation of holding land assets
  - Valuation of own assets
- $\theta_{d\ solar} \in [0,\ 1]$ → The solar developer's valuation of holding solar panel assets
  - Valuation of own assets
- $\theta_{d\ land} \in [0,\ 1]$ → The solar developer's valuation of holding land assets

Each parameter is coupled with the asset to generate the final payoff for each player given their action.

<table>
<tr><td colspan="2">Game 1: Rooftop Rental Agreement for Solar Development Site Payoff Matrix</td><td colspan="2">Solar Developer</td></tr>
<tr><td colspan="2"></td><td>Offer</td><td>Not Offer Land Rent</td></tr>
<tr><td rowspan="2">Property Developer</td><td>Sign</td><td>(a_{11}, d_{11})</td><td>(a_{12}, d_{12})</td></tr>
<tr><td>Not Sign/ Renegotiate</td><td>(a_{21}, d_{21})</td><td>(a_{22}, d_{22})</td></tr>
<tr><td colspan="4">Assumptions:
● $a_{22} \leq a_{11}$
● $a_{11} \leq a_{21}$ (max)
● $a_{12} \leq a_{11}$

● $d_{22} \leq d_{11}$
● $d_{11} \leq d_{12}$ (max)
● $d_{21} \leq d_{11}$</td></tr>
</table>

Payoff Equations for Property Developer:

$$a_{11}(t) = A_{panels} * (P_{standard}(t) - P_{real}(t)) + \theta_{a\ solar} * N_{panels} * NPV_{Solar\ Developer}(t) + B_{GreenBuilding}(t)$$

$$a_{12}(t) = N_{panels} * (NPV_{Solar\ Developer}(t)) + B_{GreenBuilding}(t)$$

$$a_{21}(t) = P_{real}(t) * A_{panels} + \theta_{a\ solar} * N_{panels} * NPV_{Solar\ Developer}(t) + B_{GreenBuilding}(t)$$

$$a_{22}(t) = \theta_{a\ land} * A_{panels} * NPV_{Land\ Value}(t)$$

Payoff Equations for Solar Developer:

$$d_{11}(t) = \theta_{d\ land} * A_{panels} * NPV_{Land\ Value}(t) + V_{main}(t) - A_{panels} * P_{standard}(t) - C_{maintenance}(t) - C_{installation}$$

$$d_{12}(t) = V_{main}(t) - C_{maintenance}(t) - C_{installation}$$

$$d_{21}(t) = \theta_{d\ land} * A_{panels} * NPV_{Land\ Value}(t) + V_{main}(t) - A_{panels} * P_{real}(t) - C_{maintenance}(t) - C_{installation}$$

$$d_{22}(t) = \theta_{d\ solar} * NPV_{Solar\ Developer}(t)$$

Each parameter is critical to determining if a stable equilibrium exists for the rental agreement. The parameters will be varied to determine if a bifurcation exists within the rental agreement game.

2.1.3. Solar Power Purchase Agreements between Solar Developers and Utility Companies:

The power purchase agreement is modeled as a financial contract allowing the utility company to purchase generated solar power at a discount rate while maintaining control over a real high-value asset. A power purchase agreement is usually offered to the utility company to incentivize approving interconnection to the main grid. Without an approved interconnection, solar developers are unable to sell RECs or sell electricity to the main grid .

Since the utility company controls the operation of the main grid and entry to the wholesale market, it holds the power to accept and reject a solar development site. The utility company wants to be offered a power purchase agreement to receive financial benefits and discount its own power generation operations. The solar developer wants their field site to be accepted in order to profit from the generated power.

However in this case the utility company is able to value the RECs they are offered by a certain parameter. The value of the RECs depends on if the utility company needs the REC. If there have been many approved solar development projects in the area, then a new project will hold less value to the utility company. But if there is a shortage of solar development projects or an increase in required RECs, then the new project will hold its market value.

The parameter will range from $x \in [0, 2]$, where x = 0 means asset holds no value and x = 2 means asset holds double the market value:

- $\theta_{credit\ value} \in [0, 2]$ → The utility company's valuation of holding a REC and avoiding compliance free.

Each parameter is coupled with the asset to generate the final payoff for each player given their action.

<u>Table: Solar Power Purchase Agreement for Solar Development Site - Payoff Matrix</u>

<table>
<tr><td colspan="2" rowspan="2">Game 2: Solar Power Purchase Agreement for Solar Development Site</td><td colspan="2">Utility Company</td></tr>
<tr><td>Reject Site</td><td>Accept Site</td></tr>
<tr><td rowspan="2">Solar Developer</td><td>Offer</td><td>(a_{11}, d_{11})</td><td>(a_{12}, d_{12})</td></tr>
<tr><td>No offer</td><td>(a_{21}, d_{21})</td><td>(a_{22}, d_{22})</td></tr>
<tr><td colspan="4">Assumptions about the solar developer's payoffs:
● $a_{22} \leq a_{11}$
● $a_{11} \leq a_{21}$ (max)
● $a_{12} \leq a_{11}$
● $a_{22} \rightarrow a_{11}$ (desired to converge to a signed deal)

Assumptions about the utility company's payoffs:
● $d_{22} \leq d_{11}$
● $d_{11} \leq d_{12}$ (max)
● $d_{21} \leq d_{11}$
● $d_{22} \rightarrow a_{11}$ (desired to converge to a signed deal)</td></tr>
</table>

Payoff Equations for Solar Developer:

$$a_{11}(t) = (V_{discount-main} - V_{local}(t)) - C_{maintenance}(t) - C_{installation}$$

$$a_{12}(t) = V_{discount-main}(t) + P_{RECredits}(t) - C_{maintenance}(t) - C_{installation} - C_{interconnection}$$

$$a_{21}(t) = (V_{main} - V_{local}(t)) - C_{maintenance}(t) - C_{installation}$$

$$a_{22}(t) = V_{main}(t) + P_{RECredits}(t) - C_{maintenance}(t) - C_{installation}$$

Payoff Equations for Utility Company:

$$d_{11}(t) = (V_{main} - V_{discount-main}(t)) - \theta_{credit\ value} * B_{RECredits}(t)$$

$$d_{12}(t) = (V_{main}(t) - V_{discount-main}(t)) + \theta_{credit\ value} * B_{RECredits}(t) + C_{interconnection} - P_{RECredits}(t)$$
$$d_{21}(t) = -\theta_{credit\ value} * B_{RECredits}(t)$$
$$d_{22}(t) = \theta_{credit\ value} * B_{RECredits}(t) - P_{RECredits}(t)$$

This parameter affects the game's symmetry as well.

2.2. Modeling Microgrid Energy Management as 2 player Learning Games

The energy management system assumes a decentralized approach. The system has no main controller observing all the states of each microgrid. Each local microgrid acts as an independent player to provide its local load with power, sell its excess, store in a common shared battery, and request power. The local microgrid assumes that once its power is sold, it is bid automatically within the main interconnection queue. Each microgrid is assumed to be binded with a power purchase agreement, so selling to the local grid vs main grid isn't differentiable to the agent. The microgrid always sells at the bid price. Trading between microgrids hasn't been explored because the overall game assumes players are for-profit.

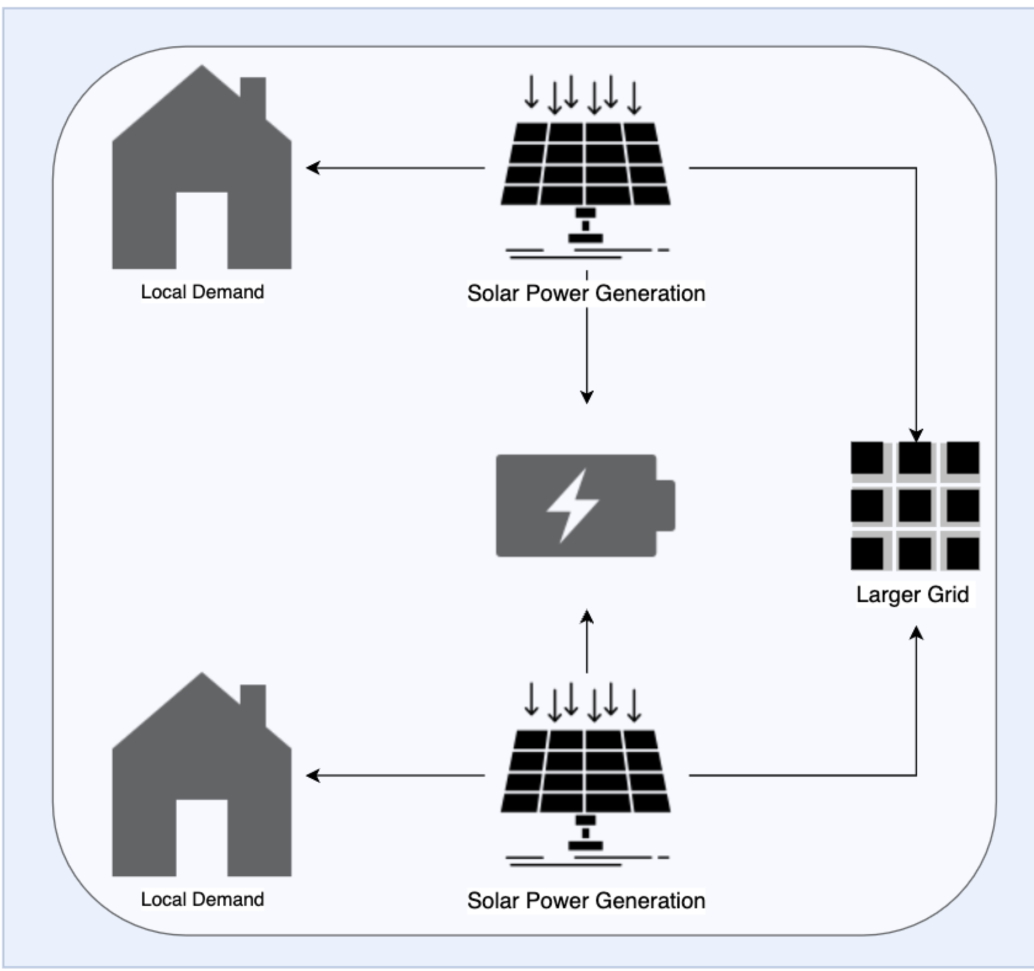


Figure 3: Modeling Engineering Game Interactions

It is assumed there is no limit to how much power can be requested or sold from the main grid. It is also assumed that the battery has no storage limit. To represent real power grid interactions, there is a cost when requesting energy transfers from another grid (main-grid). When there is a shortage of power each microgrid takes action to minimize that shortage. When there is an excess of power each microgrid takes action to maximize the profit without hurting the system in the future.

The agent does not observe variables that are uncontrolled like the main grid parameters. Each microgrid is responsible for managing its own shortages and excess. Through managing its shortage and excess it can measure its own reliability through fuzzy logic systems. A highly reliable system means the microgrid is self-sufficient. A low reliable system indicates the microgrid is dependent on the main grid for support.

2.2.1. Solar Generation Equations

Solar panels use solar radiation to generate electricity, transforming photons that hit the photovoltaic panels into DC current. When the photons hit the panel they are absorbed by the panel's semiconducting silicon material. The movement of the electrons generates the DC current. Solar panels rely on solar elevation, cloud cover, topography, and solar irradiance.

For this paper the solar panel chosen is the Vertex 670W+ Module. The area of the panel is A = 2.9106 from 66 210 mm silicon wafers. The solar panel yield is rated at 21.6%. The losses are estimated to be 0.0651 based on DC to AC loss and random loss (Skiparev, 2020).

<u>Power Generation Equation:</u>

A is the area of the solar panel, y is the solar panel yield, H is the solar radiation, and r is the performance ratio.

- $E = AyHr$

<u>Solar Radiation Equations:</u>

The solar radiation changes throughout the year as it is dependent on solar elevation and cloud cover. R_0 is clear sky insolation, η is cloud cover percentage, φ_{tp} is the solar elevation at the previous hour, and φ_p is the solar elevation at the current hour (Vallee, 2020)

- $H = R_0(1 - 0.75\eta^{3.4})$
- $R_0 = 990sin(\frac{\varphi_{tp} + \varphi_p}{2}) - 30$

2.2.2. 2 Player Reinforcement Learning using Fuzzy Q - Learning

The objective of reinforcement learning is to find a policy - a mapping from states to actions - that maximizes a reward. Learning is essentially a trial and error process where an agent learns through exploration and exploitation by receiving feedback from the system. The learning agent reinforces itself through successes and failures. Actions that are good when performed in a given state are rewarded, while actions that are bad are punished. In this case attempting to sell energy during a shortage is punished.

1. Initialize Q(s, a) arbitrarily for all states and actions
2. Repeat
    a. Solve Q for each player in matrix game G
    b. Find V where $V(s) = \max_a[Q(s, a)]$
    c. Find A where A(s) = argmax of V(s) → the chosen action to maximize Q at state s
3. Matrix A gives us dominant actions at each state

Fig 4: Minimax-Q-Learning Algorithm (Bowling, 2000)

The dominant strategy will emerge by identifying the dominant state using the value function from Q-value where V = max of Q over every state action pair. By mapping V to the learned policy the dominant action will be found for each agent in this symmetric game.

Q learning is a type of model-free or decentralized reinforcement learning, where the agent does not need to know all the details about the model. Q-learning learns through the action-value function "Q" that maps state-action pairs to returns. An agent tries an action at a state and evaluates its reward immediately.

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize S
  Loop for each step of episode:
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Take action A, observe R, S'
    $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$
    $S \leftarrow S'$
  until S is terminal

Fig 5: Q-Learning Algorithm (Sutton, 2020)

2.2.2.1. Observations

These observations are observed by both learning agents when interacting with the environment. Resets to the environment start the agent at random days at hour 0.

Observation	**Notes**
Current Energy Demand (MWh)	-
Current Energy Supply (MWh)	-
Battery Supply (MWh)	-
Total Supply (MWh)	Current Energy Supply + Battery Supply

Current Delta (MWh)	Total Supply - Current Demand
Main Grid Request Price ($)	Dynamic based on necessity of local demand. Larger the delta, larger the cost to request.
Main Grid Bid Price ($)	Constant $0.14/kWh
Storage Price ($)	Constant $0.05/kWh
Current Econ Return	$Profit

2.2.2.2. States

In order to best preserve information about the state of the system given the observations, the learning agent learns a fuzzy 2D state.The state space represents the degree of autonomy of a system. The state is defined as:

S = [dependence degree, independence degree]

The dependence degree should measure how dependent each microgrid is on the main grid. The independence degree should measure how self-dependent each microgrid is. A high degree of independence indicates high reliability if the microgrid system should need to disconnect from the main grid.

The fuzzy inference engine uses 8 rules. Each fuzzy rule is operated upon by approximating the crisp output. For each output linguistic variable, the probabilistic t-conorm operates on all of the individual strengths for all the corresponding rules. This iterative probabilistic t-conorm operation reduces the number of variables from 8 to 2.

```
1. x = [x1, x2, x3, x4]
    a. idx = 0
    b. for i in range(0, 4):
        i.  a = x[i]
        ii. for j in range(i + 1, 4):
            1. b = x[j]
            2. Y[0, idx] = a + b - (a * b)
            3. idx = idx + 1
```

Fig 6: Algorithm for Probabilistic T-conorm

2.2.2.3. Rules

The final fuzzy output state of s = [dependence degree, independence degree], is generated through a fuzzy inference engine. The rules require the crisp inputs of the observations be fuzzified before inputting into the inference engine. The rules are as follows:

- Rule 1 if *current_delta* is *not_reliable* and *battery_usage* is low and *current_economic_profit* is low, then Z is not independent
- Rule 2 if *current_delta* is *not_reliable* and *battery_usage* is low and *current_economic_profit* is high, then Z is not independent

- Rule 3 if *current_delta* is *not_reliable* and *battery_usage* is high and *current_economic_profit* is low, then Z is not independent
- Rule 4 if *current_delta* is *not_reliable* and ba*battery_usage*tt is high and *current_economic_profit* is high, then Z is independent
- Rule 5 if *current_delta* is *reliable* and *battery_usage* is high and *current_economic_profit* is high, then Z is independent
- Rule 6 if *current_delta* is *reliable* and *battery_usage* is low and *current_economic_profit* is high, then Z is independent
- Rule 7 if *current_delta* is *reliable* and *battery_usage* is high and *current_economic_profit* is low, then Z is independent
- Rule 8 if *current_delta* is *reliable* and *battery_usage* is low and *current_economic_profit* is low, then Z is not independent

2.2.2.4. Actions

By default the agent serves the local demand immediately with the current energy generation and battery supply, this allows for the system to maintain a level of virtual inertia control (Skiparev 2020). This is critical to energy generation systems that are not motor driven (Skiparev 2021). Once the current energy demand is met there is a delta. The actions are designed to manage the delta. The actions in this environment are:

- Action 0: Sell (delta) to Main
- Action 1: Store (delta) to Battery
- Action 2: Buy (delta) from Main

2.2.2.5. Reward

The agent receives a reward for certain actions taken in a given state. The default reward at every step is +10. The agent always receives a reward for serving the local demand. The reward of interest is dependent on delta. The reward shaping is as such:

- Reward 0: Main Grid Request Price * Delta → i.e. selling during a shortage is very bad
- Reward 1: Storage Price * Delta → storing during a shortage isn't rewarded
- Reward 2: (-1) * Main Grid Bid Price * Delta → negation taken so that the agent is rewarded for requesting help during a shortage. However it should not request if in a state of excess

3. Simulation Results for Economic Agreements and Energy Management System

Simulations have been performed to evaluate the dominant strategy in each game.

3.1. Simulation Results for Economic Agreements

3.1.1. Simulation Results for Rental Agreement: Property Developer vs Solar Developer

The simulation is run with a fixed rental agreement time of 15 years. The time step is t - day. There are a total of 15*365 time steps. Simulations have been run with a combination of parameter relations. The parameters used are: $\theta_{a\ solar}$, $\theta_{a\ land}$, $\theta_{d\ solar}$, $\theta_{d\ land}$.

The relations explored are listed in terms of players. Property developer is referred to as "A", while the solar developer is referred to as "D". For each combination the dominant action is graphed.

- {A values assets equally, D values assets equally}: **Stable Equilibrium → (not sign/renegotiate, no offer of land rent) → no agreement or negotiation war till land rent met**

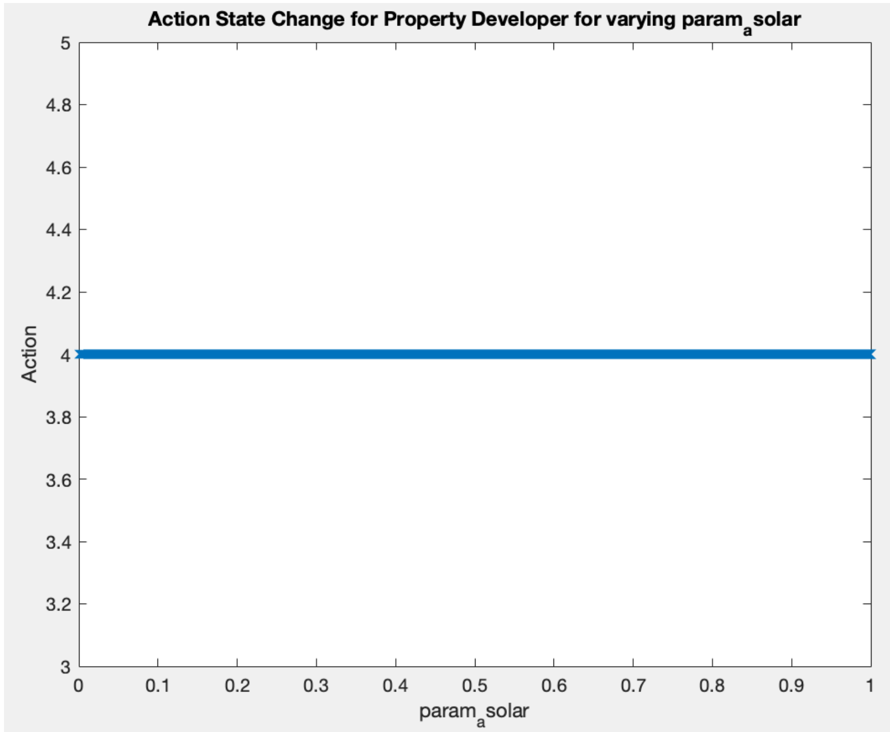


Figure 7: Action State Change for Property Developer while varying $\theta_{a\ solar}$

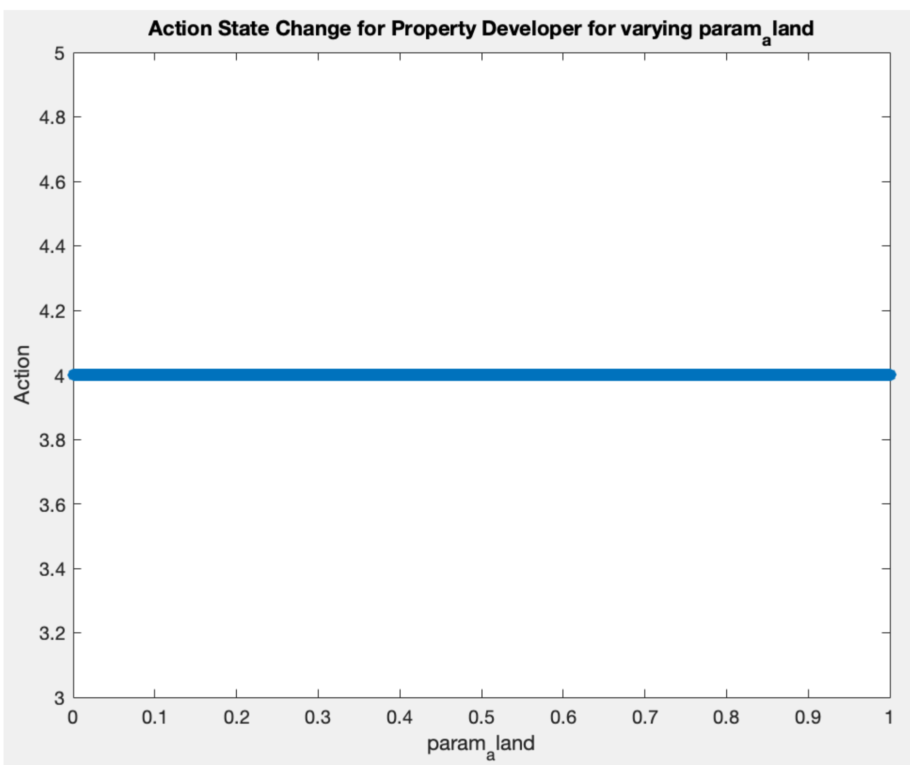


Figure 8: Action State Change for Property Developer while varying $\theta_{a\ land}$

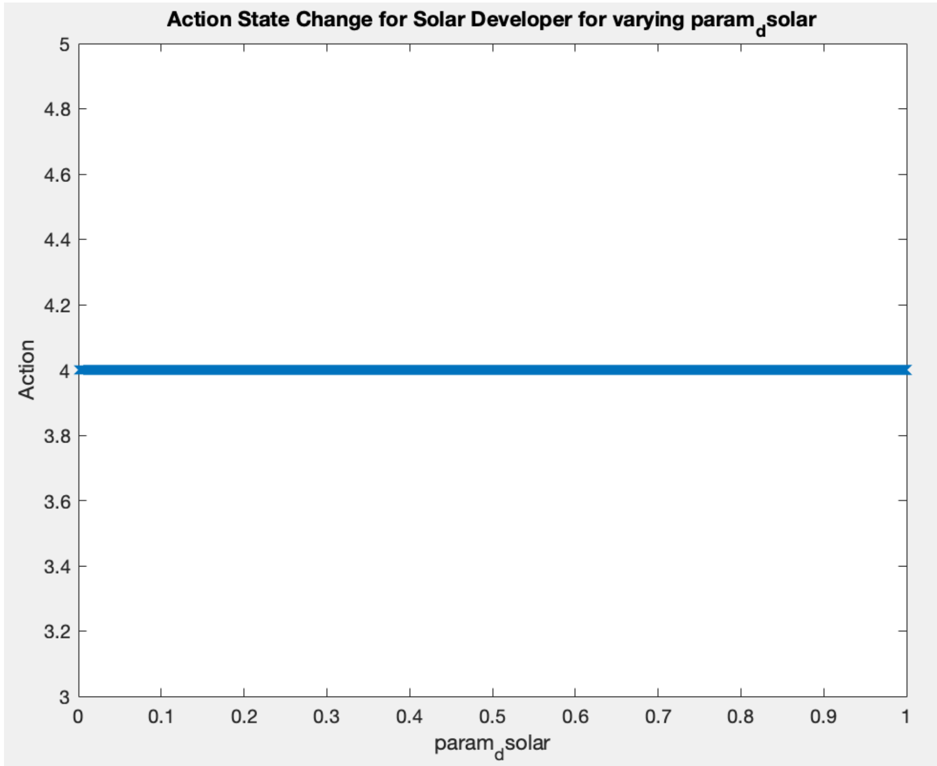


Figure 9: Action State Change for Property Developer while varying $\theta_{d\ solar}$

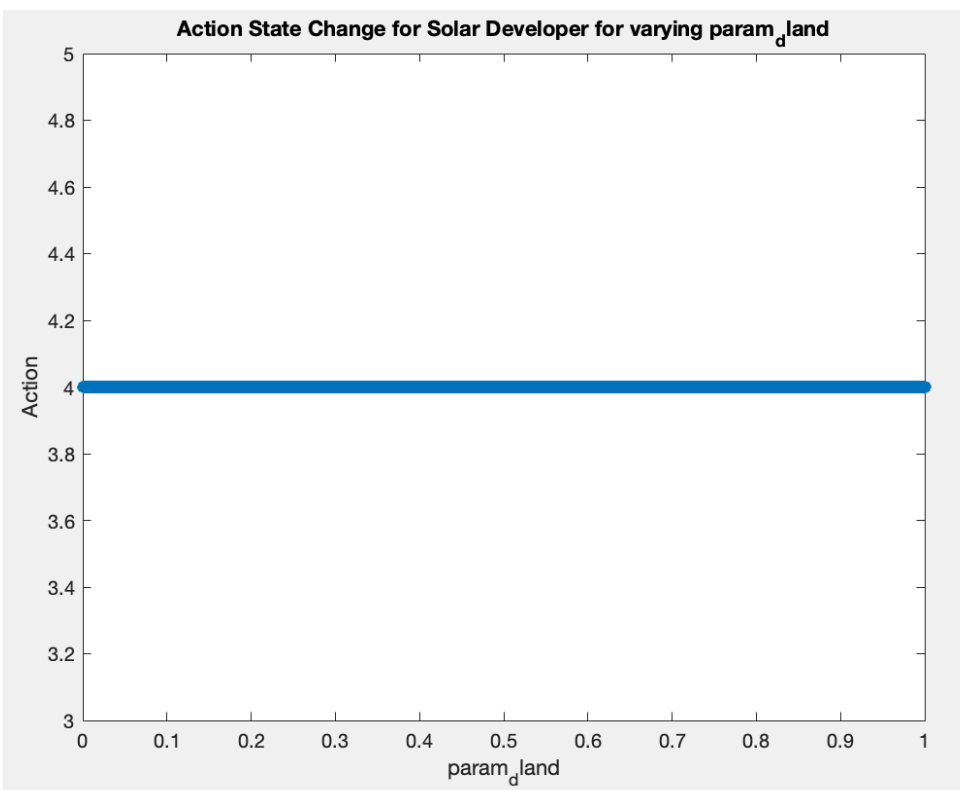


Figure 10: Action State Change for Property Developer while varying $\theta_{d\ land}$

- {A values assets inversely, D values assets equally}**Bifurcation present: Stable Equilibrium→ (renegotiate/no sign, offer of land rent) → agreement! Unstable Equilibrium→no agreement when property developer values land and doesn't value solar panels**

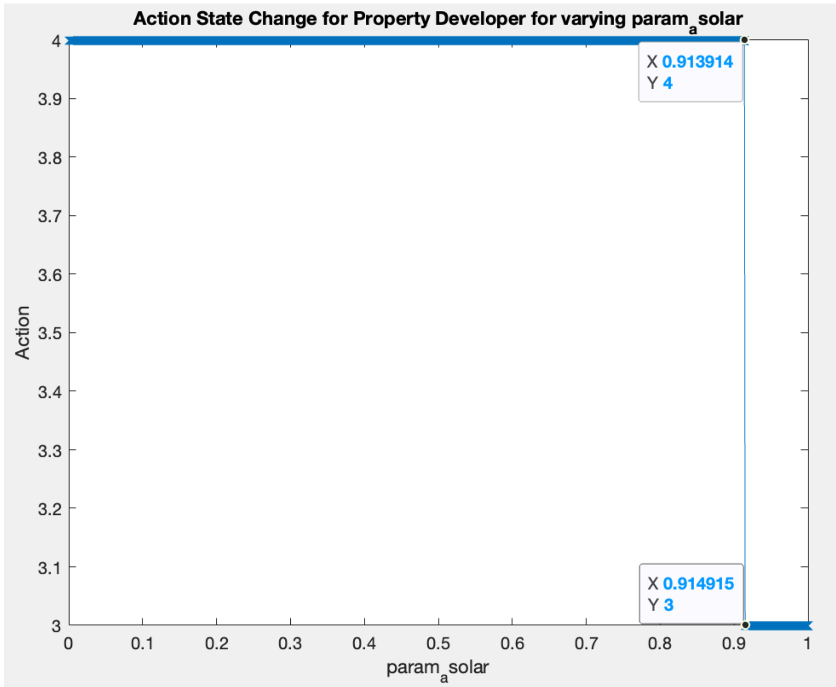


Figure 11: Action State Change for Property Developer while varying $\theta_{a\ solar}$

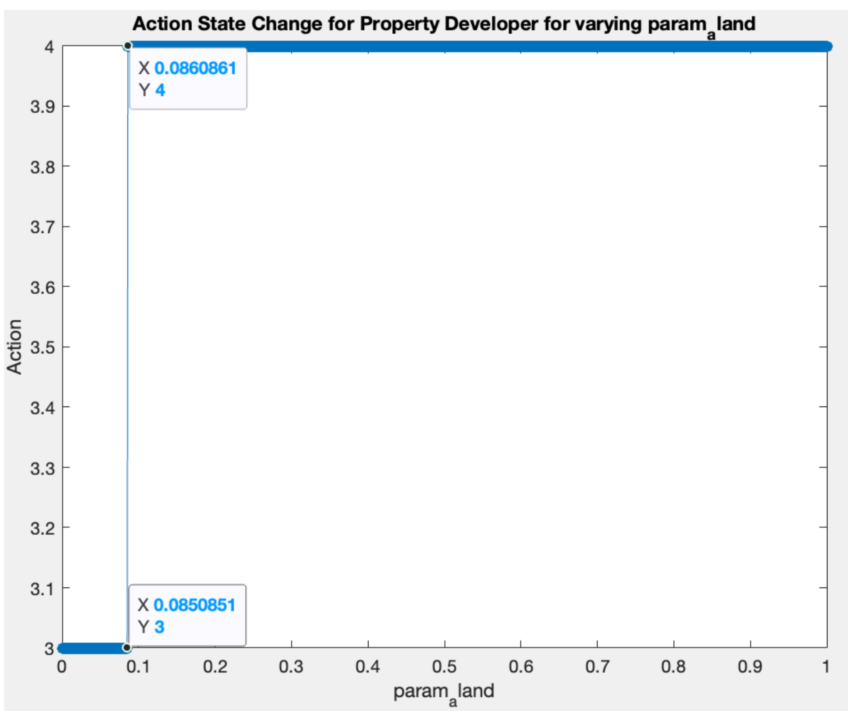


Figure 12: Action State Change for Property Developer while varying $\theta_{a\ land}$

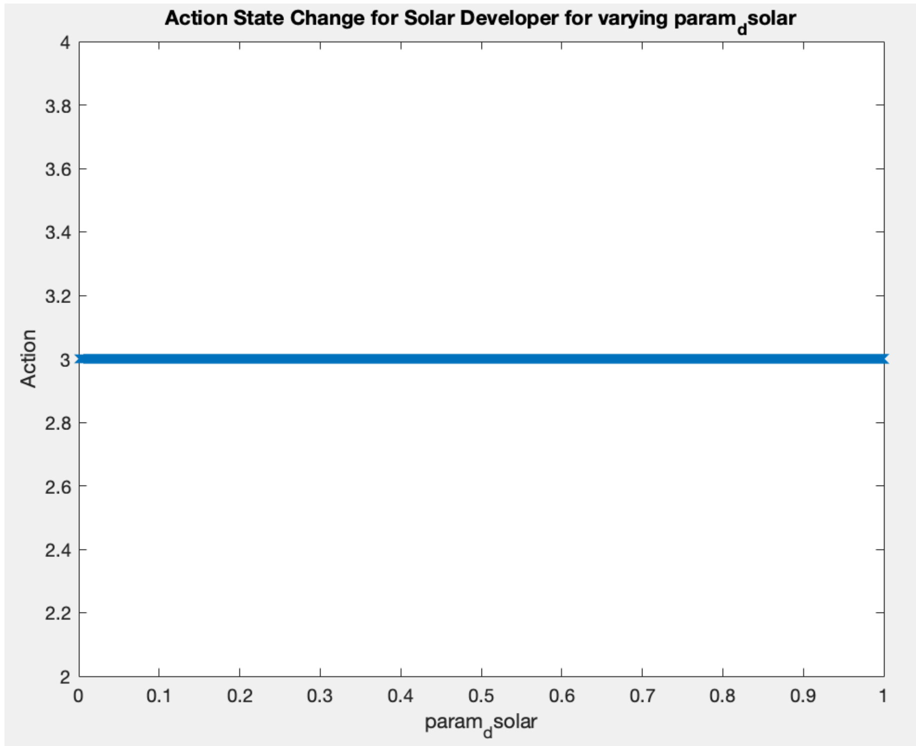


Figure 13: Action State Change for Property Developer while varying $\theta_{d\ solar}$

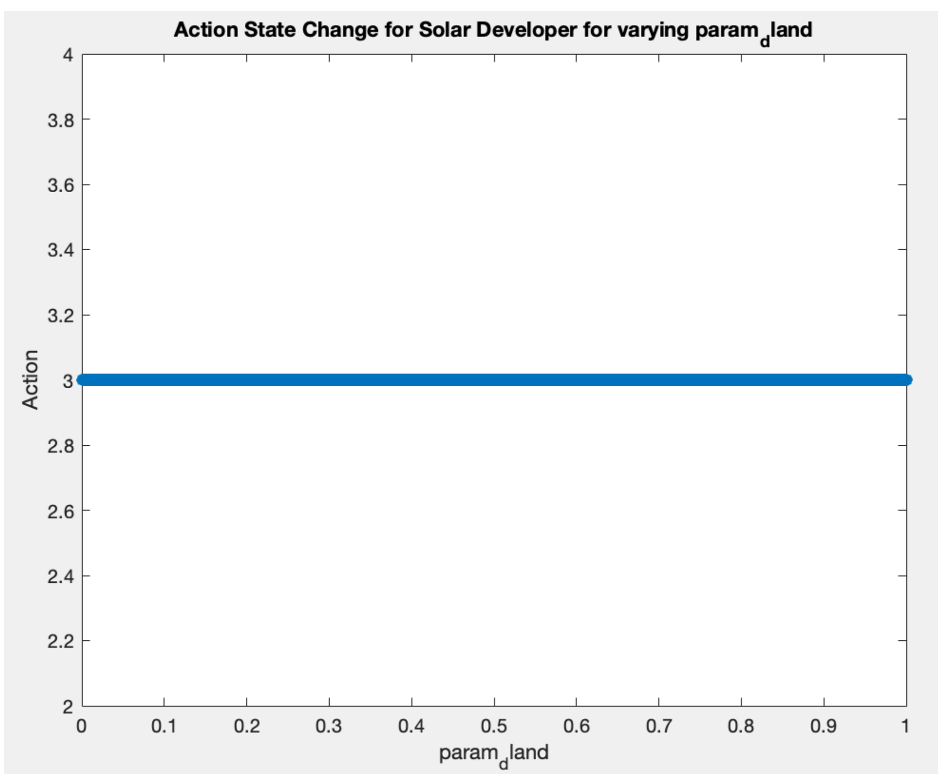


Figure 14: Action State Change for Property Developer while varying $\theta_{d\ land}$

- {A values assets equally, D values assets inversely}

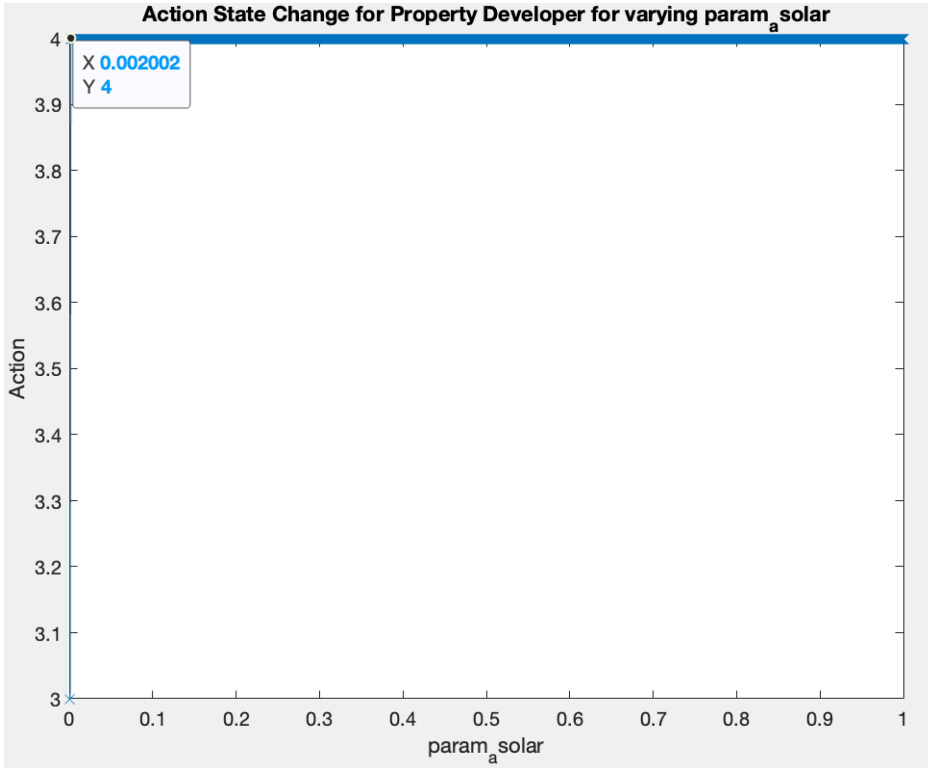


Figure 15: Action State Change for Property Developer while varying $\theta_{a\ solar}$

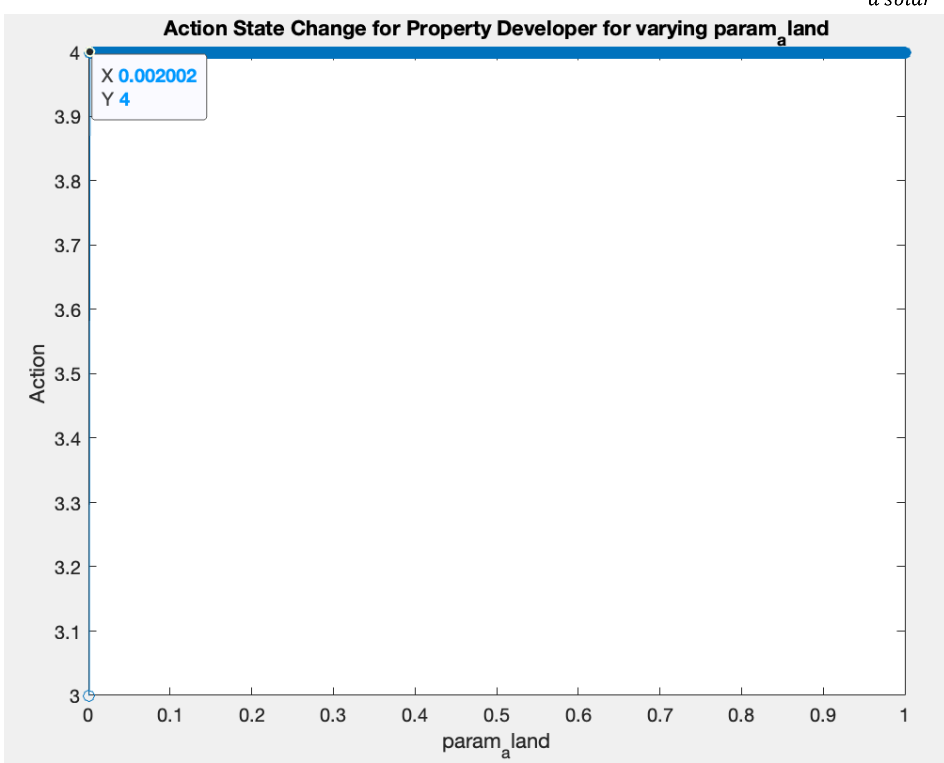


Figure 16: Action State Change for Property Developer while varying $\theta_{a\ land}$

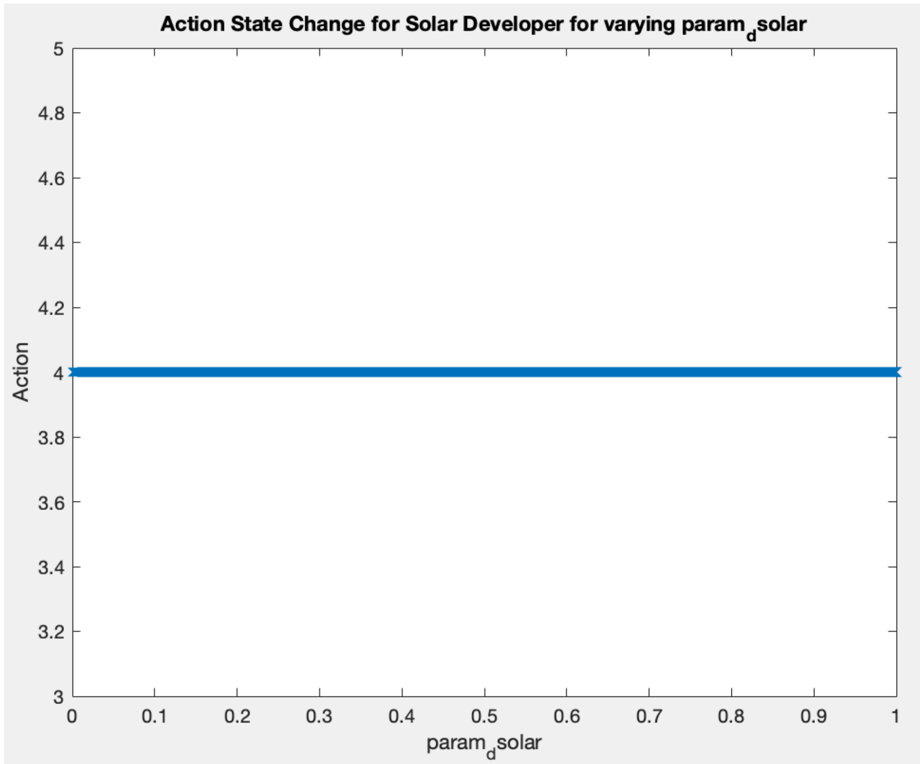


Figure 17: Action State Change for Property Developer while varying $\theta_{d\ solar}$

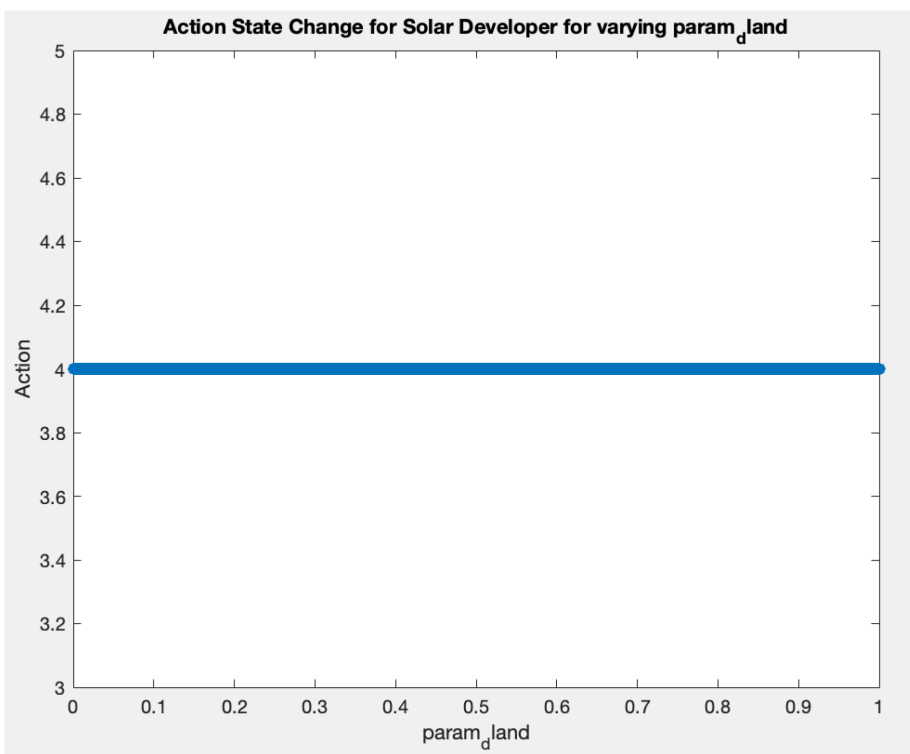


Figure 18: Action State Change for Property Developer while varying $\theta_{d\ land}$

- {A values assets inversely, D values assets inversely}: **Bifurcation present: Stable Equilibrium→ (not sign/renegotiate, no offer of land rent) → no agreement or negotiation war till land rent met! Unstable Equilibrium→no agreement when property developer values doesn't value land or over values solar panels**

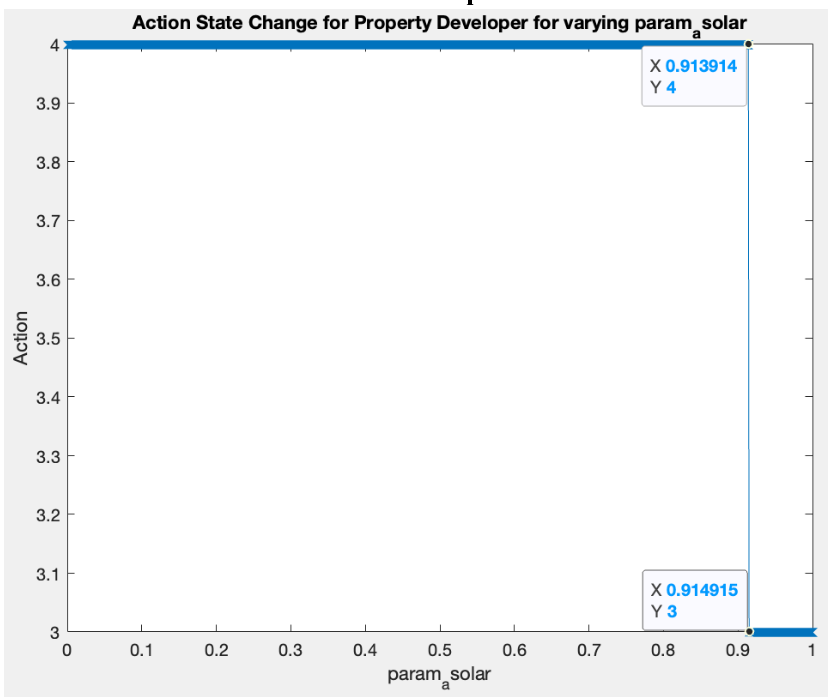


Figure 19: Action State Change for Property Developer while varying $\theta_{a\ solar}$

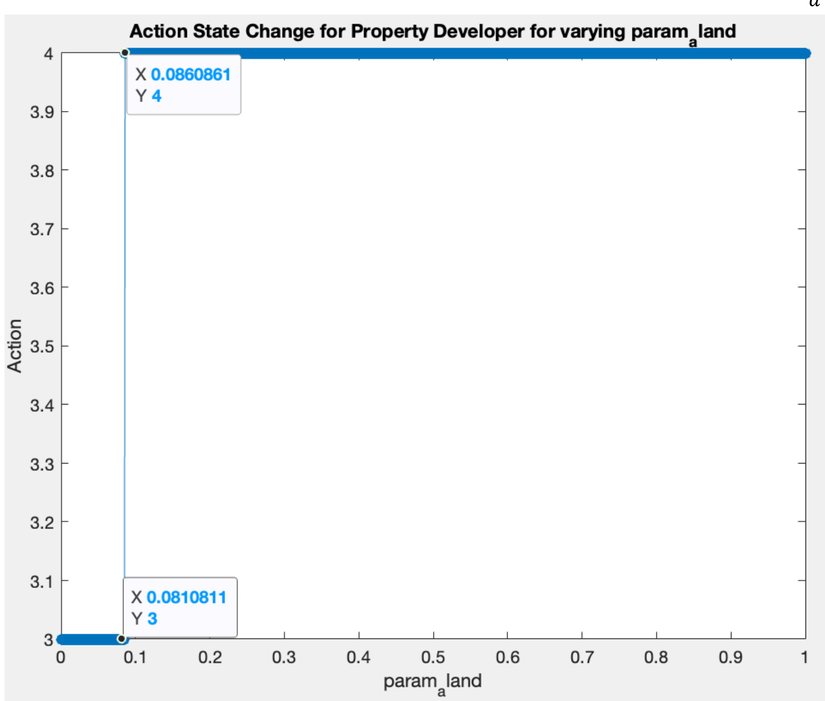


Figure 20: Action State Change for Property Developer while varying $\theta_{a\ land}$

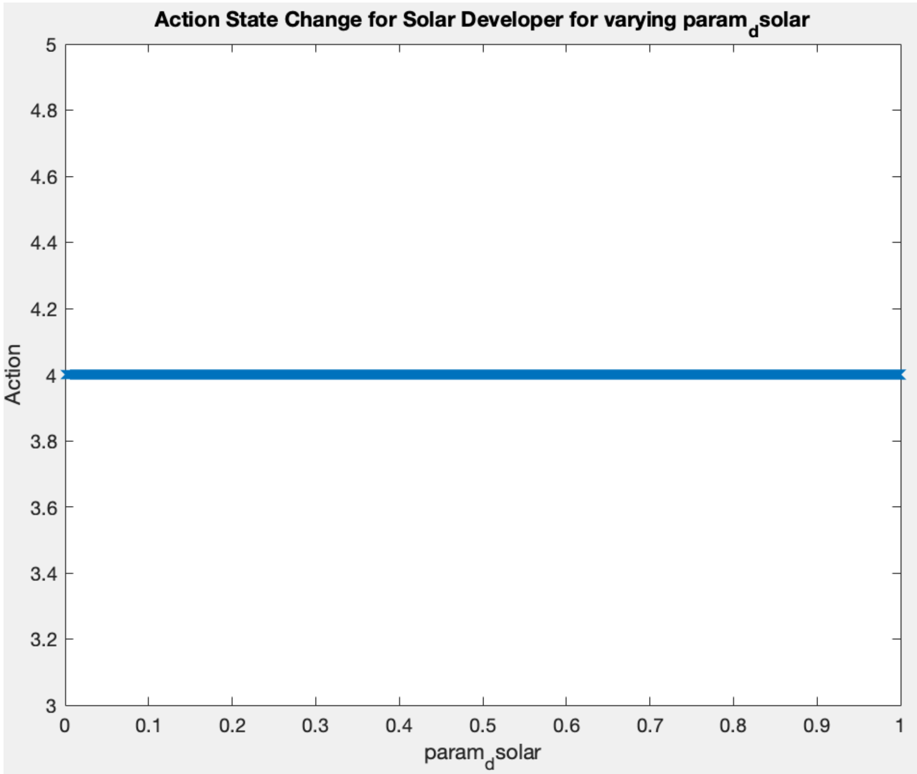


Figure 21: Action State Change for Property Developer while varying $\theta_{d\ solar}$

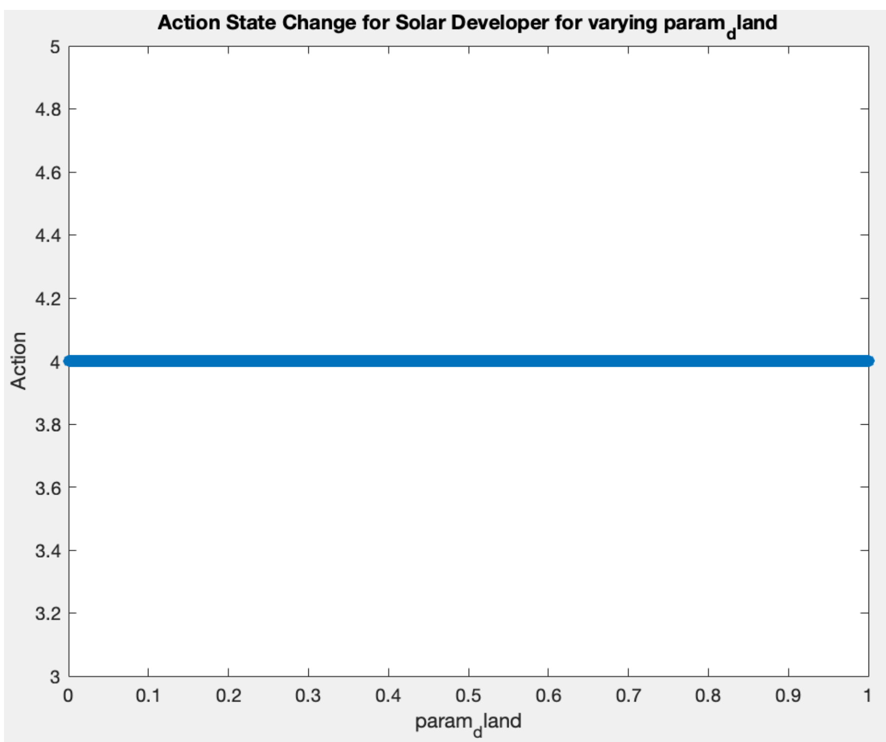


Figure 22: Action State Change for Property Developer while varying $\theta_{d\ land}$

The simulation shows that the most common strategy for both is action 4 which is for the solar developer to offer no land rent and the property developer to not sign or renegotiate in turn. This action makes sense since it is likely that the solar developer would initiate the negotiation with a bad offer and in turn the solar developer would not sign. The second stable equilibrium occurs while varying the parameters for an inverse and equal relationship. This equilibrium settles on Action 3 which is to offer land rent and renegotiate. The property developer will always renegotiate. The solar developer however is flexible and is willing to transition from not offering to offering land rent if it values both assets equally.

There is an instability when the property developer values land much higher than solar panels. In that case there will be no agreement because the property developer wishes to hold the value of the land at market value and not risk signing a long term contract. It appears with the right incentives and if each asset is valued that a rental agreement would be signed in the long term. Note all figures show the converging dominant action only, not the varying dominant action at each t. This is appropriate for a bifurcation diagram which analyzes stability.

3.1.2. Simulation Results for Purchase Power Agreement: Utility Company vs Solar Developer

The simulation is run with a fixed rental agreement time of 15 years. The time step is t - day. There are a total of 15*365 time steps. Simulations have been run with a single combination parameter for the utility. The parameter used is: $\theta_{credit\ value}$.

- The dominant strategy for the solar developer alone is Action 4 corresponding to the utility company accepting the site with no PPA:

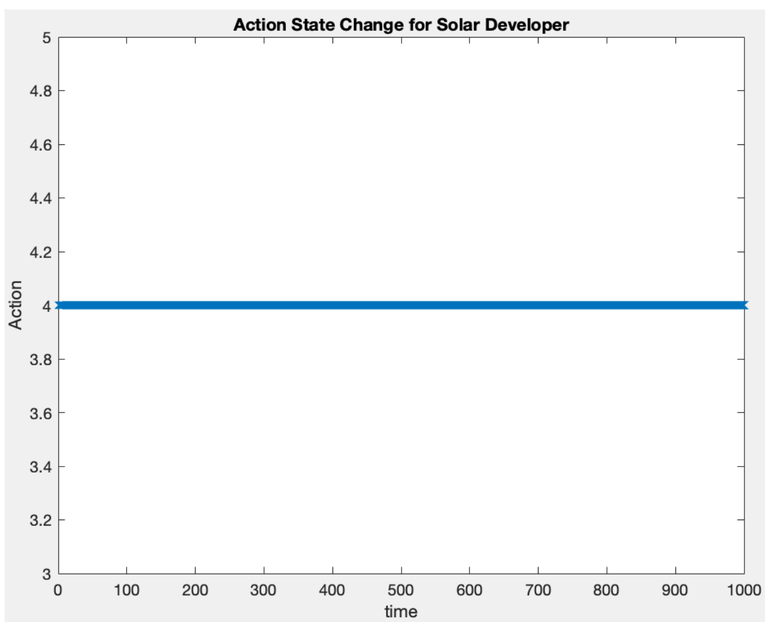


Figure 23: Dominant Action State Change for Solar Developer

- The dominant strategy for the utility company while varying parameter $\theta_{credit\ value} = 0.6556$ is Action 1 to Action 2 → reject to accept a site with a PPA.

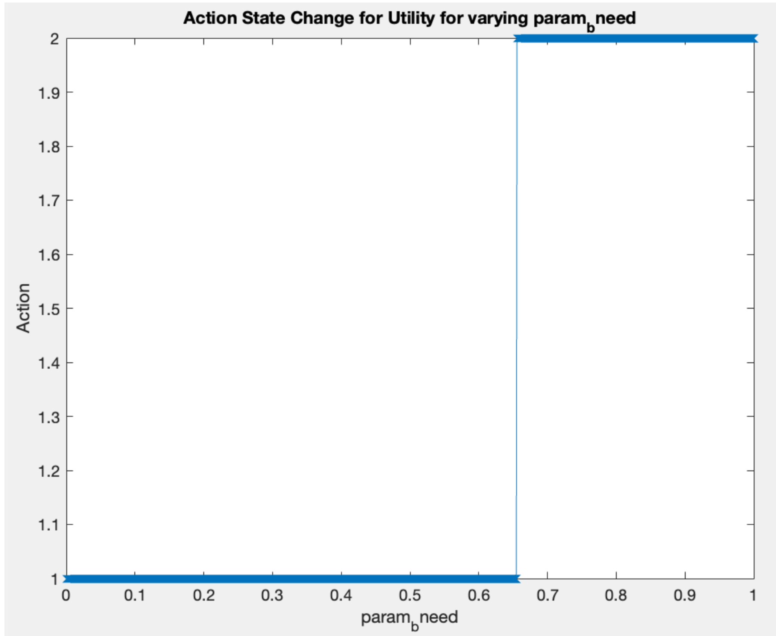


Figure 24: Dominant Action State Change for Utility Company

- The common strategy or stable equilibrium is when the Solar Developer chooses Action 2 to offer the PPA while the utility company accepts the site.

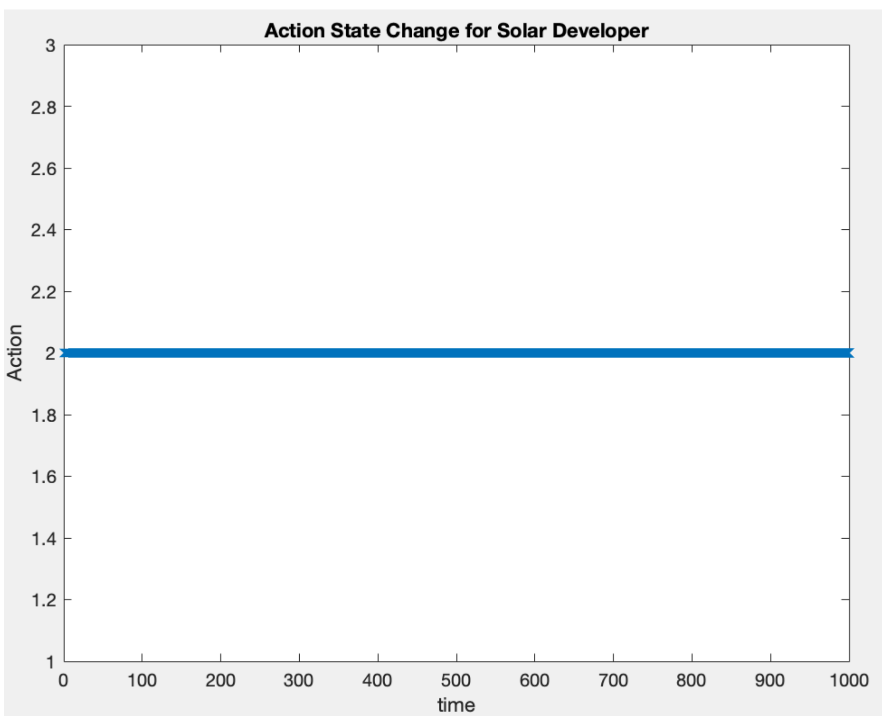


Figure 25: Dominant Action State Change for Solar Developer - stable equilibrium

The simulation shows that the dominant strategy for the solar developer is to not offer the PPA. The dominant strategy for the utility company switches from rejecting to accepting a site depending on its need for RECs. If the utility company is willing to accept the site then the solar developer will offer a

PPA. Otherwise the solar developer does not want to risk the utility company knowing the discount price or strike price. This price is confidential and is used to help the utility company stay in control of the wholesale market. The system will settle on state 2 to accept the site and offer a PPA if the utility company needs RECs. Otherwise the utility will choose to reject the site and the developer will continue to not offer a PPA. The bifurcation results at $\theta_{credit\ value} = 0.6556$.

3.2. Simulation Results for Energy Management System: Microgrid vs Microgrid

The simulation setup treats one episode as 24 hours. The environment resets at a random day at hour 0. As the experiment is limited to the month of August, each hour of the day is treated as a random process using the data from each hour of all days. The experiment is run for a various number of episodes in sets of 155 to ensure that all the data has been explored at least once.

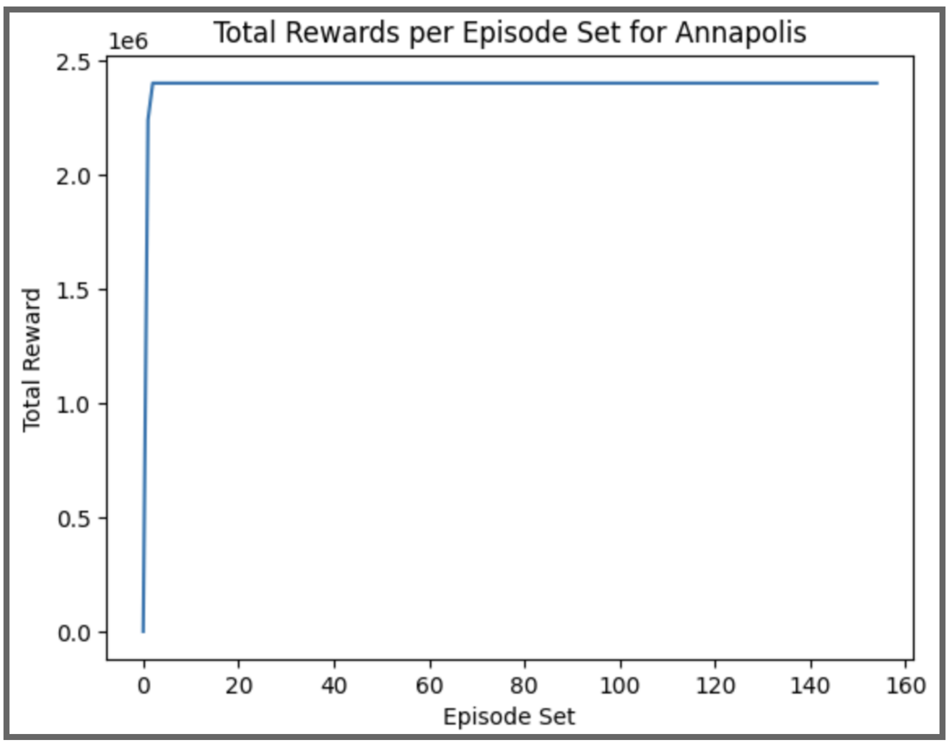


Figure 26: Convergence of Average Reward over 15 sets for Annapolis (smaller microgrid)

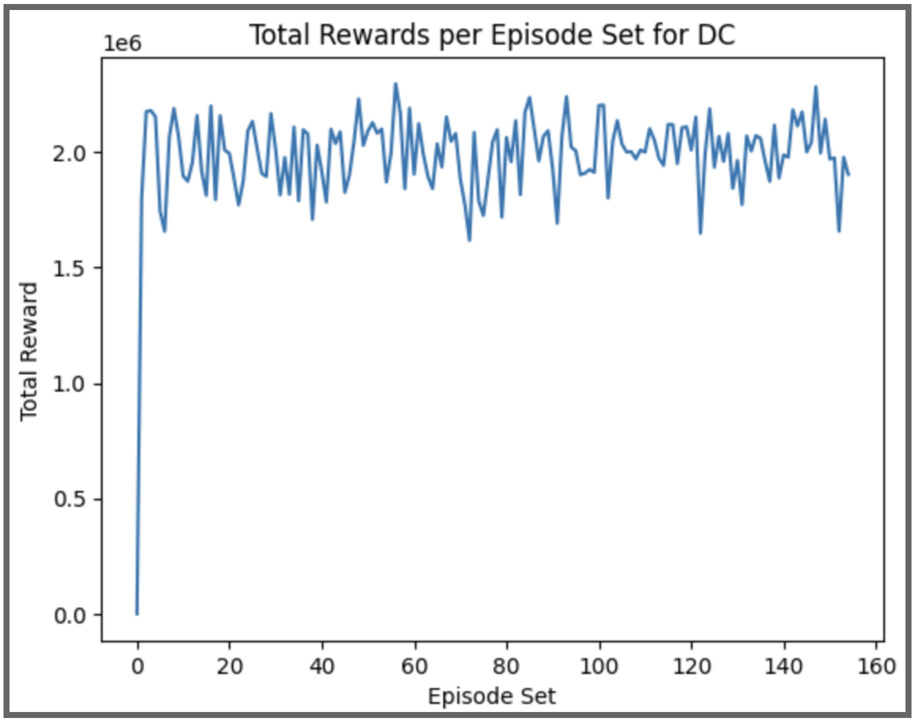


Figure 27: Convergence of Average Reward over 15 sets for DC (larger microgrid)

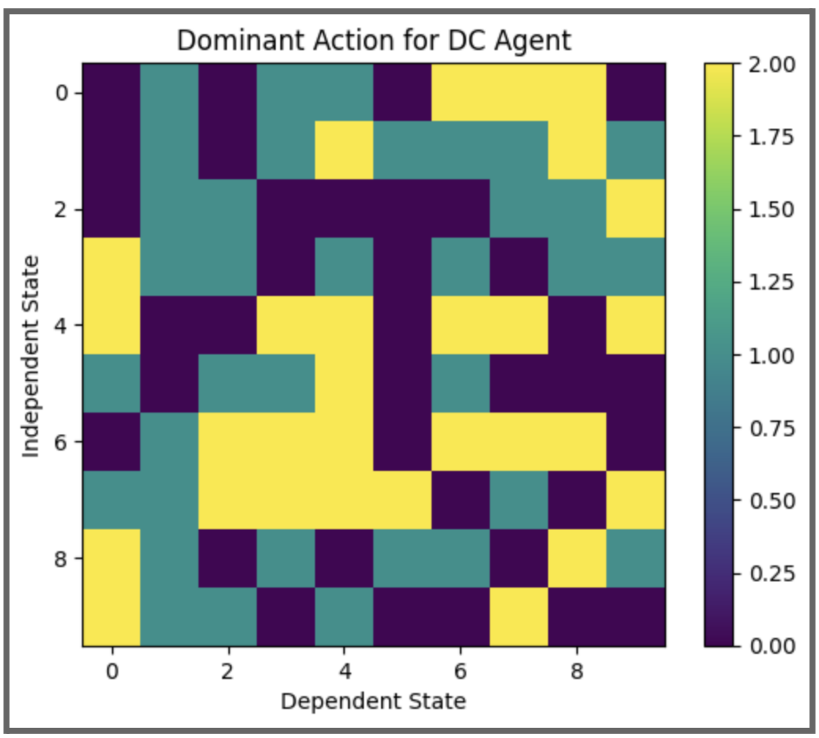


Figure 28: Dominant Action per State for DC (larger microgrid)

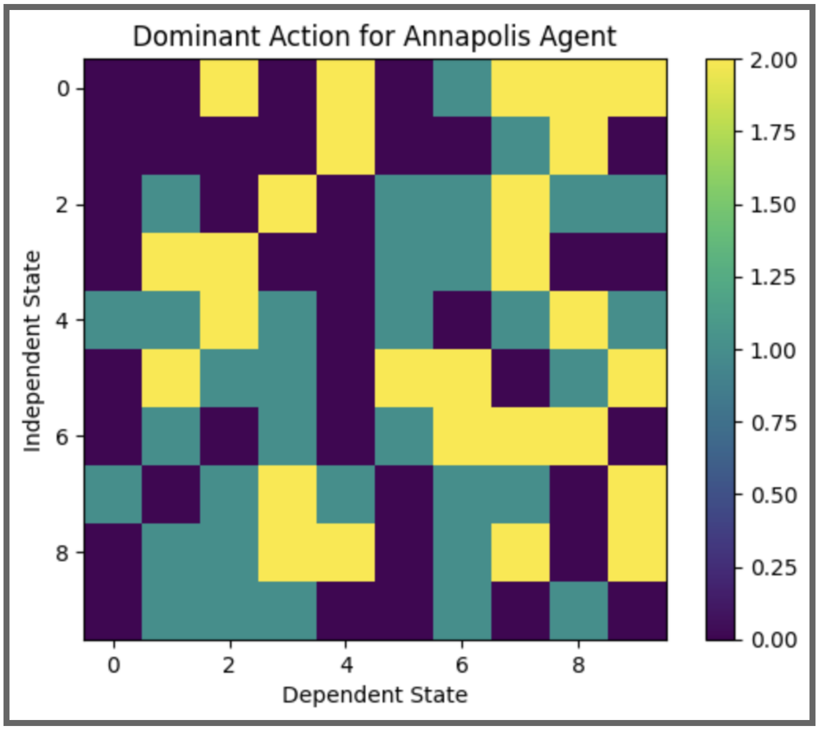


Figure 29: Dominant Action per State for Annapolis (smaller microgrid)

The dominant action for the DC agent appears to be action 0 - selling to the main grid which is what is desired for a microgrid from the utility company's perspective and the solar developer's. The dominant action for the Annapolis agent also appears to be action 0 - selling to the main grid which is what is desired for a microgrid from the utility company's perspective and the solar developer's. It can be concluded then that the dominant action for both microgrids in this symmetric game is action 0 to sell to the main grid. Since the action is common for both, the stable equilibrium for the game is action 0: sell to the main grid.

4. Discussion

This paper presented a game theoretic analysis of the economic agreements and energy management system needed to develop viable microgrids for Washington DC. The economic agreements were treated as negotiations of financial contracts and were modeled as matrix games. Each economic game was played independent of the other. The rental agreement game shows that the property developer wishes to always negotiate for a higher rent while the solar developer is willing to be flexible. The power purchase agreement game shows that the utility company is willing to accept a site given a PPA and vice versa only if the utility company needs RECs. Otherwise the solar developer will not offer a PPA to conceal confidential prices. The 2 player microgrid system was treated as individual free agents made up of complex systems. The 2 players shared a common battery storage but did not track the status of the other because the microgrid sells excess energy to the highest bidder. Through fuzzy Q-learning an optimal policy was learned for both agents and showed convergence. The dominant strategy for both agents was to sell excess energy. This final result supports the economic agreements pursued because the solar developer and utility company wish to generate profit from excess power being sold. Further research should be done in playing a policy-making game for utility companies to update distribution infrastructure. The energy management system should also be simulated with a real battery to sell excess stored energy. Improvements to the energy management system game can result in stronger confidence that microgrids being developed will support utility companies and solar developers.

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