Conservation of Oil

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1 Introduction

Harnessing the power of oil for uses in automation has played a crucial role in the economic development of the world over the past two centuries, first in the development of the industrial revolution in Europe, and then in the automation of farming equipment used for agricultural production [14]. Cars, trucks, and airplanes fueled by oil have revolutionized the transportation of people and goods. Not to mention, electricity is also able to be produced by oil [8]. Despite these numerous advances in modern day society, we have begun to realize that there are consequences to the industrial revolution. The emissions of greenhouse gases and other pollutants have caused unprecedented amounts of climate change in the past century [19]. Today, as companies and governments worldwide begin to look for alternatives to oil for the industries that have grown to rely on them, we seek to model how oil usage will continue in the future as the world begins to cut down on its use of oil.

We have developed four models that explore the usage of oil, both within the United States and worldwide, and the effects of various policy models on oil consumption in the United States. Below, we will detail the purpose of each model and our conclusions from each model.

Model 1: Oil Depletion How do the consumption and production amounts of oil and renewable energy affect one another in the long run? Using historical data on the consumption and production of oil in the US for the past 10 years, we will create a model to predict the consumption and production into the future and test the different relationships the resources can have with each other.

Model 2: Vehicles With the advancement of automotive technology, how can vehicles provide a means of reducing oil consumption? We seek to create policies that will increase the number of fuel efficient and environmentally friendly vehicle options.

Model 3: Biomass Energy Without petroleum based means of creating energy, what alternatives are there? We seek to come up with more carbon neutral means of generating energy in industries where petroleum is most common today.

Model 4: US Oil Trade With oil production and consumption in the US going down, how will that effect the oil trade and the countries that rely on it to make money? Furthermore, could the US save much more money than just from the savings on petroleum alone?

Based on the findings in this report, we conclude that it is possible to reduce the United States' oil consumption and oil production. Despite the upward trend in both consumption and production of oil, we can implement policies that will explore alternative renewable sources to oil and that will gauge the necessity of oil usage based on recent advancements in technology.

2 Statement and Analysis of the Problem

As the world continues to evolve past the need for fossil fuels, specifically petroleum-based oil, we wish to model the economic and environmental factors that will drive down the usage of oil and create an idealized model for reduced oil usage in the future. We will begin by looking into historical data for oil trade among the US and other countries. Then we will model how much oil the US uses for different industries like the automotive industry and petroleum-based products. Using dynamic models for how much oil is currently being produced, alongside the more environmentally friendly alternatives, we hope to create an outlook for the decrease in oil consumption and production within the United States.

Model 1 We want to model the production and consumption of oil and renewable energy sources to see how they compare in the long run in the United States. The topics we will cover in this project will be production and consumption of each resource. We are defining consumption as the thousands of barrels per day consumed by the US and production as the thousands of barrels per day drilled by the US and imported from varying countries to be used in the US. We will calculate the interaction between oil and renewable energy by using the production and consumption data that we have for previous years (similar to the Owls vs. Hawks model explored in the homework). We will use the sub-models for oil and renewable energy to come up with the growth rates for each type for consumption and production, respectively.

Model 2 Gasoline, which is mostly used in vehicles, is the most commonly used petroleum product in the United States [5]. In fact, over half of oil consumption in the United States goes towards transportation [5]. In this section, we seek to develop three alternative policies that will mitigate oil consumption due to light motor vehicles, which constitute about 22% of the transportation sector in the United States [17]. First, we define the terms “hybrid/electric cars” and “standard gasoline cars”, which will be referenced later in this section.

Hybrid electric vehicles, or “hybrids” are cars that contain both an electric and a gasoline powered motor in order to maximize fuel efficiency [10]. Plug-in hybrid electric vehicles, or “plug-in hybrids”, are hybrids that have batteries which significantly reduce the amount of gasoline used under normal driving circumstances. The batteries can be charged with a charging cord that plugs into the car on one end and an electrical outlet on the other end. All-electric vehicles, or “electric cars”, are cars that run solely on electricity [12]. For the sake of simplicity in the following model, all hybrids, plug-in hybrids, and electric vehicles are combined into one category called “hybrid/electric cars”. All other vehicles that do not fit into this category are referred to as “standard gasoline cars”.

Model 3 Biomass is a type of renewable material that comes from animal and plant sources. Some sources for biomass include wood, agricultural crops, paper, cotton, wool products, yard waste, food waste, animal manure, and human sewage. Biomass can be converted into energy by direct combustion, or burning, which produces heat. This energy can be used to heat water and buildings, run industrial processes, and generate electricity in steam turbines. There are other ways to convert biomass into energy, but direct combustion is the most common method [1]. A couple benefits of using biomass over petroleum include the fact that biomass is almost carbon neutral, and it is cheaper than petroleum. Carbon neutral means that the carbon dioxide consumed by plants and trees is released back into the atmosphere when the plants and trees are burned to make biomass fuels. This process uses some fossil fuels which is why biomass is described as "almost carbon neutral" [11]. In this section, we seek to develop three alternative policies that will mitigate oil consumption due to the industrial sector of the United States, which constitutes about 28% of all oil consumption in the United States [2].

Model 4 The impacts of a reduction in oil consumption and production across the US would have massive implications across the world. The US is one of the top Oil importers in the world, with a sizable amount of exports to other countries as well. In this section, we wish to model how changes in oil production and oil consumption in the united states will affect our trade imports and exports. The large scale effect this would have on the worlds economy and oil trade is hard to quantify and predict, so there may be gaps in areas of discussion in this section, however there will be some thought and deliberation over the grand worldwide effect outside of the US.

3 Description of the Model

First, let us state some general assumptions that are used throughout all of our models:

- All data referenced in our model is accurate.
- The amount of petroleum consumption in the United States is equivalent to the amount of crude oil consumption because petroleum is the most abundant form of crude oil.
- We will use data collected from the past 10 years because we see that there were a lot of fluctuations in the oil import by countries data and creating a dynamical system model from a longer period of time would stray away from the actual data in the recent years.

3.1 Model 1: Consumption and Production of Oil and Renewable Energy

3.1.1 Assumptions

- We will assume that the dynamical system models we calculate from 2010-2020 data will maintain the same relationship for the two resources as time goes on. No external factors will affect this model.
- We will define the annual US oil production amount as the amount of oil the US exports + the amount of oil in US Reserves - the amount of oil the US imports [7] [4].
- We will assume that the relationship between oil and renewable energy is similar to modeling two populations in a natural environment because many companies are switching over to using renewable energy, meaning it would affect the usage amount of oil/petroleum. Therefore, we will be using a dynamical system model to investigate the different long term behaviors possible.
  - Because of this assumption, there will be two sub-models for Oil Consumption since it'll depend on the respective resource we're modeling oil against. In our project, we modeled

Renewable Energy Consumption as well as Biomass Consumption.

3.1.2 Approach

To prepare out data, we will convert both resources' units into thousands of barrels per day. For oil amounts, this will involve converting a quadrillion barrels of oil per day to thousands of barrels per day by dividing the starting amount by 1,000,000,000,000. For the renewable energy amounts, this will involve converting a million British Thermal Unit (BTU) to thousands of barrels per day by multiplying by a factor of 0.00018013586919434 [15].

To create our dynamical system models, we will use previous existing data and calculated the average growth rates and interaction factors for each sub-model we want to consider.

For example, with the Oil Consumption sub-model, we will use the initial data of oil consumption amounts, with units in thousands of barrels per day, from 2010 to 2020 [5]. We will approach the Renewable Energy Consumption, Oil Production, and Renewable Energy Production sub-models in the same way [2] [3] [6]. We will find the growth rate between each year using the growth rate equation.

Growth Rate Equation

$$G_A = \frac{A_{n+1} - A_n}{A_n},$$

where A_n = thousands of barrels consumed in year n for resource A and

G_A = growth rate of resource A.

Next, we will take the average of the ten growth rates, between each year from 2010-2020, to find the average growth rate we'll use for the sub-model of Oil Consumption.

After that, we will plug the average growth rate we have calculated into the dynamical system sub-model framework we established earlier. Using the interaction factor equation, we will find the interaction factor between Oil Consumption and Renewable Energy Consumption.

Interaction Factor Equation

$$I_A = \frac{A_{n+1} - A_n + ((1 + G_A) * A_n)}{A_n * B_n},$$

where A_n = thousands of barrels consumed in year n for resource A,

B_n = thousands of barrels consumed in year n for resource B,

I_A = interaction factor for resource A due to resource B, and

G_A = growth rate of resource A.

Then, we will substitute the growth rates and interaction factors we found into a dynamical system model to produce prediction data for each resource's consumption and production.

3.1.3 Oil and Renewable Energy Consumption Model

See Appendix A.1 for the variables used in this model.

Models

$$OC_{n+1} = (0.9939879236) * OC_n + (-0.00000004382777105 * OC_n * RC_n)$$
$$RC_{n+1} = (1.020247218) * RC_n + (-0.00000001382597676 * OC_n * RC_n)$$

Long-term Behavior

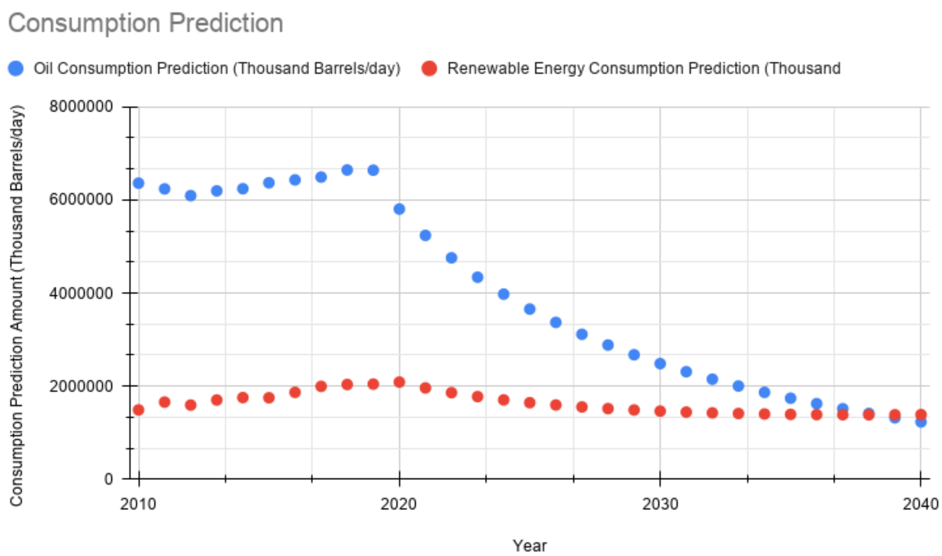


Figure 1: Consumption Prediction Data

3.1.4 Oil and Renewable Energy Production Model

See Appendix A.2 for the variables used in this model.

Models

$$OP_{n+1} = (1.1372710762) * OP_n + (-0.0000000399281668 * OP_n * RP_n)$$
$$RP_{n+1} = (1.041262958) * RP_n + (-0.00000001586660302 * OP_n * RP_n)$$

Long-term Behavior

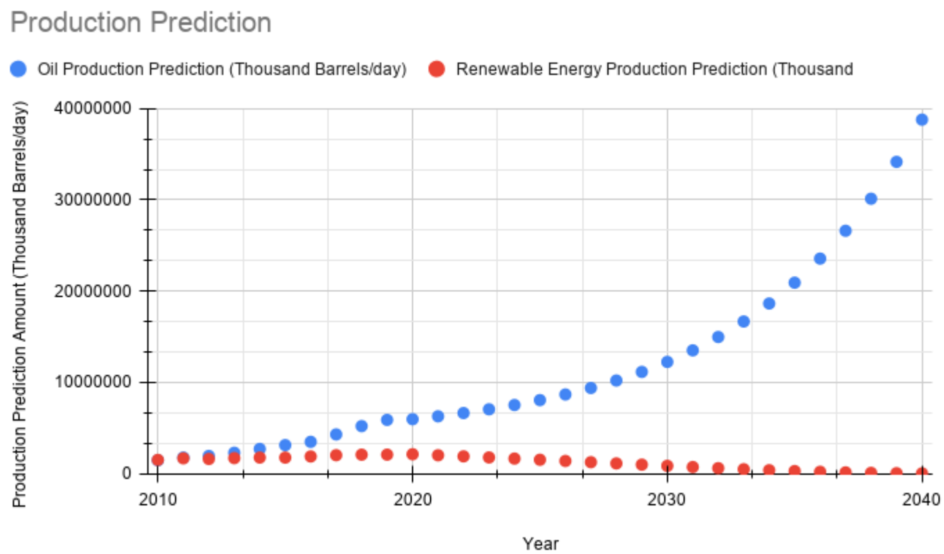


Figure 2: Production Prediction Data

3.2 Model 2: Incentives for Reducing Oil Consumption

3.2.1 Assumptions

- 4.1% of cars sold in the United States are hybrid/electric cars [21].
- 95.9% of cars sold in the United States are standard gasoline cars [21].
- For the sake of simplicity, there are only two states that describe types of light motor vehicles sold: standard gasoline vehicles and hybrid/electric vehicles.
- Hybrid/electric cars save approximately 30% of oil used compared to standards gasoline cars [20].
- 22% of oil consumed in the United States is used in light motor vehicles [17].
- The tax deductible percentage for production of hybrid/electric vehicles is directly proportional to the production of hybrid/electric vehicles, which is in turn, directly proportional to the percentage of hybrid/electric vehicles that are sold.
- The tax deductible percentage for consumers of hybrid/electric vehicles is directly proportional to the percentage of hybrid/electric vehicles that are sold.
- All tax incentives mentioned below are the same for every state, and each policy's incentives do not change over a span of 20 years, starting from the year 2020.

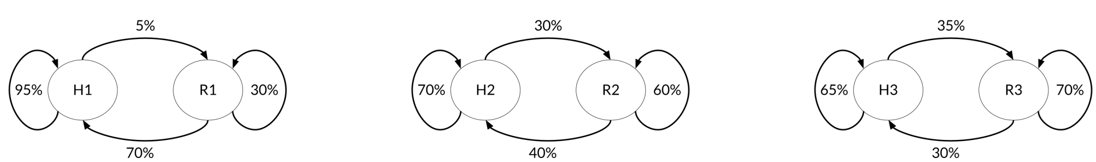
3.2.2 Model

Markov Chains were used to model the effect of three different policies on the consumption of oil in light motor vehicles in the United States. The policies introduce tax incentives to car manufacturers and car buyers, which allow them to deduct costs associated with producing and buying hybrid/electric vehicles [9]. The goal of these policies is to increase the long-term percentage of hybrid/electric vehicles sold, which will hopefully decrease the amount of oil consumed by light motor vehicles in the transportation sector. The overall structure of each model is the same, though they vary slightly.

Policy 1: Suppose a new tax incentive is introduced that allows car manufacturers to deduct 95% of all manufacturing costs associated with the production of hybrid/electric vehicles. Then, by our stated assumptions, car manufacturers will sell 95% of hybrid/electric vehicles and 5% of standard gasoline vehicles based on the previous year's amount of vehicles sold. Also, suppose a new tax incentive is introduced that allows consumers to deduct 70% from their purchase of hybrid/electric vehicles. Then, by our stated assumptions, car manufacturers will sell 70% of hybrid/electric vehicles and 30% of standard gasoline vehicles based on the previous year's amount of vehicles sold. Figure 3a depicts this model.

Policy 2: Suppose a new tax incentive is introduced that allows car manufacturers to deduct 70% of all manufacturing costs associated with the production of hybrid/electric vehicles. Then, by our stated assumptions, car manufacturers will sell 70% of hybrid/electric vehicles and 30% of standard gasoline vehicles based on the previous year's amount of vehicles sold. Also, suppose a new tax incentive is introduced that allows consumers to deduct 40% from their purchase of hybrid/electric vehicles. Then, by our stated assumptions, car manufacturers will sell 40% of hybrid/electric vehicles and 60% of standard gasoline vehicles based on the previous year's amount of vehicles sold. Figure 3b depicts this model.

Policy 3: Suppose a new tax incentive is introduced that allows car manufacturers to deduct 65% of all manufacturing costs associated with the production of hybrid/electric vehicles. Then, by our stated assumptions, car manufacturers will sell 65% of hybrid/electric vehicles and 35% of standard gasoline vehicles based on the previous year's amount of vehicles sold. Also, suppose a new tax incentive is introduced that allows consumers to deduct 30% from their purchase of hybrid/electric vehicles. Then, by our stated assumptions, car manufacturers will sell 30% of hybrid/electric vehicles and 70% of standard gasoline vehicles based on the previous year's amount of vehicles sold. Figure 3c depicts this model.



(a) Policy 1 (b) Policy 2 (c) Policy 3

Figure 3: Policy models for hybrid/electric and standard gasoline vehicles

Python was used to analyze the long-term effects of these three policies on the consumption of oil due to light motor vehicles. The variables used are listed in Appendix B.1. The code used is listed in Appendix B.2.

3.3 Model 3: Incentives for Increasing Biomass Consumption

3.3.1 Assumptions

- 28% of oil consumed in the United States is used by industrial companies [2].
- For the sake of simplicity, there are only two states that describe the primary energy source of companies: petroleum and biomass.
- An investment in biomass property is considered a "green investment", or an energy-saving investment [18].
- An investment in biomass property means the installment, research and development, and/or financing of biomass property [18].
- The tax credit percentage for the installment of biomass property is directly proportional to the percentage of industrial companies that have biomass as their primary source of energy.
- The tax credit percentage for the research and development of biomass property is directly proportional to the percentage of industrial companies that have biomass as their primary source of energy.
- All tax incentives mentioned below are the same for every state, and each policy's incentives do not change over a span of 20 years, starting from the year 2020.

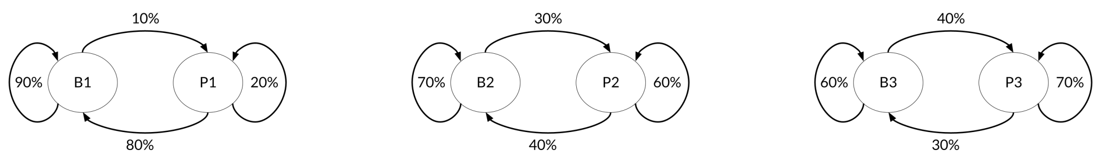
3.3.2 Model

Markov Chains were used to model the effect of three different policies on the consumption of oil by the industrial sector in the United States. The policies introduce tax incentives to industrial companies, which allow them to deduct costs associated with installing, researching, and developing biomass property [18]. The goal of these policies is to increase the long-term percentage of industrial companies that utilize biomass as their primary source of energy, which will hopefully decrease the amount of oil consumption by the industrial sector. The overall structure of each model is the same, though they vary slightly.

Policy 1: Suppose a new tax incentive is introduced that allows companies to receive a 80% tax credit for the installment of biomass property. Therefore, by our assumptions, 80% of industrial companies will make biomass their primary source of energy, and only 20% of industrial companies will keep petroleum as their primary source of energy. Also, suppose a new tax incentive is introduced that allows companies to receive a 10% tax credit for the research and development of biomass property. Therefore, by our assumptions, 10% of industrial companies will make biomass their primary source of energy, while 90% of industrial companies will keep petroleum as their primary source of energy. Figure 4a depicts this model.

Policy 2: Suppose a new tax incentive is introduced that allows companies to receive a 40% tax credit for the installment of biomass property. Therefore, by our assumptions, 40% of industrial companies will make biomass their primary source of energy, while 60% of industrial companies will keep petroleum as their primary source of energy. Also, suppose a new tax incentive is introduced that allows companies to receive a 70% tax credit for the research and development of biomass property. Therefore, by our assumptions, 70% of industrial companies will make biomass their primary source of energy, and only 30% of industrial companies will keep petroleum as their primary source of energy. Figure 4b depicts this model.

Policy 3: Suppose a new tax incentive is introduced that allows companies to receive a 30% tax credit for the installment of biomass property. Therefore, by our assumptions, 30% of industrial companies will make biomass their primary source of energy, while 70% of industrial companies will keep petroleum as their primary source of energy. Also, suppose a new tax incentive is introduced that allows companies to receive a 60% tax credit for the research and development of biomass property. Therefore, by our assumptions, 60% of industrial companies will make biomass their primary source of energy, while 40% of industrial companies will keep petroleum as their primary source of energy. Figure 4c depicts this model.



(a) Policy 1

(b) Policy 2

(c) Policy 3

Figure 4: Policy models for biomass and petroleum powered companies

Python was used to analyze the long-term effects of these three policies on the consumption of oil due to light motor vehicles. The variables used are listed in Appendix C.1. The code used is listed in Appendix C.2.

3.4 Model 4: Oil Trading

3.4.1 Assumptions

- The amount of oil put into or taken out of the US oil Reserves is negligible, or can be accounted for with the linear regression.
- The amount of Oil the US consumes in a given year is roughly proportional to the amount they import and export combined. For this, we will also use a linear regression to make as good a prediction as possible.
- From both assumptions thus far, we will make the final assumption that the two proportionality equations can be expressed as linear regressions.

3.4.2 Model

This final model, we wish to see how production and consumption of oil will affect oil trade with other countries as we advance into the future. Using the standard model of accumulation in chemical engineering, which is $IN - OUT + GENERATION - CONSUMPTION = ACCUMULATION$. If we exchange those variables for our related terms for Oil usage in the US we get that $Imports - Exports + Production - Consumption = Reserves$. The first assumption we will make is that the reserve accumulation is negligible, and any error that will persist can be accounted for with a linear regression rather than a perfect one to one application of this formula. With this assumption we get that:

$$Imports - Exports + Production - Consumption = 0 \tag{1}$$

We can then look at a graphical representation of this model using nodes, or vertices, for each country. We can label each country with a vertex v_i where they each have some production of oil

$$p(i) = Some\ amount\ of\ oil\ in\ thousands\ of\ barrels\ each\ year.$$

Then we can create one-way edges or arrows to show which countries import and export to whom. However, in our case we will only be modeling the US's imports and exports, so every country will have at most two arrows, one importing into the US, or exporting from the US. We only want to model the total Usage of the US's oil. So if we label the US's imports between countries i and the US as a_i and the US's exports to country j as b_j then our model will look something like:

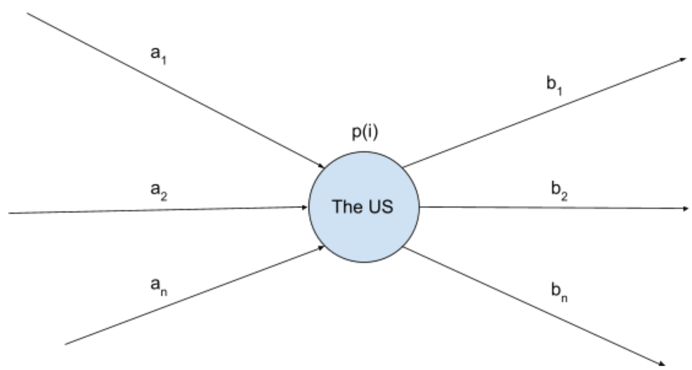


Figure 5: Model of oil imports and exports

However, what we really care about is the values a_i and b_j themselves as they will be the major contributors to the economic effects around the world. So how do we go about calculating these values for future years? If we take a look at Equation 1 we can rearrange the values to obtain a new equation to model Imports and Exports for the future. You can see that:

$$Imports - Exports = Usage - Production \tag{2}$$

Which is very useful because from section 3.1.4 we have already obtained the data for consumption and production of oil for the next 20 years. So, all we need to do is use the data we have for production and consumption and we already have the difference between imports and exports. But, we still need another equation if we want to separately calculate the imports and exports, so we make a general assumption that if the US uses a lot of oil, their imports and exports will directly increase, and vice versa if the US uses less oil, that the sum of the imports and exports will directly decrease. Suffice to say we assume the that:

$$Imports + Exports \propto Consumption \tag{3}$$

To account for error with equations 2 and 3 rather than just use them at face value to calculate the imports and exports, I'll make a linear regression based on the two equations to balance out any ulterior factors that might be playing a role as well. So our final assumption leads us to the equations for the linear regression to be:

$$(Imports - Exports) = \alpha_1 * (Consumption - Production) + \beta_1 \tag{4}$$

$$(Imports + Exports) = \alpha_2 * Consumption + \beta_2 \tag{5}$$

And with this, Given the Consumption and production data for years into the future, we can produce an estimate for the Imports and Exports. First we can obtain the Exports by $((Equation\, 5) - (Equation\, 4))/2$. we start with exports because as you will see in the next section, they will quickly drop below 0 exports, so anything less than zero we just assumed to be 0. Then with Exports we can obtain the data for Imports by $(Equation\, 4) + Exports$.

Next we need to decide how we're going to generate the data for each country. We currently have the total US imports and exports by year, but we wish to model how each country is individually affected. Our solution was to look back at the historical data, and see what percentage of oil had been imported and exported from each country that year, for example, in 2015 the US imported 1374189 thousand barrels of oil from Canada. Which in proportion to the total amount of thousands of barrels, comes out to be 39.85% of the total imports in 2015. Doing this for each year, we obtain an average of around 36.66% from Canada. Then we make the general assumption that for future years, the average will roughly stay the same. We'll say roughly because rather than take a direct proportion of our estimates for each year, we run a Monte Carlo simulation with the total number of barrels for each year. For each barrel we generate a random number between 0 and 1. Then we check to see where that number lies in relation to the total proportion of oil. Each country has an interval equal to their proportion and depending on where that random number lies, that's where we allocated that specific barrel for that year, and we do this with every barrel for every year from 2021 to 2040.

With that, we have come up with a method to view the potential import and export data for future years based on the production and consumption of oil in that year. Next, in section 4 we will report our findings and explain all the results we obtained. Finally, in section 5 we will look into the ramifications of these results, like the worldwide political impact these results could have.

4 Analysis and Testing of the Model

To test our dynamical systems model, we tried to 'predict' the oil production and consumption amounts from 2010-2020 using the previous data and see how well our model predicts the data with the actual data we collected from various sources [6] [3]. Using our production and consumption dynamical systems, we predicted the oil production and consumption amounts in the US from years 2020-2040. We developed a model that used the predicted consumption data to make three policies aimed at slowing down the consumption of oil in the transportation sector of the United States. We developed a third model that used the predicted consumption data to make three policies aimed at increasing the use of an alternative renewable resource in the industrial sector of the United States. Finally, we developed a fourth model that includes a worldwide perspective on the production and consumption of oil, which is aimed at reducing the amount of oil imports and oil exports of the United States. We describe the testing of each of these four models in further detail below.

4.1 Model 1

4.1.1 Testing the Consumption Model

To explore the different possibilities of the dynamical systems, we will split each topic, consumption and production, into five cases. Let's use the generalized version of the consumption sub-models to narrate our process:

- Oil Consumption
$$OC_{n+1} = (1 + a_1) * OC_n + (c_1 * OC_n * RC_n)$$
- Renewable Energy Consumption
$$RC_{n+1} = (1 + b_1) * RC_n + (d_1 * OC_n * RC_n)$$

Using the consumption sub-models as an example, the five cases are:

Cases	OC's growth rate (a_1)	RC's growth rate (b_1)	OC's interaction factor (c_1)	RC's interaction factor (d_1)
$a_1 > b_1$ & $c_1 < d_1$	0.020	-0.006	-0.000000044	-0.000000014
$a_1 > b_1$ & $c_1 > d_1$	0.020	-0.006	-0.000000014	-0.000000044
$a_1 < b_1$ & $c_1 < d_1$	-0.006	0.020	-0.000000044	-0.000000014
$a_1 < b_1$ & $c_1 > d_1$	-0.006	0.020	-0.000000014	-0.000000044
$a_1 = b_1$ & $c_1 > d_1$	0.15	0.15	-0.000000014	-0.000000014

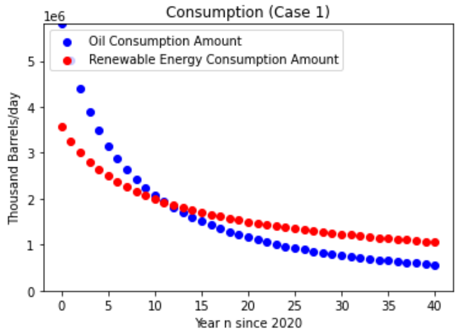
Table 1: Consumption Model Test Case Values

For each case, we will iterate the dynamical system to predict data all the way to the year 2060 and took note of the ending behavior of the two resources' consumption.

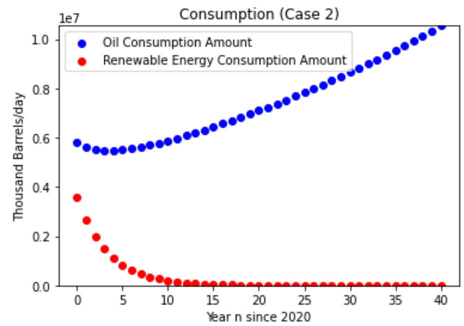
Long-term Behaviors

- Case (1): $a_1 > b_1$ & $c_1 < d_1$ In this case, we're modeling the scenario that the amount of oil used is increasing when compared to renewable energy's usage amount, but that renewable energy consumption is preferred over oil. (Figure 6a)

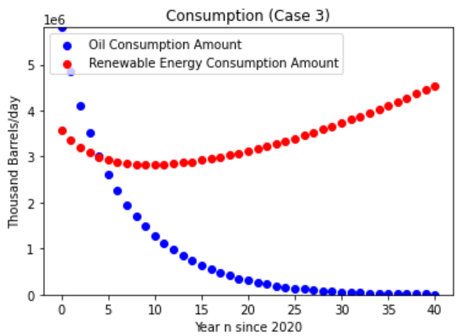
- Case (2): $a_1 > b_1$ & $c_1 > d_1$ In this case, we're modeling the scenario that the amount of oil used is increasing when compared to renewable energy's usage amount, and that oil consumption is preferred over renewable energy. (Figure 6b)
- Case (3): $a_1 < b_1$ & $c_1 < d_1$ In this case, we're modeling the scenario that the amount of oil used is decreasing when compared to renewable energy's usage amount, and that renewable energy consumption is preferred over oil. (Figure 6c)
- Case (4): $a_1 < b_1$ & $c_1 > d_1$ In this case, we're modeling the scenario that the amount of oil used is decreasing when compared to renewable energy's usage amount, but that oil consumption is preferred over renewable energy. (Figure 6d)
- Case (5): $a_1 = b_1$ & $c_1 > d_1$ In this case, we're modeling the scenario that the amount of oil used is equal to the amount of renewable energy used, but that oil consumption is preferred over renewable energy. (Figure 6e)



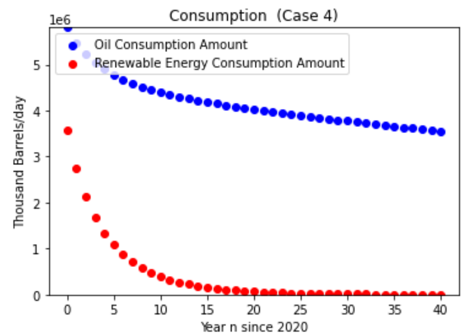
(a) Consumption: Case (1)



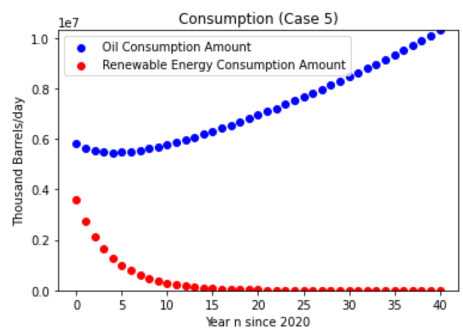
(b) Consumption: Case (2)



(c) Consumption: Case (3)



(d) Consumption: Case (4)



(e) Consumption: Case (5)

Figure 6: Oil Consumption Case Models

4.1.2 Testing the Production Model

To explore the different possibilities of the dynamical systems, we will split each topic into five cases. Let's use the generalized version of the production sub-models to narrate our process:

- Oil Production
$$OP_{n+1} = (1 + a_2) * OP_n + (c_2 * OP_n * RP_n)$$

- Renewable Energy Production
$$RP_{n+1} = (1 + b_2) * RP_n + (d_2 * OP_n * RP_n)$$

Using the production sub-models as an example, the five cases are:

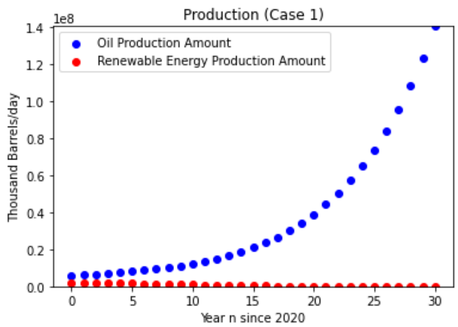
Cases	OP's growth rate (a_2)	RP's growth rate (b_2)	OP's interaction factor (c_2)	RP's interaction factor (d_2)
$a_2 > b_2$ & $c_2 < d_2$	0.020	-0.006	-0.000000044	-0.000000014
$a_2 > b_2$ & $c_2 > d_2$	0.020	-0.006	-0.000000014	-0.000000044
$a_1 < b_1$ & $c_1 < d_1$	-0.006	0.020	-0.000000044	-0.000000014
$a_1 < b_1$ & $c_1 > d_1$	-0.006	0.020	-0.000000014	-0.000000044
$a_1 = b_1$ & $c_1 > d_1$	0.15	0.15	-0.000000014	-0.000000014

Table 2: Production Model Test Case Values

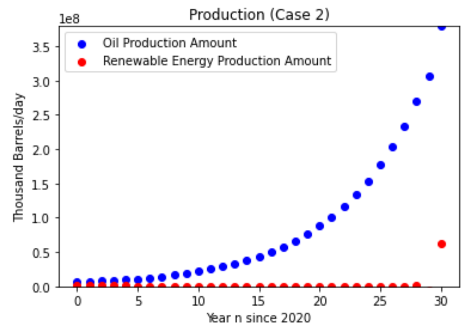
For each case, we will iterate the dynamical system to predict data all the way to the year 2060 and took note of the ending behavior of the two resources' production.

Long-term Behaviors

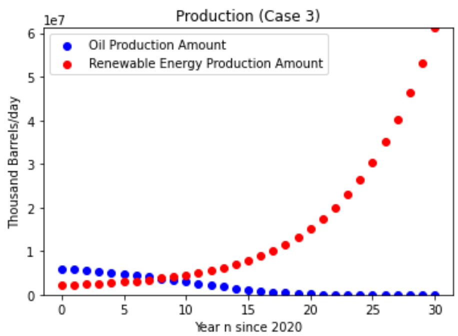
- Case (1): $a_2 > b_2$ & $c_2 < d_2$ In this case, we're modeling the scenario that the amount of oil produced is increasing when compared to renewable energy's production amount, but renewable energy production is preferred over oil. (Figure 7a)
- Case (2): $a_2 > b_2$ & $c_2 > d_2$ In this case, we're modeling the scenario that the amount of oil produced is increasing when compared to renewable energy's production amount, and oil production is preferred over renewable energy. (Figure 7b)
- Case (3): $a_2 < b_2$ & $c_2 < d_2$ In this case, we're modeling the scenario that the amount of oil produced is decreasing when compared to renewable energy's production amount, and renewable energy production is preferred over oil. (Figure 7c)
- Case (4): $a_2 < b_2$ & $c_2 > d_2$ In this case, we're modeling the scenario that the amount of oil produced is decreasing when compared to renewable energy's production amount, but oil production is preferred over renewable energy. (Figure 7d)
- Case (5): $a_2 = b_2$ & $c_2 > d_2$ In this case, we're modeling the scenario that the amount of oil produced is equal to the amount of renewable energy produced, but oil production is preferred over renewable energy. (Figure 7e)



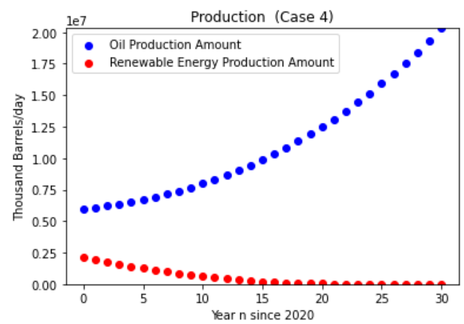
(a) Production: Case (1)



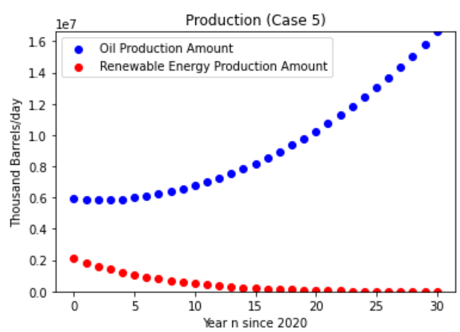
(b) Production: Case (2)



(c) Production: Case (3)



(d) Production: Case (4)



(e) Production: Case (5)

Figure 7: Oil Production Case Models

4.2 Model 2

We used Markov chains to test Model 2. Markov chains are processes in which there are a specific number of states that can occur at a certain time, and these states are disjoint. That is, they cover all possible outcomes, and they do not overlap with one another. It is possible for the system to move from one state to another state after each time step, and there is a probability associated with that. After some time, the long-term behavior of the system will become apparent, as the percentages of each state occurring will converge, and when summed together, these long-term probabilities of each state will equal one [13]. The solutions are therefore stable because each state converges to some probability value in the long-term no matter what the initial percentages are.

The graphs of the long-term probabilities for the percentage of hybrid/electric vehicles sold and the percentage of standard gasoline vehicles sold under Policies 1, 2 and 3 are shown in Appendix B.3. It was found that under Policy 1, the percentage of hybrid/electric vehicles sold will increase sharply from years 2020-2025 until it reaches 93% around year 2040, at which point, the percentage will remain constant. On the other hand, under Policy 1, the percentage of standard gasoline vehicles sold will decrease sharply from years 2020-2025 until it reaches 7% around year 2040, at which point, the percentage will remain constant. Under Policy 2, the percentage of hybrid/electric vehicles sold will steadily increase until it reaches 57% around year 2040, at which point, the percentage will remain constant. On the other hand, the percentage of standard gasoline vehicles sold will steadily decrease until it reaches 43% around year 2040, at which point, the percentage will remain constant. Finally, under Policy 3, the percentage of hybrid/electric vehicles sold will steadily increase until it reaches 46% around year 2040, at which point, the percentage will remain constant. On the other hand, the percentage of standard gasoline vehicles sold will steadily decrease until it reaches 54% around year 2040, at which point, the percentage will remain constant.

Based on the long-term probabilities of hybrid/electric vehicles and standard gasoline vehicles for each policy, Policy 1 produced the "best" results in terms of most oil saved by hybrid/electric vehicles. However, Policy 3 is probably the most realistic policy, at least for the short-term, because it would be difficult to drastically increase the number of hybrid/electric vehicles sold in the United States in a five year period, despite the numerous automotive technological advances the country has made in recent years.

The three policies above were also tested with Markov chains against the five different cases that were sub-models of Model 1 in Section 3.1. Further explanation and results of these additional tests are depicted in Appendix B.4.

4.3 Model 3

We used Markov chains to test Model 3. As described above for Model 2, Markov chains are processes in which there are a specific number of states that can occur at a certain time, and these states are disjoint. As subsequent iterations of the model occur, the long-term behavior of the system will become apparent, as the percentages of each state occurring will converge. These solutions are stable [13].

The graphs of the long-term probabilities for the percentage of industrial companies using biomass as their primary source of energy and the percentage of industrial companies using petroleum as their primary source of energy under Policies 1, 2 and 3 are shown in Appendix C.3. It was found that under Policy 1, the percentage of industrial companies that use biomass as their primary source of energy will increase sharply from years 2020-2025 until it reaches 88% around year 2040, at which point, the percentage will remain constant. On the other hand, under Policy 1, the percentage of industrial companies that use petroleum as their primary source of energy will decrease sharply from years 2020-2025 until it reaches 12% around year 2040, at which point, the percentage will remain constant. It was found that under Policy 2, the percentage of industrial companies that use biomass as their primary source of energy will increase until it reaches 57% around year 2040, at which point, the percentage will remain constant. On the other hand, under Policy 2, the percentage of industrial companies that use petroleum as their primary source of energy will decrease until it reaches 43% around year 2040, at which point, the percentage will remain constant. It was found that under Policy 3, the percentage of industrial companies that use biomass as their primary source of energy will increase until it reaches 43% around year 2040, at which point, the percentage will remain constant. On the other hand, under Policy 3, the percentage of industrial companies that use petroleum as their primary source of energy will decrease until it reaches 57% around year 2040, at which point, the percentage will remain constant.

Based on the long-term probabilities of industrial companies that use petroleum as their primary energy source versus industrial companies that use biomass as their primary energy source, Policy 1 yielded the "best" results in terms of least amount of oil consumption. However, Policy 3 is probably the most realistic of the three in the short-term, because it would be difficult to drastically increase the number of industrial companies that use biomass as their primary resource in the next five years.

4.4 Model 4

To start this model, we need accurate historical data for US imports and exports of oil. We got this data from the United States Energy Information Administration. They have data dating back to the 1980's for both imports and exports, but all we needed was information from the past 10 years [7] [4]. We took the data into an excel spreadsheet and found the average percentages for the past 10 years of the amount of oil the US imported from and exported to each country. Here's two tables with the top 5 countries' data from the past 5 years:

Year	2016	2017	2018	2019	2020	Avg. %
Canada	1383.5	1479.8	1566.5	1617.6	1508.6	36.66%
Saudi Arabia	404.9	348.6	328.7	193.6	190.9	10.17%
Mexico	244.9	249.1	262.6	237.4	274.3	8.63%
Venezuela	291.5	246.0	213.9	33.7	0.0	6.61%
Russia	161.3	142.0	137.0	189.8	196.9	4.71%

Table 3: Import Data From Top 5 Countries (Millions of Barrels)

Year	2016	2017	2018	2019	2020	Avg. %
Mexico	322.2	394.4	436.0	422.6	380.9	15.79%
Canada	342.2	317.9	373.6	378.0	333.2	14.29%
Netherlands	96.8	91.8	123.0	164.5	163.3	5.90%
Brazil	95.3	144.2	145.9	173.0	161.2	5.17%
Japan	91.9	127.6	170.1	202.5	200.2	4.44%

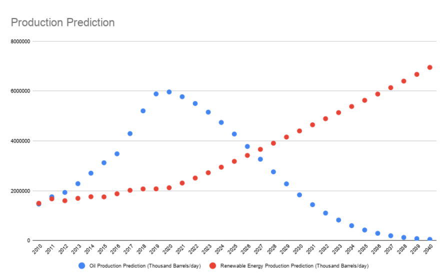
Table 4: Export Data From Top 5 Countries (Millions of Barrels)

Next, we need the historical data of the US's production and consumption of oil for the past 10 years [3] [6]. With these two sets of data, we can use Equations 2 and 3 to create a linear regression to find the future imports and exports. Using the current data we found that the two regressions come out to be:

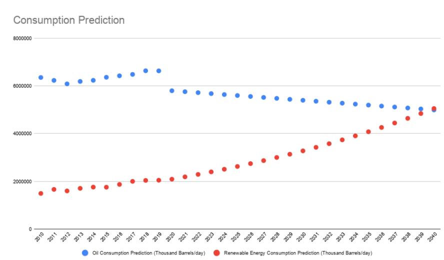
$$(Imports - Exports) = 1.394 * (Consumption - Production) - 2.33 * 10^6 \tag{6}$$

$$(Imports + Exports) = 2.946 * Consumption - 1.3 * 10^7 \tag{7}$$

What is notable is that Equation 6 is quite similar to if the slope were 1 and the y intercept 0, like we predicted with Equation 2. Now the problem remains that we need data for the future consumption and production of oil in the US, for this information we go back to Model 1 and use the same model to generate our own data for production and consumption. After making some slight adjustments to the constants in the equations for the predictions, we end up with the following graphs that model the future data, based on the overall assumption that oil usage will go down in the future. With that we generate the following graphs:



(a) Production Prediction



(b) Consumption Prediction

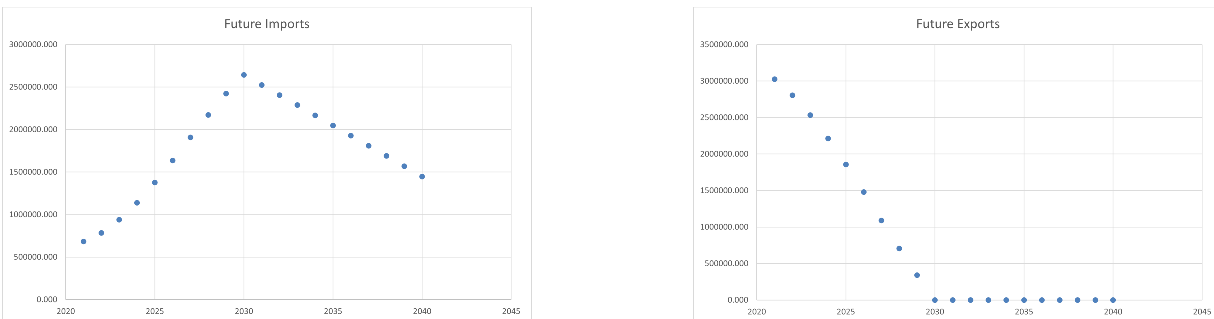
Figure 8: Oil Production and Consumption Predictions

Data for these models can be found in the files with the excel spreadsheets in them. From here we have the Production and Consumption figures for the years 2021 to 2040, which is our outlook for this model, so using the same process as described in section 3, the values for imports and exports can be obtained for the US in total for each year, and are as follows:

Year	2021	2022	2023	2024	2025
Production Data	5772.9	5501.0	5153.7	4740.6	4275.9
Consumption Data	765.7	5725.5	5685.4	5645.2	5605.1
Consumption - Production	-7.1	224.5	531.7	904.7	1329.2
Imports - Exports	-2343.6	-2020.7	-1592.6	-1072.8	-481.1
Imports + Exports	3708.2	3589.9	3471.5	3353.3	3235.0
Imports	682.3	784.6	939.5	1140.2	1376.9
Exports	3025.9	2805.3	2532.1	2213.0	1858.1

Table 5: Future Prediction Data for First 5 Years (Millions of Barrels)

The graphs of imports and exports over time look like the following:



(a) Future Import Prediction

(b) Future Export Prediction

Figure 9: Future Import and Export Predictions (Thousands of Barrels)

With this we have our data to conduct the Monte Carlo Simulation. Under the appendix section D, we have listed the code that we used in the construction of this Monte Carlo simulation. Using the same countries as before, but this time with future data, here's a 5 year snippet from each of the 5 countries we used for historical data:

Year	2026	2027	2028	2029	2030
Canada	699.6	796.3	888.8	969.6	925.481
Saudi Arabia	193.9	221.5	245.6	268.7	256.304
Mexico	165.0	187.6	208.5	227.8	218.2
Venezuela	45.2	51.9	62.0	75.1	91.3
Russia	89.5	103.1	114.7	124.2	118.6

Table 6: Import Data From Top 5 Countries (Millions of Barrels)

Year	2026	2027	2028	2029	2030
Mexico	232.9	172.5	111.4	53.9	0.067
Canada	211.9	155.5	101.2	48.6	0.061
Netherlands	87.3	64.5	41.9	19.88	0.027
Brazil	76.5	56.3	36.6	17.4	0.022
Japan	65.7	48.8	31.4	15.1	0.023

Table 7: Export Data From Top 5 Countries (Millions of Barrels)

As you can see from the results obtained, the amount of Oil the US imports under these assumptions according to the model drastically decreases for each country, almost by 50%. These changes are even more noticeable for our exports in 5 to 10 years as by 2030 they have dropped to almost zero. In the next section we will discuss the possible outcomes for this massive decreases in oil trade.

5 Results and Quality of the Model

From the results of our testing, we conclude that it is possible to reduce the United States' oil consumption and oil production in the future. One of our strengths is the stability testing we conducted with our different models, where we considered the different relationships the variables in our models can have with each other. The goal of the testing is to end with a few reasonable policies we see the government inciting so that oil usage will decrease its air pollution contribution and so that there are initiatives toward renewable resources instead.

One of our biggest shortcomings with the models that we proposed is that we made very general assumptions for the sake of simplicity with the calculations. For example, in Models 2 and 3, we made vague assumptions about tax laws that definitely do not hold true for all states, if any, but we used those assumptions to make our model more feasible to work with. Below, we describe the strengths and weaknesses of each individual model and go into more detail about how we would improve these models in the future.

5.1 Model 1

The test cases for Consumption emphasizes that the interaction factors impact the models more than the growth rates of the resources' consumption. We see that when Oil Consumption's interaction factor is greater than Renewable Energy Consumption, the Oil Consumption amount increases and wins over their competitor, the Renewable Energy Consumption, as shown in Figure 6b and Figure 6d. The same relation is seen in the test cases where Renewable Energy Consumption's interaction factor is greater than Oil Consumption's interaction factor, as shown in Figure 6a and Figure 6c.

The test cases for Production emphasizes that the growth rates impact the models the most. We see that when Oil Production's growth rate is greater than Renewable Energy Production's growth rate, the Oil Production amount grows exponentially while the Renewable Energy amount goes toward 0, as shown in Figure 7a and Figure 7b. The same happens when Renewable Energy Production's growth rate is greater than Oil Production's growth rate, as shown in Figure 7c and Figure 7d.

When modeling the depletion of oil over a long horizon, we see that there's a decrease in oil consumption while there's a dramatic increase in oil production, as shown in Figure 1 and Figure 2. This is modeling the outcome that more residential and industrial usages will turn to renewable energy consumption as time progresses. However, the conflicting long-term predictions for production amounts come from the existing data we collected on production amounts. From 2010 to 2020, the oil production amounts increased exponentially, while the renewable energy production amounts increased linearly. The different growths cause the dynamical system model between the two resources to predict a positive impact on oil production, as shown in Figure 2.

Something we can do to improve our model is to edit our existing model to include a factor that regards the other sources of impact on oil consumption and production amounts. When starting this model, we find that it is more complicated to investigate how other nonrenewable and renewable resources has impacted the growth or decrease in consumption and production due to the varying amounts over the years. It is possible to do further analysis on the trends of the historical data by sectioning it off by year. Another weakness of this model is that it doesn't take into account any societal factors that could occur year-by-year. For example, the amount of oil production decreases in amount in 202 due to COVID-19, but if we used our established model to predict 2020's oil consumption amount using 2009-2019's data, it wouldn't produce the actual amount in 2020. The only way to address this is to follow up with a sentiment-analysis on more current events each year and simply not predicting too off into the future.

5.2 Model 2

Based on the results of Model 2, it can be concluded that each policy had an effect on the amount of oil consumed by the transportation sector in the United States. Policy 1, the most extreme policy, caused the greatest decrease in oil consumption. Policy 2, the moderate policy, caused the second greatest decrease in oil consumption. Policy 3, the least extreme policy, caused the third greatest decrease in oil consumption. Of the three policies, Policy 3 is probably the most realistic because the switch from standard gasoline cars to hybrid/electric cars will not happen instantly. Policy 3 offers a short-term quality solution that still allows for a decrease in oil consumption due to light motor vehicles. Figure 10 below depicts the difference between each policy's predicted amount of oil consumption.

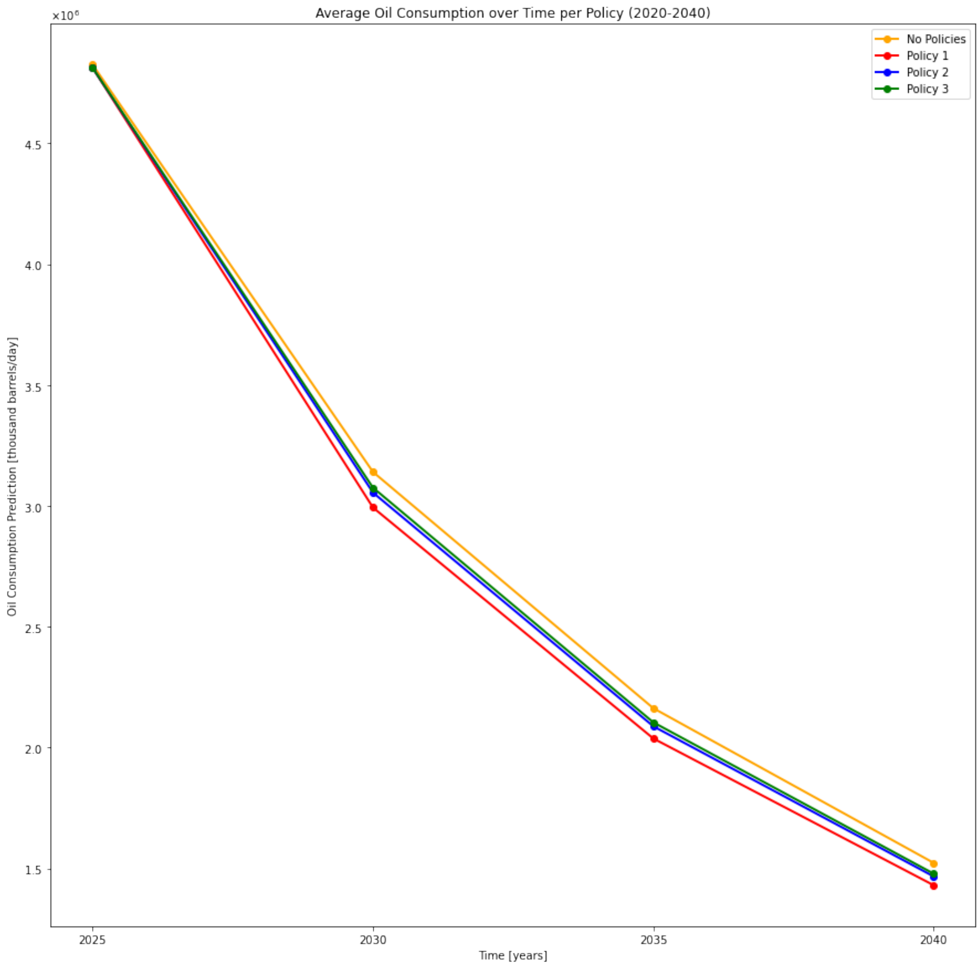


Figure 10: Effect of Policy 1, Policy 2, and Policy 3 on Oil Consumption in the United States

Due to our limited knowledge of how tax incentives work state by state, Model 2 is very vague about how the proposed percentages in each of the Markov Chains (Figure 3) were reached. For example, with Policy 1, we first picked the percentages that had very dramatic long-term solutions, which led to greatly reduced oil consumption by standard gasoline vehicles. Then we tried to find a way to best explain how it would be possible to get those percentages in the real world. Similarly, for Policies 2 and 3, we picked the numbers first and then tried to come up with an explanation for those numbers, but on a less extreme scale.

In this model, we combined hybrid vehicles and electric vehicles into a single category called hybrid/electric vehicles. Something that would improve this model is to is to separate hybrid/electric vehicles into their individual categories, do more research into pollution by each type of vehicle, and determine the environmental impact of oil consumption. We could research vehicle sales by type (standard gasoline, hybrid, and electric) per state, the average greenhouse gas emissions per type by state, and then perform similar testing that we did for Model 2. In this case, there would be Markov Chains for each state, and we would predict the average greenhouse gas emissions in the future with the implementation of each of the policies described in Model 2. Then we would combine the results from each state to predict overall pollution by each type of vehicle for light motor vehicles in the United States.

5.3 Model 3

Based on the results of Model 3, it can be concluded that each policy had an effect on the amount of oil consumed by the industrial sector in the United States. Policy 1, the most extreme policy, caused the greatest decrease in oil consumption. Policy 2, the moderate policy, caused the second greatest decrease in oil consumption. Policy 3, the least extreme policy, caused the third greatest decrease in oil consumption. Of the three policies, Policy 3 is probably the most realistic because the switch to biomass as the primary resource that an industrial company uses will not happen instantly. Policy 3 offers a short-term quality solution that still allows for a decrease in oil consumption by industrial companies. Figure 11 below depicts the difference between each policy's predicted amount of oil consumption.

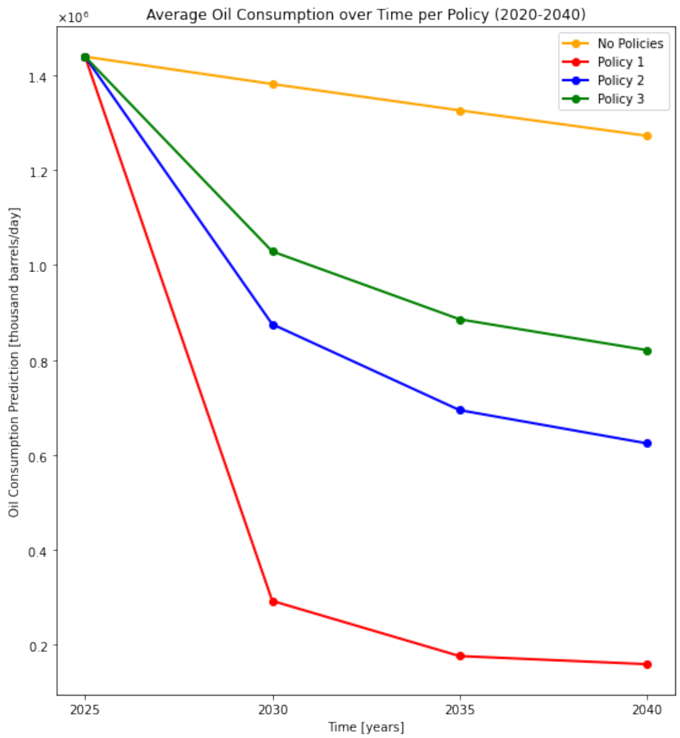


Figure 11: Effect of Policy 1, Policy 2, and Policy 3 on Oil Consumption in the United States

Due to our limited knowledge of how tax incentives work state by state, Model 3 is very vague about how the proposed percentages in each of the Markov Chains (Figure 4) were reached. For example, with Policy 1, we first picked the percentages that had very dramatic long-term solutions, which led to greatly reduced oil consumption by industrial companies. Then we tried to find a way to best explain how it would be possible to get those percentages in the real world. Similarly, for Policies 2 and 3, we picked the numbers first and then tried to come up with an explanation for those numbers, but on a less extreme scale.

Something that would improve this model is to do more research into tax incentives, industrial companies, and energy sources available state by state. We would find data about the percentage of industrial companies that operate in each state, research the types of energy those companies use, and figure out how to best reduce oil consumption with tax incentives that are already in place. For example, we might not only look at biomass versus petroleum. We could include other renewable energy sources such as wind and solar, and develop policies that increase those types of energy sources so that overall oil consumption is decreased, but this decrease does not rely on the drastic increase of a single renewable resource such as biomass. We could still use Markov Chains to analyze the long-term probabilities of the sources of energy used by each state's companies, but there would be more chains added to the model to account for other resources. Finally, we would analyze the effects of each policy on the oil consumption by industrial companies per state and then combine each state's predicted oil consumption amounts to make an overall prediction of future oil consumption by the industrial sector in the United States.

5.4 Model 4

Based on the results from model 4, it can safely be concluded that the models we used for consumption and production will have a direct impact on not just oil in the US, but the world as a whole. With oil imports down by almost 50%, and oil exports down completely by the year 2030, the question is how sustainable would this be, and what would this mean for the US? With exports down so much the US would need to increase profits in another place to make up for the money lost. Most likely new tariffs would be put into place to raise taxes on imports so the US could afford to produce so much less oil. The hope however is that this is merely a temporary measure while the US is switching from an oil based mode of consumption to a more sustainable one. Some of the major implications of such a decrease in imports is the US military. The US Oil industry and the US Military Industrial Complex are two of the biggest corporations in the US. The Oil industry uses their money to lobby politicians to not sign off on laws that would help increase renewable energy usage in the US, then instead because they have little access to green energy, the government's only other option is to continue to fund wars in the Middle East to be able to take their Oil [16]. If we were able to implement our policies as efficiently as we want to the savings would be tremendous. The amount of money we would save on just oil trade and production would pale in comparison to the money would would have left over from no longer having to fund the worlds single largest military nearly as much. This leads to the limitations of our model.

The clear limitation for this model is that it would be impossible to implement the policies we wish to because of the way the US government currently operates. At best, we would be able to do a bit better than we're currently doing, and looking at model 1 from section 3, specifically Figure 2, we're not really setting ourselves up to do that well with the current outlook on our situation. In a more positive light, our model does have some of it's strengths. First off was it's accuracy. The linear regression for the data in past years fit extremely well and seems to have a definite correlation. Also, we believe that the Monte Carlo simulation does a good job of modeling random behavior like oil trading quite well, and gives us a possible look into how our trade could play out in the future.

Overall, while we believe this model to be idealistic and simplistic, we find it to be robust enough to be an accurate model of a potential future oil trade with the US. While Oil consumption and production are the most difficult to predict with how little we can estimate the policies that will get put into place, given the fully accurate data for oil consumption and production we believe this model makes a very accurate guess to the Imports and Exports in and out of the US.

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Appendices

A Model 1

A.1 Consumption Model Variables

OC_n = oil consumption at time n

a_1 = oil consumption growth rate

c_1 = interaction factor between oil and renewable energy for oil consumption

RC_n = renewable energy consumption at time n

b_1 = renewable energy consumption growth rate

d_1 = interaction factor between oil and renewable energy for renewable energy consumption

A.2 Python Code

consumption_eda

May 6, 2021

[1]:
```
##########################
# Math380 Final Project
# Model Exploration
##########################

#%% import pyplot
from matplotlib import pyplot as plt
import numpy as np
import pandas as pd
```

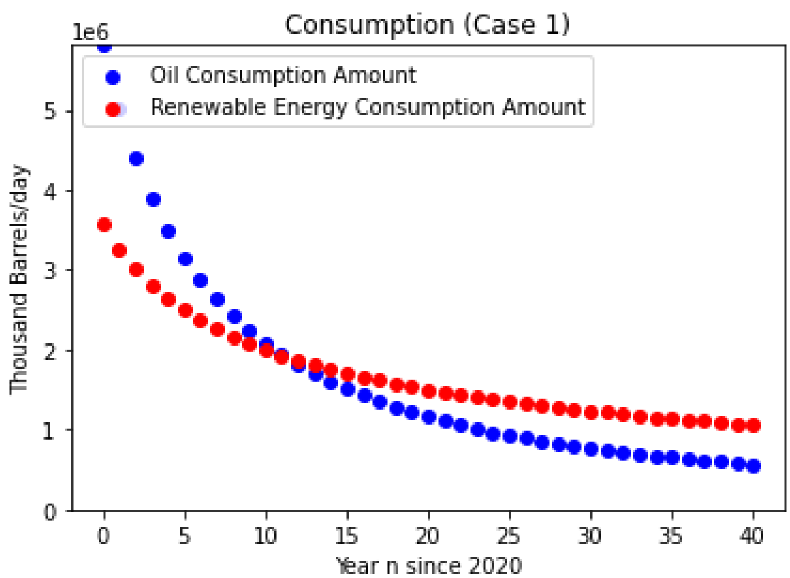
[2]:
```
#%% CONSUMPTION

# using 2020's data for this!!!
start_OC = 5805959.921
start_RC = 3573412.701
```

[3]:
```
#%%
# case 1: OC growth > RC growth & OC's i-factor < RC's i-factor
OC = [start_OC]
RC = [start_RC]
n = np.arange(41) #until 2060!!!

# growth factor of oil consumption
a = 0.020

# growth factoer of renewable energy consumption
b = -0.006

# interaction factor of OC and RC for OC
c = -0.000000044

# interaction factor of OC and RC for RC
d = -0.000000014

for i in range(40):
    OC.append(((1+a)*OC[i]) + (c*OC[i]*RC[i]))
    RC.append(((1+b)*RC[i]) + (d*OC[i]*RC[i]))
```

```python
data = {'years': n, 'Oil': OC, 'Renewable Energy': RC}
df = pd.DataFrame(data=data)
print(df)
df.to_csv(r'/Users/tiffwong/Desktop/math380/final project/consumption_case1.
↪csv', index = False)

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OC, color="b", label="Oil Consumption Amount")
ax.scatter(n, RC, color="r", label="Renewable Energy Consumption Amount")
plt.title("Consumption (Case 1)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OC),max(RC))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.805960e+06      3.573413e+06
1       1  5.009207e+06      3.261513e+06
2       2  4.390537e+06      3.013218e+06
3       3  3.896244e+06      2.809923e+06
4       4  3.492450e+06      2.639790e+06
5       5  3.156648e+06      2.494880e+06
6       6  2.873261e+06      2.369655e+06
7       7  2.631146e+06      2.260116e+06
8       8  2.422115e+06      2.163301e+06
9       9  2.240007e+06      2.076965e+06
10     10  2.080101e+06      1.999369e+06
11     11  1.938712e+06      1.929148e+06
12     12  1.812923e+06      1.865213e+06
13     13  1.700396e+06      1.806681e+06
14     14  1.599233e+06      1.752831e+06
15     15  1.507878e+06      1.703070e+06
16     16  1.425042e+06      1.656899e+06
17     17  1.349652e+06      1.613902e+06
18     18  1.280804e+06      1.573723e+06
19     19  1.217733e+06      1.536062e+06
20     20  1.159785e+06      1.500659e+06
21     21  1.106401e+06      1.467288e+06
22     22  1.057099e+06      1.435757e+06
23     23  1.011461e+06      1.405894e+06
24     24  9.691215e+05      1.377551e+06
25     25  9.297634e+05      1.350595e+06
26     26  8.931063e+05      1.324911e+06
```

27	27	8.589038e+05	1.300396e+06
28	28	8.269377e+05	1.276957e+06
29	29	7.970140e+05	1.254511e+06
30	30	7.689603e+05	1.232986e+06
31	31	7.426223e+05	1.212315e+06
32	32	7.178619e+05	1.192437e+06
33	33	6.945550e+05	1.173298e+06
34	34	6.725896e+05	1.154849e+06
35	35	6.518648e+05	1.137046e+06
36	36	6.322893e+05	1.119847e+06
37	37	6.137801e+05	1.103215e+06
38	38	5.962620e+05	1.087116e+06
39	39	5.796662e+05	1.071518e+06
40	40	5.639301e+05	1.056393e+06

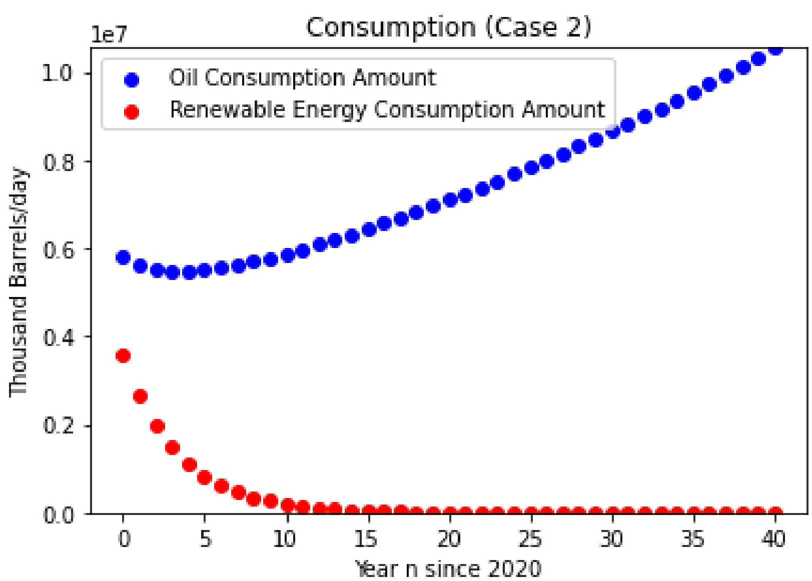


[4]:
```
#%%
# case 2: OC growth > RC growth & OC's i-factor > RC's i-factor
OC = [start_OC]
RC = [start_RC]
n = np.arange(41) #until 2060!!!

# growth factor of oil consumption
a = 0.020
```

```
# growth factoer of renewable energy consumption
b = -0.006

# interaction factor of OC and RC for OC
c = -0.000000014

# interaction factor of OC and RC for RC
d = -0.000000044

for i in range(40):
    OC.append(((1+a)*OC[i]) + (c*OC[i]*RC[i]))
    RC.append(((1+b)*RC[i]) + (d*OC[i]*RC[i]))

data = {'years': n, 'Oil': OC, 'Renewable Energy': RC}
df = pd.DataFrame(data=data)
print(df)
df.to_csv(r'/Users/tiffwong/Desktop/math380/final project/consumption_case2.
 ↪csv', index = False)

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OC, color="b", label="Oil Consumption Amount")
ax.scatter(n, RC, color="r", label="Renewable Energy Consumption Amount")
plt.title("Consumption (Case 2)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OC),max(RC))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.805960e+06      3.573413e+06
1       1  5.631620e+06      2.639100e+06
2       2  5.536179e+06      1.969320e+06
3       3  5.494267e+06      1.477793e+06
4       4  5.490481e+06      1.111673e+06
5       5  5.514840e+06      8.364441e+05
6       6  5.560557e+06      6.284598e+05
7       7  5.622844e+06      4.709272e+05
8       8  5.698229e+06      3.515919e+05
9       9  5.784145e+06      2.613305e+05
10     10  5.878666e+06      1.932533e+05
11     11  5.980335e+06      1.421066e+05
12     12  6.088043e+06      1.038608e+05
13     13  6.200952e+06      7.541602e+04
14     14  6.318424e+06      5.438687e+04
```

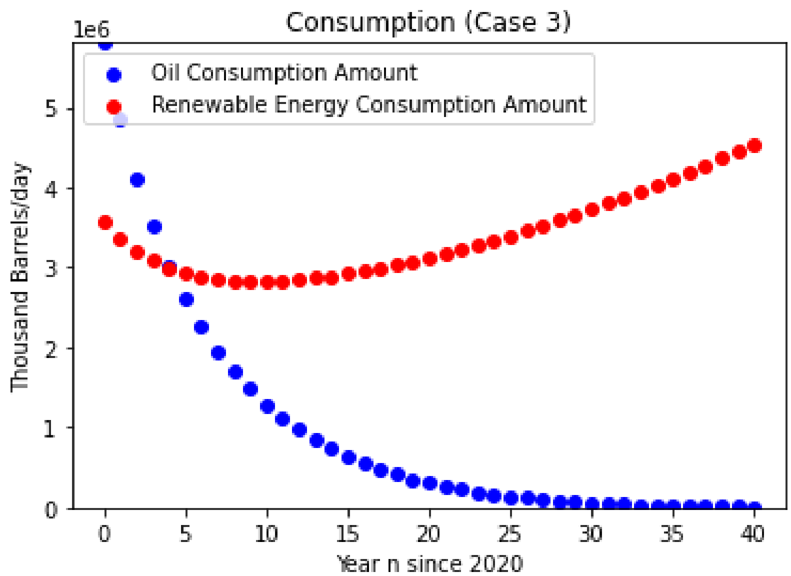
15	15	6.439981e+06	3.894042e+04
16	16	6.565270e+06	2.767265e+04
17	17	6.694032e+06	1.951277e+04
18	18	6.826084e+06	1.364845e+04
19	19	6.961301e+06	9.467279e+03
20	20	7.099605e+06	6.510673e+03
21	21	7.240950e+06	4.437788e+03
22	22	7.385319e+06	2.997274e+03
23	23	7.532715e+06	2.005314e+03
24	24	7.683158e+06	1.328642e+03
25	25	7.836678e+06	8.715108e+02
26	26	7.993316e+06	5.657728e+02
27	27	8.153119e+06	3.633925e+02
28	28	8.316140e+06	2.308497e+02
29	29	8.482436e+06	1.449944e+02
30	30	8.652068e+06	9.000855e+01
31	31	8.825098e+06	5.520306e+01
32	32	9.001593e+06	3.343625e+01
33	33	9.181621e+06	1.999254e+01
34	34	9.365251e+06	1.179577e+01
35	35	9.552554e+06	6.864300e+00
36	36	9.743605e+06	3.937964e+00
37	37	9.938476e+06	2.226058e+00
38	38	1.013725e+07	1.239262e+00
39	39	1.033999e+07	6.790675e-01
40	40	1.054679e+07	3.660448e-01



[5]:
```python
#%%
# actual (case 3): OC growth < RC growth & OC's i-factor < RC's i-factor
OC = [start_OC]
RC = [start_RC]
n = np.arange(41)
# growth factor of oil consumption
a = -0.006012076354

# growth factoer of renewable energy consumption
b = 0.020247218

# interaction factor of OC and RC for OC
c = -0.00000004382777105

# interaction factor of OC and RC for RC
d = -0.00000001382597676

for i in range(40):
    OC.append(((1+a)*OC[i]) + (c*OC[i]*RC[i]))
    RC.append(((1+b)*RC[i]) + (d*OC[i]*RC[i]))

data = {'years': n, 'Oil': OC, 'Renewable Energy': RC}
df = pd.DataFrame(data=data)
print(df)
df.to_csv(r'/Users/tiffwong/Desktop/math380/final project/consumption_case3.
↪csv', index = False)

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OC, color="b", label="Oil Consumption Amount")
ax.scatter(n, RC, color="r", label="Renewable Energy Consumption Amount")
plt.title("Consumption (Case 3)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OC),max(RC))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.805960e+06      3.573413e+06
1       1  4.861755e+06      3.358916e+06
2       2  4.116809e+06      3.201143e+06
3       3  3.514474e+06      3.083752e+06
4       4  3.018350e+06      2.996346e+06
```

5	5	2.603824e+06	2.931972e+06
6	6	2.253574e+06	2.885784e+06
7	7	1.954999e+06	2.854298e+06
8	8	1.698680e+06	2.834939e+06
9	9	1.477408e+06	2.825757e+06
10	10	1.285553e+06	2.825250e+06
11	11	1.118642e+06	2.832238e+06
12	12	9.730586e+05	2.845778e+06
13	13	8.458446e+05	2.865112e+06
14	14	7.345454e+05	2.889616e+06
15	15	6.371024e+05	2.918776e+06
16	16	5.517718e+05	2.952163e+06
17	17	4.770625e+05	2.989415e+06
18	18	4.116900e+05	3.030224e+06
19	19	3.545391e+05	3.074330e+06
20	20	3.046367e+05	3.121506e+06
21	21	2.611282e+05	3.171561e+06
22	22	2.232608e+05	3.224326e+06
23	23	1.903685e+05	3.279656e+06
24	24	1.618604e+05	3.337428e+06
25	25	1.372116e+05	3.397533e+06
26	26	1.159550e+05	3.459878e+06
27	27	9.767462e+04	3.524384e+06
28	28	8.199999e+04	3.590984e+06
29	29	6.860145e+04	3.659620e+06
30	30	5.718582e+04	3.730246e+06
31	31	4.749280e+04	3.802824e+06
32	32	3.929168e+04	3.877323e+06
33	33	3.237844e+04	3.953722e+06
34	34	2.657315e+04	4.032004e+06
35	35	2.171755e+04	4.112159e+06
36	36	1.767290e+04	4.194185e+06
37	37	1.431799e+04	4.278080e+06
38	38	1.154730e+04	4.363853e+06
39	39	9.269364e+03	4.451512e+06
40	40	7.405185e+03	4.541072e+06

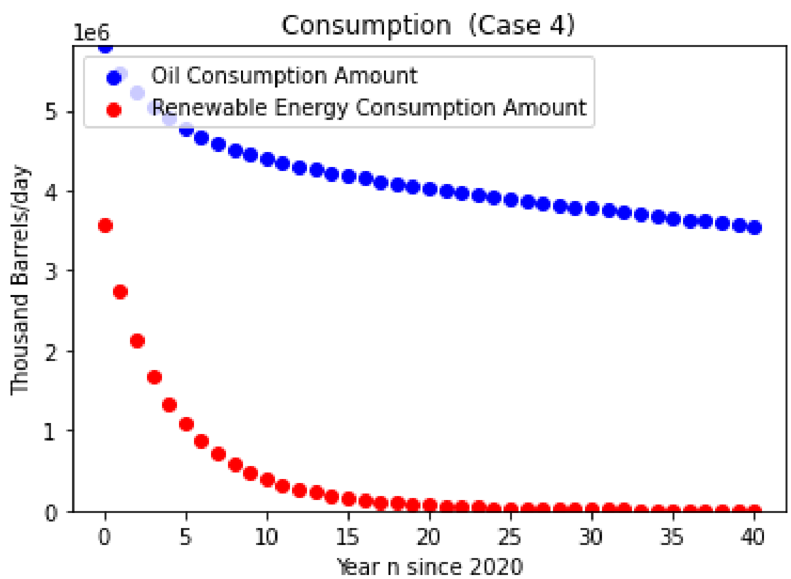


[6]:
```
#%%
# case 4: OC growth < RC growth & OC's i-factor > RC's i-factor
OC = [start_OC]
RC = [start_RC]
n = np.arange(41)
# growth factor of oil consumption
a = -0.006012076354

# growth factoer of renewable energy consumption
b = 0.020247218

# interaction factor of OC and RC for OC
c = -0.000000014

# interaction factor of OC and RC for RC
d = -0.000000044



for i in range(40):
    OC.append(((1+a)*OC[i]) + (c*OC[i]*RC[i]))
    RC.append(((1+b)*RC[i]) + (d*OC[i]*RC[i]))
```

```python
data = {'years': n, 'Oil': OC, 'Renewable Energy': RC}
df = pd.DataFrame(data=data)
print(df)
df.to_csv(r'/Users/tiffwong/Desktop/math380/final project/consumption_case4.
 ↪csv', index = False)

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OC, color="b", label="Oil Consumption Amount")
ax.scatter(n, RC, color="r", label="Renewable Energy Consumption Amount")
plt.title("Consumption  (Case 4)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OC),max(RC))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.805960e+06      3.573413e+06
1       1  5.480595e+06      2.732892e+06
2       2  5.237955e+06      2.129199e+06
3       3  5.050327e+06      1.681593e+06
4       4  4.901067e+06      1.341967e+06
5       5  4.779523e+06      1.079747e+06
6       6  4.678539e+06      8.745388e+05
7       7  4.593129e+06      7.122170e+05
8       8  4.519716e+06      5.827000e+05
9       9  4.455673e+06      4.786180e+05
10     10  4.399029e+06      3.944758e+05
11     11  4.348287e+06      3.261092e+05
12     12  4.302293e+06      2.703193e+05
13     13  4.260145e+06      2.246208e+05
14     14  4.221136e+06      1.870644e+05
15     15  4.184703e+06      1.561085e+05
16     16  4.150399e+06      1.305254e+05
17     17  4.117862e+06      1.093320e+05
18     18  4.086802e+06      9.173623e+04
19     19  4.056983e+06      7.709769e+04
20     20  4.028214e+06      6.489621e+04
21     21  4.000336e+06      5.470788e+04
22     22  3.973222e+06      4.618617e+04
23     23  3.946765e+06      3.904696e+04
24     24  3.920879e+06      3.305675e+04
25     25  3.895492e+06      2.802315e+04
26     26  3.870544e+06      2.378733e+04
27     27  3.845985e+06      2.021788e+04
```

```
28      28  3.821774e+06      1.720590e+04
29      29  3.797877e+06      1.466096e+04
30      30  3.774264e+06      1.250786e+04
31      31  3.750912e+06      1.068396e+04
32      32  3.727800e+06      9.136997e+03
33      33  3.704911e+06      7.823316e+03
34      34  3.682231e+06      6.706390e+03
35      35  3.659748e+06      5.755619e+03
36      36  3.637450e+06      4.945333e+03
37      37  3.615330e+06      4.253973e+03
38      38  3.593379e+06      3.663405e+03
39      39  3.571591e+06      3.158363e+03
40      40  3.549960e+06      2.725974e+03
```

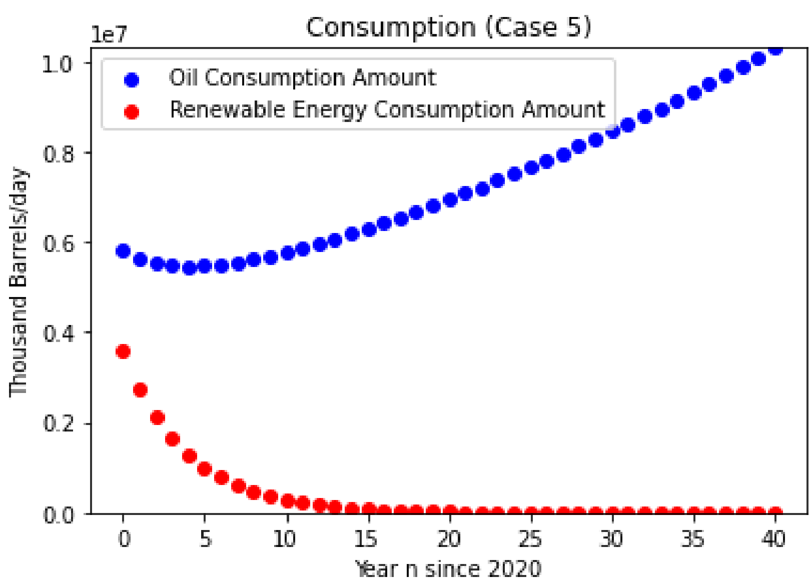


[7]:
```
#%%
# case 5: OC growth = RC growth & OC's i-factor > RC's i-factor
OC = [start_OC]
RC = [start_RC]
n = np.arange(41) #until 2060!!!

# growth factor of oil consumption
a = 0.020

# growth factoer of renewable energy consumption
```

```python
b = 0.020

# interaction factor of OC and RC for OC
c = -0.000000014

# interaction factor of OC and RC for RC
d = -0.000000044

for i in range(40):
    OC.append(((1+a)*OC[i]) + (c*OC[i]*RC[i]))
    RC.append(((1+b)*RC[i]) + (d*OC[i]*RC[i]))

data = {'years': n, 'Oil': OC, 'Renewable Energy': RC}
df = pd.DataFrame(data=data)
print(df)
df.to_csv(r'/Users/tiffwong/Desktop/math380/final project/consumption_case5.
 ↪csv', index = False)


#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OC, color="b", label="Oil Consumption Amount")
ax.scatter(n, RC, color="r", label="Renewable Energy Consumption Amount")
plt.title("Consumption (Case 5)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OC),max(RC))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.805960e+06      3.573413e+06
1       1  5.631620e+06      2.732009e+06
2       2  5.528853e+06      2.109681e+06
3       3  5.476133e+06      1.638654e+06
4       4  5.460027e+06      1.276593e+06
5       5  5.471644e+06      9.954349e+05
6       6  5.504823e+06      7.756904e+05
7       7  5.555139e+06      6.033225e+05
8       8  5.619321e+06      4.679211e+05
9       9  5.694895e+06      3.615860e+05
10     10  5.779965e+06      2.782132e+05
11     11  5.873051e+06      2.130227e+05
12     12  5.972997e+06      1.622350e+05
13     13  6.078890e+06      1.228425e+05
14     14  6.190014e+06      9.244249e+04
```

15	15	6.305803e+06	6.911365e+04
16	16	6.425817e+06	5.131997e+04
17	17	6.549717e+06	3.783637e+04
18	18	6.677242e+06	2.768913e+04
19	19	6.808198e+06	2.010788e+04
20	20	6.942446e+06	1.448651e+04
21	21	7.079887e+06	1.035108e+04
22	22	7.220458e+06	7.333584e+03
23	23	7.364126e+06	5.150375e+03
24	24	7.510878e+06	3.584550e+03
25	25	7.660718e+06	2.471624e+03
26	26	7.813668e+06	1.687942e+03
27	27	7.969756e+06	1.141384e+03
28	28	8.129024e+06	7.639634e+02
29	29	8.291518e+06	5.059905e+02
30	30	8.457289e+06	3.315114e+02
31	31	8.626396e+06	2.147794e+02
32	32	8.798898e+06	1.375530e+02
33	33	8.974859e+06	8.705021e+01
34	34	9.154345e+06	5.441563e+01
35	35	9.337425e+06	3.358580e+01
36	36	9.524169e+06	2.045890e+01
37	37	9.714650e+06	1.229450e+01
38	38	9.908941e+06	7.285175e+00
39	39	1.010712e+07	4.254590e+00
40	40	1.030926e+07	2.447609e+00



```
[ ]:
```

A.3 Production Model Variables

OP_n = oil production at time n

a_2 = oil production growth rate

c_2 = interaction factor between oil and renewable energy for oil production

RP_n = renewable energy production at time n

b_2 = renewable energy production growth rate

d_2 = interaction factor between oil and renewable energy for renewable energy production

A.4 Python Code

production_eda

May 6, 2021

[1]:
```
##########################
# Math380 Final Project
# Model Exploration
##########################

#%% import pyplot
from matplotlib import pyplot as plt
import numpy as np
import pandas as pd
```

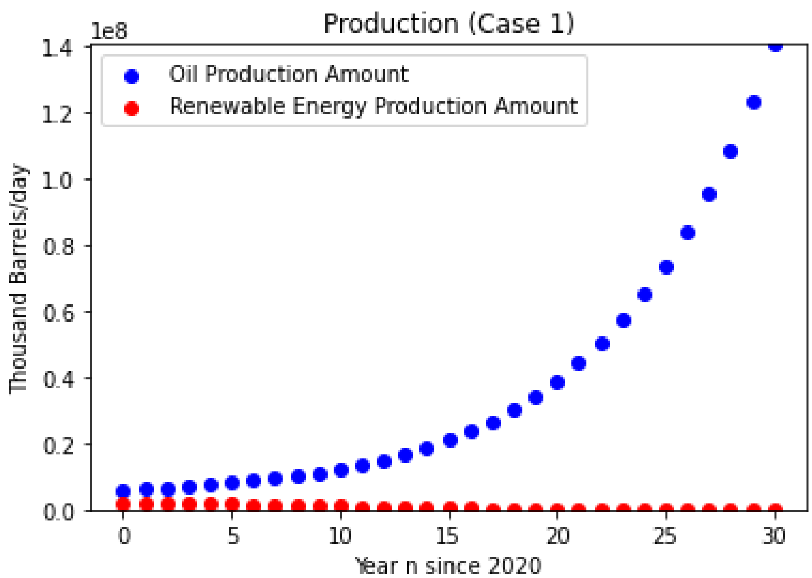
[2]:
```
#%% PRODUCTION

start_OP = 5964297
start_RP = 2120823.171
```

[3]:
```
#%%
# actual: OP growth > RP growth & OP's i-factor < RP's i-factor
OP = [start_OP]
RP = [start_RP]
n = np.arange(31)
# growth factor of oil production
a = 0.1372710762

# growth factoer of renewable energy production
b = 0.041262958

# interaction factor of OP and RP for OP
c = -0.0000000399281668

# interaction factor of OP and RP for RP
d = -0.00000001586660302

for i in range(30):
    OP.append(((1+a)*OP[i]) + (c*OP[i]*RP[i]))
    RP.append(((1+b)*RP[i]) + (d*OP[i]*RP[i]))

data = {'years': n, 'Oil': OP, 'Renewable Energy': RP}
```

```python
df = pd.DataFrame(data=data)
print(df)


#create array for n years
n = np.arange(31)
i = 0

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OP, color="b", label="Oil Production Amount")
ax.scatter(n, RP, color="r", label="Renewable Energy Production Amount")
plt.title("Production (Case 1)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OP),max(RP))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.964297e+06      2.120823e+06
1       1  6.277962e+06      2.007634e+06
2       2  6.636496e+06      1.890495e+06
3       3  7.046546e+06      1.769436e+06
4       4  7.515992e+06      1.644617e+06
5       5  8.054171e+06      1.516353e+06
6       6  8.672135e+06      1.385144e+06
7       7  9.382945e+06      1.251707e+06
8       8  1.020201e+07      1.117007e+06
9       9  1.114744e+07      9.822870e+05
10     10  1.224045e+07      8.490801e+05
11     11  1.350573e+07      7.192121e+05
12     12  1.497183e+07      5.947690e+05
13     13  1.667148e+07      4.780223e+05
14     14  1.864179e+07      3.713006e+05
15     15  2.092440e+07      2.767975e+05
16     16  2.356546e+07      1.963225e+05
17     17  2.661559e+07      1.310176e+05
18     18  3.012990e+07      8.109520e+04
19     19  3.416831e+07      4.567312e+04
20     20  3.879632e+07      2.279673e+04
21     21  4.408661e+07      9.704506e+03
22     22  5.012135e+07      3.316594e+03
23     23  5.699492e+07      8.159068e+02
24     24  6.481682e+07      1.117361e+02
25     25  7.371400e+07      1.434716e+00
```

26	26	8.383280e+07	-1.841141e-01
27	27	9.534062e+07	5.318667e-02
28	28	1.084281e+08	-2.507586e-02
29	29	1.233122e+08	1.702959e-02
30	30	1.402394e+08	-1.558689e-02

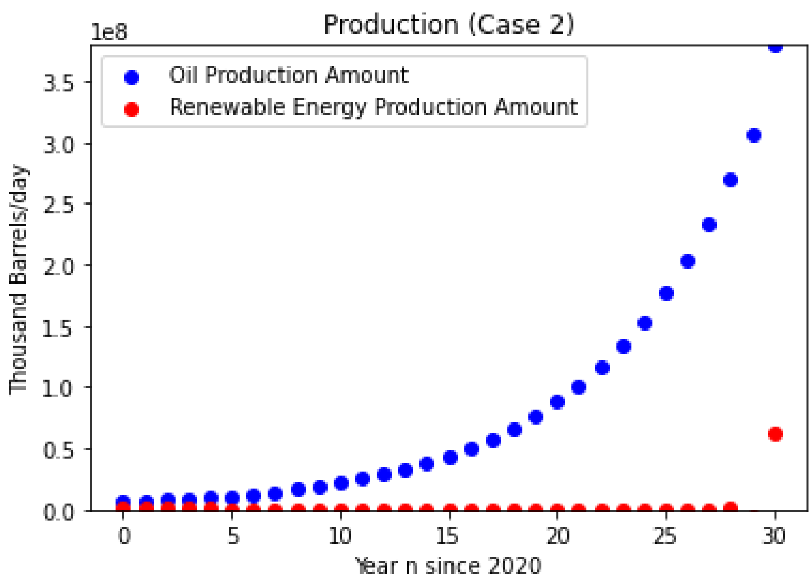


[4]:
```
#%%
# case 2: OP growth > RP growth & OP's i-factor > RP's i-factor

OP = [start_OP]
RP = [start_RP]
n = np.arange(31)
# growth factor of oil production
a = 0.15

# growth factor of renewable energy production
b = 0.05

# interaction factor of OP and RP
c = -0.000000015

# interaction factor of OP and RP
d = -0.000000040
```

```python
for i in range(30):
    OP.append(((1+a)*OP[i]) + (c*OP[i]*RP[i]))
    RP.append(((1+b)*RP[i]) + (d*OP[i]*RP[i]))

data = {'years': n, 'Oil': OP, 'Renewable Energy': RP}
df = pd.DataFrame(data=data)
print(df)


#create array for n years
n = np.arange(31)
i = 0

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OP, color="b", label="Oil Production Amount")
ax.scatter(n, RP, color="r", label="Renewable Energy Production Amount")
plt.title("Production (Case 2)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OP),max(RP))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.964297e+06      2.120823e+06
1       1  6.669203e+06      1.720896e+06
2       2  7.497429e+06      1.347860e+06
3       3  8.470461e+06      1.011034e+06
4       4  9.612571e+06      7.190286e+05
5       5  1.095078e+07      4.785115e+05
6       6  1.251480e+07      2.928341e+05
7       7  1.433705e+07      1.608854e+05
8       8  1.645300e+07      7.666483e+04
9       9  1.890203e+07      3.004341e+04
10     10  2.172882e+07      8.830319e+03
11     11  2.498526e+07      1.596939e+03
12     12  2.873245e+07      8.078825e+01
13     13  3.304229e+07     -8.022127e+00
14     14  3.799864e+07      2.179544e+00
15     15  4.369843e+07     -1.024267e+00
16     16  5.025319e+07      7.148739e-01
17     17  5.779117e+07     -6.863703e-01
18     18  6.645985e+07      8.659570e-01
19     19  7.642883e+07     -1.392800e+00
20     20  8.789315e+07      2.795563e+00
```

```
21      21  1.010771e+08     -6.893092e+00
22      22  1.162387e+08      2.063161e+01
23      23  1.336745e+08     -7.426447e+01
24      24  1.537258e+08      3.191129e+02
25      25  1.767839e+08     -1.627167e+03
26      26  2.033058e+08      9.797750e+03
27      27  2.337718e+08     -6.938995e+04
28      28  2.690809e+08      5.759971e+05
29      29  3.071182e+08     -5.594797e+06
30      30  3.789599e+08      6.285602e+07
```

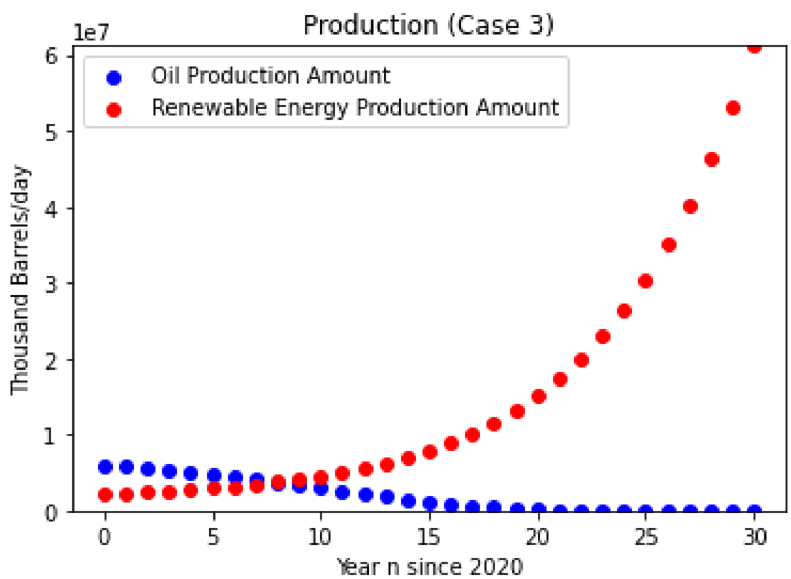


[5]:
```
#%%
# case 3: OP growth < RP growth & OP's i-factor < RP's i-factor

OP = [start_OP]
RP = [start_RP]
n = np.arange(31)
# growth factor of oil production
a = 0.05

# growth factor of renewable energy production
b = 0.15

# interaction factor of OP and RP
```

```
c = -0.000000040

# interaction factor of OP and RP
d = -0.000000015

for i in range(30):
    OP.append(((1+a)*OP[i]) + (c*OP[i]*RP[i]))
    RP.append(((1+b)*RP[i]) + (d*OP[i]*RP[i]))

data = {'years': n, 'Oil': OP, 'Renewable Energy': RP}
df = pd.DataFrame(data=data)
print(df)


#create array for n years
n = np.arange(31)
i = 0

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OP, color="b", label="Oil Production Amount")
ax.scatter(n, RP, color="r", label="Renewable Energy Production Amount")
plt.title("Production (Case 3)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OP),max(RP))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.964297e+06      2.120823e+06
1       1  5.756543e+06      2.249208e+06
2       2  5.526464e+06      2.392375e+06
3       3  5.273932e+06      2.552910e+06
4       4  4.999074e+06      2.733889e+06
5       5  4.702351e+06      2.938968e+06
6       6  4.384666e+06      3.172513e+06
7       7  4.047483e+06      3.439733e+06
8       8  3.692967e+06      3.746860e+06
9       9  3.324134e+06      4.101333e+06
10     10  2.945005e+06      4.512032e+06
11     11  2.560737e+06      4.989518e+06
12     12  2.177700e+06      5.546293e+06
13     13  1.803459e+06      6.197064e+06
14     14  1.446586e+06      6.958982e+06
15     15  1.116244e+06      7.851827e+06
```

```
16      16  8.214743e+05       8.898133e+06
17      17  5.701645e+05       1.012321e+07
18      18  3.677970e+05       1.155511e+07
19      19  2.161894e+05       1.322463e+07
20      20  1.126379e+05       1.516544e+07
21      21  4.994166e+04       1.741463e+07
22      22  1.765012e+04       2.001378e+07
23      23  4.402800e+03       2.301055e+07
24      24  5.705060e+02       2.646061e+07
25      25 -4.806225e+00       3.042948e+07
26      26  8.035004e-01       3.499390e+07
27      27 -2.810291e-01       4.024299e+07
28      28  1.572975e-01       4.627943e+07
29      29 -1.260232e-01       5.322135e+07
30      30  1.359606e-01       6.120455e+07
```

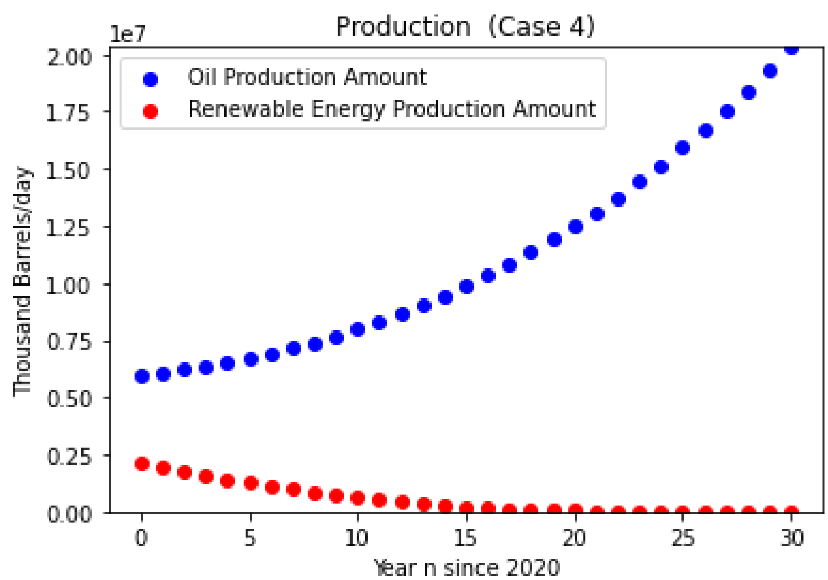


[6]:
```
#%%
# case 4: OP growth < RP growth & OP's i-factor > RP's i-factor

OP = [start_OP]
RP = [start_RP]
n = np.arange(31)
# growth factor of oil production
a = 0.05
```

```
# growth factor of renewable energy production
b = 0.15

# interaction factor of OP and RP
c = -0.000000015

# interaction factor of OP and RP
d = -0.000000040

for i in range(30):
    OP.append(((1+a)*OP[i]) + (c*OP[i]*RP[i]))
    RP.append(((1+b)*RP[i]) + (d*OP[i]*RP[i]))

data = {'years': n, 'Oil': OP, 'Renewable Energy': RP}
df = pd.DataFrame(data=data)
print(df)


#create array for n years
n = np.arange(31)
i = 0

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OP, color="b", label="Oil Production Amount")
ax.scatter(n, RP, color="r", label="Renewable Energy Production Amount")
plt.title("Production  (Case 4)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OP),max(RP))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.964297e+06      2.120823e+06
1       1  6.072774e+06      1.932978e+06
2       2  6.200334e+06      1.753383e+06
3       3  6.347277e+06      1.581528e+06
4       4  6.514065e+06      1.417221e+06
5       5  6.701291e+06      1.260530e+06
6       6  6.909647e+06      1.111722e+06
7       7  7.139906e+06      9.712161e+05
8       8  7.392885e+06      8.395229e+05
9       9  7.669432e+06      7.171915e+05
10     10  7.970397e+06      6.047521e+05
```

```
11      11  8.296615e+06      5.026604e+05
12      12  8.648890e+06      4.112443e+05
13      13  9.027982e+06      3.306586e+05
14      14  9.434604e+06      2.608502e+05
15      15  9.869419e+06      2.015370e+05
16      16  1.033305e+07      1.522054e+05
17      17  1.082612e+07      1.121264e+05
18      18  1.134921e+07      8.038961e+04
19      19  1.190299e+07      5.595370e+04
20      20  1.248815e+07      3.770611e+04
21      21  1.310549e+07      2.452685e+04
22      22  1.375594e+07      1.534842e+04
23      23  1.444057e+07      9.205402e+03
24      24  1.516061e+07      5.268960e+03
25      25  1.591744e+07      2.864079e+03
26      26  1.671263e+07      1.470138e+03
27      27  1.754789e+07      7.078639e+02
28      28  1.842510e+07      3.171827e+02
29      29  1.934627e+07      1.309952e+02
30      30  2.031354e+07      4.927374e+01
```

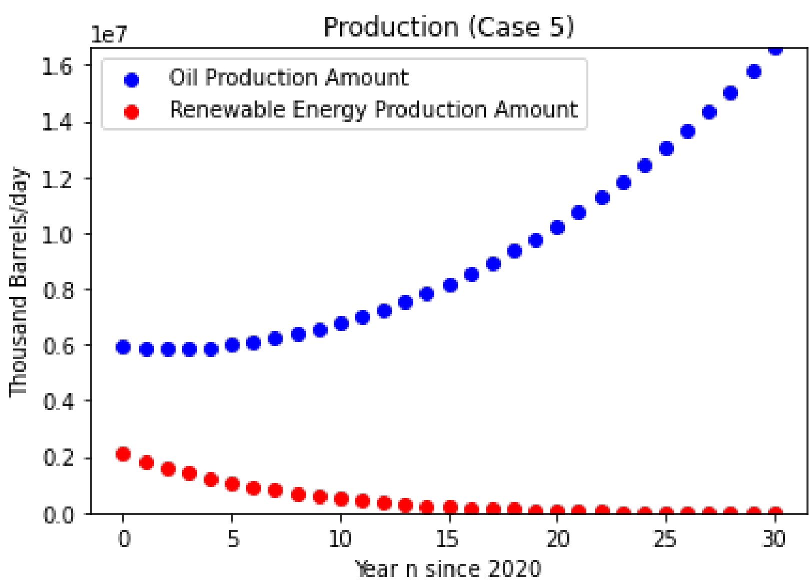


[7]:
```
#%%
# case 5: OP growth < RP growth & OP's i-factor > RP's i-factor
```

```python
OP = [start_OP]
RP = [start_RP]
n = np.arange(31)
# growth factor of oil production
a = 0.05

# growth factor of renewable energy production
b = 0.05

# interaction factor of OP and RP
c = -0.000000030

# interaction factor of OP and RP
d = -0.000000030

for i in range(30):
    OP.append(((1+a)*OP[i]) + (c*OP[i]*RP[i]))
    RP.append(((1+b)*RP[i]) + (d*OP[i]*RP[i]))

data = {'years': n, 'Oil': OP, 'Renewable Energy': RP}
df = pd.DataFrame(data=data)
print(df)


#create array for n years
n = np.arange(31)
i = 0

#plot actual data and modeled data on the same graph to compare
ax = plt.gca()

ax.scatter(n, OP, color="b", label="Oil Production Amount")
ax.scatter(n, RP, color="r", label="Renewable Energy Production Amount")
plt.title("Production (Case 5)")
plt.xlabel("Year n since 2020")
plt.ylabel("Thousand Barrels/day")
plt.legend(loc="upper left")
ax.set_ylim([0, max(max(OP),max(RP))])
plt.show()
```

```
    years           Oil  Renewable Energy
0       0  5.964297e+06      2.120823e+06
1       1  5.883035e+06      1.847388e+06
2       2  5.851140e+06      1.613710e+06
3       3  5.860435e+06      1.411134e+06
4       4  5.905361e+06      1.233595e+06
5       5  5.982085e+06      1.076730e+06
```

6	6	6.087956e+06	9.373337e+05
7	7	6.221161e+06	8.130070e+05
8	8	6.380483e+06	7.019220e+05
9	9	6.565149e+06	6.026600e+05
10	10	6.774710e+06	5.140964e+05
11	11	7.008960e+06	4.353156e+05
12	12	7.267875e+06	3.655481e+05
13	13	7.551566e+06	3.041228e+05
14	14	7.860246e+06	2.504308e+05
15	15	8.194205e+06	2.038989e+05
16	16	8.553792e+06	1.639702e+05
17	17	8.939404e+06	1.300917e+05
18	18	9.351486e+06	1.017080e+05
19	19	9.790527e+06	7.825978e+04
20	20	1.025707e+07	5.918663e+04
21	21	1.075171e+07	4.393353e+04
22	22	1.127512e+07	3.195939e+04
23	23	1.182807e+07	2.274698e+04
24	24	1.241140e+07	1.581274e+04
25	25	1.302608e+07	1.071563e+04
26	26	1.367320e+07	7.063932e+03
27	27	1.435396e+07	4.519532e+03
28	28	1.506971e+07	2.799313e+03
29	29	1.582193e+07	1.673733e+03
30	30	1.661224e+07	9.629692e+02



[ ]:

B Model 2

B.1 Python Variables

- $H1, H2, H3$: represent the percentage of hybrid/electric vehicles that are sold under Policy 1, Policy 2, and Policy 3, respectively
- $R1, R2, R3$: represent the percentage of standard gasoline vehicles that are sold under Policy 1, Policy 2, and Policy 3, respectively
- $time$: represents the time in increments of 5 years from 2020-2060
- $time2$: represents the time in increments of 5 years from 2020-2040
- $consumption$: represents the predicted oil consumption data each year from 2020-2040
- $avg\_consumption$: represents the average predicted oil consumption every 5 years from 2020-2040
- LMV : represents the amount of oil consumed by light motor vehicles
- H_OC : represents the amount of oil consumed by hybrid/electric vehicles without any of the policies in place
- H_OCS : represents the amount of oil saved by hybrid/electric vehicles without any of the policies in place
- $H1\_OC$: represents the amount of oil consumed by hybrid/electric vehicles with Policy 1 in place
- $H1\_OCS$: represents the amount of oil saved by hybrid/electric vehicles with Policy 1 in place
- $savedOC1$: represents the percentage of oil saved by hybrid/electric vehicles with Policy 1 in place
- $diff\_S1$: represents the difference in hybrid/electric vehicle savings with Policy 1 in place
- $H2\_OC$: represents the amount of oil consumed by hybrid/electric vehicles with Policy 2 in place
- $H2\_OCS$: represents the amount of oil saved by hybrid/electric vehicles with Policy 2 in place
- $savedOC2$: represents the percentage of oil saved by hybrid/electric vehicles with Policy 2 in place
- $diff\_S2$: represents the difference in hybrid/electric vehicle savings with Policy 2 in place
- $H3\_OC$: represents the amount of oil consumed by hybrid/electric vehicles with Policy 1 in place
- $H3\_OCS$: represents the amount of oil saved by hybrid/electric vehicles with Policy 3 in place

- $savedOC3$: represents the percentage of oil saved by hybrid/electric vehicles with Policy 3 in place
- $diff\_S3$: represents the difference in hybrid/electric vehicle savings with Policy 3 in place
- $newOC1, newOC2, newOC3$: represent the new oil consumption predictions for years 2020-2040 under Policy 1, Policy 2, and Policy 3, respectively

B.2 Python Code

Math 380 Project Code

May 6, 2021

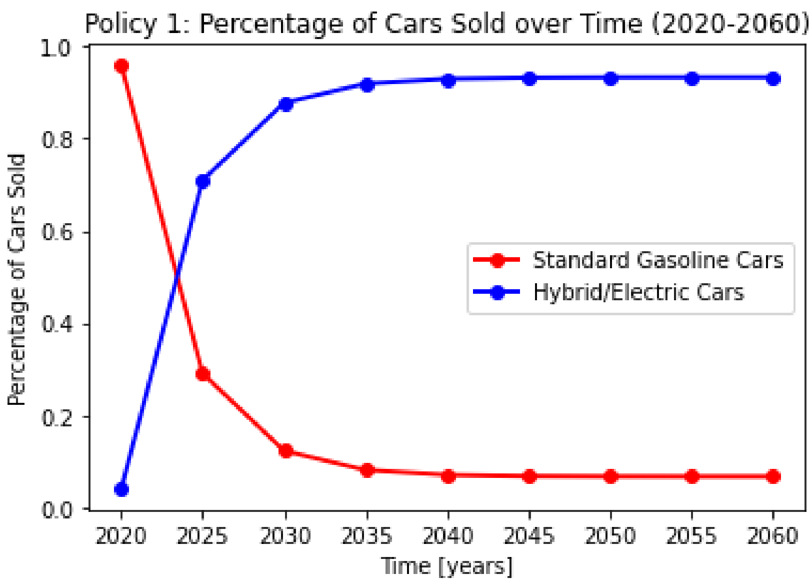
[1]:
```
# 3 Submodels that incentivize less oil consumption in the US
# Markov Chains are used to describe the % of Cars that are Hybrid/Electric vs.␣
↪% of Standard Gasoline Cars

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import random

# Time is measured in increments of 5 years in these submodels (years 2020 -␣
↪2060)
time = [2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060]
time2 = [2025, 2030, 2035, 2040]

# Predicted Oil Consumption Data for Years 2020-2040
consumption = [5805959.921, 5239840.467, 4757698.798, 4341279.534, 3977420.227,␣
↪3656365.816, 3370717.377, 3114751.13, 2883962.958, 2674755.238, 2484216.34,␣
↪2309962.07, 2150019.541, 2002740.683, 1866736.878, 1740828.893, 1624008.051,␣
↪1515405.796, 1414269.58, 1319943.59, 1231853.204]

# Average Predicted Oil Consumption for Years 2020-2040 in 5 year increments
avg_consumption = [0,0,0,0]
avg_consumption[0] = np.average(consumption[0:5]) # years 2020-2025
avg_consumption[1] = np.average(consumption[5:10]) # years 2025-2030
avg_consumption[2] = np.average(consumption[10:15]) # years 2030-2035
avg_consumption[3] = np.average(consumption[15:20]) # years 2035-2040
```

[2]:
```
# Model 1: Extreme Policy
# Markov Chains are used to model impact of this policy over time

H1 = [0] * 9  # array that stores the percentage of cars that are hybrid/
↪electric
R1 = [0] * 9  # array that stores the percentage of regular cars

H1[0] = 0.041  # initial value for percentage of cars that are hybrid/electric
R1[0] = 0.959  # initial value for percentage of regular cars
```

```python
# Test the stability of the solutions by changing the intial values
# Start with equal intial values
#H1[0] = 0.5
#R1[0] = 0.5

# Make H1[0] > R1[0]
#H1[0] = 0.959
#R1[0] = 0.041

# When starting at different initial values, the long-term probabilities still␣
↪yield the same percentages, so the solutions are stable

# Store the long-term probabilities for each car option in their respective␣
↪arrays

for i in range(8):
    H1[i+1] = 0.95*H1[i] + 0.70*R1[i] # 95% stay hybrid, 70% switch to hybrid
    R1[i+1] = 0.05*H1[i] + 0.30*R1[i] # 5% switch to regular, 30% stay regular

# Output the long-term probabilities for each car option

print("Long term probabilities for each car option: \n")
print("Regular Cars:", R1, "\n")
print("Hybrid Cars:", H1, "\n")

# Plot the long-term solutions
df=pd.DataFrame({'Long term probabilities': time, 'Standard Gasoline Cars': R1,␣
↪'Hybrid/Electric Cars': H1})

# multiple line plots
plt.plot( 'Long term probabilities', 'Standard Gasoline Cars', data=df,␣
↪marker='o', color='red', linewidth=2)
plt.plot( 'Long term probabilities', 'Hybrid/Electric Cars', data=df,␣
↪marker='o', color='blue', linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Percentage of Cars Sold")
plt.title("Policy 1: Percentage of Cars Sold over Time (2020-2060)")
# show graph
plt.show()
```

```
Long term probabilities for each car option:

Regular Cars: [0.959, 0.28974999999999995, 0.12243749999999998,
0.08060937499999998, 0.07015234374999998, 0.06753808593749999,
0.06688452148437499, 0.06672113037109373, 0.06668028259277342]
```

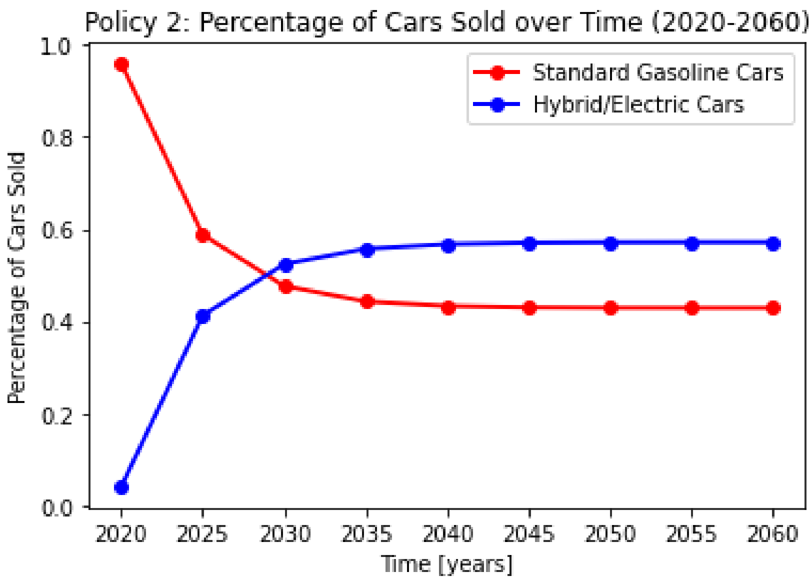
```
Hybrid Cars: [0.041, 0.7102499999999999, 0.8775624999999998, 0.9193906249999998,
0.9298476562499998, 0.9324619140624998, 0.9331154785156247, 0.9332788696289059,
0.9333197174072262]
```



[3]:
```
# Model 2: Medium Policy
# Markov Chains are used to model impact of this policy over time

H2 = [0] * 9  # array that stores the percentage of cars that are hybrid/
 ↪electric
R2 = [0] * 9  # array that stores the percentage of regular cars

H2[0] = 0.041  # initial value for percentage of cars that are hybrid/electric
R2[0] = 0.959  # initial value for percentage of regular cars

# Test the stability of the solutions by changing the intial values
# Start with equal intial values
#H2[0] = 0.5
#R2[0] = 0.5

# Make H2[0] > R2[0]
#H2[0] = 0.959
```

```
#R2[0] = 0.041

# When starting at different initial values, the long-term probabilities still␣
↪yield the same percentages, so the solutions are stable

# Store the long-term probabilities for each car option in their respective␣
↪arrays

for i in range(8):
    H2[i+1] = 0.70*H2[i] + 0.40*R2[i] # 70% stay hybrid, 40% switch to hybrid
    R2[i+1] = 0.30*H2[i] + 0.60*R2[i] # 30% switch to regular, 60% stay regular

# Output the long-term probabilities for each car option

print("Long term probabilities for each car option: \n")
print("Regular Cars:", R2, "\n")
print("Hybrid Cars:", H2, "\n")

# Plot the long-term solutions
df=pd.DataFrame({'Long term probabilities': time, 'Standard Gasoline Cars': R2,␣
↪'Hybrid/Electric Cars': H2})
# multiple line plots
plt.plot( 'Long term probabilities', 'Standard Gasoline Cars', data=df,␣
↪marker='o', color='red', linewidth=2)
plt.plot( 'Long term probabilities', 'Hybrid/Electric Cars', data=df,␣
↪marker='o', color='blue', linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Percentage of Cars Sold")
plt.title("Policy 2: Percentage of Cars Sold over Time (2020-2060)")
# show graph
plt.show()
```

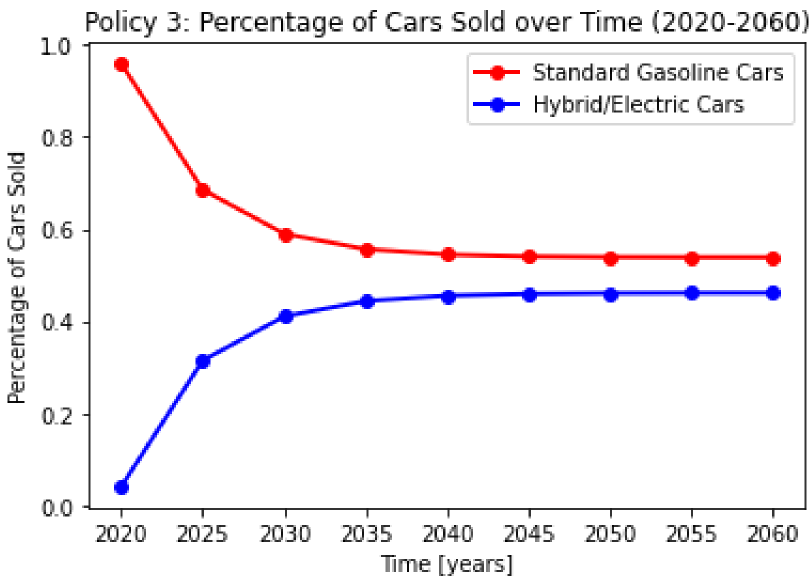
```
Long term probabilities for each car option:

Regular Cars: [0.959, 0.5876999999999999, 0.4763099999999999,
0.4428929999999999, 0.43286789999999997, 0.42986037, 0.428958111,
0.4286874332999999, 0.42860622998999987]

Hybrid Cars: [0.041, 0.4123, 0.52369, 0.557107, 0.5671321, 0.57013963,
0.571041889, 0.5713125667, 0.5713937700099999]
```



[4]:
```
# Model 3: Realistic Policy
# Markov Chains are used to model impact of this policy over time

H3 = [0] * 9  # array that stores the percentage of cars that are hybrid/
 ↪electric
R3 = [0] * 9  # array that stores the percentage of regular cars

# Use the actual initial values proposed in the model
H3[0] = 0.041  # initial value for percentage of cars that are hybrid/electric
R3[0] = 0.959  # initial value for percentage of regular cars

# Test the stability of the solutions by changing the intial values
# Start with equal intial values
#H3[0] = 0.5
#R3[0] = 0.5

# Make H3[0] > R3[0]
#H3[0] = 0.959
#R3[0] = 0.041

# When starting at different initial values, the long-term probabilities still␣
 ↪yield the same percentages, so the solutions are stable
```

```python
# Store the long-term probabilities for each car option in their respective␣
↪arrays

for i in range(8):
    H3[i+1] = 0.65*H3[i] + 0.30*R3[i] # 65% stay hybrid, 30% switch to hybrid
    R3[i+1] = 0.35*H3[i] + 0.70*R3[i] # 35% switch to regular, 70% stay regular

# Output the long-term probabilities for each car option

print("Long term probabilities for each car option: \n")
print("Regular Cars:", R3, "\n")
print("Hybrid Cars:", H3, "\n")

# Plot the long-term solutions
df=pd.DataFrame({'Long term probabilities': time, 'Standard Gasoline Cars': R3,␣
↪'Hybrid/Electric Cars': H3})
# multiple line plots
plt.plot( 'Long term probabilities', 'Standard Gasoline Cars', data=df,␣
↪marker='o', color='red', linewidth=2)
plt.plot( 'Long term probabilities', 'Hybrid/Electric Cars', data=df,␣
↪marker='o', color='blue', linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Percentage of Cars Sold")
plt.title("Policy 3: Percentage of Cars Sold over Time (2020-2060)")
# show graph
plt.show()
```

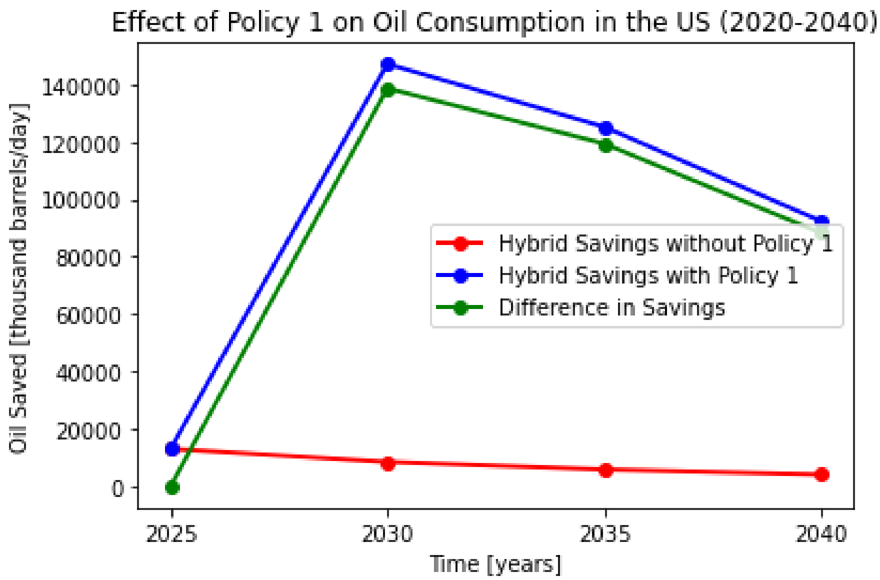
```
Long term probabilities for each car option:

Regular Cars: [0.959, 0.6856499999999999, 0.5899774999999998,
0.5564921249999998, 0.5447722437499998, 0.5406702853124998, 0.5392345998593748,
0.538732109950781, 0.5385562384827731]

Hybrid Cars: [0.041, 0.31434999999999996, 0.41002249999999996,
0.44350787499999994, 0.4552277562499999, 0.45932971468749983,
0.46076540014062484, 0.46126789004921853, 0.4614437615172263]
```



[5]:
```
# Policy 1's effect on Oil Consumption

# 22% of tranpsortation goes toward light motor vehicles
LMV = .22*np.array(avg_consumption)

# Without Policy 1: calculate oil consumption savings
# Assumptions:
    # 4.1% of cars that are sold are hybrid/electric cars
    # hybrid/electric cars save on average 30% of oil compared to regular cars

H_OC = 0.041*np.array(LMV)
H_OCS = 0.30*np.array(H_OC)
print("Hybrid Savings every 5 years without Policy 1:\n",H_OCS,"\n")

# With Policy 1: calculate oil consumption savings
H1_OC = np.multiply(H1[0:4],LMV)
H1_OCS = 0.30*np.array(H1_OC)
print("Hybrid Savings every 5 years with Policy 1:\n",H1_OCS,"\n")

# Calculate Percentage of Oil that is Saved with Policy 1
savedOC1 = np.divide(H1_OCS,LMV)
print("Percentage of Oil that is Saved every 5 years with Policy 1:
 ↪\n",savedOC1,"\n")
```

```python
# Calculate Difference in Total Hybrid Savings with Policy 1
diff_S1 = np.array(H1_OCS) - np.array(H_OCS)
print("Difference in Hybrid Savings every 5 years:\n",diff_S1,"\n")

# Plot the savings
df=pd.DataFrame({'Time': time2, 'Hybrid Savings without Policy 1': H_OCS,␣
↪'Hybrid Savings with Policy 1': H1_OCS, 'Difference in Savings':diff_S1})
# multiple line plots
plt.plot( 'Time', 'Hybrid Savings without Policy 1', data=df, marker='o',␣
↪color='red', linewidth=2)
plt.plot( 'Time', 'Hybrid Savings with Policy 1', data=df, marker='o',␣
↪color='blue', linewidth=2)
plt.plot( 'Time', 'Difference in Savings', data=df, marker='o', color='green',␣
↪linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Effect of Policy 1 on Oil Consumption in the US (2020-2040)")
# show graph
plt.show()
```

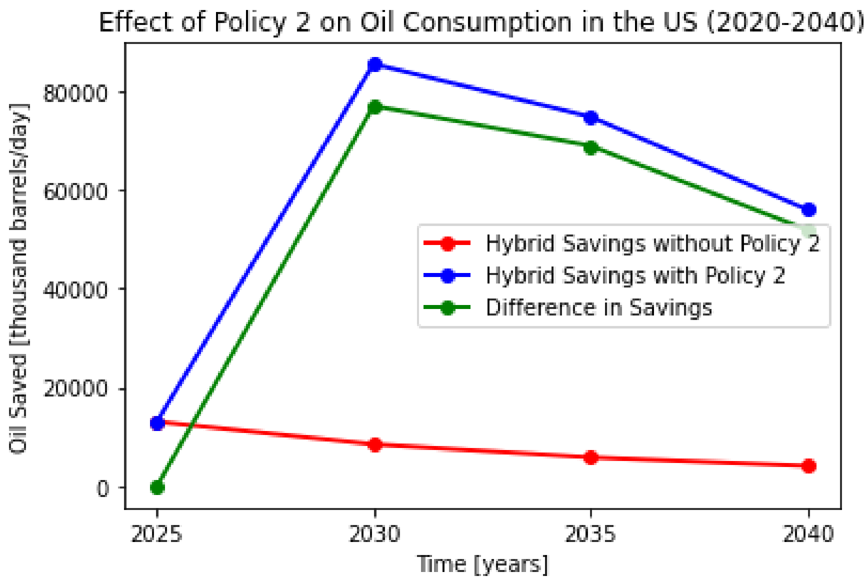
```
Hybrid Savings every 5 years without Policy 1:
 [13054.93407012  8497.13902328  5852.36118709  4120.94353849]

Hybrid Savings every 5 years with Policy 1:
 [ 13054.93407012 147197.39003138 125263.72473779  92408.70379131]

Percentage of Oil that is Saved every 5 years with Policy 1:
 [0.0123     0.213075   0.26326875 0.27581719]

Difference in Hybrid Savings every 5 years:
 [     0.         138700.2510081  119411.3635507   88287.76025282]
```



[6]:
```
# Policy 2's effect on Oil Consumption

# 22% of tranpsortation goes toward light motor vehicles
LMV = .22*np.array(avg_consumption)

# Without Policy 2: calculate oil consumption savings
print("Hybrid Savings every 5 years without Policy 2:\n",H_OCS,"\n")

# With Policy 2: calculate oil consumption savings
H2_OC = np.multiply(H2[0:4],LMV)
H2_OCS = 0.30*np.array(H2_OC)
print("Hybrid Savings every 5 years with Policy 2:\n",H2_OCS,"\n")

# Calculate Percentage of Oil that is Saved with Policy 2
savedOC2 = np.divide(H2_OCS,LMV)
print("Percentage of Oil that is Saved every 5 years with Policy 2:
 ↪\n",savedOC2,"\n")

# Calculate Difference in Total Hybrid Savings with Policy 2
diff_S2 = np.array(H2_OCS) - np.array(H_OCS)
print("Difference in Hybrid Savings every 5 years:\n",diff_S2,"\n")

# Plot the savings
```

```
df=pd.DataFrame({'Time': time2, 'Hybrid Savings without Policy 2': H_OCS,␣
↪'Hybrid Savings with Policy 2': H2_OCS, 'Difference in Savings':diff_S2})
# multiple line plots
plt.plot( 'Time', 'Hybrid Savings without Policy 2', data=df, marker='o',␣
↪color='red', linewidth=2)
plt.plot( 'Time', 'Hybrid Savings with Policy 2', data=df, marker='o',␣
↪color='blue', linewidth=2)
plt.plot( 'Time', 'Difference in Savings', data=df, marker='o', color='green',␣
↪linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Effect of Policy 2 on Oil Consumption in the US (2020-2040)")
# show graph
plt.show()
```

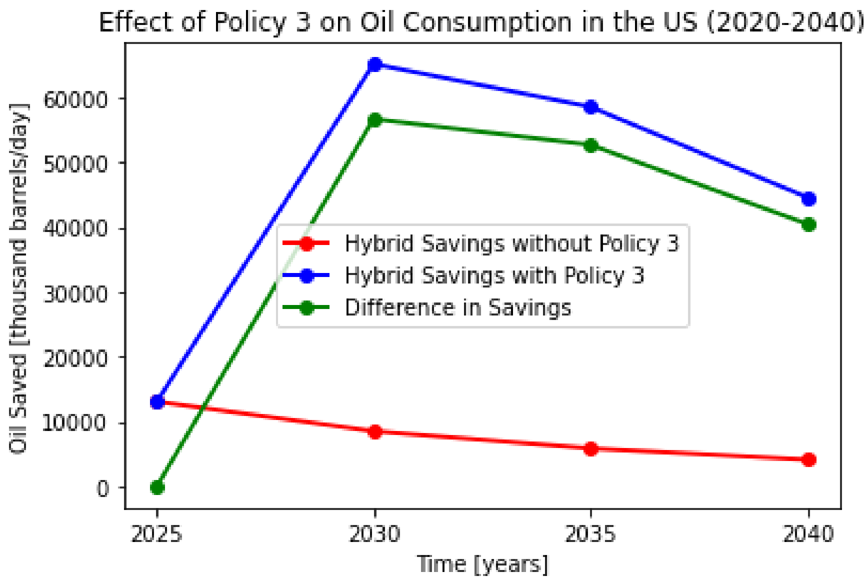
```
Hybrid Savings every 5 years without Policy 2:
 [13054.93407012  8497.13902328  5852.36118709  4120.94353849]

Hybrid Savings every 5 years with Policy 2:
 [13054.93407012 85448.0590073  74751.78122121 55995.28029021]

Percentage of Oil that is Saved every 5 years with Policy 2:
 [0.0123    0.12369   0.157107  0.1671321]

Difference in Hybrid Savings every 5 years:
 [    0.         76950.91998402 68899.42003411 51874.33675172]
```



[7]:
```
# Policy 3's effect on Oil Consumption

# 22% of tranpsortation goes toward light motor vehicles
LMV = .22*np.array(avg_consumption)

# Without Policy 3: calculate oil consumption savings
print("Hybrid Savings every 5 years without Policy 3:\n",H_OCS,"\n")

# With Policy 3: calculate oil consumption savings
H3_OC = np.multiply(H3[0:4],LMV)
H3_OCS = 0.30*np.array(H3_OC)
print("Hybrid Savings every 5 years with Policy 3:\n",H3_OCS,"\n")

# Calculate Percentage of Oil that is Saved with Policy 3
savedOC3 = np.divide(H3_OCS,LMV)
print("Percentage of Oil that is Saved every 5 years with Policy 3:
 ↪\n",savedOC3,"\n")

# Calculate Difference in Total Hybrid Savings with Policy 3
diff_S3 = np.array(H3_OCS) - np.array(H_OCS)
print("Difference in Hybrid Savings every 5 years:\n",diff_S3,"\n")

# Plot the savings
```

```python
df=pd.DataFrame({'Time': time2, 'Hybrid Savings without Policy 3': H_OCS,␣
↪'Hybrid Savings with Policy 3': H3_OCS, 'Difference in Savings':diff_S3})
# multiple line plots
plt.plot( 'Time', 'Hybrid Savings without Policy 3', data=df, marker='o',␣
↪color='red', linewidth=2)
plt.plot( 'Time', 'Hybrid Savings with Policy 3', data=df, marker='o',␣
↪color='blue', linewidth=2)
plt.plot( 'Time', 'Difference in Savings', data=df, marker='o', color='green',␣
↪linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Effect of Policy 3 on Oil Consumption in the US (2020-2040)")
# show graph
plt.show()
```

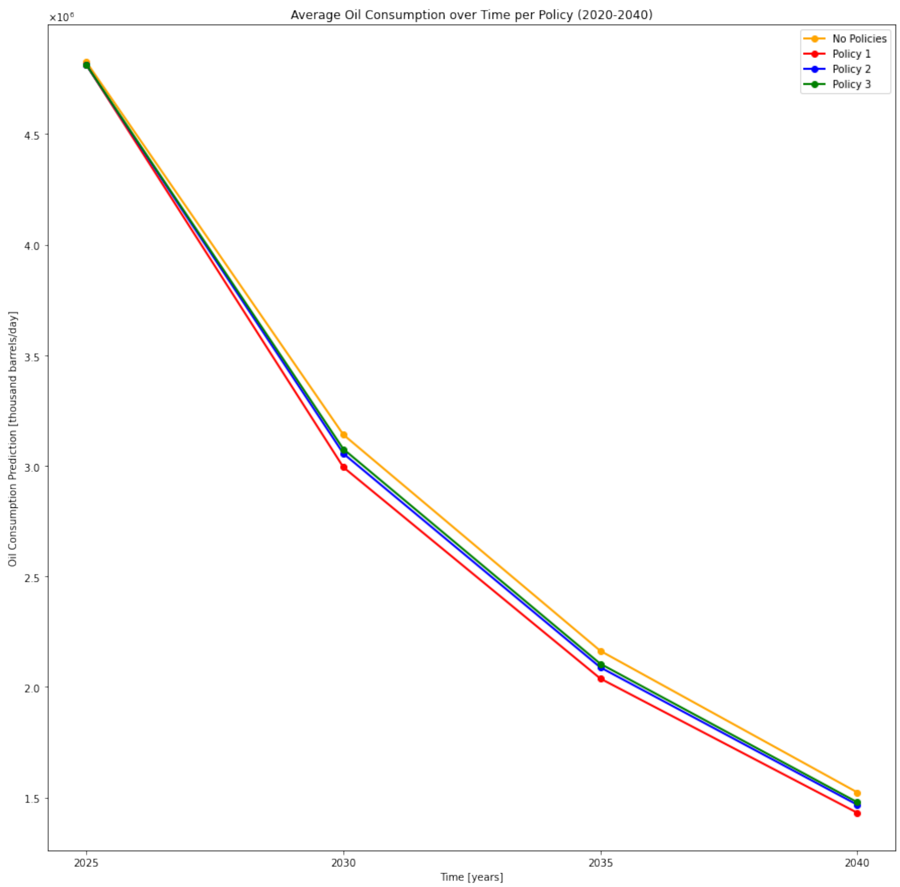
```
Hybrid Savings every 5 years without Policy 3:
 [13054.93407012  8497.13902328  5852.36118709  4120.94353849]

Hybrid Savings every 5 years with Policy 3:
 [13054.93407012 65148.18663339 58526.82353257 44577.33931101]

Percentage of Oil that is Saved every 5 years with Policy 3:
 [0.0123     0.094305   0.12300675 0.13305236]

Difference in Hybrid Savings every 5 years:
 [    0.         56651.04761011 52674.46234548 40456.39577252]
```



[11]:
```
# Average Consumption every 5 years (for years 2020-2040) without any of the␣
 ↪policies
print("Average Consumption Data without any of the Policies in Effect:
 ↪\n",avg_consumption,"\n")

# Calculate New Prediction for Oil Consumption for years 2020-2040 if each of␣
 ↪the 3 policies go into effect
newOC1 = np.array(avg_consumption) - np.array(H1_OCS)
newOC2 = np.array(avg_consumption) - np.array(H2_OCS)
newOC3 = np.array(avg_consumption) - np.array(H3_OCS)

# Plot New Oil Consumption Predictions for years 2020-2040 with each of the 3␣
 ↪policies in place
df=pd.DataFrame({'Time': time2, 'No Policies': avg_consumption,'Policy 1':␣
 ↪newOC1, 'Policy 2': newOC2, 'Policy 3':newOC3})
plt.figure(figsize=(15, 15))
# multiple line plots
plt.plot( 'Time', 'No Policies', data=df, marker='o', color='orange',␣
 ↪linewidth=2)
plt.plot( 'Time', 'Policy 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Policy 2', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Policy 3', data=df, marker='o', color='green', linewidth=2)
# show legend and axes
```

```python
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Consumption Prediction [thousand barrels/day]")
plt.xticks(time2,time2)
plt.ticklabel_format(style='sci', axis='y', scilimits=(0,0), useMathText=True)
plt.title("Average Oil Consumption over Time per Policy (2020-2040)")
# show graph
plt.show()
```

```
Average Consumption Data without any of the Policies in Effect:
 [4824439.789399999, 3140110.5038, 2162735.1024, 1522891.182]
```

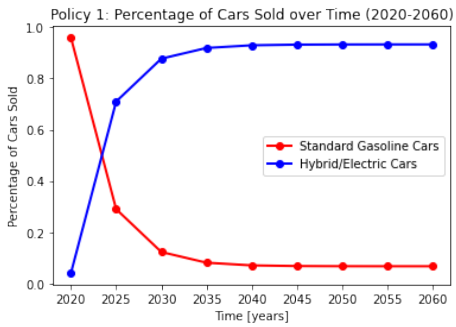


```
[ ]:
```

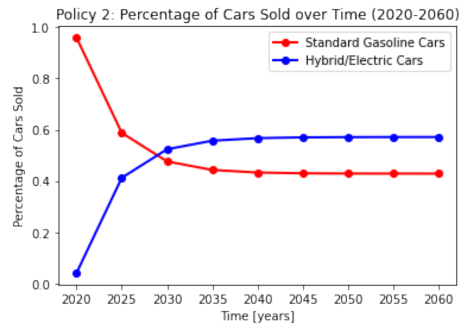
```
[ ]:
```

B.3 Results

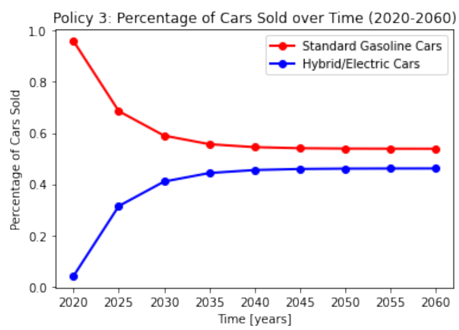
The long-term solutions of each of the three policies for Model 2 are graphed in Figure 12.



(a) Policy 1



(b) Policy 2

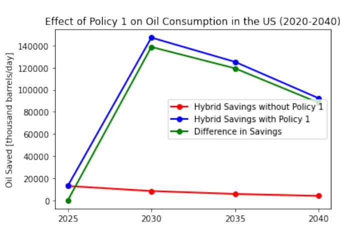


(c) Policy 3

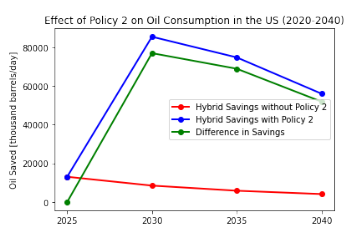
Figure 12: Solutions for hybrid/electric and standard gasoline cars

B.4 Analysis

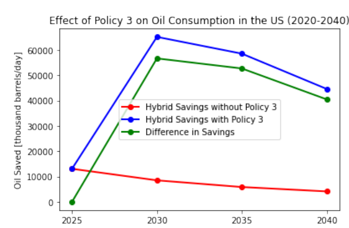
The long-term oil savings for each of the three policies in Model 2 are graphed in Figure 13.



(a) Policy 1



(b) Policy 2



(c) Policy 3

Figure 13: Oil saved by hybrid/electric vehicles with Policy 1, Policy 2, and Policy 3

B.5 Testing Model 2 under 5 different Scenarios

This section depicts further analysis of Model 2. All assumptions used in Model 2 remain the same for this round of testing. Python was used to test the three policies proposed in Model 2 against each of the five sub-models created under Model 1. The variables, code, and results of these tests are shown below.

B.5.1 Python Variables

- $time$: represents the time in increments of 5 years from 2020-2060
- $time2$: represents the time in increments of 5 years from 2020-2040
- $consumption1$: represents the predicted oil consumption data for Case 1 each year from 2020-2040
- $avgc1$: represents the average predicted oil consumption for Case 1 every 5 years from 2020-2040
- $consumption2$: represents the predicted oil consumption data for Case 2 each year from 2020-2040
- $avgc2$: represents the average predicted oil consumption for Case 2 every 5 years from 2020-2040
- $consumption3$: represents the predicted oil consumption data for Case 3 each year from 2020-2040
- $avgc3$: represents the average predicted oil consumption for Case 3 every 5 years from 2020-2040
- $consumption4$: represents the predicted oil consumption data for Case 4 each year from 2020-2040
- $avgc4$: represents the average predicted oil consumption for Case 4 every 5 years from 2020-2040
- $consumption5$: represents the predicted oil consumption data for Case 5 each year from 2020-2040
- $avgc5$: represents the average predicted oil consumption for Case 5 every 5 years from 2020-2040
- $H1, H2, H3$: represent the percentage of hybrid/electric vehicles that are sold under Policy 1, Policy 2, and Policy 3, respectively
- $R1, R2, R3$: represent the percentage of standard gasoline vehicles that are sold under Policy 1, Policy 2, and Policy 3, respectively
- $LMV1, LMV2, LMV3, LMV4, LMV5$: represent the amount of oil consumed by light motor vehicles for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively

- $H\_OC1, H\_OC2, H\_OC3, H\_OC4, H\_OC5$: represent the amount of oil consumed by hybrid/electric vehicles without any of the policies in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H\_OCS1, H\_OCS2, H\_OCS3, H\_OCS4, H\_OCS5$:
represent the amount of oil saved by hybrid/electric vehicles without any of the policies in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H1\_OC1, H1\_OC2, H1\_OC3, H1\_OC4, H1\_OC5$:
represent the amount of oil consumed by hybrid/electric vehicles with Policy 1 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H1\_OCS1, H1\_OCS2, H1\_OCS3, H1\_OCS4, H1\_OCS5$:
represent the amount of oil saved by hybrid/electric vehicles with Policy 1 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H2\_OC1, H2\_OC2, H2\_OC3, H2\_OC4, H2\_OC5$:
represent the amount of oil consumed by hybrid/electric vehicles with Policy 2 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H2\_OCS1, H2\_OCS2, H2\_OCS3, H2\_OCS4, H2\_OCS5$:
represent the amount of oil saved by hybrid/electric vehicles with Policy 2 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H3\_OC1, H3\_OC2, H3\_OC3, H3\_OC4, H3\_OC5$:
represent the amount of oil consumed by hybrid/electric vehicles with Policy 3 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H3\_OCS1, H3\_OCS2, H3\_OCS3, H3\_OCS4, H3\_OCS5$:
represent the amount of oil saved by hybrid/electric vehicles with Policy 3 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H4\_OC1, H4\_OC2, H4\_OC3, H4\_OC4, H4\_OC5$:
represent the amount of oil consumed by hybrid/electric vehicles with Policy 4 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H4\_OCS1, H4\_OCS2, H4\_OCS3, H4\_OCS4, H4\_OCS5$:
represent the amount of oil saved by hybrid/electric vehicles with Policy 4 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H5\_OC1, H5\_OC2, H5\_OC3, H5\_OC4, H5\_OC5$:
represent the amount of oil consumed by hybrid/electric vehicles with Policy 5 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively
- $H5\_OCS1, H5\_OCS2, H5\_OCS3, H5\_OCS4, H5\_OCS5$:
represent the amount of oil saved by hybrid/electric vehicles with Policy 5 in place for Case 1, Case 2, Case 3, Case 4, and Case 5, respectively

B.5.2 Python Code

Math 380 Project Code Part2

May 6, 2021

[1]:
```python
# Analysis of the 5 Submodels for oil consumption in the US and the impact that the 3 policies have on each of them
# Markov Chains are used to describe the % of Cars that are Hybrid/Electric vs. % of Standard Gasoline Cars

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import random

# Time is measured in increments of 5 years in these submodels (years 2020 - 2060)
time = [2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060]
time2 = [2025, 2030, 2035, 2040]

# Predicted Oil Consumption Data for Years 2020-2040
# Case 1
consumption1 = [5805959.921,5009207.119,4390537.13,3896243.555,3492450.032,3156648.357,2873261.099,2631146.327,2422114.667,2240007.354,2080101.18,1938712.036,1812923.488,1700396.488,1599233.191,1507877.657,1425042.284,1349652.469,1280804.438,1217732.724,1159784.799]
# Case 2
consumption2 = [5805959.921,5631619.846,5536178.515,5494267.016,5490480.868,5514839.778,5560556.604,5622843.529,5698229.098,5784145.366,5878666.245,5980334.571,6088043.433,6200951.976,6318423.9,6439981.428,6565270.198,6694032.104,6826084.079,6961301.444,7099604.809]
# Case 3
consumption3 = [5805959.921,4861755.296,4116808.665,3514474.122,3018349.736,2603823.896,2253573.503,1954998.579,1698679.51,1477407.625,1285553.376,1118641.633,973058.5517,845844.5824,734545.363,637102.4149,551771.7677,477062.5333,411689.9597,354539.1391,304636.6576]
# Case 4
consumption4 = [5805959.921,5480594.774,5237954.761,5050326.682,4901067.41,4779522.862,4678538.576,4593128.954,4519716.449,4455672.625,4399028.872,4348287.229,4302292.766,4260145.157,4221135.999,4184703.468,4150398.965,4117862.193,4086802.294,4056983.417,4028213.547]
# Case 5
```

```
consumption5 = [5805959.921,5631619.846,5478140.605,5341215.366,5217575.141,5104679.552,5000512.449,4903442.663,4812126.637,4725438.713,4642420.187,4562241.359,4484172.762,4407562.984,4331821.313,4256403.935,4180802.817,4104536.624,4027143.215,3948173.389,3867185.65]

# Average Predicted Oil Consumption for Case 1 for Years 2020-2040 in 5 year increments
avgc1 = [0,0,0,0]
avgc1[0] = np.average(consumption1[0:5]) # years 2020-2025
avgc1[1] = np.average(consumption1[5:10]) # years 2025-2030
avgc1[2] = np.average(consumption1[10:15]) # years 2030-2035
avgc1[3] = np.average(consumption1[15:20]) # years 2035-2040

# Average Predicted Oil Consumption for Case 2 for Years 2020-2040 in 5 year increments
avgc2 = [0,0,0,0]
avgc2[0] = np.average(consumption2[0:5]) # years 2020-2025
avgc2[1] = np.average(consumption2[5:10]) # years 2025-2030
avgc2[2] = np.average(consumption2[10:15]) # years 2030-2035
avgc2[3] = np.average(consumption2[15:20]) # years 2035-2040

# Average Predicted Oil Consumption for Case 3 for Years 2020-2040 in 5 year increments
avgc3 = [0,0,0,0]
avgc3[0] = np.average(consumption3[0:5]) # years 2020-2025
avgc3[1] = np.average(consumption3[5:10]) # years 2025-2030
avgc3[2] = np.average(consumption3[10:15]) # years 2030-2035
avgc3[3] = np.average(consumption3[15:20]) # years 2035-2040

# Average Predicted Oil Consumption for Case 4 for Years 2020-2040 in 5 year increments
avgc4 = [0,0,0,0]
avgc4[0] = np.average(consumption4[0:5]) # years 2020-2025
avgc4[1] = np.average(consumption4[5:10]) # years 2025-2030
avgc4[2] = np.average(consumption4[10:15]) # years 2030-2035
avgc4[3] = np.average(consumption4[15:20]) # years 2035-2040

# Average Predicted Oil Consumption for Case 5 for Years 2020-2040 in 5 year increments
avgc5 = [0,0,0,0]
avgc5[0] = np.average(consumption5[0:5]) # years 2020-2025
avgc5[1] = np.average(consumption5[5:10]) # years 2025-2030
avgc5[2] = np.average(consumption5[10:15]) # years 2030-2035
avgc5[3] = np.average(consumption5[15:20]) # years 2035-2040
```

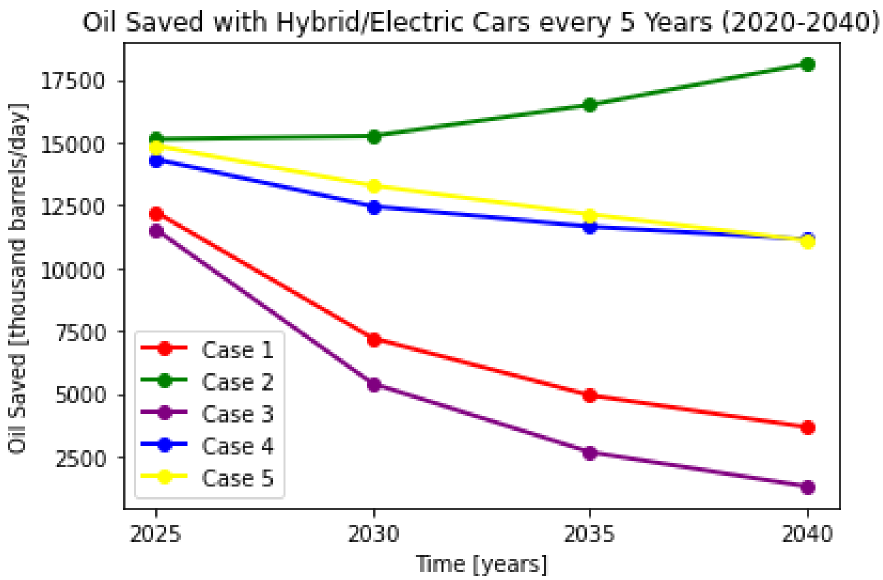
[2]:
```python
# Code the 3 policies from before

# Model 1: Extreme Policy

H1 = [0] * 9  # array that stores the percentage of cars that are hybrid/
 ↪electric
R1 = [0] * 9  # array that stores the percentage of regular cars

H1[0] = 0.041  # initial value for percentage of cars that are hybrid/electric
R1[0] = 0.959  # initial value for percentage of regular cars

# Store the long-term probabilities for each car option in their respective␣
 ↪arrays
for i in range(8):
    H1[i+1] = 0.95*H1[i] + 0.70*R1[i] # 95% stay hybrid, 70% switch to hybrid
    R1[i+1] = 0.05*H1[i] + 0.30*R1[i] # 5% switch to regular, 30% stay regular


# Model 2: Medium Policy

H2 = [0] * 9  # array that stores the percentage of cars that are hybrid/
 ↪electric
R2 = [0] * 9  # array that stores the percentage of regular cars

H2[0] = 0.041  # initial value for percentage of cars that are hybrid/electric
R2[0] = 0.959  # initial value for percentage of regular cars

# Store the long-term probabilities for each car option in their respective␣
 ↪arrays
for i in range(8):
    H2[i+1] = 0.70*H2[i] + 0.40*R2[i] # 70% stay hybrid, 40% switch to hybrid
    R2[i+1] = 0.30*H2[i] + 0.60*R2[i] # 30% switch to regular, 60% stay regular


# Model 3: Realistic Policy

H3 = [0] * 9  # array that stores the percentage of cars that are hybrid/
 ↪electric
R3 = [0] * 9  # array that stores the percentage of regular cars

H3[0] = 0.041  # initial value for percentage of cars that are hybrid/electric
R3[0] = 0.959  # initial value for percentage of regular cars

# Store the long-term probabilities for each car option in their respective␣
 ↪arrays

for i in range(8):
```

```
    H3[i+1] = 0.65*H3[i] + 0.30*R3[i] # 65% stay hybrid, 30% switch to hybrid
    R3[i+1] = 0.35*H3[i] + 0.70*R3[i] # 35% switch to regular, 70% stay regular
```

[3]:
```
# Effect on Oil Consumption with no policy in place

# 22% of tranpsortation goes toward light motor vehicles
LMV1 = .22*np.array(avgc1)
LMV2 = .22*np.array(avgc2)
LMV3 = .22*np.array(avgc3)
LMV4 = .22*np.array(avgc4)
LMV5 = .22*np.array(avgc5)

# Without any of the policies: calculate oil consumption savings
# Assumptions:
    # 4.1% of cars that are sold are hybrid/electric cars
    # hybrid/electric cars save on average 30% of oil compared to regular cars

H_OC1 = 0.041*np.array(LMV1)
H_OCS1 = 0.30*np.array(H_OC1)
print("Hybrid Savings every 5 years without any policy for Case 1:
 ↪\n",H_OCS1,"\n")

H_OC2 = 0.041*np.array(LMV2)
H_OCS2 = 0.30*np.array(H_OC2)
print("Hybrid Savings every 5 years without any policy for Case 2:
 ↪\n",H_OCS2,"\n")

H_OC3 = 0.041*np.array(LMV3)
H_OCS3 = 0.30*np.array(H_OC3)
print("Hybrid Savings every 5 years without any policy for Case 3:
 ↪\n",H_OCS3,"\n")

H_OC4 = 0.041*np.array(LMV4)
H_OCS4 = 0.30*np.array(H_OC4)
print("Hybrid Savings every 5 years without any policy for Case 4:
 ↪\n",H_OCS4,"\n")

H_OC5 = 0.041*np.array(LMV5)
H_OCS5 = 0.30*np.array(H_OC5)
print("Hybrid Savings every 5 years without any policy for Case 5:
 ↪\n",H_OCS5,"\n")

# Plot the hybrid savings for each case without any policies in place
df=pd.DataFrame({'Time': time2, 'Case 1': H_OCS1, 'Case 2': H_OCS2, 'Case 3':␣
 ↪H_OCS3, 'Case 4': H_OCS4, 'Case 5': H_OCS5})
# multiple line plots
plt.plot( 'Time', 'Case 1', data=df, marker='o', color='red', linewidth=2)
```

```
plt.plot( 'Time', 'Case 2', data=df, marker='o', color='green', linewidth=2)
plt.plot( 'Time', 'Case 3', data=df, marker='o', color='purple', linewidth=2)
plt.plot( 'Time', 'Case 4', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Case 5', data=df, marker='o', color='yellow', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Oil Saved with Hybrid/Electric Cars every 5 Years (2020-2040)")
# show graph
plt.show()
```

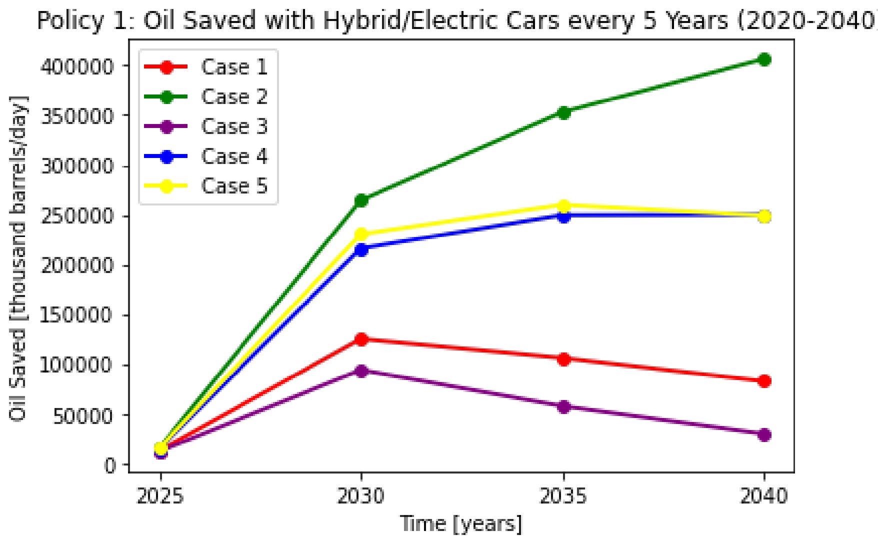
```
Hybrid Savings every 5 years without any policy for Case 1:
 [12228.08806609  7210.50382752  4941.89548648  3669.93650037]

Hybrid Savings every 5 years without any policy for Case 2:
 [15131.14353704 15251.34849975 16488.42657165 18122.98539972]

Hybrid Savings every 5 years without any policy for Case 3:
 [11536.94859689  5405.76706076  2683.0766655   1316.28813892]

Hybrid Savings every 5 years without any policy for Case 4:
 [14328.75900018 12461.984807   11652.51768045 11146.96128238]

Hybrid Savings every 5 years without any policy for Case 5:
 [14869.20528771 13284.40344758 12138.15190903 11103.83286118]
```



[4]:
```
# Policy 1: Effect on Oil Consumption

# Calculate oil consumption savings
# Assumptions:
    # 4.1% of cars that are sold are hybrid/electric cars
    # hybrid/electric cars save on average 30% of oil compared to regular cars

H1_OC1 = np.multiply(H1[0:4],LMV1)
H1_OCS1 = 0.30*np.array(H1_OC1)
print("Hybrid Savings every 5 years with Policy 1 for Case 1:\n",H1_OCS1,"\n")

H1_OC2 = np.multiply(H1[0:4],LMV2)
H1_OCS2 = 0.30*np.array(H1_OC2)
print("Hybrid Savings every 5 years with Policy 1 for Case 2:\n",H1_OCS2,"\n")

H1_OC3 = np.multiply(H1[0:4],LMV3)
H1_OCS3 = 0.30*np.array(H1_OC3)
print("Hybrid Savings every 5 years with Policy 1 for Case 3:\n",H1_OCS3,"\n")

H1_OC4 = np.multiply(H1[0:4],LMV4)
H1_OCS4 = 0.30*np.array(H1_OC4)
print("Hybrid Savings every 5 years with Policy 1 for Case 4:\n",H1_OCS4,"\n")
```

```
H1_OC5 = np.multiply(H1[0:4],LMV5)
H1_OCS5 = 0.30*np.array(H1_OC5)
print("Hybrid Savings every 5 years with Policy 1 for Case 5:\n",H1_OCS5,"\n")


# Plot the hybrid savings for each case with Policy 1 in place
df=pd.DataFrame({'Time': time2, 'Case 1': H1_OCS1, 'Case 2': H1_OCS2, 'Case 3':␣
↪H1_OCS3, 'Case 4': H1_OCS4, 'Case 5': H1_OCS5})
# multiple line plots
plt.plot( 'Time', 'Case 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Case 2', data=df, marker='o', color='green', linewidth=2)
plt.plot( 'Time', 'Case 3', data=df, marker='o', color='purple', linewidth=2)
plt.plot( 'Time', 'Case 4', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Case 5', data=df, marker='o', color='yellow', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Policy 1: Oil Saved with Hybrid/Electric Cars every 5 Years␣
↪(2020-2040)")
# show graph
plt.show()
```

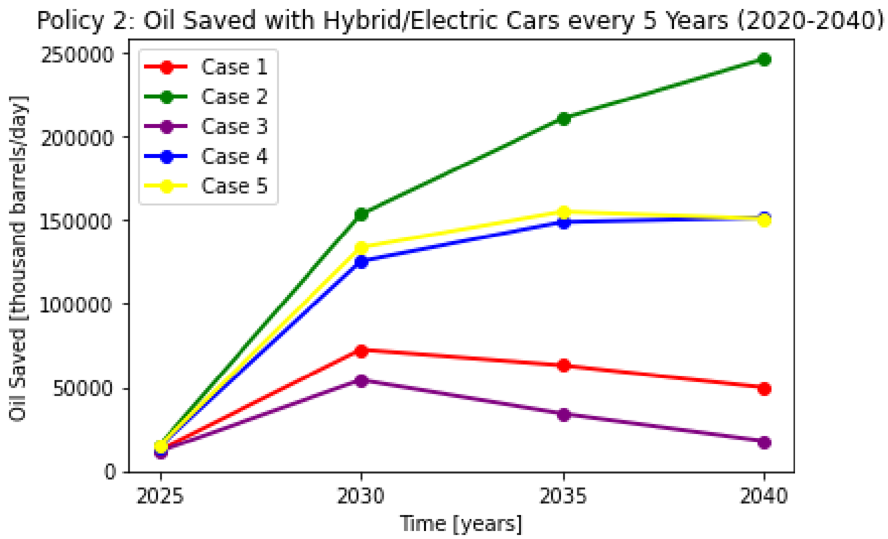
```
Hybrid Savings every 5 years with Policy 1 for Case 1:
 [ 12228.08806609 124908.78886584 105776.15019155  82295.24909225]

Hybrid Savings every 5 years with Policy 1 for Case 2:
 [ 15131.14353704 264201.71394994 352917.67910448 406392.75301263]

Hybrid Savings every 5 years with Policy 1 for Case 3:
 [11536.94859689 93645.02572931 57428.47478705 29516.65791994]

Hybrid Savings every 5 years with Policy 1 for Case 4:
 [ 14328.75900018 215881.09046759 249410.06212068 249961.260982  ]

Hybrid Savings every 5 years with Policy 1 for Case 5:
 [ 14869.20528771 230127.98899125 259804.55938206 248994.14229591]
```



[5]:
```
# Policy 2: Effect on Oil Consumption

# Calculate oil consumption savings
# Assumptions:
    # 4.1% of cars that are sold are hybrid/electric cars
    # hybrid/electric cars save on average 30% of oil compared to regular cars

H2_OC1 = np.multiply(H2[0:4],LMV1)
H2_OCS1 = 0.30*np.array(H2_OC1)
print("Hybrid Savings every 5 years with Policy 2 for Case 1:\n",H2_OCS1,"\n")

H2_OC2 = np.multiply(H2[0:4],LMV2)
H2_OCS2 = 0.30*np.array(H2_OC2)
print("Hybrid Savings every 5 years with Policy 2 for Case 2:\n",H2_OCS2,"\n")

H2_OC3 = np.multiply(H2[0:4],LMV3)
H2_OCS3 = 0.30*np.array(H2_OC3)
print("Hybrid Savings every 5 years with Policy 2 for Case 3:\n",H2_OCS3,"\n")

H2_OC4 = np.multiply(H2[0:4],LMV4)
H2_OCS4 = 0.30*np.array(H2_OC4)
print("Hybrid Savings every 5 years with Policy 2 for Case 4:\n",H2_OCS4,"\n")

H2_OC5 = np.multiply(H2[0:4],LMV5)
H2_OCS5 = 0.30*np.array(H2_OC5)
```

```python
print("Hybrid Savings every 5 years with Policy 2 for Case 5:\n",H2_OCS5,"\n")


# Plot the hybrid savings for each case with Policy 2 in place
df=pd.DataFrame({'Time': time2, 'Case 1': H2_OCS1, 'Case 2': H2_OCS2, 'Case 3': H2_OCS3, 'Case 4': H2_OCS4, 'Case 5': H2_OCS5})
# multiple line plots
plt.plot( 'Time', 'Case 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Case 2', data=df, marker='o', color='green', linewidth=2)
plt.plot( 'Time', 'Case 3', data=df, marker='o', color='purple', linewidth=2)
plt.plot( 'Time', 'Case 4', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Case 5', data=df, marker='o', color='yellow', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Policy 2: Oil Saved with Hybrid/Electric Cars every 5 Years (2020-2040)")
# show graph
plt.show()
```

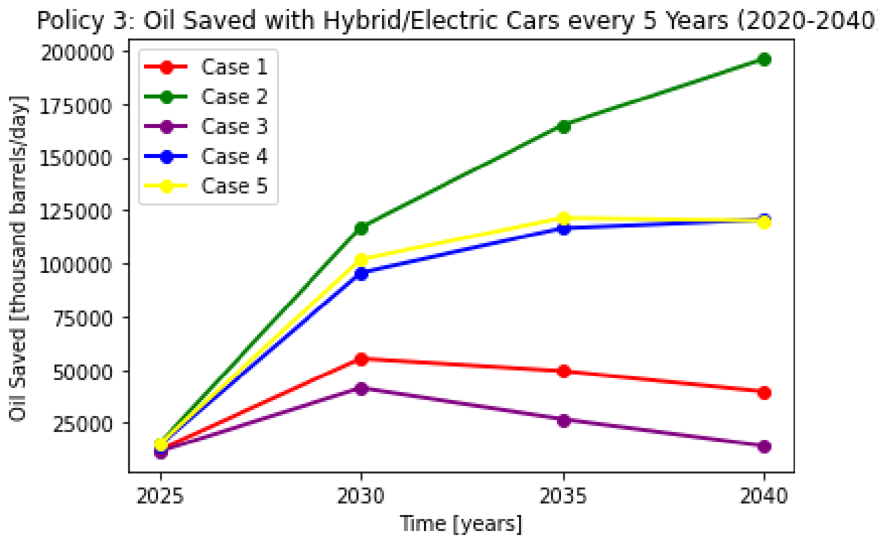
```
Hybrid Savings every 5 years with Policy 2 for Case 1:
 [12228.08806609 72509.52995338 63122.4694467  49867.00765633]

Hybrid Savings every 5 years with Policy 2 for Case 2:
 [ 15131.14353704 153369.04844993 210605.46612945 246254.68358741]

Hybrid Savings every 5 years with Policy 2 for Case 3:
 [11536.94859689 54360.92095487 34270.74192577 17885.691127  ]

Hybrid Savings every 5 years with Policy 2 for Case 4:
 [ 14328.75900018 125318.93502258 148836.75570911 151464.63802793]

Hybrid Savings every 5 years with Policy 2 for Case 5:
 [ 14869.20528771 133589.25710819 155039.72617653 150878.61009247]
```



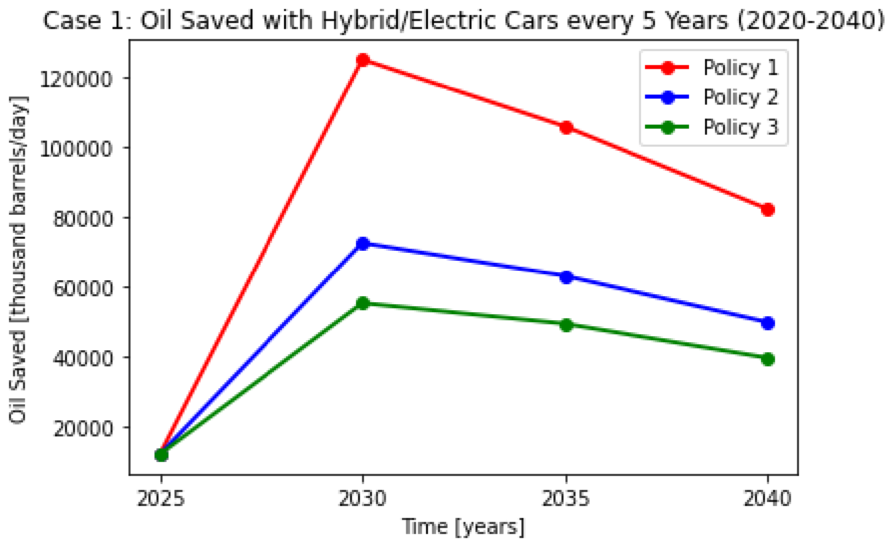
[6]:
```
# Policy 3: Effect on Oil Consumption

# Calculate oil consumption savings
# Assumptions:
    # 4.1% of cars that are sold are hybrid/electric cars
    # hybrid/electric cars save on average 30% of oil compared to regular cars

H3_OC1 = np.multiply(H3[0:4],LMV1)
H3_OCS1 = 0.30*np.array(H3_OC1)
print("Hybrid Savings every 5 years with Policy 3 for Case 1:\n",H3_OCS1,"\n")

H3_OC2 = np.multiply(H3[0:4],LMV2)
H3_OCS2 = 0.30*np.array(H3_OC2)
print("Hybrid Savings every 5 years with Policy 3 for Case 2:\n",H3_OCS2,"\n")

H3_OC3 = np.multiply(H3[0:4],LMV3)
H3_OCS3 = 0.30*np.array(H3_OC3)
print("Hybrid Savings every 5 years with Policy 3 for Case 3:\n",H3_OCS3,"\n")

H3_OC4 = np.multiply(H3[0:4],LMV4)
H3_OCS4 = 0.30*np.array(H3_OC4)
print("Hybrid Savings every 5 years with Policy 3 for Case 4:\n",H3_OCS4,"\n")

H3_OC5 = np.multiply(H3[0:4],LMV5)
H3_OCS5 = 0.30*np.array(H3_OC5)
```

```python
print("Hybrid Savings every 5 years with Policy 3 for Case 5:\n",H3_OCS5,"\n")


# Plot the hybrid savings for each case with Policy 3 in place
df=pd.DataFrame({'Time': time2, 'Case 1': H3_OCS1, 'Case 2': H3_OCS2, 'Case 3':␣
↪H3_OCS3, 'Case 4': H3_OCS4, 'Case 5': H3_OCS5})
# multiple line plots
plt.plot( 'Time', 'Case 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Case 2', data=df, marker='o', color='green', linewidth=2)
plt.plot( 'Time', 'Case 3', data=df, marker='o', color='purple', linewidth=2)
plt.plot( 'Time', 'Case 4', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Case 5', data=df, marker='o', color='yellow', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Policy 3: Oil Saved with Hybrid/Electric Cars every 5 Years␣
↪(2020-2040)")
# show graph
plt.show()
```

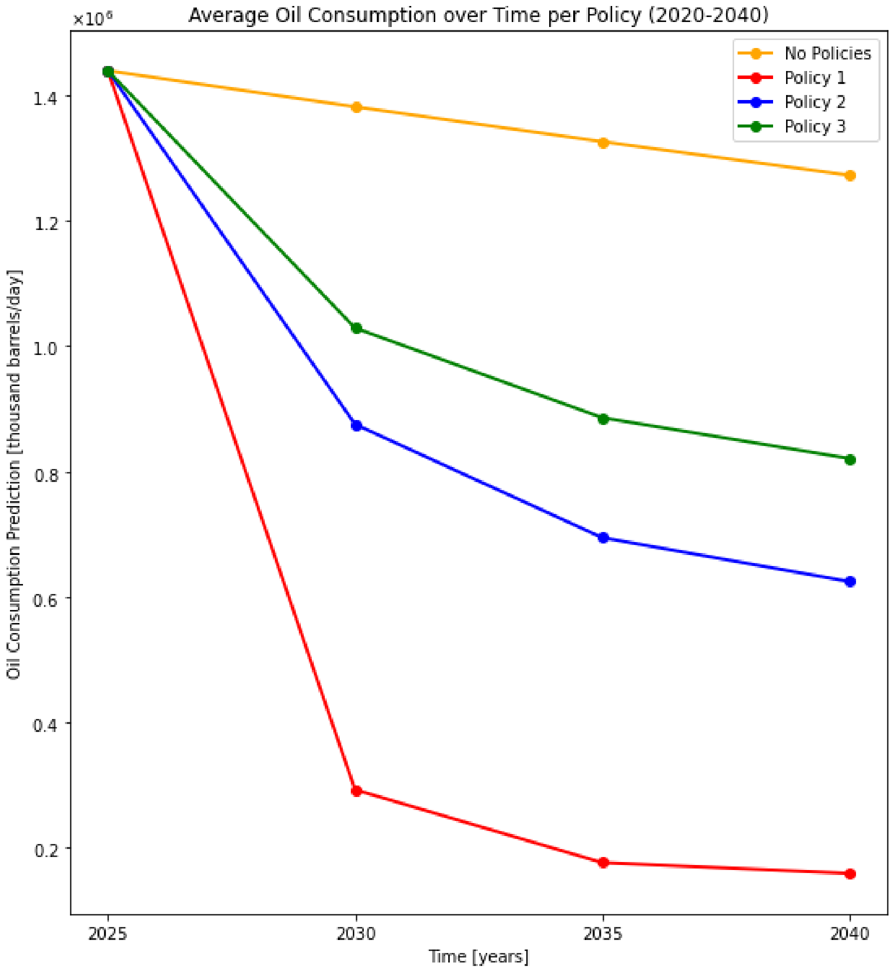
```
Hybrid Savings every 5 years with Policy 3 for Case 1:
 [12228.08806609 55283.46044347 49421.66688061 39698.67655274]

Hybrid Savings every 5 years with Policy 3 for Case 2:
 [ 15131.14353704 116933.20489991 164893.31424328 196041.14008018]

Hybrid Savings every 5 years with Policy 3 for Case 3:
 [11536.94859689 41446.41159874 26832.23907513 14238.63793605]

Hybrid Savings every 5 years with Policy 3 for Case 4:
 [ 14328.75900018  95546.94936781 116531.57147881 120579.63685506]

Hybrid Savings every 5 years with Policy 3 for Case 5:
 [ 14869.20528771 101852.49326209 121388.18027119 120113.1052833 ]
```



[7]:
```
# Plot Case 1 oil consumption savings for each of the 3 policies

df=pd.DataFrame({'Time': time2, 'Policy 1': H1_OCS1, 'Policy 2': H2_OCS1,␣
 ↪'Policy 3': H3_OCS1})
# multiple line plots
plt.plot( 'Time', 'Policy 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Policy 2', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Policy 3', data=df, marker='o', color='green', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Case 1: Oil Saved with Hybrid/Electric Cars every 5 Years␣
 ↪(2020-2040)")
# show graph
plt.show()
```

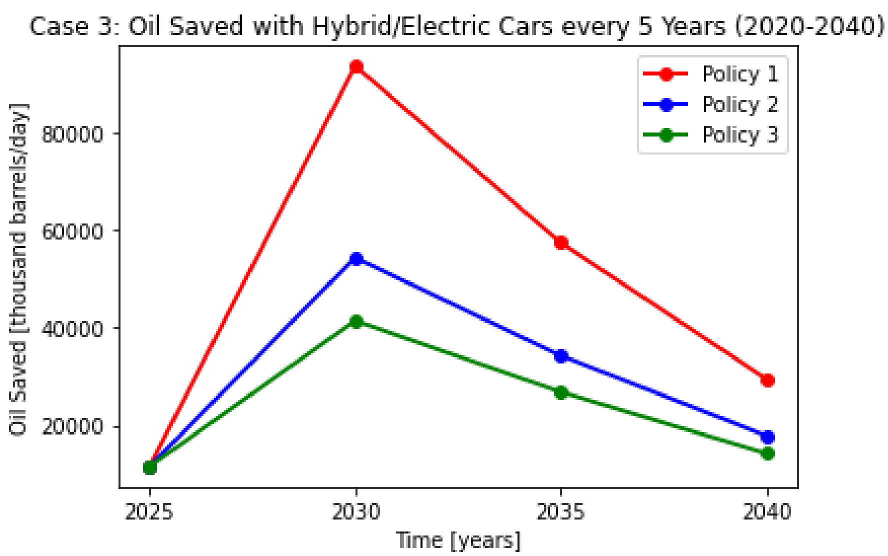


[8]:
```
# Plot Case 2 oil consumption savings for each of the 3 policies

df=pd.DataFrame({'Time': time2, 'Policy 1': H1_OCS2, 'Policy 2': H2_OCS2,␣
↪'Policy 3': H3_OCS2})
# multiple line plots
plt.plot( 'Time', 'Policy 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Policy 2', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Policy 3', data=df, marker='o', color='green', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Case 2: Oil Saved with Hybrid/Electric Cars every 5 Years␣
↪(2020-2040)")
# show graph
plt.show()
```



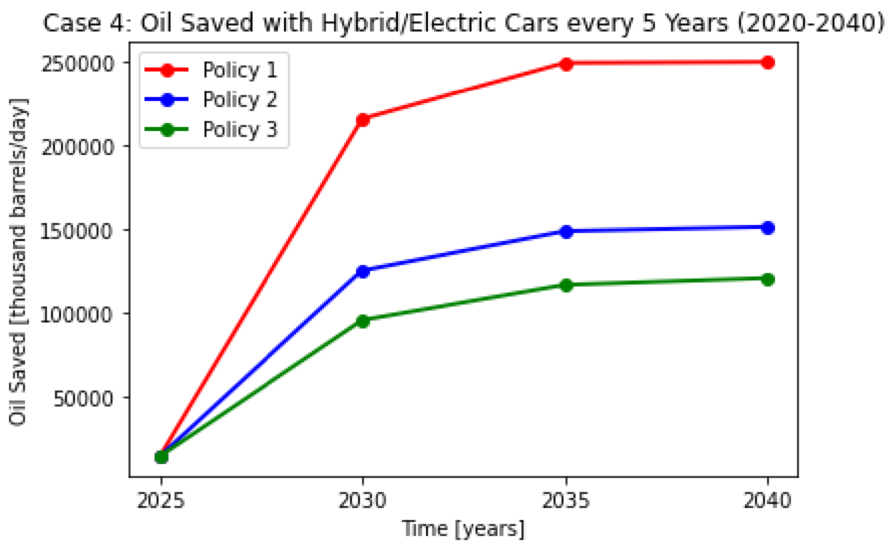
[9]:
```python
# Plot Case 3 oil consumption savings for each of the 3 policies

df=pd.DataFrame({'Time': time2, 'Policy 1': H1_OCS3, 'Policy 2': H2_OCS3,␣
↪'Policy 3': H3_OCS3})
# multiple line plots
plt.plot( 'Time', 'Policy 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Policy 2', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Policy 3', data=df, marker='o', color='green', linewidth=2)
# show legend and axes
plt.legend()
```

```
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Case 3: Oil Saved with Hybrid/Electric Cars every 5 Years␣
↪(2020-2040)")
# show graph
plt.show()
```

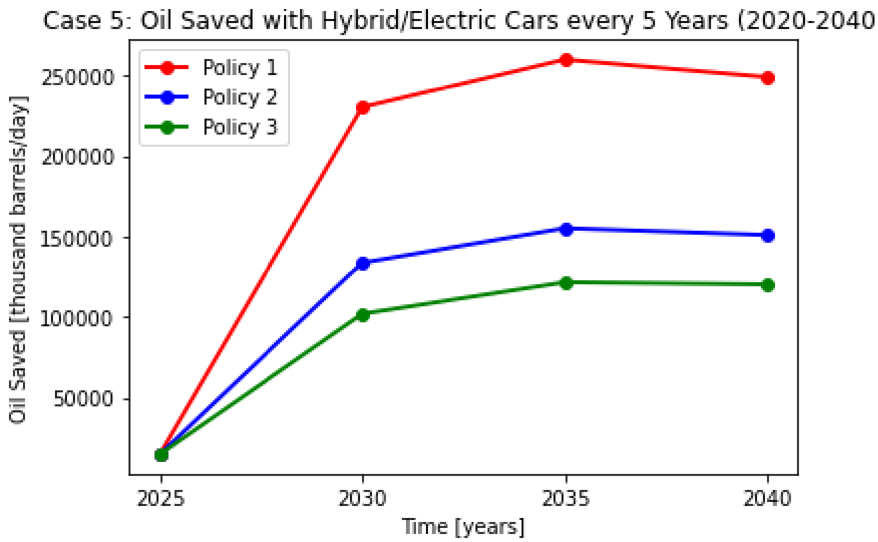


[10]:
```
# Plot Case 4 oil consumption savings for each of the 3 policies

df=pd.DataFrame({'Time': time2, 'Policy 1': H1_OCS4, 'Policy 2': H2_OCS4,␣
↪'Policy 3': H3_OCS4})
# multiple line plots
plt.plot( 'Time', 'Policy 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Policy 2', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Policy 3', data=df, marker='o', color='green', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Case 4: Oil Saved with Hybrid/Electric Cars every 5 Years␣
↪(2020-2040)")
# show graph
```

```
plt.show()
```



[11]:
```
# Plot Case 5 oil consumption savings for each of the 3 policies

df=pd.DataFrame({'Time': time2, 'Policy 1': H1_OCS5, 'Policy 2': H2_OCS5,␣
↪'Policy 3': H3_OCS5})
# multiple line plots
plt.plot( 'Time', 'Policy 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Policy 2', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Policy 3', data=df, marker='o', color='green', linewidth=2)
# show legend and axes
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Oil Saved [thousand barrels/day]")
plt.xticks(time2,time2)
plt.title("Case 5: Oil Saved with Hybrid/Electric Cars every 5 Years␣
↪(2020-2040)")
# show graph
plt.show()
```


Case 5: Oil Saved with Hybrid/Electric Cars every 5 Years (2020-2040)
Policy 1
Policy 2
Policy 3
Oil Saved [thousand barrels/day]
250000
200000
150000
100000
50000
2025
2030
2035
2040
Time [years]

[ ]:

B.5.3 Results

From the testing in the code above, we see that Case 2 yielded the highest oil savings from hybrid/electric cars, followed by Case 5, Case 4, Case 1, and Case 3. This makes sense because Case 2 also started with the highest oil consumption values compared to the other cases, so there was more oil to save. In all five cases, Policy 1 yielded the most oil savings from hybrid/electric cars, followed by Policy 2 and Policy 3. Again, this makes sense because Policy 1 was the most extreme policy.

C Model 3

C.1 Python Variables

- $B1, B2, B3$: represent the percentage of industrial companies that use biomass as their primary resource under Policy 1, Policy 2, and Policy 3, respectively
- $P1, P2, P3$: represent the percentage of industrial companies that use petroleum as their primary resource under Policy 1, Policy 2, and Policy 3, respectively
- $time$: represents the time in increments of 5 years from 2020-2060
- $time2$: represents the time in increments of 5 years from 2020-2040
- $petroleum$: represents the predicted oil consumption data each year from 2020-2040
- avg_pet : represents the average predicted oil consumption every 5 years from 2020-2040
- $biomass$: represents the predicted biomass consumption data each year from 2020-2040
- $avg\_biomass$: represents the average predicted biomass consumption every 5 years from 2020-2040
- new_pet : represents the amount of oil consumed by industrial companies
- $oiluse$: represents the amount of oil consumed by industrial companies without any of the policies in place
- $oiluse1$: represents the amount of oil consumed by industrial companies with Policy 1 in place
- $diff1$: represents the amount of oil saved by industrial companies with Policy 1 in place
- $oiluse2$: represents the amount of oil consumed by industrial companies with Policy 2 in place
- $diff2$: represents the amount of oil saved by industrial companies with Policy 2 in place
- $oiluse3$: represents the amount of oil consumed by industrial companies with Policy 3 in place
- $diff3$: represents the amount of oil saved by industrial companies with Policy 3 in place

C.2 Python Code

Math 380 Project Code Part3

May 6, 2021

[2]:

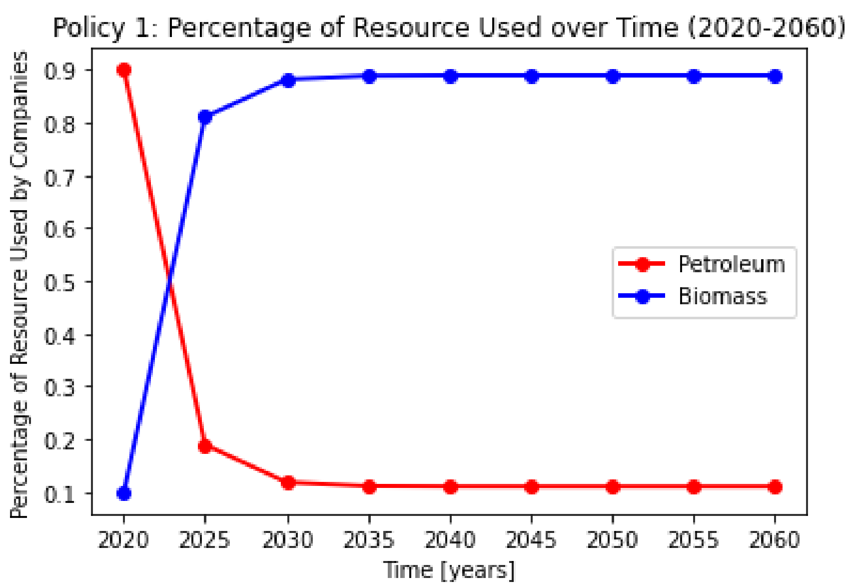
```python
# 3 Submodels that incentivize more research on the use of biomass fuels in the US
# Markov Chains are used to describe the % of Companies that use Biomass Fuels vs. % of Companies that use Petroleum

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import random

# Time is measured in increments of 5 years in these submodels (years 2020 - 2060)
time = [2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060]
time2 = [2025, 2030, 2035, 2040]

# Predicted Oil Consumption Data for Years 2020-2040
petroleum = [5805959.921,5758889.845,5712163.105,5665776.337,5619726.228,5574009.507,5528622.949,5483563.376,5438827.649,5394412.674,5350315.397,5306532.806,5263061.928,5219899.828,5177043.612,5134490.423,5092237.439,5050281.877,5008620.988,4967252.059,4926172.411]

# Predicted Biomass Consumption Data for Years 2020-2040
biomass = [816362.249,818951.7292,821623.0291,824376.3499,827211.9152,830129.9712,833130.7864,836214.6513,839381.8787,842632.803,845967.7805,849387.1894,852891.4291,856480.9209,860156.1074,863917.4527,867765.4421,871700.5825,875723.402,879834.4499,884034.2971]

# Average Predicted Petroleum Consumption for Years 2020-2040 in 5 year increments
avg_pet = [0,0,0,0]
avg_pet[0] = np.average(petroleum[0:5]) # years 2020-2025
avg_pet[1] = np.average(petroleum[5:10]) # years 2025-2030
avg_pet[2] = np.average(petroleum[10:15]) # years 2030-2035
avg_pet[3] = np.average(petroleum[15:20]) # years 2035-2040

# Average Predicted Biomass Consumption for Years 2020-2040 in 5 year increments
avg_biomass = [0,0,0,0]
```

```
avg_biomass[0] = np.average(biomass[0:5]) # years 2020-2025
avg_biomass[1] = np.average(biomass[5:10]) # years 2025-2030
avg_biomass[2] = np.average(biomass[10:15]) # years 2030-2035
avg_biomass[3] = np.average(biomass[15:20]) # years 2035-2040
```

[3]:
```
# Model 1: Extreme Policy
# Markov Chains are used to model impact of this policy over time
# Assume companies only use one type of resource or the other (exclusively␣
↪petroleum or exclusively biomass)

P1 = [0] * 9  # array that stores the percentage of companies that use petroleum
B1 = [0] * 9  # array that stores the percentage of companies that use biomass␣
↪fuels

P1[0] = 0.9  # initial value for percentage of companies that use petroleum
B1[0] = 0.1  # initial value for percentage of companies that use biomass fuels

# Test the stability of the solutions by changing the intial values
# Start with equal intial values
#P1[0] = 0.5
#B1[0] = 0.5

# Make B1[0] > P1[0]
#P1[0] = 0.1
#B1[0] = 0.9

# When starting at different initial values, the long-term probabilities still␣
↪yield the same percentages, so the solutions are stable

# Store the long-term probabilities for each energy option in their respective␣
↪arrays

for i in range(8):
    P1[i+1] = 0.20*P1[i] + 0.10*B1[i] # 20% stay with petroleum, 80% switch to␣
↪biomass fuels
    B1[i+1] = 0.80*P1[i] + 0.90*B1[i] # 90% stay with biomass fuels, 10% switch␣
↪to petroleum

# Output the long-term probabilities for each resource

print("Long term probabilities for each energy option: \n")
print("Petroleum powered companies:", P1, "\n")
print("Biomass Fuel powered companies:", B1, "\n")

# Plot the long-term solutions
df=pd.DataFrame({'Long term probabilities': time, 'Petroleum': P1, 'Biomass':␣
↪B1})
```

```python
# multiple line plots
plt.plot( 'Long term probabilities', 'Petroleum', data=df, marker='o',␣
 ↪color='red', linewidth=2)
plt.plot( 'Long term probabilities', 'Biomass', data=df, marker='o',␣
 ↪color='blue', linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Percentage of Resource Used by Companies")
plt.title("Policy 1: Percentage of Resource Used over Time (2020-2060)")
# show graph
plt.show()
```

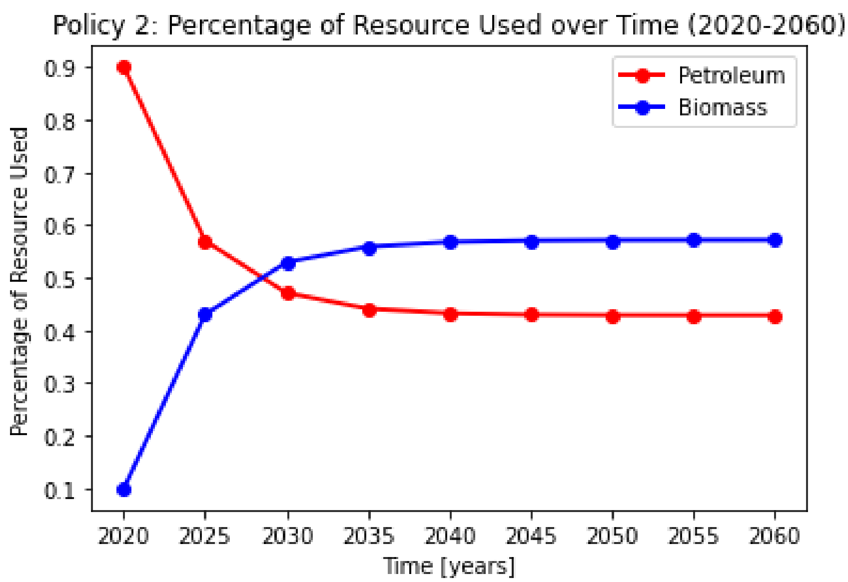
```
Long term probabilities for each energy option:

Petroleum powered companies: [0.9, 0.19000000000000003, 0.11900000000000002,
0.11190000000000001, 0.11119000000000004, 0.11111900000000004,
0.11111190000000004, 0.11111119000000005, 0.11111111900000004]

Biomass Fuel powered companies: [0.1, 0.81, 0.8810000000000001,
0.8881000000000002, 0.8888100000000002, 0.8888810000000003, 0.8888881000000003,
0.8888888100000003, 0.8888888810000003]
```



[4]:
```
# Model 2: Medium Policy
# Markov Chains are used to model impact of this policy over time
# Assume companies only use one type of resource or the other (exclusively␣
 ↪petroleum or exclusively biomass)

P2 = [0] * 9  # array that stores the percentage of companies that use petroleum
B2 = [0] * 9  # array that stores the percentage of companies that use biomass␣
 ↪fuels

P2[0] = 0.9  # initial value for percentage of companies that use petroleum
B2[0] = 0.1  # initial value for percentage of companies that use biomass fuels

# Test the stability of the solutions by changing the intial values
# Start with equal intial values
#P2[0] = 0.5
#B2[0] = 0.5

# Make B2[0] > P2[0]
#P2[0] = 0.1
#B2[0] = 0.9

# When starting at different initial values, the long-term probabilities still␣
 ↪yield the same percentages, so the solutions are stable

# Store the long-term probabilities for each energy option in their respective␣
 ↪arrays

for i in range(8):
    P2[i+1] = 0.60*P2[i] + 0.30*B2[i] # 60% stay with petroleum, 40% switch to␣
 ↪biomass fuels
    B2[i+1] = 0.40*P2[i] + 0.70*B2[i] # 70% stay with biomass fuels, 30% switch␣
 ↪to petroleum

# Output the long-term probabilities for each resource

print("Long term probabilities for each energy option: \n")
print("Petroleum powered companies:", P2, "\n")
print("Biomass Fuel powered companies:", B2, "\n")

# Plot the long-term solutions
df=pd.DataFrame({'Long term probabilities': time, 'Petroleum': P2, 'Biomass':␣
 ↪B2})

# multiple line plots
plt.plot( 'Long term probabilities', 'Petroleum', data=df, marker='o',␣
 ↪color='red', linewidth=2)
```

```
plt.plot( 'Long term probabilities', 'Biomass', data=df, marker='o',␣
↪color='blue', linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Percentage of Resource Used")
plt.title("Policy 2: Percentage of Resource Used over Time (2020-2060)")
# show graph
plt.show()
```

```
Long term probabilities for each energy option:

Petroleum powered companies: [0.9, 0.5700000000000001, 0.47100000000000003,
0.4413, 0.43239, 0.429717, 0.4289151, 0.4286745299999999, 0.4286023589999999]

Biomass Fuel powered companies: [0.1, 0.43000000000000005, 0.529, 0.5587,
0.56761, 0.5702829999999999, 0.5710848999999999, 0.5713254699999999,
0.5713976409999999]
```

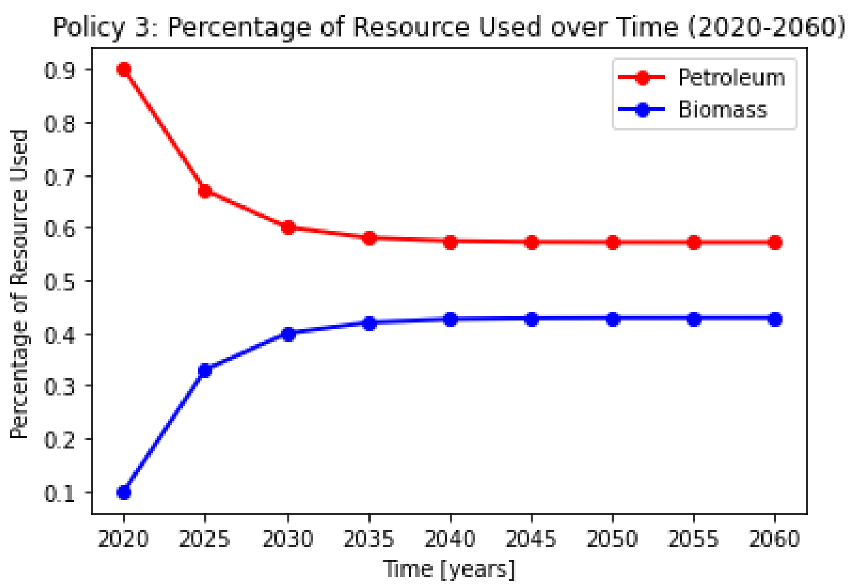


[5]:
```
# Model 3: Realistic Policy
# Markov Chains are used to model impact of this policy over time
```

```
# Assume companies only use one type of resource or the other (exclusively␣
↪petroleum or exclusively biomass)

P3 = [0] * 9  # array that stores the percentage of companies that use petroleum
B3 = [0] * 9  # array that stores the percentage of companies that use biomass␣
↪fuels

P3[0] = 0.9  # initial value for percentage of companies that use petroleum
B3[0] = 0.1  # initial value for percentage of companies that use biomass fuels

# Test the stability of the solutions by changing the intial values
# Start with equal intial values
#P3[0] = 0.5
#B3[0] = 0.5

# Make B3[0] > P3[0]
#P3[0] = 0.1
#B3[0] = 0.9

# When starting at different initial values, the long-term probabilities still␣
↪yield the same percentages, so the solutions are stable

# Store the long-term probabilities for each resource in their respective arrays

for i in range(8):
    P3[i+1] = 0.70*P3[i] + 0.40*B3[i] # 70% stay with petroleum, 30% switch to␣
↪biomass fuels
    B3[i+1] = 0.30*P3[i] + 0.60*B3[i] # 60% stay with biomass fuels, 40% switch␣
↪to petroleum

# Output the long-term probabilities for each energy option

print("Long term probabilities for each energy option: \n")
print("Petroleum powered companies:", P3, "\n")
print("Biomass Fuel powered companies:", B3, "\n")

# Plot the long-term solutions
df=pd.DataFrame({'Long term probabilities': time, 'Petroleum': P3, 'Biomass':␣
↪B3})

# multiple line plots
plt.plot( 'Long term probabilities', 'Petroleum', data=df, marker='o',␣
↪color='red', linewidth=2)
plt.plot( 'Long term probabilities', 'Biomass', data=df, marker='o',␣
↪color='blue', linewidth=2)
# show legend
```

```
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Percentage of Resource Used")
plt.title("Policy 3: Percentage of Resource Used over Time (2020-2060)")
# show graph
plt.show()
```

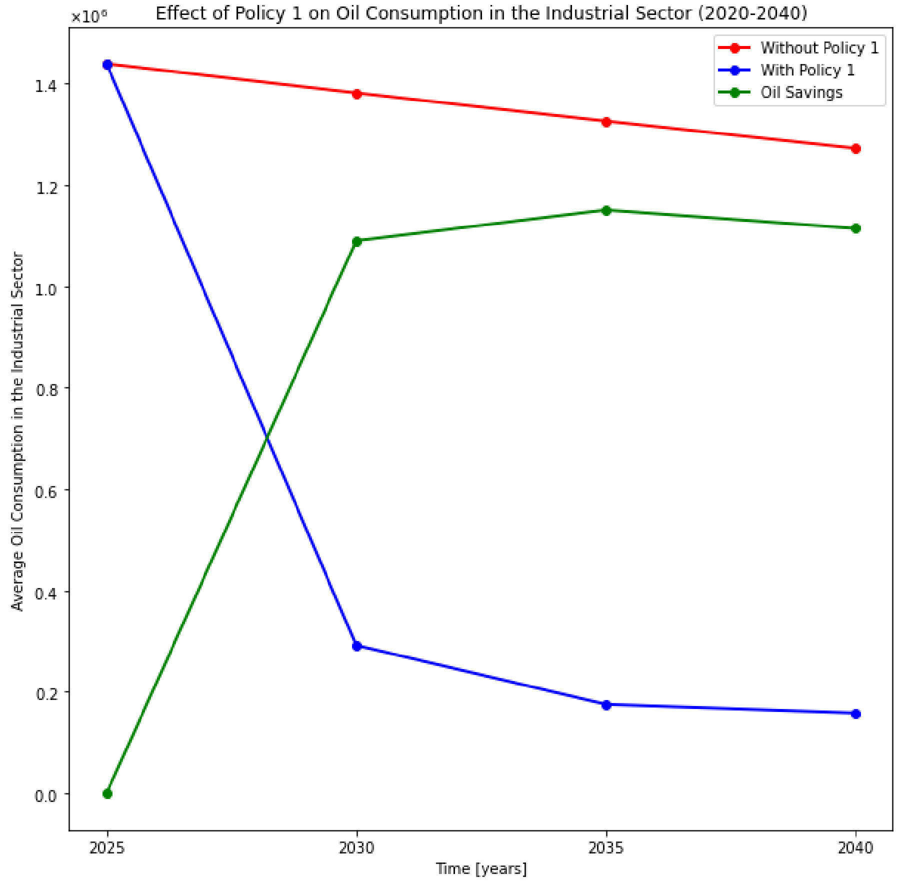
```
Long term probabilities for each energy option:

Petroleum powered companies: [0.9, 0.67, 0.601, 0.5803, 0.57409, 0.572227,
0.5716681, 0.57150043, 0.5714501289999999]

Biomass Fuel powered companies: [0.1, 0.33, 0.399, 0.41969999999999996, 0.42591,
0.42777299999999996, 0.4283319, 0.42849956999999994, 0.42854987099999997]
```



[6]:
```
# Policy 1's effect on Oil Consumption

# Assume 28% of oil consumption in the US is used in the industrial sector
new_pet = 0.28*np.array(avg_pet)

# Calculate Average Amount of Oil that is Used without any of the policies in␣
 ↪place
```

```python
oiluse = 0.9*np.array(new_pet)
print("Average Amount of Oil consumed by industry without Policy 1:
 ↪\n",oiluse,"\n")

# Calculate Average Amount of Oil that is Used with Policy 1
oiluse1 = np.multiply(new_pet,P1[0:4])
print("Average Amount of Oil consumed by industry with Policy 1:
 ↪\n",oiluse1,"\n")

# Calculate Amount of Oil Saved
diff1 = np.array(oiluse) - np.array(oiluse1)
print("Average Amount of Oil Saved with Policy 1:\n",diff1,"\n")

# Plot the oil saved
df=pd.DataFrame({'Time': time2, 'Without Policy 1': oiluse, 'With Policy 1':␣
 ↪oiluse1, 'Oil Savings': diff1})
plt.figure(figsize=(10, 10))
# multiple line plots
plt.plot( 'Time', 'Without Policy 1', data=df, marker='o', color='red',␣
 ↪linewidth=2)
plt.plot( 'Time', 'With Policy 1', data=df, marker='o', color='blue',␣
 ↪linewidth=2)
plt.plot( 'Time', 'Oil Savings', data=df, marker='o', color='green',␣
 ↪linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Average Oil Consumption in the Industrial Sector")
plt.xticks(time2,time2)
plt.ticklabel_format(style='sci', axis='y', scilimits=(0,0), useMathText=True)
plt.title("Effect of Policy 1 on Oil Consumption in the Industrial Sector␣
 ↪(2020-2040)")
# show graph
plt.show()
```

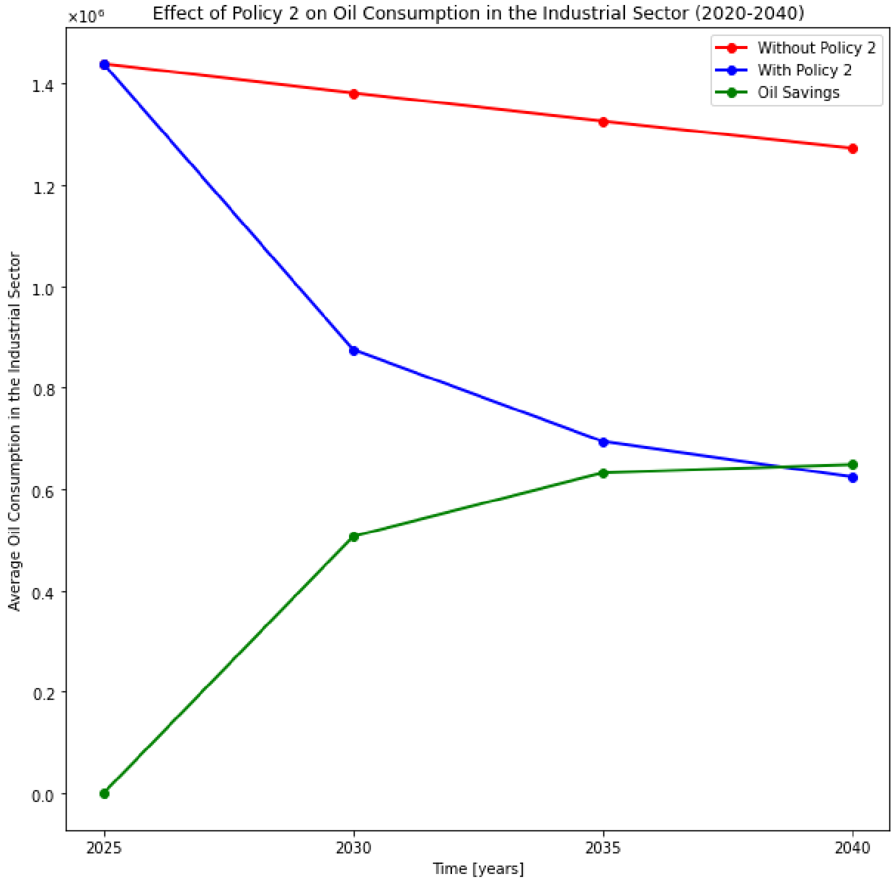
```
Average Amount of Oil consumed by industry without Policy 1:
 [1439550.7779744 1381939.582212  1326369.4199784 1272745.2924144]

Average Amount of Oil consumed by industry with Policy 1:
 [1439550.7779744   291742.8006892   175375.51219714  158244.66469019]

Average Amount of Oil Saved with Policy 1:
 [      0.          1090196.7815228  1150993.90778126 1114500.62772421]
```



[7]:
```
# Policy 2's effect on Oil Consumption

# Calculate Average Amount of Oil that is Used with Policy 2
oiluse2 = np.multiply(new_pet,P2[0:4])
print("Average Amount of Oil consumed by industry with Policy 2:
 ↪\n",oiluse2,"\n")

# Calculate Amount of Oil Saved
diff2 = np.array(oiluse) - np.array(oiluse2)
print("Average Amount of Oil Saved with Policy 2:\n",diff2,"\n")

# Plot the oil saved
```

```
df=pd.DataFrame({'Time': time2, 'Without Policy 2': oiluse, 'With Policy 2':␣
↪oiluse2, 'Oil Savings': diff2})
plt.figure(figsize=(10, 10))
# multiple line plots
plt.plot( 'Time', 'Without Policy 2', data=df, marker='o', color='red',␣
↪linewidth=2)
plt.plot( 'Time', 'With Policy 2', data=df, marker='o', color='blue',␣
↪linewidth=2)
plt.plot( 'Time', 'Oil Savings', data=df, marker='o', color='green',␣
↪linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Average Oil Consumption in the Industrial Sector")
plt.xticks(time2,time2)
plt.ticklabel_format(style='sci', axis='y', scilimits=(0,0), useMathText=True)
plt.title("Effect of Policy 2 on Oil Consumption in the Industrial Sector␣
↪(2020-2040)")
# show graph
plt.show()
```

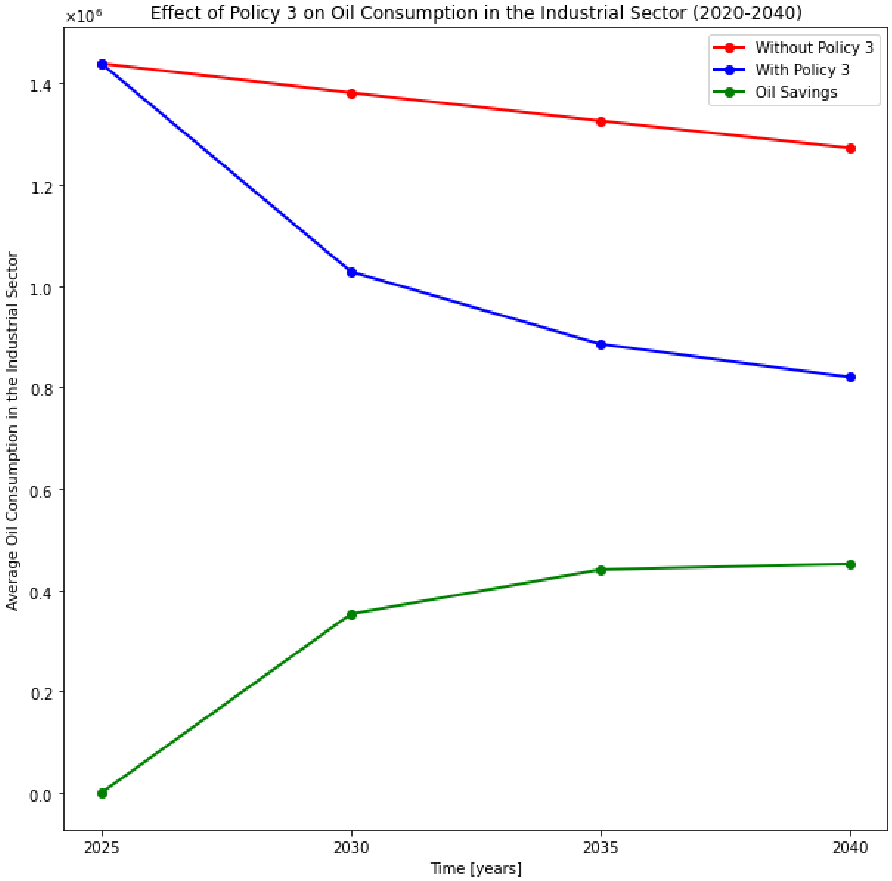
```
Average Amount of Oil consumed by industry with Policy 2:
 [1439550.7779744   875228.4020676   694133.3297887   624069.44171386]

Average Amount of Oil Saved with Policy 2:
 [     0.         506711.1801444  632236.0901897  648675.85070054]
```



[8]:
```
# Policy 3's effect on Oil Consumption

# Calculate Average Amount of Oil that is Used with Policy 3
oiluse3 = np.multiply(new_pet,P3[0:4])
print("Average Amount of Oil consumed by industry with Policy 3:
 ↪\n",oiluse3,"\n")

# Calculate Amount of Oil Saved
diff3 = np.array(oiluse) - np.array(oiluse3)
print("Average Amount of Oil Saved with Policy 3:\n",diff3,"\n")

# Plot the oil saved
```

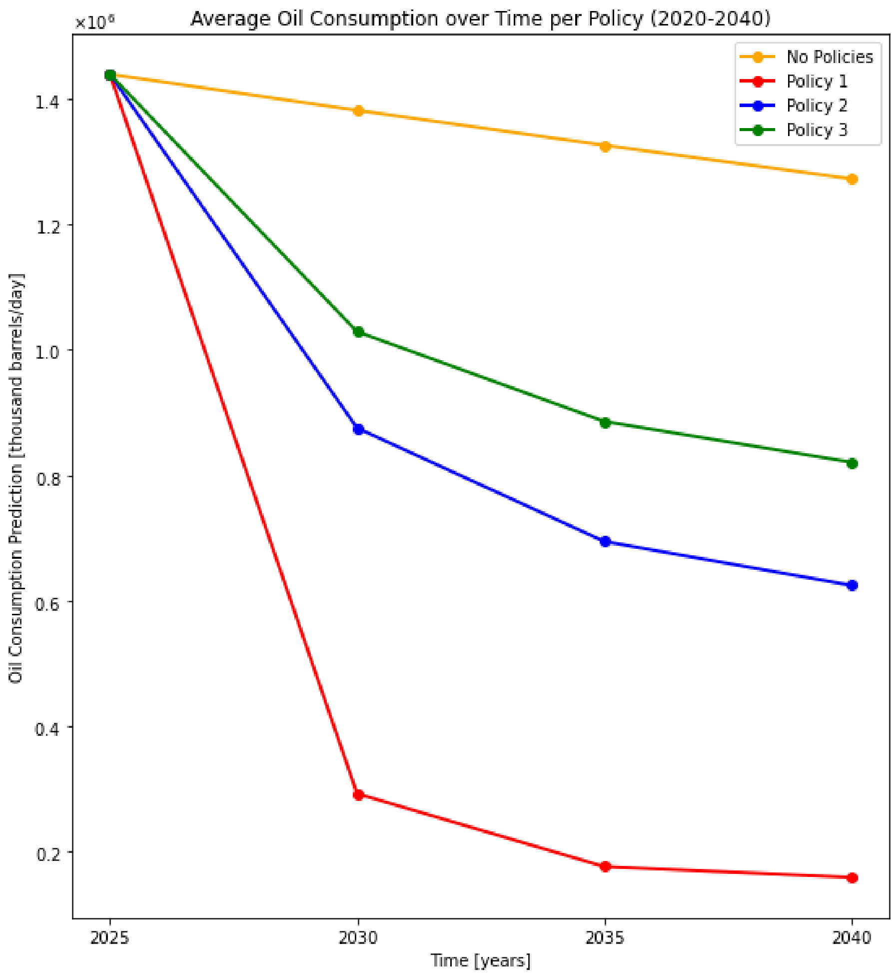
```
df=pd.DataFrame({'Time': time2, 'Without Policy 3': oiluse, 'With Policy 3': oiluse3, 'Oil Savings': diff3})
plt.figure(figsize=(10, 10))
# multiple line plots
plt.plot( 'Time', 'Without Policy 3', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'With Policy 3', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Oil Savings', data=df, marker='o', color='green', linewidth=2)
# show legend
plt.legend()
plt.xlabel("Time [years]")
plt.ylabel("Average Oil Consumption in the Industrial Sector")
plt.xticks(time2,time2)
plt.ticklabel_format(style='sci', axis='y', scilimits=(0,0), useMathText=True)
plt.title("Effect of Policy 3 on Oil Consumption in the Industrial Sector (2020-2040)")
# show graph
plt.show()
```

```
Average Amount of Oil consumed by industry with Policy 3:
 [1439550.7779744  1028777.2445356   885720.02378558  820637.88132008]

Average Amount of Oil Saved with Policy 3:
 [     0.         353162.3376764  440649.39619282 452107.41109432]
```



[13]:
```python
# Plot New Oil Consumption Predictions for years 2020-2040 with each of the 3 policies in place
df=pd.DataFrame({'Time': time2, 'No Policies': oiluse,'Policy 1': oiluse1, 'Policy 2': oiluse2, 'Policy 3':oiluse3})
plt.figure(figsize=(9, 10))
# multiple line plots
plt.plot( 'Time', 'No Policies', data=df, marker='o', color='orange', linewidth=2)
plt.plot( 'Time', 'Policy 1', data=df, marker='o', color='red', linewidth=2)
plt.plot( 'Time', 'Policy 2', data=df, marker='o', color='blue', linewidth=2)
plt.plot( 'Time', 'Policy 3', data=df, marker='o', color='green', linewidth=2)
# show legend and axes
plt.legend()
```

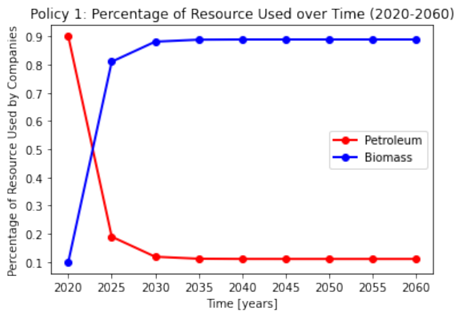
```
plt.xlabel("Time [years]")
plt.ylabel("Oil Consumption Prediction [thousand barrels/day]")
plt.xticks(time2,time2)
plt.ticklabel_format(style='sci', axis='y', scilimits=(0,0), useMathText=True)
plt.title("Average Oil Consumption over Time per Policy (2020-2040)")
# show graph
plt.show()
```



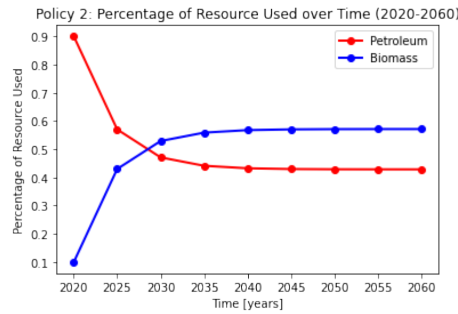

```
[ ]:
```

C.3 Results

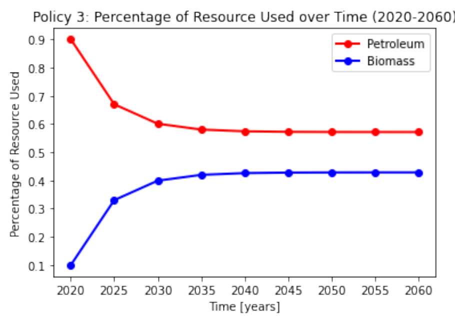
The long-term solutions of each of the three policies for Model 3 are graphed in Figure 14.



(a) Policy 1



(b) Policy 2

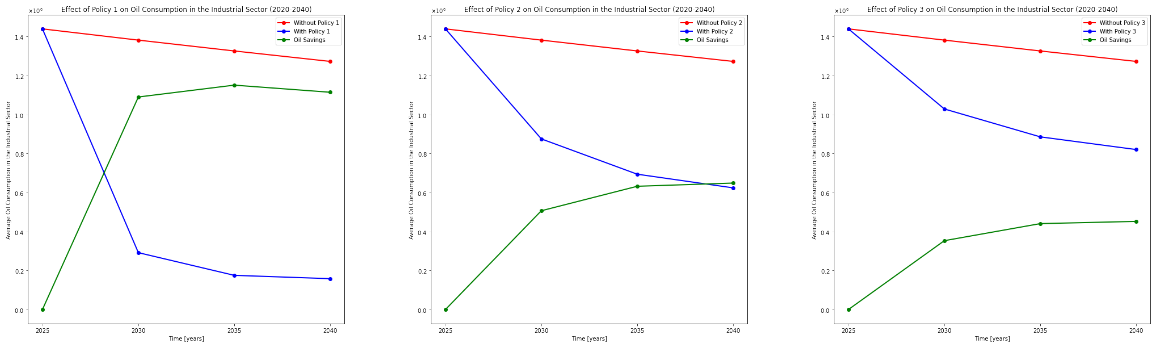


(c) Policy 3

Figure 14: Solutions for biomass and petroleum powered companies

C.4 Analysis

The long-term oil savings for each of the three policies in Model 3 are graphed in Figure 15.



(a) Policy 1 (b) Policy 2 (c) Policy 3

Figure 15: Oil saved by industrial companies with Policy 1, Policy 2, and Policy 3

D Model 4

D.1 MATLAB Variables

- $totalBarrels$ is a variable that just lists the total number of Barrels of Oil the model predicts for that year. The vector is of length 20, so $totalBarrel(i)$ gives you the number of barrels the US expects to import/export in the year $2020 + i$ (Remember that in MATLAB vectors start at index 1 not 0).
- $numberOfYears$ Pretty self explanatory, it's the number of years the simulation will run for. In this case it will always be 20 because we're modeling from the year 2021 to 2040.
- $countryPercentage$ This is a vector of length 215, for each country on the list from the EIA website. we arranged them in alphabetical order and put all the percentages in order in MATLAB, so when we paste it back into excel everything aligns. The percentage is the rough percentage we expect that country to give or receive based on the amount they have in previous years.
- $totalCountries$ A single integer that holds the value of the number of countries in the list $countryPercentage$. It remains at 215 for both instances though.
- $countryBarrelsFuture$ Finally, this matrix stores each countries total barrel imoports and exports for each year from 2021 to 2040, so it's a 215x20 matrix.

D.2 MATLAB Code

```
clear
clc
totalBarrels = [682327.439 784570.7069 939473.0214 1140236.733
 1376947.95 ...
                1637216.736 1907213.989 2172964.215 2421677.156
 2642880.773 ...
                2524689.386 2405950.601 2287044.838 2167946.681
 2048630.426 ...
                1929070.106 1809239.503 1689112.175 1568661.48
 1447860.605];
numberOfYears = length(totalBarrels);
countryPercentage = [0.0000000 0.0001270 0.0179366 0.0000000
 0.0169249...
                    0.0000000 0.0000000 0.0035951 0.0000000
 0.0007126...
                    0.0004110 0.0000014 0.0018740 0.0000000
 0.0008902...
                    0.0002041 0.0000013 0.0001481 0.0061234
 0.0001062...
                    0.0000000 0.0001626 0.0000027 0.0000000
 0.0195300...
                    0.0000000 0.0006967 0.0000634 0.0000000
 0.0000000...
                    0.0000000 0.0000000 0.0015041 0.3666245
 0.0000000...
                    0.0000000 0.0038990 0.0001445 0.0009877
 0.0000000...
                    0.0381463 0.0000000 0.0019372 0.0001659
 0.0000249...
                    0.0000078 0.0000000 0.0002281 0.0000088
 0.0000021...
                    0.0005216 0.0000000 0.0000000 0.0000557
 0.0211433...
                    0.0018648 0.0000365 0.0016913 0.0000000
 0.0003765...
                    0.0000000 0.0000000 0.0000000 0.0000000
 0.0015166...
                    0.0034322 0.0000012 0.0000000 0.0016523
 0.0000000...
                    0.0000595 0.0007664 0.0009442 0.0000001
 0.0001480...
                    0.0000000 0.0000000 0.0000000 0.0007845
 0.0000000...
                    0.0000000 0.0003147 0.0000000 0.0000000
 0.0000424...
                    0.0000019 0.0000000 0.0077447 0.0026341
 0.0000351...
                    0.0393682 0.0003675 0.0000925 0.0023511
 0.0003778...
                    0.0000605 0.0019683 0.0000365 0.0022551
 0.0000000...
```

```
                   0.0000000 0.0091422 0.0000000 0.0000003
 0.0000000...
                   0.0183915 0.0000000 0.0002547 0.0000722
 0.0000000...
                   0.0038247 0.0000000 0.0004083 0.0000000
 0.0000000...
                   0.0000000 0.0000000 0.0000000 0.0005110
 0.0000000...
                   0.0000000 0.0000341 0.0000000 0.0000184
 0.0001059...
                   0.0000000 0.0863055 0.0000000 0.0000000
 0.0000000...
                   0.0000000 0.0000000 0.0000000 0.0000000
 0.0000118...
                   0.0000080 0.0000000 0.0000000 0.0084263
 0.0001036...
                   0.0000000 0.0000000 0.0000020 0.0000000
 0.0321044...
                   0.0000000 0.0072559 0.0009733 0.0000000
 0.0000000...
                   0.0001262 0.0000167 0.0000000 0.0000000
 0.0031622...
                   0.0000214 0.0001345 0.0022297 0.0000000
 0.0010026...
                   0.0000271 0.0471304 0.0000000 0.0000000
 0.0000000...
                   0.0000000 0.0000000 0.0000000 0.0000000
 0.1016918...
                   0.0000127 0.0000000 0.0000042 0.0000000
 0.0000000...
                   0.0000000 0.0016423 0.0000000 0.0000011
 0.0000000...
                   0.0000000 0.0000532 0.0047256 0.0000000
 0.0000007...
                   0.0000693 0.0000213 0.0012214 0.0000119
 0.0001414...
                   0.0004377 0.0000000 0.0006330 0.0000000
 0.0000114...
                   0.0042491 0.0002300 0.0007383 0.0000477
 0.0000000...
                   0.0000000 0.0001628 0.0017721 0.0140805
 0.0000055...
                   0.0000011 0.0000000 0.0660861 0.0006914
 0.0035438...
                   0.0000706 0.0000000 0.0000000 0.0000000
 0.0000000];

totalCountries = length(countryPercentage);
countryBarrelsFuture = zeros(totalCountries,numberOfYears);
for i=1:numberOfYears
    for j=1:totalBarrels(i)
        x = rand;
        if 0<=x && x<sum(countryPercentage(1))
```

```
            countryBarrelsFuture(1,i) = countryBarrelsFuture(1,i) + 1;
        end
        for k=2:totalCountries
            if sum(countryPercentage(1:k-1))<=x &&
 x<sum(countryPercentage(1:k))
                countryBarrelsFuture(k,i) = countryBarrelsFuture(k,i)
 + 1;
            end
        end
    end
    disp(i);
end
```

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```
clear
clc
totalBarrels = [3025925.283 2805287.598 2532059.541 2213016.838
 1858051.073...
                1479529.504 1091258.184 707189.187 340088.9986
 405.5320821...
                0 0 0 0 0 0 0 0 0 0];
numberOfYears = length(totalBarrels);
countryPercentage = [0.0000013 0.0001246 0.0006505 0.0000001
 0.0000353...
                     0.0000048 0.0007972 0.0107285 0.0000000
 0.0038512...
                     0.0038627 0.0000227 0.0000151 0.0000006
 0.0101040...
                     0.0001413 0.0001718 0.0000176 0.0075813
 0.0004626...
                     0.0001388 0.0002538 0.0000005 0.0000000
 0.0517656...
                     0.0000195 0.0000096 0.0008352 0.0000000
 0.0000002...
                     0.0006515 0.0000137 0.0000087 0.1429031
 0.0000000...
                     0.0010114 0.0000001 0.0315634 0.0394672
 0.0000000...
                     0.0240009 0.0000000 0.0000027 0.0000328
 0.0105795...
                     0.0003582 0.0000000 0.0014295 0.0000791
 0.0000030...
                     0.0019826 0.0000276 0.0002425 0.0127777
 0.0202354...
                     0.0037420 0.0045081 0.0000032 0.0000000
 0.0000698...
                     0.0000000 0.0001010 0.0000000 0.0000032
 0.0008321...
                     0.0200505 0.0000070 0.0000005 0.0000961
 0.0000069...
                     0.0000463 0.0040422 0.0008657 0.0124305
 0.0026489...
                     0.0000000 0.0000066 0.0003281 0.0137013
 0.0001136...
                     0.0000000 0.0000326 0.0005642 0.0113588
 0.0003247...
                     0.0000012 0.0005080 0.0248502 0.0029430
 0.0000000...
                     0.0000088 0.0016647 0.0034133 0.0127126
 0.0003419...
                     0.0042386 0.0444252 0.0006964 0.0000056
 0.0001066...
                     0.0000000 0.0238137 0.0000000 0.0000000
 0.0000000...
                     0.0000232 0.0000000 0.0000451 0.0039823
 0.0000266...
```

```
                    0.0000881 0.0000005 0.0001197 0.0000000
 0.0000003...
                    0.0000062 0.0000755 0.0000000 0.0019699
 0.0000000...
                    0.0000000 0.0024107 0.0001444 0.0004913
 0.0002580...
                    0.0002011 0.1578662 0.0000002 0.0000000
 0.0000000...
                    0.0000433 0.0000006 0.0000155 0.0000001
 0.0083263...
                    0.0007003 0.0001668 0.0000000 0.0589723
 0.0017121...
                    0.0000016 0.0005481 0.0011851 0.0000000
 0.0053241...
                    0.0000000 0.0039725 0.0003489 0.0001528
 0.0000000...
                    0.0285668 0.0000001 0.0000000 0.0006392
 0.0153955...
                    0.0008291 0.0003366 0.0020322 0.0008928
 0.0002869...
                    0.0009016 0.0000592 0.0000030 0.0022597
 0.0000000...
                    0.0000042 0.0000006 0.0000000 0.0000000
 0.0005711...
                    0.0004425 0.0000000 0.0000097 0.0000000
 0.0000000...
                    0.0000000 0.0312839 0.0000452 0.0000020
 0.0004836...
                    0.0000000 0.0018357 0.0131439 0.0000000
 0.0000039...
                    0.0000000 0.0000284 0.0014351 0.0021508
 0.0000001...
                    0.0075774 0.0001494 0.0030432 0.0000000
 0.0023827...
                    0.0011576 0.0015350 0.0130819 0.0000002
 0.0002048...
                    0.0000018 0.0000550 0.0032039 0.0216396
 0.0010937...
                    0.0000069 0.0000003 0.0130384 0.0005178
 0.0000457...
                    0.0038295 0.0000043 0.0000272 0.0000000
 0.0000000];

totalCountries = length(countryPercentage);
countryBarrelsFuture = zeros(totalCountries,numberOfYears);
for i=1:numberOfYears
    for j=1:totalBarrels(i)
        x = rand;
        if 0<=x && x<sum(countryPercentage(1))
            countryBarrelsFuture(1,i) = countryBarrelsFuture(1,i) + 1;
        end
        for k=2:totalCountries
            if sum(countryPercentage(1:k-1))<=x &&
 x<sum(countryPercentage(1:k))
```

```
                countryBarrelsFuture(k,i) = countryBarrelsFuture(k,i)
 + 1;
            end
        end
    end
    disp(i);
end
```

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