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Dynamic Behavior of Nascent Bioenergy Supply Chains
Competing for Shared Resources

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In our previous work, we presented a novel multi-time-stage input-output-based modeling framework for simulating the dynamics of nascent bioenergy supply chains. The production level within the supply chain at any given time interval is assumed to be dependent on the output surplus or deficit relative to targets in the previous interval or intervals. In our approach, the technology matrix, A, includes coefficients denoting flows of products (e.g., biofuels), intermediates (e.g., feedstock) and environmental goods (e.g., resources, pollutants), while the influence matrix, B, signifies the strength of the influence of flow surpluses and deficits on the supply chain. Introducing a feedback control term enables the system to suppress the undesirable dynamic behavior of the uncontrolled dynamic model such as oscillation or instability. In this paper, we apply our modeling framework to analyze the dynamic behavior of three nascent bioenergy supply chains competing for shared resources. Numerical simulations are used to assess the effects of key system parameters on the growth trajectories of the competing bioenergy systems and the effects of relative time lags in the development of one of the supply chains within the competing system. These numerical simulations show that policy interventions can be systematically imposed to suppress undesirable dynamic behavior in complex energy systems.

Key Words
Renewable energy, Solar energy, Bioenergy, Competition, Importation

1. Introduction

In recent years, global production of liquid biofuels for transportation has grown in response to two key factors. First, there are concerns regarding the long-term sustainability of petroleum supplies 1. Several years ago, the surge in international oil prices led to increased interest in many countries in biofuels derived from indigenous feedstock as a means of enhancing energy security 2. Even as oil prices have dropped to moderate levels since 2008, such biofuel programs remain in place as a hedge against growth of energy demand (particularly in China and India) as well as the eventual decline of global oil reserves 3-5. Secondly, with climate change now being widely regarded as the single most important environmental issue facing the world, the potentially carbon-neutral nature of biofuel systems make them an attractive alternative energy source for mitigating greenhouse gas emissions 6. Nevertheless, it is recognized that the establishment of large-scale bioenergy systems may pose significant risks 7. In the case of first-generation biofuels (i.e., those derived from conventional crops using relatively mature conversion technologies), the main problems arise from the strain that may be placed on agricultural resources such as land and fresh water, even at relatively modest levels of biofuel production 8-9. Thus, countries that implement biofuel programs must develop effective policies to achieve an appropriate balance between energy security and food security 10,11. In practice, these tradeoffs give rise to complex decision-making problems that require an integrated approach to account for economic, environmental and political considerations 12. Often, the decisions in such scenarios involve the identification of feedstock that maximize energy output or economic benefits while staying within regional resource and environmental footprint limits 13,14. Furthermore, historical experience clearly illustrates how interest in industrial scale production of biofuels has periodically risen and fallen in response to fluctuations in global oil prices. Thus, in prin-
picle, the vital role of governments is to develop policies with a long-term perspective, thereby providing a stabilizing influence on volatile energy markets.

Mathematical models are essential to providing rigorous decision support for complex policy issues associated with bioenergy systems\(^{15\text{–}16}\). Such systems consist of a physical component (which can be easily described from first principles or empirically using historical data) and a behavioral component. In this case, the modeling is undertaken not merely to describe or elucidate the system behavior; the ultimate goal is to prescribe new policy interventions, which have to be systematically designed to lead to desired behavior of the complex system. Note that validation of such prescriptive models is inherently difficult, since historical data which may be used for calibration usually contains the combined effects of intrinsic system behavior and the influence of past policy interventions. In our previous work\(^{17}\), we developed a novel multi-timestage input-output-based modeling framework for simulating the dynamics of nascent bioenergy supply chains. For this discrete-time model, the production level within the supply chain at any given time interval was assumed to be dependent on the output surplus or deficit relative to targets in the previous interval or intervals. In this paper, we extend our previous work by examining the behavior of nascent bioenergy supply chains where multiple processes compete for shared resources or for a common market of the final fuel product. This situation is illustrated by three case studies on biodiesel and ethanol production. We explore different scenarios in each case to show the dynamic behavior of such systems, both with and without government intervention.

2. Modeling Approach

The dynamic model for nascent bioenergy supply chains\(^{17}\) makes use of a discrete-time input-output model:
\begin{equation}
Ax_t = y_t
\end{equation}
where \(A\) is the \(m \times n\) technology matrix, \(x_t\) is the \(n\)-dimensional sectoral gross output or capacity vector at time \(t\), and \(y_t\) is the \(m\)-dimensional final output vector at time \(t\). For the technology matrix, \(A\), each row corresponds to a different product stream and each column represents a sector or process within the system. Each element \(a_{ij}\) of the technology matrix denotes the magnitude of flow of stream \(i\) in sector \(j\), where a positive value corresponds to an output while a negative value denotes an input. Each column of the technology matrix gives the relative proportions of these flows, which reflects the physical relationships (i.e. conversion or production rates) for the given technological processes. These ratios are assumed to be scale invariant. The model assumes that gross output or capacity responds to any deficit or surplus production:
\begin{equation}
x_{t+1} = B(z_t - y_t) + x_t
\end{equation}
where \(x_{t+1}\) is the \(n\)-dimensional gross output vector at \(t+1\), \(B\) is the \(n \times m\) influence matrix, and \(z_t\) is the \(m\)-dimensional vector of desired production level, or target, at \(t\). For the influence matrix, \(B\), each row corresponds to a given sector and each column represents a product stream within the system. The influence matrix describes the strength of the effect of the surplus or deficit of stream \(j\) on the change in production of sector \(i\). A positive coefficient \(b_{ij}\) indicates that the production capacity of sector \(i\) increases when there is a deficit of stream \(j\) and vice-versa. However, a negative coefficient in \(B\) indicates the inverse relationship (i.e., production capacity of \(j\) decreases in response to deficit of \(i\)), while a value close to zero indicates that capacity growth in sector \(i\) is not significantly affected by stream \(j\). The elements, \(b_{ij}\) in the influence matrix have behavioral rather than physical basis; thus, \(B\) can be calibrated econometrically from relevant historical data\(^{17}\). Although there are many factors that influence system behavior, both direct (i.e. technology, cost) and indirect (i.e. societal acceptability), the influence matrix used here provides a computationally economical description of the collective behavior of agents in the supply chain. Substituting Equation 1 into Equation 2 gives:
\begin{equation}
x_{t+1} = (I - BA)x_t + Bz_t
\end{equation}
It is possible that the target output is made to vary as a function of current output or capacity:
\begin{equation}
z_t = Kx_t + z_0
\end{equation}
where \(K\) is the \(m \times n\) control matrix and \(z_0\) is the \(m\)-dimensional baseline or default target output vector. Equation 4 shows that, in practice, the targets should be adjusted periodically based on the latest available production data. This systematic approach allows the system to avoid targets which result in supply deficits or supply chain imbalances. Substituting Equation 4 into Equation 3 gives:
\begin{equation}
x_{t+1} = (I - BA + BK)x_t + Bz_0
\end{equation}
This model describes the trajectory of sectoral capacity or output levels as a function of physical characteristics of the system (\(A\)), spontaneous behavior of sectors that comprise the supply chain (\(B\)) and government control through policies (\(K\)). Note that, in the absence of government intervention, Equation 5 reduces to Equation 3 with \(z_t = z_0\). Also it is clear that the choice of policy embodied in \(K\) depends on the specific characteristics of the biofuel supply chain, as described by \(A\) and \(B\). Different types of intervention strategies are used by different countries\(^{18}\), including:
- Tax credits
3. Case studies

This section describes three illustrative case studies. These examples are hypothetical, and focus primarily on modeling general dynamic trends of energy systems as a consequence of their structural characteristics, as opposed to the precise prediction of the systems’ states\textsuperscript{30}. However, in the succeeding examples, qualitative comparisons are made with similar trends observed in actual data.

3.1 Case 1: Biodiesel System

3.1.1 Scenario A

This case study illustrates production level trajectories for the uncontrolled case of biodiesel production from three different feedstocks. The parameters for the case study are as follows. The technology matrix is:

\[
A = \begin{bmatrix}
1 & 1 & 1 & -1 \\
-0.1 & -0.1 & -0.1 & 0.63 \\
-0.4 & -0.4 & -0.5 & -0.1
\end{bmatrix}
\]  

In Equation 6, the first three columns of A represent the three competing agricultural sectors (i.e., coconut, microalgae and jatropha farming) while the fourth column is the biodiesel production sector. Likewise, the three rows of A represent vegetable oil (t), biodiesel (t) and land resources (ha-year). In Fig. 1, a diagram is showing illustrating the first column in the technology matrix. The convention used is such that positive values denote outflows while negative ones denote inflows. Each column thus gives a fixed ratio of inputs and outputs\textsuperscript{17}.

Next, the influence matrix is:

\[
B = \begin{bmatrix}
0.5 & 0.1 & -0.3 \\
0.3 & 0.3 & -0.1 \\
-0.1 & 0.4 & -0.2 \\
0.4 & 0.7 & 0
\end{bmatrix}
\]  

The rows of B in Equation 7 correspond to the four processes denoted by the columns of A, while its three columns correspond to the flows of vegetable oil, biodiesel and land resource. As shown in Equation 2, each entry denotes the strength of the influence of the current surplus or deficit of a given stream on the change of capacity of a given process in the subsequent time interval. For example, in Row 1, Column 1, the entry of 0.5 denotes that a deficit of vegetable oil production (Column 1) results in a moderately strong response in the growth of the production capacity of the coconut oil production sector (Row 1). Note that negative entries indicate reverse sensitivity (i.e., deficit results in a subsequent decline in capacity) while 0 indicates complete insensitivity. In practice, such coefficients may be determined empirically from historical data\textsuperscript{15}. The target output vector is assumed to be constant:

\[
Z_0 = \begin{bmatrix}
0 \\
150 \\
-50
\end{bmatrix}
\]  

Finally, an additional assumption is made that the initial production capacity for the nascent system is zero. Calculations are made within a 50 year period using one year intervals. Trajectories of production levels of coconut, jatropha, microalgae and biodiesel over time are shown in Fig. 2. In the early stages of the simulation, the jatropha sector grew rapidly, compared to the other two feedstock. The coconut sector exhibited the most sluggish growth; it was initially the weakest among the three feedstock, and actually died out for a period of time. However, as the jatropha sector output began to deteriorate, the coconut sector quickly grew in capacity to cover the difference. The coconut sector gradually surpassed the microalgae sector in output to eventually become the dominant source of feedstock for the production of biodiesel. The growth of the biodiesel conversion sector was not heavily affected by the unsteady situation of the biofuel feedstock, although there was temporarily a period of excess capacity.

3.1.2 Scenario B

This scenario illustrates the effect of government intervention on production level trajectories using the same conditions as in the previous example. The following con-
The control matrix is introduced:

\[
K = \begin{bmatrix}
0 & 0 & -3.8 & 0 \\
0 & 0 & 0.4 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\] (9)

These values can be interpreted as government interventions (i.e., taxes or subsidies) in the jatropha sector. Trajectories of production levels of coconut, jatropha, microalgae and biodiesel over time are shown in Fig. 3. Even with intervention of the government, the jatropha sector was still unable to sustain its growth, thus declining to zero output eventually. The coconut sector was again originally the weakest among the three biofuel feedstock and died out for a longer period compared to that in Case 1. But as the jatropha sector output began to die down, the coconut sector output grew rapidly to compensate, and eventually became the only source of feedstock for the production of biodiesel.

Unlike the previous case, the microalgae sector was not a factor at all in the production of biodiesel. The biodiesel conversion sector was more noticeably affected by the situation of the biofuel feedstock, with a sudden decline in growth. Nevertheless the biodiesel conversion sector was eventually stabilized, due to the growth in the coconut sector.

### 3.1.3 Scenario C

This is a similar scenario as the one presented in Scenario B except for the introduction of a time lag on the microalgae sector, which provides a head start in the development of the coconut and jatropha sector. This illustrates the effect on the supply chain in the competing system. The microalgae sector lags both the coconut and jatropha sector by five (5) years, which results from the relative immaturity of the technology. The time lag is introduced simply by imposing the condition that this sector has zero output in the first five time intervals of the simulation. As in the other case studies, the state of the system is still assumed to be influenced only by the state in the previous time period. Trajectories of production levels of coconut, jatropha, microalgae and biodiesel over time with time lag for one of the biodiesel feedstock are shown in Fig. 4. The relationship of increasing the time delay of the micro-algae production is that its production growth decreases as we increase the time lag (e.g., if we set the time lag to \( t = 10 \) then the micro-algae production does not exhibit any growth at all). It was found out that this has insignificant effect on the amount of biodiesel produced by the system as the coconut sector was able to make up for the required feedstock production.

One major insight is that, although it is the micro-algae sector that has the time lag, the jatropha sector also suffered heavily, dying out more than twice as fast as compared to Scenario B. This effect can be explained as follows. The growth of the jatropha sector was dependent on meeting a large portion of the biodiesel demand, which the micro-algae was unable to meet, at a time when the coconut sector was still experiencing sluggish growth. For this scenario the coconut sector did not reach zero production and was able to grow faster since there was less competition in the supply chain.

### 3.2 Case 2: Bioethanol System

#### 3.2.1 Scenario A

This case study demonstrates the annual bioethanol production level trajectories for the uncontrolled case throughout a 20 year period using one year intervals in the simulations. It has been studied that water availability is considered a limiting factor in the production of the crops required for the production of bioenergy\(^{19}\). The parameters for the case study are as follows. The technology matrix is:

\[
A = \begin{bmatrix}
1 & 1 \\
-1 & 0
\end{bmatrix}
\] (10)

In Equation 10, the first column of A represents the local production sector while the second column is the imported ethanol. The two rows of A represent the ethanol output, in \(10^6\) L, and water resource consumed, in \(10^6\) t. As
mentioned earlier, it is assumed that importing does not consume any local natural resources. The influence matrix is:

\[
B = \begin{bmatrix}
0.4 & 0.2 \\
1 & 0 \\
\end{bmatrix}
\]

(11)

As in the previous example, the rows of B in Equation 11 correspond to the two processes denoted by the columns of A, while its two columns correspond to the flows of ethanol output and water resources consumed. For this example, importation is much more sensitive to a change in demand than is local production, as shown by the larger magnitudes in the influence matrix. This is because it is easier to increase or decrease volume of imports, than it is to ramp up or cut down local ethanol production capacities. It should also be noted that \( b_0 \) shows that water deficit results in the drop of local production; while \( b_2 \) being zero means that water availability does not affect imports since the ethanol is produced outside the system boundaries. The final output vector is assumed to be constant:

\[
z_0 = \begin{bmatrix}
100 \\
-50 \\
\end{bmatrix}
\]

(12)

The target ethanol production is considered to be at \( 100 \times 10^6 \) L/year, while the water resource set for consumption is \( 50 \times 10^6 \) t/year. Trajectories of production levels of local production and imports over time are shown in Fig. 5. Without any control or restriction, there is a tendency for imported ethanol to become dominant in the system. Although this state does not consume local water resources, it is undesirable since it defeats one of the main objectives of typical biofuel programs, which is to enhance energy security by sourcing fuel locally. In this case, some local production capacity exists within the first five years, but the ethanol sector output eventually collapses back to zero.

The result of this case study is qualitatively similar to the current situation of the Philippines, where existing legislation targets 10% displacement of gasoline demand with ethanol by early 2011 [2]; however production capacity as of 2010, at \( 110 \times 10^6 \) L, falls short of the actual ethanol requirement of about \( 400 \times 10^6 \) L [20]. Fig. 6 shows that the actual ethanol production level of the Philippines is nowhere near the target production levels. Similarly, many other countries have failed to meet overly ambitious biofuel blending targets, forcing most to import their ethanol demands [20]. One of the main objectives in using biofuels is energy independence, but with current scenarios as it is, the biofuel producing countries still require energy imports to satisfy their needs. This recurring trend necessitates the use of models and simulations for the investigation of conditions under which local production can be induced to grow into the major source of ethanol in the system. Such a scenario is investigated in the next section.

### 3.2.2 Scenario B

This scenario illustrates the effect of government intervention (i.e., subsidies and taxes) on local production and importation using the same conditions as in the previous example. The following control matrix is introduced:

\[
k = \begin{bmatrix}
-0.25 & 1 \\
0 & 0 \\
\end{bmatrix}
\]

(13)

Trajectories of the controlled production levels of local production and imports over time are shown in Fig. 7-9. \( k_{11} \) denotes the support given to the local production sector (i.e., subsidies) while \( k_{12} \) is a disincentive imposed on imported ethanol (i.e., taxes). Fig. 7 shows the system with \( k_{11} \) set to \(-0.25\) while \( k_{12} \) to 0. It can easily be seen that it is practically the same with the uncontrolled scenario. This shows that government support of local production has minimal effect on the system. On the other hand, keeping \( k_{11} \) constant at \(-0.25\) while increasing \( k_{12} \) increases the system imports until these end up supplying more than what the system requires. The level of the system’s local production also begins to improve. At a \( k_{12} \) value of 0.8, local production became self-sustaining. For the same \( k_{12} \) value, the system imports start to slowly level off, eventually reaching zero.

Fig. 8 depicts the system when \( k_{12} \) is set to 1 and \( k_{11} \)
to 0. There is a noticeable improvement to the system; not only did the imports eventually diminish to zero, but local production was also able to stabilize, although it actually exceeded the total demand. When \( k_{12} \) was set to a constant value of 1.0, it was seen that the system’s imports show minimal sensitivity to varying the \( k_{11} \) values. On the other hand, as \( k_{11} \) decreases, the local production of the system reaches the desired steady-state value faster while producing the necessary amount of ethanol. For a \( k_{11} \) value of -0.25, there is a tradeoff that arises when \( k_{12} \) is varied between values of 1.0 and 1.2, since for \( k_{12} = 1.0 \) (See Fig. 9) it is possible to reach the desired steady-state for local production faster; however ethanol imports persist longer. On the other hand, for \( k_{12} = 1.2 \), the system experiences a larger transient overshoot in ethanol supply; however, ethan-

ol imports are eliminated much faster. Thus, the decision maker has the option of choosing interventions (e.g., tariff or subsidy levels) depending on how much importation is acceptable in the interim.

### 3.3 Case 3: Multiple Feedstock Bioethanol System

#### 3.3.1 Scenario A

This scenario involves another uncontrolled bioethanol system, consisting of multiple competing feedstock and imports. The parameters for the case study are as follows. The technology matrix is:

\[
A = \begin{bmatrix}
1 & 0 & 0 & -0.0035 & 0 & 0 \\
0 & 1 & 0 & 0 & -0.014 & 0 \\
0 & 0 & 1 & 0 & 0 & -0.0056 \\
0 & 0 & 0 & 1 & 1 & 1 \\
-0.57 & -0.16 & -0.122 & 0 & 0 & 0 \\
-0.664 & -0.128 & -0.156 & -0.005 & -0.005 & 0
\end{bmatrix}
\]  

(14)

In Equation 14, the first three columns of \( A \) represent the three competing agricultural sectors (i.e., corn, sugarcane and cassava farming) that have been identified in previous work as the most promising \(^{20}\); the fourth till sixth columns are the ethanol productions of the mentioned agricultural sectors, while the last column is for the imported ethanol. The first three rows of \( A \) represents the feedstock yield of the agricultural sectors (t), the fourth row is the total bioethanol (L) and that last two rows are the land (ha-year) and water (t) resources, respectively. Data for the land requirements and the yield of ethanol from the raw agricultural feedstock are obtained from Ang \(^{21}\). The water footprint of the agricultural sectors are from the work of Gerbens-Leenes et al. \(^{22}\) while the water requirements for the ethanol production is taken from the paper of Tan \(^{23}\).

The influence matrix is:

\[
B = \begin{bmatrix}
0.8 & 0 & 0 & 0 & 0 \\
0 & 0.8 & 0 & -0.05 & 0 \\
0 & 0 & 0.8 & 0 & 0 \\
-0.9 & 0 & 0 & 0.25 & 0 \\
-0 & -0.9 & 0 & 0.5 & 0 \\
0 & 0 & -0.9 & 0.3 & 0 \\
0 & 0 & 0 & 0.8 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}
\]  

(15)

As stated earlier, the rows of \( B \) in Equation 15 correspond to the processes denoted by the columns of \( A \), while its columns correspond to the flows of agricultural feedstock, ethanol output and natural resources consumed. In this example, the agricultural sectors are not only influenced by the amount of raw feedstock, but also by the amount of ethanol produced from a given feedstock. It should also be noted that the ethanol producers are sensitive to the total ethanol that is produced by the system, however, as in the previous case study, importation has a
more sensitive reaction, as this activity requires no substantial capital investment. The final output vector is assumed to be constant:

\[
\mathbf{z}_0 = \begin{bmatrix} 0 \\ 0 \\ 4 \times 10^4 \\ -6 \times 10^5 \\ -7.2 \times 10^3 \end{bmatrix}
\]

(16)

The target ethanol production is considered to be at 400 \times 10^6 L/year, while the land and water resource set for consumption is 6 \times 10^5 ha/year and 7.2 \times 10^6 t, respectively. The land consumption is set at 2% of the total Philippine land area, while the water consumption assumes rainfall of 12,000 t/ha/year. Trajectories of the different production levels of ethanol production and imports over time are shown in Fig. 10. The time period for this case study spans 10 years, with intervals of 0.1 years being used in the simulations. Without any interventions, imports are the largest source of bioethanol for the system, followed closely by sugarcane. Both corn and cassava ethanol production remain at a moderate level. In this scenario, ethanol productions and imports were able to stabilize their output during the fourth year. This is desirable from the standpoint of energy security. It should also be mentioned that the target output of total ethanol production was achieved by the system. As with the previous case study, the necessary conditions must be determined, such that local production can be induced to grow into the major source of ethanol in the system. This scenario will be shown in the next section.

3.3.2 Scenario B

This section uses the same conditions as in the previous scenario, and its goal is to illustrate the effect of government intervention on imports and local production with multiple feedstock. The following control matrix is used:

\[
k = \begin{bmatrix} 0 & 0 & -0.03 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.05 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.04 & 0 \\ 0 & 0 & 0 & 0 & 0 & -0.05 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
\]

(17)

In the control matrix in Equation 17, \( k_{14} \), \( k_{26} \), and \( k_{36} \) denote the incentives (i.e., tax exemptions) given to the three agricultural sectors, corn, sugarcane, and cassava, respectively. This is in response to the amount of ethanol produced from their own raw feedstock. While \( k_{26} \) is the disincentive imposed on imported ethanol (i.e., tariffs) depending upon the amount of ethanol produced by the system. The trend of the controlled production levels of imports and local production with multiple feedstock over time are shown in Fig. 11.

From the simulations, it can be seen that the system is able to completely move away from importation at the fourth year, thus allowing room for the local production of biofuels to develop. However, it was found that the ethanol produced from corn and cassava were not able to compete with sugarcane ethanol, which resulted into the system stopping their production at the sixth and eighth year, respectively. The results show that it is not simply enough to limit the amount of ethanol being imported, rather intervention on the agricultural sectors are also required to successfully induce the growth of biofuels locally. Therefore, cooperation between the agricultural sectors and ethanol producers is necessary for the successful development of biofuels.

There is a need to emphasize that all of the simulations are projections into the future over a period of several years. The simulations are "what if" scenarios, which illustrate different possible interventions to show different possible futures. The simulations derived from this modeling approach are prescriptive guidelines. The decision or policy maker may modify the suggested intervention to
conform to some political or other constraints and repeat the simulation for the modified policy. Alternatively, the simulation could be interpreted as the projected or forecasted future scenario if a policy maker wishes to consider the impact of a prospective intervention.

4. Conclusion

In this paper, we have extended a dynamic input-output modeling approach to simulate the behavior of nascent bioenergy supply chains competing for common resources. Numerical simulations involving the production of biodiesel from multiple feedstock, as well as the competition between locally produced and imported bioethanol were shown to illustrate key behavioral features of such systems. The case studies show that, for both uncontrolled and controlled scenarios, complex interactions exist among the outputs of competing industrial sectors. In particular, it is interesting to note that the collapse of output of some sectors was only temporary and that proper control of the system can guide the growth of a sector to the desired outcome. Another finding is that introducing a time lag to one of the sectors does not necessarily mean that competing sectors benefit, as these might be partly dependent on the other sector. These simulations illustrate the complexity of the interactions within the system, which exhibit trends similar to those seen in some real systems, as shown in the second case study. Sensitivity analysis shows that the system may be more responsive to adjusting the control of one sector than the other. Thus, it is possible to identify for the decision makers the most effective policy interventions. While the precise calibration of B and K remains an unresolved research issue, the current methodology provides a semi-quantitative approach of estimating the effects of different policy measures through sensitivity analysis. The next step in this work is to develop rigorous techniques to identify precise values of parameters in K corresponding to specific levels of taxation or subsidy. Other areas for further research include modeling uncertainties using fuzzy model parameters and the development of a game theoretic extension to the model.

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