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Evaluating the Role of Energy Demand Prediction on Energy Dependency Mitigation: A Generic System Dynamics Model

Emad Rabiei Hosseinabad
Department of Industrial and Systems Engineering,
Northern Illinois University

Reinaldo J. Moraga
Department of Industrial and Systems Engineering,
Northern Illinois University

ABSTRACT
Utilizing available renewable energy resources has been characterized as a reliable indicator to mitigate energy dependency in countries as well as securing the supplying of energy-based needs in the future. This research explores the impact of renewable energy as trustworthy resources in mitigating energy imports and how accurately predicting the energy consumption can lead to better examination of energy dependency. A system dynamics model with special aim on the role of renewable energy resources on decreasing energy dependency has been constructed. By analyzing the dynamics of the model, different scenarios of renewable energy policies are employed as interventions to be implemented and assessed in the model while investigating the applicability of renewable energies to manage national energy supply sustainably. To illustrate the benefits of renewable energy utilization, the proposed model is applied to a case study to analyze the decrease in imported energy resources from external sources. The results indicate that the system dynamics approach outperforms in predicting energy demand compared to the most commonly used techniques in energy forecasting studies and under which policies the desired level of energy dependency will be sustainably achieved.

Keywords: Renewable Energy Policy, System Dynamics Modeling, Energy Dependency, Energy Demand Forecasting, Predictive Modeling, Model Validation

INTRODUCTION
As the International Energy Administration (IEA) states, energy security is defined as "the uninterrupted availability of energy sources at an affordable price" ("What is energy security?", 2017). The definition points to the relation of natural resources and government's capability in meeting daily energy consumption. Energy security is tied with economic and sustainable developments, energy supply-demand balance, and social interactions in countries. Further, long-term and short-term unavailability of energy security can result in unbalanced distribution of energy along with negative economic impacts on both people and the government ("What is energy security?", 2017). According to Shin, Shin and Lee (2013), energy security elements and indicators are categorized as availability, accessibility, affordability and acceptability; each element comprises different components associated with them.

Concerns such as limitation of fossil fuel reservoirs, growing energy demands and instability of energy supply have made governments and policymakers to look for possible alternatives of fossil fuels to stabilize energy security. Utilization of renewable energy resources has been introduced as one of the replacements of fossil fuel reservoirs to secure energy supply in countries (Aslani, Helo, Feng, Antila, & Hiltunen, 2013). Additionally, renewable energy resources are favored because of their diversification and interminable usage in energy-dependent countries. Therefore, the countries relying on renewable energy do not widely import energy sources from other countries for utilization/consumption purposes. In order to be successful in implementing renewable energy policies for countries depending on external energy sources, different scenarios should be employed such as governmental support, strengthening the economy spectrum, and technological renewable energy improvements in countries. This would increase the energy security and provide electricity/energy to people for lower prices (Lean & Smyth, 2013).

Knowing that fossil fuels will be depleted in less than 100 years, it is mandatory that countries alleviate their dependency on finite sources and make a greater attempt to utilize alternative sources such as renewable energies and nuclear energies (Ritchie, 2017). However, there are always constraints for supplying energy in developing and developed countries, which are mostly due to global climate change, energy pricing, increased competition for energy exploiting, and most importantly, growing energy demand (Shin *et al.*, 2013). For instance, in the United States, as the second largest energy consumer in the world, the demand growth in natural gas was more than 60% between the years 2000 and 2016 (Primary Energy Consumption, 2017). The state of Illinois is also considered as the fifth largest energy consumer in end-use sector, which indicates its potentiality in encountering difficulties in supplying the electricity/energy for people ("State of Illinois: Goals Status Report for Energy Efficiency and Renewable Energy," 2016). In this research, the dominant role of renewable energy in security of energy supply will be discussed. The research analyzes the dependency of countries on external energy resources and investigates the role of renewable resources in reducing the dependency from external resources. Different qualitative and quantitative factors are modeled in terms of a causal loop diagram and a stock and flow diagram, which establishes the system dynamics (SD) model.

The rest of the paper is organized as follows: First, we give an overview of previous studies on SD modeling in energy systems and the gap existed to investigate the role of renewable energy in reducing the energy dependency on imported sources. Then, we describe the two steps in development of our proposed SD model to show dynamic interactions between Renewable Energy Utilization (REU), energy dependency, and energy demand in one unique system. After building the model, we investigate the performance of the proposed SD model in predicting electricity/energy demand as the variable that has direct effect in accurately predicting our target variable (energy dependency) in comparison with the most commonly used techniques in energy demand forecasting studies. We then outline an architecture to validate (calibrate) the proposed SD model. Finally, we discuss a real case study developed to test the applicability of the model in predicting the behavior of energy dependency and the role of renewable energy resources in mitigating energy dependency.

LITERATURE REVIEW

In general, the studies focusing on system dynamics (SD) modeling in the energy system field have been discussed for more than 20 years (Aslani *et al.*, 2013). Researchers in the energy system domain have proposed SD as a systematic approach since it provides a more comprehensive understanding of complex systems and the links among their diverse variables. The use of SD model in energy systems is mostly because of its conceptualizing feature that is able to capture not only the factors affecting energy systems but also the interaction between their various factors. SD model enables us to track all the changes that occur among the variables of energy demand and security of energy supply as well as analyzing the effect of different energy policies into the model (Shin *et al*., 2013). Based on literature review investigation, there are four main areas researchers have addressed in the use of SD modeling in energy systems. The four main areas can be divided to physical structure, environmental effects, evaluation of pricing policies, and evaluation of renewable energy policies.

Several researchers have worked on the dynamic modeling of energy physical structures to assess the reliability of the energy transition structure in different areas (Naill, 1977; Naill, 1992; Sauer & Pai, 1998; Ford, 2001; Ballardin, 2005; Olsina, Garcés, & Haubrich, 2006; Chi, Nuttall, & Reiner, 2009). The application of SD modeling in energy resources and structures started in the 1970s. Naill (1977) proposed one of the first extensive energy models with the help of SD modeling to assess the energy transition structure on dependency on oil and gas for the U.S. government. Recently, Chi *et al*. (2009) created an SD model of natural gas resources in the UK and investigated the effect of long-term energy policies in reducing gas consumption. They found that the management of the supply-side policy alone is not able to delay the electricity discovery and production peak. Their explanation variables in the model of the indigenous natural gas industry structure were sensitive to gas price as well as demand rate where they have tried to compensate that with taking advantage of effective policy selections.

The second group of researchers assessed the environmental effect of CO2 emission, industrial pollution, and other waste in energy systems by successfully applying the SD approach (Karavezyris, Timpe, & Marzi, 2002; Güneralp & Barlas, 2003; Anand, Vrat, & Dahiya, 2006; Kunsch & Springael, 2008; Han & Hayashi, 2008; Trappey, Trappey, Lin, & Chang, 2012; Feng, Chen, & Zhang, 2013). The environmental factors are considered to be among the highest probability of occurrence and can be the least effectively mitigated since they tend to be uncontrollable. In one of the few studies conducted in favor of environmental issues using the SD approach, Güneralp and Barlas (2003) performed a dynamic modeling of shallow freshwater lake to establish a balance between the ecosystem and economic activities in the region. Since SD modeling is able to show the trend of target variable with sustainable development perspective, this approach is well-fit for the ecological and economic sustainability balance practice. Therefore, the environmental effects in energy systems can be discussed and categorized with the above description.

With the third group of studies, researchers put their focus on the effect of pricing system and economic indicators such as Gross Domestic Product (GDP) and Feed-in-Tariffs (FITs) on energy indicators to estimate energy market scenarios such as oil, natural gas, gasoline, diesel, and electricity (Bunn & Larsen, 1992; Bunn & Larsen, 1994; Botterud, Korpas, Vogstad, & Wangensteen, 2002; Caselles-Moncho, Ferrandiz-Serrano, & Peris-Mora, 2006; Esmaeeli, Shakouri, & Sedighi, 2006; Sánchez, Barquin, Centeno, & Lopez-Pena, 2007; Wu, Huang, & Liu, 2011). Fundamentally, these studies look for the changes of the pricing mechanism for different energy market behaviors in order to convey the relative applications of SD and to understand the impacting factors of energy market behaviors. Bunn and Larsen (1992) investigated the investment in the electricity market of England and Wales. Using an SD model of investment, they generated insights into the unpredictability of the variations in the Loss of Load Probability (LOLP) and several market share scenarios. In recent years, new works have emerged in pricing systems to improve some modeling aspects of previous studies such as market price representation, the model dynamics in investment policies, and risk analysis of investors in the electricity market.

A few works have also been conducted to evaluate the impact of dynamic modeling of renewable energy policies on security of energy supply by implementing SD models (Bennett, 2012; Hsu, 2012; Aslani *et al*., 2013; Mediavilla, de Castro, Capellán, Miguel, Arto, & Frechoso, 2013; Shin *et al.,* 2013). The developed models help predict observable patterns of behavior of renewable energy resources in micro-level energy structures, their impact in eliminating environmental issues, and assess the renewable resources as a replacement of non-renewable resources and fossil fuels, which led to identifying the key energy policies on security of energy supply in different countries. This could potentially influence the rate of interest value in terms of different policies.

In summary, the literature reveals a lack of research that explore the utilization of renewable energy resources for reducing the dependency of energy from imported sources sustainably as well as considering the dynamic interactions among REU, energy imports, and energy consumption as one unique system. Further, validation of presented models and how reliable the renewable action plans are on securing energy supply and energy dependency in a sustainable fashion is another gap that has been left intact.

This research aims to address this existing research gap by accurately predicting electricity/energy consumption compared to other methods and evaluating the effect of renewable sources in reducing energy dependency. In order to do so, the effectiveness of SD modeling in predicting electricity/energy demand and consumption in the future is compared and discussed with the most commonly used techniques in energy demand forecasting studies (Jebaraj & Iniyan, 2006). The main effort in this research is to address predicting the behavior of the energy demand and energy dependency to investigate the role of renewable energy in reducing the energy dependency on imported sources in the future. The current research will also suggest that policy and decision makers should review their RE promotion plans to achieve a desirable level of dependency and security of energy supply.

METHODOLOGY

SD is a system thinking approach which enables us to model a complex system with all the variables and factors affecting the system over time (Sterman, 2000). SD modeling will involve addressing the development of a causal loop model (which is conceptual) and stock & flow model (which is quantitative). The SD approach can predict the behavior of the system based on the interactions between the variables and factors contributing in the model. The process of developing the two steps of system dynamics modeling (causal loop modeling and stock and flow modeling) involve computer simulation for the energy-related problem. Causal loop modeling includes defining the objectives, determining the variables, causal relations, and policy framework of the system with the help of self-judgment as well as experts' opinions. Stock and flow diagrams are the fundamental structure in generating a simulation model since they assist capturing the most important variables in causing behaviors and trends (Behzad, Moraga, & Chen, 2011). After setting up the causal loop diagram (CLD) and stock & flow diagram (SFD), a numerical example with real-life data is solved using the proposed model in order to verify the model validity on predicting the behavior of energy demand as well as predicting the energy dependency in a metropolis. Recently, this approach has been a trend to address to environmental and energy systems. After setting up the CLD and SFD, it is crucial to calibrate the model in order to assure that all variables' behavior within the model make sense. When the model is validated, it opens a path to more investigation on the model by intervening with different policies.

Causal Loop Modeling of Energy Demand, Renewable Energy Utilization, and Energy Dependency

In order to set up the causal loop diagram, first the variables affecting the model should be identified. This process is achieved by reviewing the literature and inquiring from the experts in the particular subject matter. The variables developed in the CLD can be both quantitative and qualitative. Moreover, the interrelations between the proposed variables in causal loop modeling can be validated by justifiable explanation or referring to literature in the subject matter (Sterman, 1984). In the process of building a causal effect model, the diagram can be divided into several parts to better explain the model from different perspectives.

The causal loop feedback proposed in this article comprises three different subdivisions (Sisodia, Sahay, & Singh, 2016). The first CLD model is designed to explain the energy demand module, which represents the indicators that affect the energy demand in a country (economic indicators, governmental regulations). The second CLD indicates the dependency of energy on imported sources and the gap between energy demand and the imported energy and its indicators in a country. The third CLD focuses on renewable interactions as a replacement for non-renewables and as sources of reducing energy insecurity and energy dependency.

In Figure 1, shows the feedback structure of energy demand and energy security. As energy consumption increases, energy demand increases but energy storage decreases. An increase in energy supply directly and negatively affects the energy storage, which causes a decrease in that variable. GDP, on the other hand, affects economic growth and positively gets affected by the population of the country. As energy security increases, the government is more encouraged to invest and implement plans of action on energy R&D systems to increase the security of supplying energy as well as energy consumption. The relationship among variables represented in this first CLD is concordant with what Berry (2014) and Peterson (2017) explain. Two balancing loops are identified in the first CLD. Both represent the interactions between energy consumption, energy security, and energy storage.

In Figure 2, energy dependency, energy imports, and their indicators are shown. Importing energy from other countries or external sources is directly associated with the fact that the targeted countries are energy dependent. Also, the political stability and energy consumption of the supplier country can raise the amount of imported energy to the targeted country (Sisodia et al., 2016). However, importing energy from external sources can increase the risks involved with energy transportation and that can result in increasing energy importing costs.

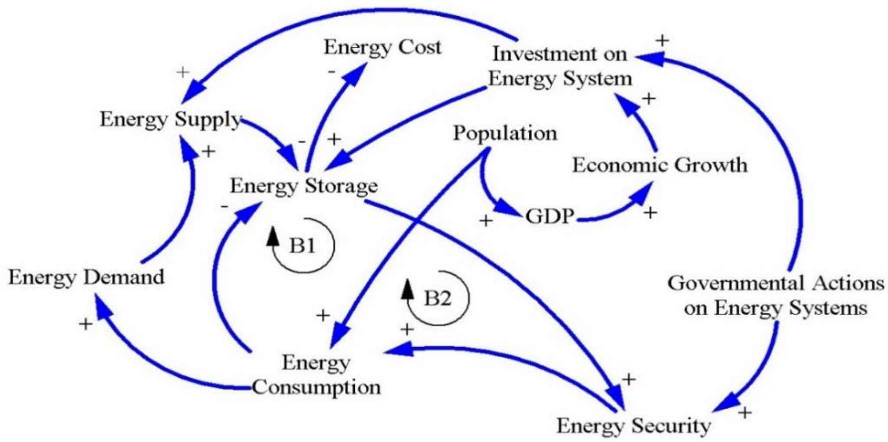

Figure 1: Structure of Energy Demand and Energy Security Interactions

Consequently, the tendency to import energy will decrease. All of these interactions can affect the energy dependency of countries and should encourage policy makers to reconsider their renewable energy policy development. Also, the only loop existing in module 2 includes the interaction of import energy, risk of energy transportation, importing energy price, and shift to alternative energy.

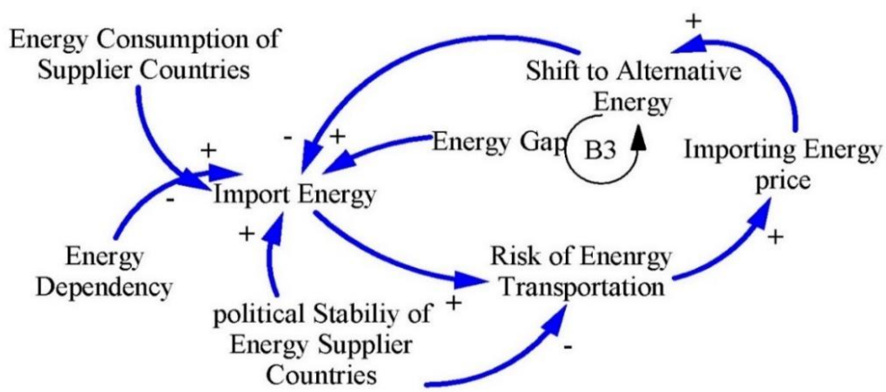

Figure 2: Structure of Energy Dependency and Energy Imports Interactions

In Figure 3, the main focus is on establishing appropriate renewable energy action plans by investing and considering the risk of establishing renewable resources. When a country is energy dependent, the potential capacity of utilizing renewables will increase. As the renewable energy generation increases by some extent, the cost of installation of renewable resources will be increased accordingly, and that will result in decrease in the rate of return gained from renewables, which boosts the uncertainty on REU and discourages the government to grant more financial initiatives in renewable energy investment (Aslani *et al.*, 2013; Feili, Ahmadian, & Rabiei Hosseinabad, 2014). As far as renewable energy investment and renewable energy generation are concerned, the technology, as well as public awareness, should be increased to help develop renewable energy infrastructure. It is worth noting that as the number of renewable energy resources increases, the number of depreciated renewable energy resources increases respectively and that will reduce the capacity of renewable energies respectively.

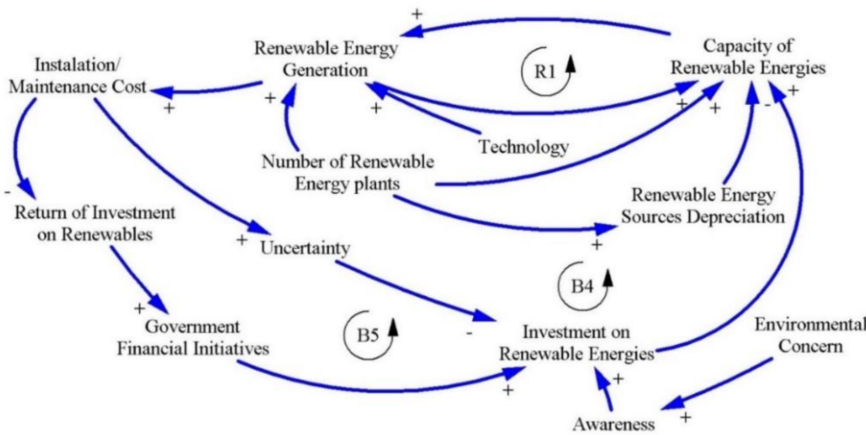

Figure 3: Structure of Renewable Energy Interactions

All of the illustrated CLDs can be integrated as modules into one unique CLD to better grasp the initial dynamic behavior that contains all the comprehensive factors in terms of energy system, energy dependency, and renewable energy role along with their interactions. The interaction between variables can be reinforcing which increase in one of them results in increase in another one. The interaction between variables can be balancing as well which increase in one of them results in decrease in another one. The integrated model is illustrated in Figure 4 which shows five balancing loops and one reinforcing loop. For instance, loop B1 indicates that as energy supply increases, energy storage will decrease, which will reduce the energy security in providing energy for people. This will lead to energy consumption and energy demand reduction. Loop B2 is a subset of loop B1 and illustrates that energy consumption will reduce the energy storage, and that will result in energy insecurity.

Stock and Flow Modeling of Energy Demand, Renewable Energy Utilization, and Energy Dependency

The creation of stock and flow diagram (SFD) is the second step of SD modeling. SFD captures a snapshot of the integrated CLD by including the most important variables in causing behaviors and trends and removing insignificant policies to simplify the model (Sterman, 2000). SFDs help in simulating the behavior of a system as well as each variable in specific periods of time. The equations, numerical quantities, and trends are to be performed in the SFD. After inputting data and equations, the simulation is run (Rabiei Hosseinabad & Moraga, 2017). The stocks in a system tell decision makers where they are, providing them with the information needed to act. Figure 5 shows the SFD model of renewable energy policies to evaluate the level of energy dependency of a country or city. Initially, this SFD was created and developed by Aslani *et al.* (2013). However, in the case discussed in this article an attempt is made to capture the elements and the factors that were not discussed previously (interactions among REU, energy imports, and energy consumption) by presenting a generic SD model that takes all the renewable energy resources with associated variables that can be utilized for different energy dependent countries or cities.

In the presented SFD, seven stocks, in a form of renewable energy sources, are introduced that could potentially reduce energy dependency on imported sources and capturing the electricity/energy demand and its growth rate. These stocks include all the possible renewable energy sources such as capacity of biomass energy, capacity of hydropower energy, capacity of tidal energy, capacity of solar energy, and capacity of geothermal energy. Also, electricity/energy domestic demand is shown as another stock to capture the interaction between energy consumption and security of energy supply.

All the capacity of renewable energy sources is captured in a variable named renewable energy accumulation. Renewable energy accumulation is the summation of electricity generated by all renewable energy resources. The capacity of each renewable is affected by an increased number of renewable energy resources, which is influenced by governmental plans and policies on specific renewable energy resources in the future. The capacity of renewable energy resources is also affected by the number of depreciated renewable energy plants. The number of depreciated renewable energy plants is affected by delay time, which means that it is dependent on the number of added renewable energy plants and the depreciation periods of each renewable plant. In this model, it is attempted to construct an intermediate complex SD model with a number of crucial interactions and to include comprehensive factors in studying the role of renewable energy in reducing energy dependency, which can be used as a framework for further policy analysis. The total energy demand that is accumulated in a stock can be initially compensated by electricity/energy extracted from nuclear plants. However, not all of a country's entire energy demand can be supplied from nuclear plants and fossil fuel sources. The gap that exists after subtracting domestic energy demand and nuclear energy and fossil fuel should be filled by importing energy from external sources. Therefore, the dependency of importing energy from external sources should be the difference between the remaining energy demand from nuclear energy and domestic demand and renewable energy accumulation, which has the contribution in mitigating the electricity/energy demand as well.

SYSTEM DYNAMICS MODEL PERFORMANCE COMPARISON WITH FORECASTING METHODS

In order to assess the applicability of SD model built for predicting electricity/energy demand, a comparison is performed against various other predictive models developed for energy demand forecasting. Three common metrics found in literature will be used to do the comparison (Akay & Atak, 2007; Erdogdu, 2007; Hamzaçebi, 2007; Sterman, 2000; Bianco, Manca, & Nardini, 2009): R-squared value, root mean square error (RMSE), and mean absolute percentage error (MAPE). All of them are briefly defined as follows:

R-squared Value

This performance metric determines how close the estimated data are to the actual observed data. It is also used to investigate on the possible interrelations between different factors within a system. (Kankal, Akpınar, Kömürcü, & Özşahin, 2011).

Root Mean Square Error (RMSE)

This metric is used to provide measures of the average error between the simulated and actual series. RMSE is the most used and common measure in comparing SD models with other models (Sterman, 2000). The RMSE formula is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

where y_j is the actual value of a point for a given time period *j*, $\hat{y}_j$ is the simulated (estimated) value for a given time period *t*, and *n* is the total chosen number of fitted points.

Mean Absolute Percentage Error (MAPE)

This metric is used to determine the accuracy of a proposed model. It compares the absolute percentage error for each forecast and calculates the average of percentage errors (Sterman, 2008). It usually expresses accuracy as a percentage and is defined in the formula below (Hyndman & Koehler, 2006). The MAPE formula is as follows:

$$MAPE = \frac{100}{n}\sum_{j=1}^{n}\frac{|y_j - \hat{y}_j|}{|y_j|}$$

where y_j is the actual value of a point for a given time period *j*, $\hat{y}_j$ is the simulated (estimated) value for a given time period *t*, and *n* is the total chosen number of fitted points.

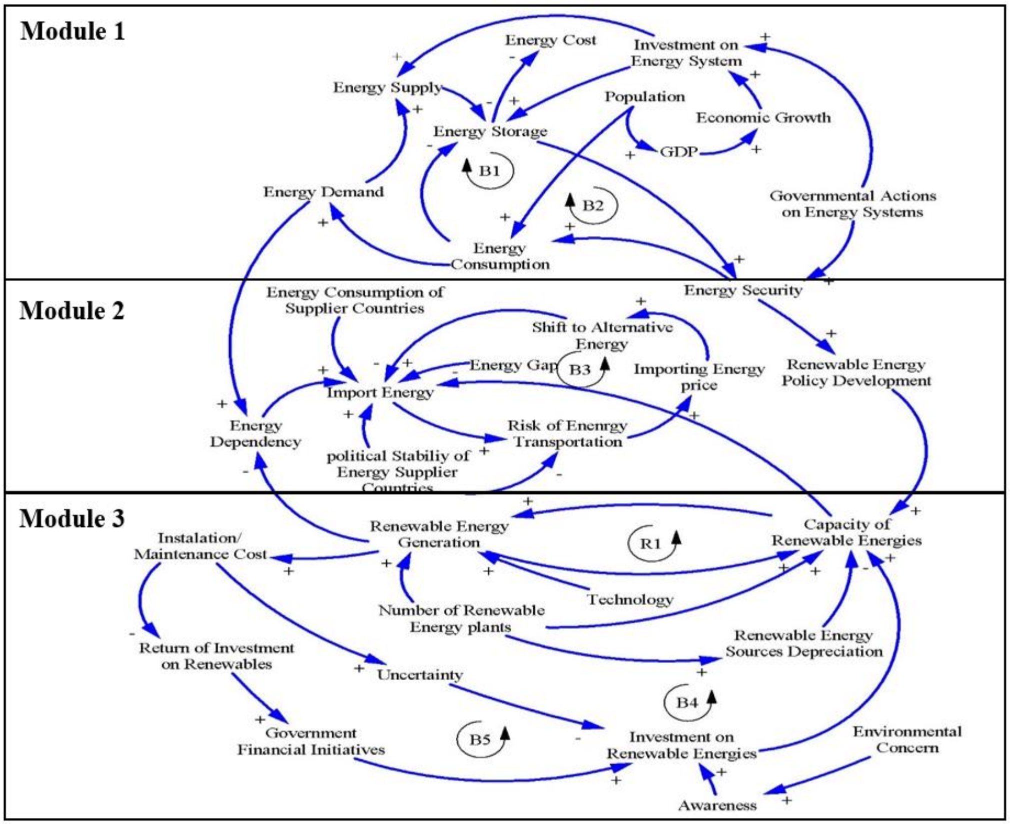

Figure 4: Causal Loop Modeling of Energy Demand, REU, and Energy Dependency

In what follows, we investigate the performance of the proposed SD model in predicting electricity/energy demand. We then validate the proposed SD model. Finally, we discuss a real case study developed to test the applicability of the model in predicting the behavior of energy dependency and the role of renewable energy resources in mitigating energy dependency.

SD Model Comparison against Forecasting Models to Fit Historical Energy Demand

In literature, remarkable works have been conducted for energy demand forecasting. Model for analysis of energy demand (MAED), grey prediction with rolling mechanism (GPRM), Box-Jenkins models (ARIMA), regression models, and neural networks are the most commonly used techniques in energy forecasting studies (Jebaraj & Iniyan, 2006). Since the selected case studies in literature conducted energy demand forecasting for different countries for different time frames, the historical energy demand values in terms of each case study is different. In the comparison performed in this study, the SD model framework remains the same.

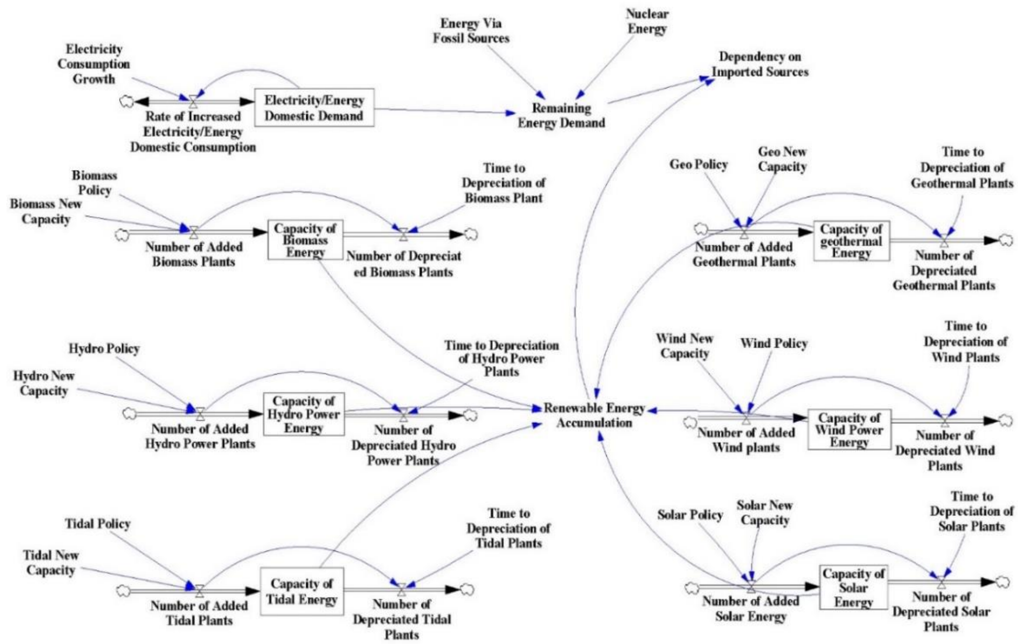

Figure 5: Stock and Flow Modeling of Energy Demand, REU, and Energy Dependency

The result of the proposed SD simulation model performed very well for fitting historical demand when compared to MAED's and GPRM's results reported by Akay and Atak (2007), using the total electricity consumption in Turkey from 1994-2004. As Table 1 shows, in both MAPE and RMSE, the proposed SD model outperforms MAED and GPRM models; hence, the SD model brings about better fitting accuracy and can be implemented reliably. The logic behind that difference is that MAED models utilize too much data as well as experimental knowledge which amplifies the error in the case of high variability between indicators. On the other hand, the smaller correlation in the GPRM model can be attributed to the fact that this method only considers the recent data, which might be reasonable for only short-term prediction (Akay & Atak, 2007). In terms of the R-squared metric, both SD and MAED models are not significantly different from each other. On the other hand, the RMSE value and average MAPE of the SD model are smaller in comparison with the GPRM model (by 0.40 and 0.18 respectively) and R-squared value of the SD model is higher than the GPRM. The smaller correlation in the GPRM model can be attributed to the fact that this method only considers the recent data, which might be reasonable for only short-term prediction (Akay & Atak, 2007).

A second case study conducted by Erdogdu (2007) is used to compare the proposed SD model. Erdogdu (2007) explores the accuracy of ARIMA modeling in predicting energy (electricity) consumption in Turkey from 2005 to 2014. The ARIMA methodology is a forecasting tool that focus on analyzing probabilistic properties of economic time series based on their own behavior rather than constructing single equation models (Box, Jenkins, Reinsel, & Ljung, 2015). Table 2 shows that the proposed SD model outperforms ARIMA model in the three metrics. This result attests to the higher accuracy of the SD model in comparison with ARIMA models in terms of energy consumption. The R-squared metric conveys the fact that the SD model was able to explain better the causal relationship between variables.

Another commonly used technique in energy forecasting studies is regression models. In this third case study done by Bianco et al. (2009) in Italy, they investigated four multiple regression models considering different factors to see which one could more accurately forecast the historical energy demand in Italy. They concluded that the fourth regression model outperformed the other three which reveals that GDP per capita and the ratio between GDP and population as the explaining variable were the leverage factors in predicting the energy demand when using regression models and, thus, the SD model is compared with their fourth model. The results are shown in Table 3 for the dataset (Terna Rete Italia, 2008) that contains the actual total electricity consumption in Italy from 2002 to 2007. The SD model has an outstanding performance compared to authors' fourth regression model. In fact, the values of the three metrics used for the comparison (RMSE, MAPE, R-squared) show the SD model has an acceptable level in fitting historical data. The regression model equation in the case study to compare with the SD model is as follows:

$$Y_{tot,t} = a + b_1 X_{3,t} + b_2 X_{tot,t-1} + e$$

Where Y_t is the annual electricity consumption in GWh, $X_{3,t}$ is the annual GDP per capita in Euro, b_1 and b_3 are the regression coefficients, and e is the error

Table 1: Comparison of SD to MAED and GPRM for Total Historical Electricity Consumption (TWH)

Year	Actual	MAED	Error (%)	GPRM	Error (%)	SD	Error (%)
1994	61.4	66.82	8.83	64.88	5.67	63.24	3
1995	67.39	74.57	10.65	65.93	2.17	67.52	0.19
1996	74.16	81.23	9.54	71.34	3.8	72.08	2.8
1997	81.88	88.48	8.05	81.4	0.59	76.95	6.02
1998	87.7	96.38	9.89	90.13	2.77	82.15	6.33
1999	91.2	104.99	15.12	95.63	4.86	87.7	3.84
2000	98.3	114.37	16.35	96.6	1.73	93.63	4.75
2001	97.07	123.6	27.33	103.6	6.69	99.96	2.98
2002	102.95	133.58	29.76	101.5	1.46	106.7	3.64
2003	111.77	144.36	29.16	104.2	6.75	113.9	1.91
2004	121.14	156.01	28.78	119.5	1.33	121.6	0.38
MAPE			17.59		3.44		3.26
RMSE		20.49		3.75		3.35	
R-Squared Value		0.986		0.977		0.985	

The last method used to compare the proposed SD model is Artificial Neural Network (ANN), which is one of most commonly techniques used in energy demand prediction. Hamzaçebi (2007) presents a case study where the electricity consumption is forecasted on sectorial bases in Turkey from 2005 to 2020 (Hamzaçebi, 2007). The results of comparing the proposed SD model and ANN are provided in Table 4. The first impression is that ANN performs better in fitting historical energy consumption trend compared to our proposed SD model. The MAPE for ANN is 0.67, which is less than that of the SD model with a MAPE value of 1.44, which indicates that error percentage for ANN method is less for the SD model. Also, RMSE of ANN is 0.58 against 1.41 for the SD model, which shows that ANN was able to better fit the historical data. R-squared value for both methods reveals that it may not be a proper metric to investigate the possible linear relationship between actual data and the two mentioned models It must be noted that the validation and testing of the ANN model has been conducted for only two years (2003 and 2004), which is not quite sufficient in establishing the applicability of one model in prediction or even addressing the advantage of one methodology over another. The R-squared value may not be a proper metric to investigate the possible linear relationship between actual data and the two mentioned models. It must be noted that the validation and testing of the ANN model has been conducted for only two years (2003 and 2004), which is not sufficient in establishing the applicability of one model in prediction or even addressing the advantage of one methodology over another. Although ANN better predicted the energy consumption, utilizing neural network methodology could lead to relatively higher processing times and is not able to represent the causal relations between variables.

Table 2: Comparison of SD to ARIMA for Total Historical Electricity Consumption (TWH)

Year	Actual	ARIMA	Error (%)	SD	Error (%)
2000	98.3	98.8	0.51	96.02	2.32
2001	97.07	101.2	4.25	101.1	4.15
2002	102.95	105.1	2.09	106.4	3.35
2003	111.77	111.1	0.6	112.1	0.3
2004	121.14	112.5	7.13	118	2.59
MAPE			2.97		2.54
RMSE		4.4		2.94	
R-Squared Value		0.944		0.954	

SD Model Comparison against Forecasting Models to Predict Energy Demand

In this section, given the availability of data, the proposed SD model is compared against ARIMA and ANN in terms of its performance for energy demand prediction accuracy. It is important to remark that the comparison timeframe for fitting the historical data of ARIMA and ANN is in the range between 2000-2004 (Erdogdu, 2007) and 2003 and 2004 (Hamzaçebi, 2007), respectively. Now, the timeframe for the prediction of energy/electricity demand is on the range of 2005-2014 and 2005-2016, respectively.

Table 3: Comparison of SD to Multiple Regression Models for Total Historical Electricity Consumption (TWH)

Year	Actual	Reg. Model	Error (%)	SD	Error (%)
2002	290.9	291.71	0.26	292	0.37
2003	299.9	296.36	1.16	297.9	0.66
2004	304.6	304.34	0.05	303.8	0.26
2005	310.2	308.35	0.47	309.9	0.09
2006	318.5	313.71	1.22	316.1	0.75
2007	319.51	320.86	0.59	322.4	0.9
MAPE			0.625		0.51

RMSE		2.62		1.83	
R-Squared Value		0.975		0.985	

Table 4: Comparison of SD to ANN for Total Historical Electricity Consumption (TWH)

Year	Actual	ANN	Error (%)	SD	Error (%)
2003	111.77	112.1	0.3	112.1	0.3
2004	121.14	122.4	1.04	118	2.59
MAPE			0.67		1.44
RMSE	0.58			1.41	
R-Squared Value	1			1	

Table 5 shows ARIMA model has more deviation from the actual data than the proposed SD model. As it can be perceived, the ARIMA model shows more deviation from the actual data than SD model. MAPE metric for the SD model is 9.05, which is less than that of ARIMA with MAPE of 11.81. Further, RMSE value of SD model shows higher prediction accuracy compared to the ARIMA model (15.67 against 24.07), and the R-squared value reveals that the SD model had more correlation to the actual values compared to the ARIMA model.

Table 6 indicates the comparison of prediction accuracy between SD and ANN models for total electricity consumption. ANN model shows more deviation from the actual data than the SD model. The MAPE measure for the SD model is 9.00, which is less than that of ANN with MAPE of 23.32. Further, the RMSE value of the SD model shows considerably higher prediction accuracy compare to ANN model (16.36 against 58.36). The R-squared value reveals that the SD model was able to show more correlation to the actual values compared to ANN model (0.990 and 0.986 respectively). This reported empirical comparison between different methods states that the SD model provided more reliable results in terms of energy consumption forecasting than common forecasting techniques.

Table 5: Comparison of Prediction Accuracy between SD and Box-Jenkins (ARIMA) for Total Electricity Consumption (TWH)

Year	Actual	ARIMA	Error (%)	SD	Error (%)
2005	130.26	129.3	0.74	123.8	4.96
2006	143.07	132.63	7.3	129.8	9.28
2007	155.14	138.1	10.98	136.2	12.21
2008	161.95	146.4	9.6	142.9	11.76
2009	156.89	145.14	7.49	149.9	4.46
2010	172.05	155.66	9.53	157.2	8.63
2011	186.1	156.01	16.17	164.9	11.39
2012	194.92	158.1	18.89	173	11.25
2013	198.04	169.2	14.56	181.5	8.35
2014	207.37	160.1	22.8	190.4	8.18
MAPE			11.81		9.05
RMSE	24.07			15.67	
R-Squared Value	0.943			0.983	

A CASE STUDY: APPLICATION THE SD MODEL ON AN ENERGY DEPENDENT FOR ILLINOIS

The state of Illinois is located in the midwestern U.S. with a population of 13 million and is considered the fifth most populated state in the U.S. ("Illinois: An Energy and Economic Analysis," 2014). Although the population of Illinois increased only 4% from 2000 to 2017, the energy consumption has been boosted more than 30%, which is mostly dependent on coal resources, fossil fuels, nuclear plants, and imported energy ("Illinois: An Energy and Economic Analysis," 2014). Therefore, the security of the energy supply should be a priority for decision makers in Illinois in order to ensure that it meets the total energy demand and reduces energy dependency on imported sources.

Figure 6, shows an increase of 20% in the total energy consumption in Illinois out of different sources from 1990 to 2017. Different types of renewable energy resources are utilized in Illinois, such as solar, wind, biomass, biogas, hydropower, etc. ("Clean Energy," n.d.). Although Illinois is among the states with the highest energy consumption in the Midwest, it only utilizes about 6% of the net energy generated from renewable energy resources. The majority of energy demand is satisfied from fossil fuels, nuclear plants and external resources. Also, projected future energy/electricity usage shows that the electricity load requirement will be increased from 145 TWH in 2016 to more than 170 TWH in 2025 ("State Profiles and Energy Estimates," 2017). Therefore, the energy dependency on non-renewable resources will increase the cost of providing energy, which makes the role of renewable energy resources significant.

Table 6: Comparison of Prediction Accuracy between SD and ANN for Total Electricity Consumption (TWH)

Year	Actual	ANN	Error (%)	SD	Error (%)
2005	130.26	133.5	2.49	123.8	5.27
2006	143.07	145.7	1.84	129.8	8.44
2007	155.14	159	2.49	136.2	10.27
2008	161.95	173.6	7.19	142.9	8.74
2009	156.89	189.5	20.79	149.9	0.07
2010	172.05	206.8	20.2	157.2	3.05
2011	186.1	225.8	21.33	164.9	4.84
2012	194.92	246.5	26.46	173	3.5
2013	198.04	269.2	35.93	181.5	2.66
2014	207.37	294	41.78	190.4	2.38
2015	217.31	321	47.72	199.7	3.72
2016	231.2	350.7	51.69	209.5	3.59
MAPE			23.32		9
RMSE	58.36			16.36	
R-Squared Value	0.986			0.99	

In Illinois case study, a renewable energy resource can act as an intervention in the model to predict the behavior of energy consumption and energy dependency based on different scenarios. The role of renewable energy resources is to meet energy demand and reduce energy dependency on imported energy resources. In order to investigate the role of renewable energy, a cause and effect diagram and stock and flow diagram are proposed to assess energy demand, REU, and energy dependency interactions together. A complete description of the proposed diagrams are explained in the methodology section (see Figure 4 and Figure 5). Table 7 illustrates the depreciation periods of renewable energy resources, which were obtained from previous studies' assumptions on depreciation periods of renewable energy plants (Aslani *et al.*, 2013). The number of added renewable energy plants is directly influenced by the U.S. Department of Energy's policies or proceedings, which are explained in Table 8 (State of Illinois: Goals Status Report for Energy Efficiency and Renewable Energy, 2016).

Model Validation

The proposed SD model is used in the Illinois case study with the objective of examining what-if scenarios to test their impact in mitigating energy dependency. Before discussing the results obtained from the simulation model, as part of the methodology it is key that the proposed model be validated through testing and refinement.

Table 7: Depreciation Periods of Renewable Energy Resource

Renewable Energy	Depreciation Period
Solar	20
Geothermal	25
Biomass	30
Windpower	25
Hydropower	15
Tidal	15

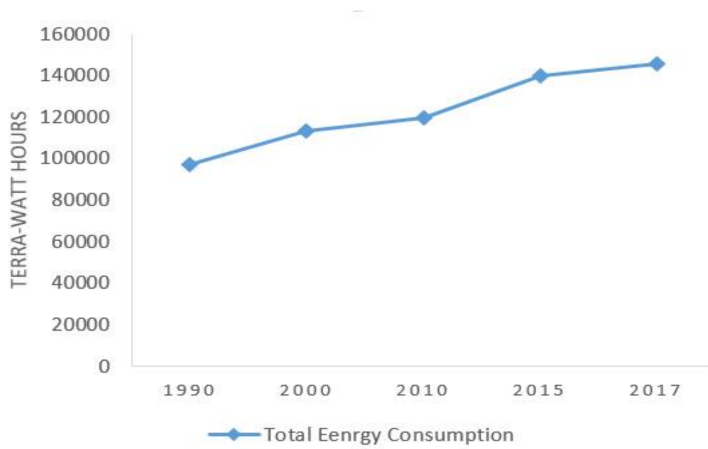

Figure 6: Major Energy Consumption Resources in Illinois

This article establishes two different validation tests to prove the accuracy of the proposed SD model. In general, the validity test is performed to evaluate reliability, consistency, and accuracy in predicting the behavior of model variables, to establish whether the model is able to be fine-tuned, and whether the model fits the actual system (Wu *et al*., 2011). The two main validation tests performed in this study are: model behavior and behavior reproduction (Senge & Forrester, 1980; Wu *et al.*, 2011):

- **Model behavior (Calibration Test)**: The target of the model behavior test was to investigate the behavior of electricity/energy domestic demand in Illinois as a target variable simulated in the model from the years 2009 to 2017 and compare the target variable with actual electricity consumption in Illinois obtained from historical data. In order to investigate the goodness of calibration process and whether the proposed model is suitable to fit historical data (in this case electricity/energy consumption), a pay-off metric is used. This pay-off metric is a negative number and states accuracy of the simulation and should be maximized. When the calibration is performed, the optimal pay-off is calculated as -0.167, which is very close to zero, indicating that the model is able to relatively fit the historical data based on chosen intervals for variables. The calibration simulation results in Figure 7 for the period 2009 to 2017 show that the proposed model could approximately be consistent with the actual behavior of electricity/energy consumption. To ensure that the gaps between the simulated model and historical data in Figure 7 are not significant, a statistical validation test was performed. The normality test performed on both actual behavior and simulated datasets show that the normal distribution cannot be discarded with α=0.05 (significance level). In order to test the difference of means between both datasets, a two sample *t*-test was performed. Therefore, the hypothesis test with respect to the two sample *t*-test is as follows:

$$\begin{cases} H_0: \mu_{real} = \mu_{model} \\ H_1: \mu_{real} \neq \mu_{model} \end{cases}$$

The result of the two sample *t*-test shows that the *p*-value is equal to 0.979 (> 0.05). In this case, the test failed to reject the null hypothesis. This means the behavior of both historical and simulated data sets cannot be considered unequal at α=0.05. Hence, the system dynamics model has the acceptable fit to the historical trends and can be utilized as a valid representation for the behavior of the electricity/energy consumption in the state of Illinois.

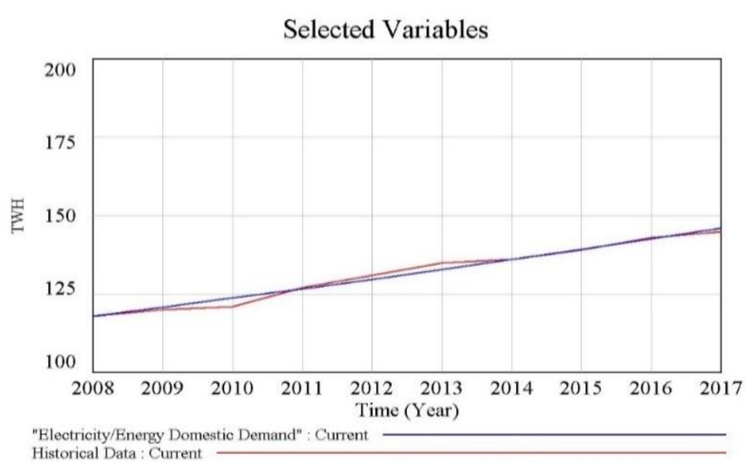

Figure 7: Model Validation by Comparison between Historical and Simulated Data

- **Behavior reproduction test**: Many tools are available to assess a model's ability to reproduce the behavior of a system. According to some authors (Sharareh, Sabounchi, Sayama, and MacDonald, 2016), to evaluate different predictive models and how closely models are able to fit the actual electricity/energy demand, a metric as the root mean square error (RMSE) of the model should be calculated. Table 9 illustrates that the RMSE value of electricity/energy demand is about 1.09, which is fairly low and indicates that the RMSE obtained from the comparison between the SD model and the actual value is only about 2% of smallest and largest value of electricity/energy demand between the years 2009 and 2017, which establishes the fact that the final simulation model has a good fit.

Discussion of Results-Energy Dependency Forecasting

After ensuring the validity of the SD model, it is necessary to use it as prediction tool of the target variables. In Figure 8, the electricity/energy prediction in the state of Illinois between the years 2018 to 2025 is highlighted. The prediction is aligned with Illinois's projected energy demand in 2025 ("State of Illinois: Goals Status Report for Energy Efficiency and Renewable Energy," 2016). Further, as Figure 8 indicates, the electricity/energy domestic demand will grow from 145.9 TWH in 2018 to 156.4 TWH in 2025, which shows about 1.5% growth in electricity/energy demand. In order to investigate the accuracy of the proposed SD model in predicting the electricity/energy demand in Illinois from 2018 to 2025, the results are compared with projected electricity/energy requirement in Illinois by the U.S. Department of Energy.

The fact that the model is able to accurately predict energy consumption eventually leads to accurately forecasting the dependency of energy from imported sources, since electricity/energy demand directly affects the energy dependency. The accuracy of the proposed simulation model in predicting the future trend on electricity/energy demand and subsequently energy dependency is not only dependent on capturing a comprehensive number of variables contributing to the electricity/energy system, but it should also be able to remain consistent when implementing different scenarios in the system (Qudrat-Ullah & Seong, 2010; Feng *et al.*, 2013).

Table 8: Description of Targets in Promoting Renewable Energy Resources in Illinois by 2025

Renewable Energy Resources	Target in 2025	Current policy schemes
Solar	Increase up to 15 TWH	The Future Energy Jobs Act (FEJA) will invest more than $750 million in low-income programs, including new Illinois Solar for All Program to prioritize new solar development
Geothermal	Increase up to 10 GWH	Funding more than $6 million for drilling geothermal system fields in Illinois
Wood and other Biomass	Increase up to 55 TWH	Illinois is in the development stages to construct five ethanol/biodiesel plants

Wind power	Increase up to 20 TWH	A minimum of 60% of the renewable energy resources must be sourced from wind power assets
Hydropower	Increase up to 25 TWH	New construction or significant expansion of hydropower dams
Tidal	Marginal increase	______

Table 9: RMSE Value from Model Validation (Actual and SD Values Are in TWH)

Year	Actual	SD	Error (%)
2009	120	120.8	0.67
2010	121	123.7	2.23
2011	127	126.7	0.24
2012	131	129.7	0.99
2013	135	132.9	1.56
2014	136	136.1	0.07
2015	139	139.3	0.22
2016	143	142.7	0.21
2017	145	146.1	0.76
RMSE	1.09		

Scenario Evaluation

It is always critical to take into consideration different policies in the model to better make decisions on what is best for managing energy dependency and reinforcing the role of renewables on meeting energy demand. The dependency of energy in each year is estimated by applying three different scenarios in the model:

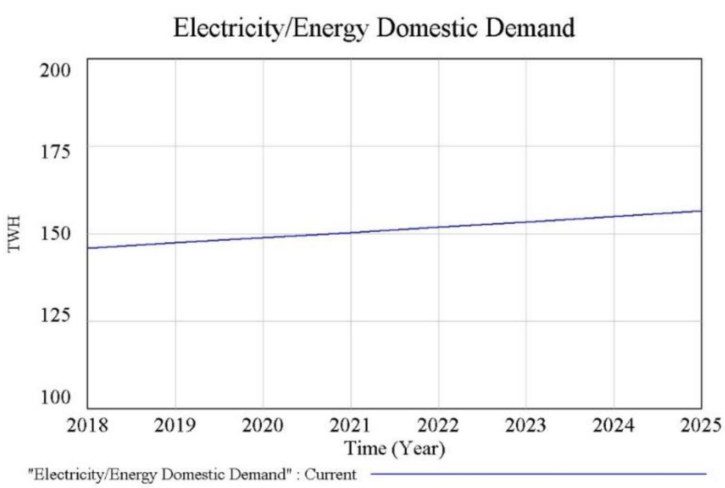

Figure 8: Electricity/Energy Domestic Demand in Illinois

1. **First Scenario:** Before implementation of any renewable energy policies or action plans in the model, a baseline needs to be set (*i.e.*, the current electricity/energy demand and its interactions were considered without any new renewable plant installation).

The first scenario is set as a baseline for other scenarios and indicates the current energy dependency status without implementing any renewable energy action plans. Based on the first scenario, the amount of the electricity/energy accumulated from renewable energy resources was fixed between 2018 to 2025 since no action plans were implemented in the model. Thus, as Figure 9 shows, the energy dependency is about 45.02 TWH in 2018 and will continue to decrease down to 40.54 TWH in 2025 (4% decrease). However, since it is assumed that a new nuclear power plant will start to operate in 2020, energy dependency will reduce in 2020 to 32.95 TWH and again rise to 40.54 TWH in 2025.

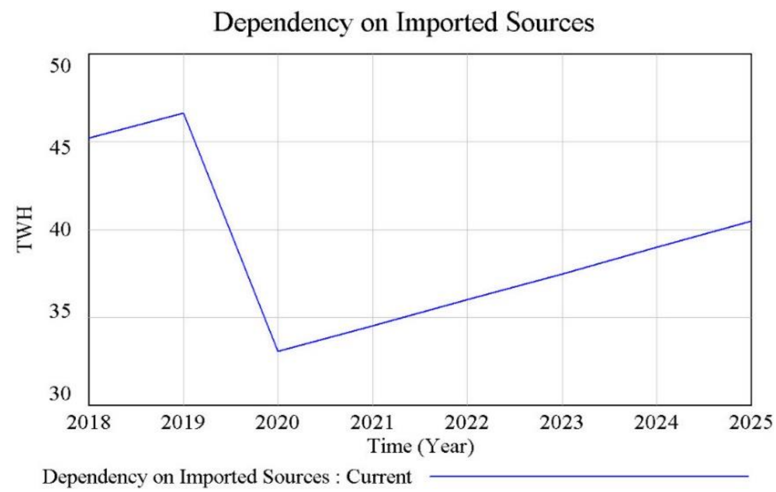

Figure 9: Dependency of Energy After First Scenario

2. **Second Scenario:** After promotion of partial renewable energy installation plans, which includes 80% hydropower, 100% wind, 50% solar, 70% biomass, 40% geothermal, and 40% tidal installation. It is worth mentioning that the assumption was based on actual progress of the renewable plant installation and the decision was made based on the observations attained when analyzing the different behaviors of different variables through trial and error.

The second scenario was designed based on experts' opinions and the trend of projected renewable energy action plans in Illinois. This scenario is known as a "conservative" scenario, which is affected by multiple factors, such as investments, economic issues, bank interests, and estimation errors in Illinois (Aslani *et al*., 2013). Based on the second scenario, the electricity generated by renewable energy resources (80% hydropower, 100% wind, 50% solar, 70% biomass, 40% geothermal, and 40% tidal plant installation) will be reduced compared to the first scenario (48% decrease rate). As a result, the energy dependency, which was about 24.39 TWH in 2018, will be less compared to the first scenario (45% decrease rate). As Figure 10 shows, the energy dependency in Illinois in 2020 will be 12.32 TWH and in 2025 will be 19.92 TWH, which indicates a 53% decrease in energy dependency compared to the first scenario.

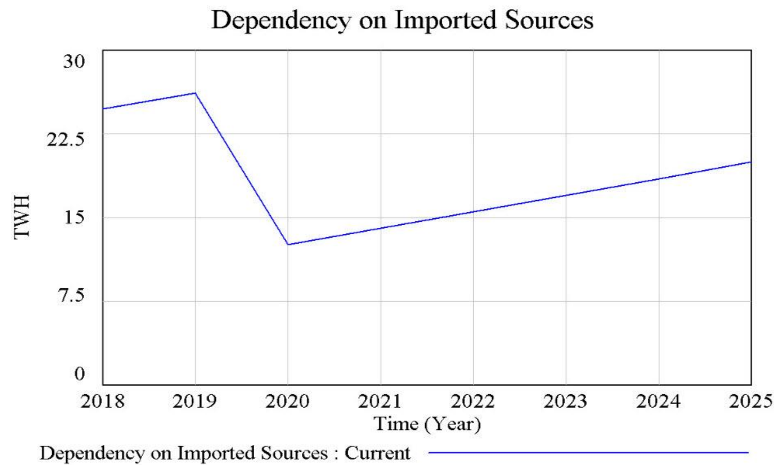

Figure 10: Dependency of Energy After Second Scenario

3. **Third Scenario:** After 100% promotion of the renewable energy action plans is implemented in the model.

In the third scenario, the action plan was proposed by the U.S. Energy Information Administration (EIA) for the state of Illinois. As Figure 11 illustrates, although the electricity consumption rate grows about 2.5% each year, the energy dependency in Illinois will be reduced to 21.75 TWH (52% decrease) in 2018 and 17.2 TWH (54% decrease) in 2025 compared to the first scenario, which was set as a baseline scenario. Based on previous assumption, by operating a new nuclear plant in 2020, the energy dependency will also be reduced up to 9.67. It needs to be noted that although the electricity/energy demand increased by 16% between the years 2018 to 2025, the energy dependency amount decreased about 8% from 2018 to 2025, which indicates the positive effect of implementing the renewable energy utilization action plans proposed by the EIA to reduce energy dependency in Illinois.

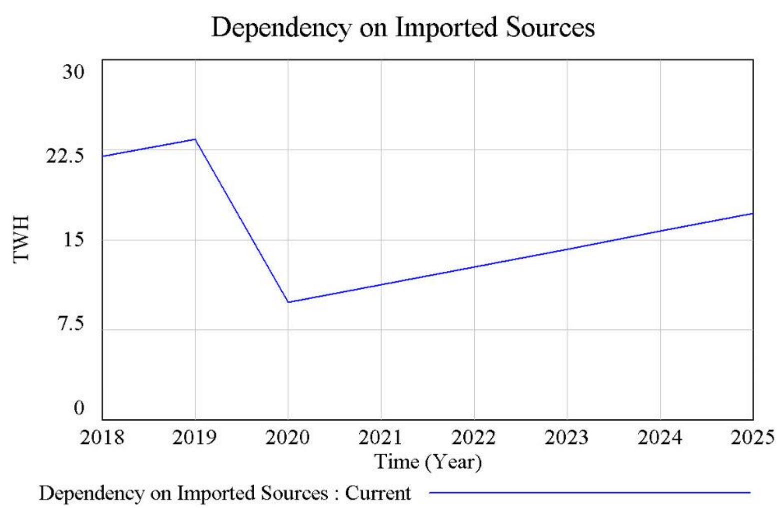

Figure 11: Dependency of Energy After Third Scenario

Another notable finding is the discrepancy between the opinions of the experts and the simulation results. The experts are optimistic about the decrease in energy dependency, but the simulation results tell a different story. Our model depends on data, and thereby complements the judgments of the experts. By examining the proposed scenarios, it can be understood that action plans of renewable energy utilization in terms of reducing energy dependency are effective. However, the result of sensitive analysis indicates that the renewable energy policies proposed by the Illinois government are not going to be effective after the year 2028, as the dependency level remounts to the same level of 2018. The system seems to support policy goals in the short term, but over the longer term, the system returns to its pre-policy-change state or produces an even worse situation. Therefore, Illinois officials need to reconsider their renewable energy action plans so that the level of energy dependency remains constant, as desired.

Different scenarios utilizing RE resources can be explored that lead to sustainability of energy dependency in Illinois. For instance, by preforming sensitivity analysis using the SD model, results demonstrate that by increasing the number of wind power plants to more than 50% of what has been planned for 2025, the energy dependency level will follow the steady-state behavior even after 2025, which indicates the efficiency of wind power plants in reducing energy dependency. This point needs to be noted that policy design is much more profound than changing the values of parameters, which requires the policy to be reachable in a foreseeable period of time. The proposed policy is selected based on the potential of the case study in renewable-energy-based structure. Figure 12 demonstrates the sustainability of energy dependency which can help the Illinois administration in reviewing its future policy making in terms of reducing energy dependency. However, this was an indication of a scenario that could be considered that signifies the potentiality of SD models in examining different scenarios. Table 10 numerically demonstrates the impact of different policy scenarios on energy dependency level and their rate of changes compared to baseline scenario. As Table 10 represents, conducting scenario two and scenario three generates meaningful difference in mitigating energy dependency when compared to the base scenario. The third scenario demonstrated to be more successful in mitigating energy dependency to the highest level.

Cost Savings of Proposed Scenarios

To determine how the results from proposed scenarios can help in reducing energy dependency in Illinois, the cost savings obtained from reducing energy dependency in Illinois by implementing renewable action plans was estimated. Table 11 illustrates the amount of energy dependency in dollars and the cost savings obtained in each scenario in 2016, 2019, and 2025.

Table 10: Summary of Results of Scenarios on Energy Dependency (TWH)

	Year	**Scenario**		
		1 (Base state)	**2**	**3**
Energy Dependency	2018	45.02	24.39	21.75
	2020	32.95	12.32	9.67
	2025	40.54	19.92	17.27

	2018	-	54%	48%
	2020	-	37%	29%
	2025	-	49%	42%

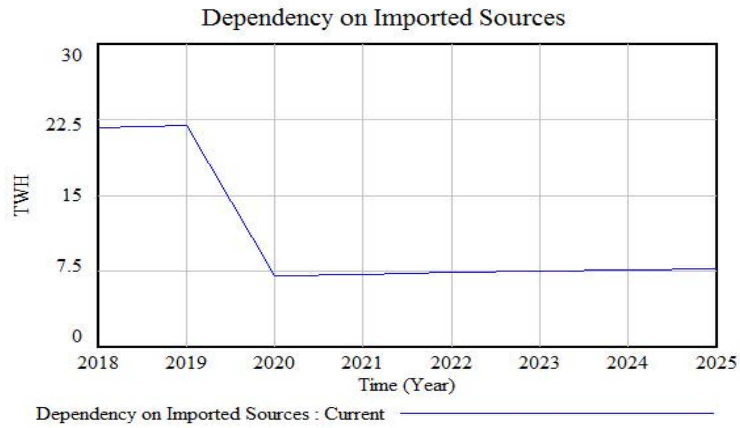

Figure 12: Dependency of Energy after Exploring Hypothetical Scenario

According to the EIA, the electricity/energy rate in Illinois per KWH was 7.149 cents in the summer of 2017 and is expected to increase with 2.6% growth each year ("Power of Choice," 2017). Hence, the cost saving obtained from reducing energy dependency on imported resources was compared with the average electricity price estimated by the U.S. Department of Energy. Table 11 reveals that the projected cost savings in energy dependency by implementing a complete renewable energy action plan (scenario 3) in Illinois would bring about savings of 28 billion dollars by 2025 (the difference between amount of energy dependency in dollars in scenario 1 and scenario 3 by 2025) from reducing electricity/energy imports. However, it is worth mentioning that the estimated cost does not include capital cost, installment cost, maintenance cost, transmission cost, and emission cost.

Table 11: Predicted Cost Saving ($ billions) in Energy Dependency by Implementing RE Action Plan in Illinois

	Year	Scenario			
		1	**2**	**3**	**Proposed policy**
Energy Dependency	2018	32.1	17.4	15.5	15.1
	2020	25.4	9.5	7.4	5.1
	2025	35.2	17.3	15	7.2
Cost Saving Compared to Scenario 1	2018	-	14.7	16.6	17
	2020	-	15.9	18	20.3
	2025	-	17.9	20.2	28

CONCLUSION

The present research has provided a systematic approach to assess renewable energy's role in meeting electricity/energy consumption, reducing energy dependency, and reducing imported energy. In order to evaluate the effect of renewable energy policies on reducing energy dependency, three different scenarios were developed. The first one is what is known as the pure state because it allows seeing the pure behavior of the system before implementation of any renewable energy policies or action plans in the model that is relatively close to the real-life scenario. This pure state was then used as a reference point for analyzing how the behavior of the system changes over time within the different scenarios. The second scenario was to partially apply renewable energy installation plans in the case study. This scenario was known as a "conservative" scenario, which means it is more realistic in terms of renewable energy action plans and is affected by multiple factors, such as investments, economic issues, bank interests, and estimation errors in Illinois. The results of scenario two reveal its applicability in reducing energy dependency as well as increasing cost saving accordingly. In the third scenario, the action plan was proposed by EIA for the case study, which means that 100% promotion of the renewable energy action plans was applied to manage energy dependency. The results are promising in terms of mitigating energy dependency when compared to the first scenario. However, the desired level of dependency could only be reached by applying more aggressive policies by further enhancing wind renewable energy. The results of a computer simulation indicated that about 17 billion dollars can be saved by 2025 by reducing electricity/energy imports by implementing complete renewable energy action plans. This represents the efficiency of renewable energy plans in reducing the energy dependency in Illinois within 10 years and saving money by being less dependent on imported energy from outsources. In spite of the established learning process and understanding of energy dependency management, and the valid findings in the research, there are always opportunities for future research to develop the current study. First, the risks associated with the implementation of renewable energy can be analyzed to identify the disadvantages of each renewable energy resource. Additionally, more sensitivity analysis can be conducted to investigate the most effective renewable energy contributor in reducing energy dependency. Aspects such as costs (including capital cost, installment cost, maintenance cost, transmission cost, and emission cost) should be incorporated into the model and policies to help improve the accuracy in estimating cost saving of the energy dependency from a cost-effective and environment-friendly perspective. Finally, integrating different economic indicators and energy markets to the model can further advance the current study.

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