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Integrating Data Mining and System Dynamics to Model Energy Policy Development and Sustainability Assessment

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Highlights

- Identification of the strategic parameters of Iran's energy-policy model;
- Sensitivity analysis of the entire dynamic model considering system stability in uncertainty conditions;
- Machine process including sentence-mining, analysis of frequent patterns, prediction of time series, and formation of dynamic analysis blocks in dynamic systems analysis;
- Extraction of the strategic parameters of the carrying capacity in the energy-policy model.

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Abstract

In recent years, the energy sector has witnessed a profound transformation driven by growing concerns over climate change, volatile energy prices, and the imperative of sustainable development. Policymakers and researchers have responded by seeking more effective energy policies to address these challenges. A powerful approach has emerged in the form of integrating data mining techniques with the system dynamics method to inform evidence-based policy decisions. This work delves into the utilization of data mining in the development of energy policies and synergizing it with system dynamics to elevate energy sustainability and efficiency. The exploration includes assessing the carrying capacities of dynamic systems, evaluating the robustness of the "plan for the future" reference scenario in dynamic settings, and extracting novel socio-economic parameters using advanced data mining techniques. The sensitivity analysis of a fully dynamic model identifies critical parameters for system stability, while an energy-economy model is constructed. The paper introduces dynamic machine algorithms designed for decision-making systems, leveraging data science to unveil the ultimate capacity of the energy policy model. This encompasses multiple indices, such as the index of economic freedom, export quality index, energy security risk, Iran's foreign direct investment, sustainable development index, country and product complexity index, international cooperation, Iran's credit rating in international trade, trade (% of GDP), export diversification index, economic resilience index, global conflict risk index, oil revenue reliance (% of GDP), and ensures energy security projections up to 2070. Furthermore, it assesses dynamic subnet connection point variables, including international bargaining power and the acceptability index of international participation in terms of their impact polarity, facilitating future research endeavors. More emphasis on balancing environmental goals with economic pressures is recommended. It is essential to outline limitations: predicting external shocks like global crises.

Keywords: Data mining, Energy policy, Occurrence scenario power, Sustainability, System dynamics, Transformation

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1. Introduction

The energy sector plays a vital role in driving economic growth, yet it is a significant contributor to environmental degradation (Wang, 2022). As the world grapples with climate change and other environmental issues, the importance of formulating and implementing effective energy policies cannot be overstated (Agency I. E., 2023). Thus, this work delves into how data mining, an advanced analytical technique, can be combined with system dynamics modeling to create comprehensive and insightful energy policy frameworks. It is essential to outline limitations, such as predicting external shocks like global crises.

Iran's economy depends on oil and gas and their derivatives to earn income and provide foreign exchange resources. However, it has faced challenges at different periods, and these crises have influenced the global oil price. The sanctions imposed by the European Union and the United States after the 1979 revolution and the Iran–Iraq war and during the president Rafsanjani's administration have had the greatest impact on Iran's export income, and most of them have been related to oil and its derivatives (Cashman, 2023). Further, Iran had and will have a considerable potential to expand economic–energy interactions in the past and future given the facts that it is neighbored by 15 countries (Hossein Aghaie Joobani, 2015). It is situated at the economic and social heart of the MENA region, which has a population of over 600 million. Additionally, it lies on the Strait of Hormuz, one of the world's most critical strategic chokepoints (Katona, 2018). Further, it is in the middle of the Silk Road, which stretches from China to Europe (Johannes Reissner, 2004).

Since our present problems are often the side effects of our past solutions (Trelstad, B., Varma, P., Blankinship, B., 2024), designing decision-making systems in response to the dynamics of complex systems for sustainable improvement in the face of big challenges can be solved and planned in a long time horizon (Hjorth, 2023) (the main source of uncertainty) and system capacities (the subsequent source of uncertainty) (Johannes Reissner, 2004). Therefore, to set goals in long-term planning, we need to develop predictive decision-making models in the field of economy and energy that include these goals: (a) ensuring the security of energy supply to maintain the stability of the energy supply system, (b) increasing energy efficiency to optimally use existing capacities, and (c) maintaining the existing environmental conditions (Mashayekhi, 1978).

We have moved from cybernetics to model recommender systems because the emergence and consolidation of research data centers along with the expansion of hardware and software capabilities have created new ecosystems of socio-economic analysis technology in which specialized people and groups participate as per the subject (Ivanova, 2023). After all, the continuous development of communication services and intelligent applications that continuously interact with the human agent creates analytical machines around specific issues (Papakyriakopoulos, 2020). A recommender system aims to change the behavior of users on a platform, while users' behavior recursively changes the system's recommendations (Ge Gao, 2023). In other words, commercial or political actors by themselves deploy an algorithmic decision-making system (ADM) so that their decisions are influenced by the results of the model (Ge Wang, 2023). Processes influencing social machines are constantly emerging and can take different forms for different participants (Papakyriakopoulos, 2020). Since the attention of economists was drawn to sustainable development in the 1990s, energy has played a more and more important role in the world economy due to the growing demand for it in all countries (Mishra, V., Smyth, R., 2020). Hence, the focus has shifted from abstract attention to the issue of energy to other important fields. In addition, in this era, energy models have been energy–economy–environment models (e.g., the computational general equilibrium (CGE) model, the energy–environment–economy (3Es) model, and the MESSAGE model), as well as composite energy models such as the National Energy Modeling System (NEMS) and the IIASA–WEC Energy Economic Environment (IIASA–WEC E3) (Leo Schrattenholzer, 2004).

So far, many energy models have been presented around the world with the help of different methods. Nevertheless, most are unable to show the mutual effects of different parts of a complex and large system on each other. These models are also weak in depicting the equilibrium path. However, system dynamics can be used as a complex modeling method that integrates these subsystems and shows the interactions between all subsystems at the same time (S.pormasomi, 2010). The dynamic analysis of feedback loops helps identify the emerging features of the studied systems. This instantaneous causality becomes the cycle that defines the emergent identity of the system (Gauthier, 2023). This identity (characteristic) with related rules creates fixed paths of system-specific behaviors or balances in the system, which are called system behavior (James Hendler, 2016). On the other hand, a recommender system changes the behavior of users in a platform, while users' behavior changes the system's recommendations recursively, as mentioned in this system. Energy policy is a subset of economic policy, foreign policy, and national and international security policy. Traditionally, energy policy has focused on the security of supply, affordability, and limited and controlled impact on the environment (Daniel Maram, 2022). It is essential to outline limitations such as predicting external shocks like global crises.

The main issue in this work is to identify the strategic parameters of Iran's energy-policy model by examining the carrying capacity of the reference energy–economic system using the sensitivity analysis of the entire dynamic model considering system stability in uncertainty conditions; this is of great importance to the economy and energy decision-makers. The problem is solved with an algorithm that solves the problem over time with machine components. These machine components include sentence-mining mechanism, analysis of frequent patterns, prediction of time series by Arima models, and finally formation of dynamic analysis blocks of Arima equations in dynamic systems analysis software. The calculated and presented strategic parameters of the carrying capacity of the energy-policy model include the export quality index, foreign direct investment, domestic product complexity index, export diversification index, oil revenue reliance (% of GDP), trade (% of GDP), global conflict risk index, and index of economic freedom in the time horizon leading to 2070. Details on quantifying uncertainties and handling unpredictable factors would enhance this section.

2. Synergy of data mining and system dynamics in energy policy

2.1. Data mining in energy policy

Data mining involves extracting valuable insights and patterns from vast datasets (McKinseyCompany, 2023). In the context of energy policy, it can help policymakers identify energy consumption trends, predict energy demand, and detect anomalies. By analyzing historical data from various sources such as smart grids, weather patterns, and socio-economic factors, policymakers can gain a deeper understanding of energy usage patterns and optimize their policy decisions accordingly (Tanveer Ahmad, 2020).

In the exploratory method of this work, while using the algorithmic decision-making method, we present the carrying capacity of Iran's energy policy system, which is obviously of crucial significance for the energy planning of the country. The method used is specific to this research because the approach of this work differs from the common method of dynamic system modeling which removes the obstacle of real-world complexity in the learning phase. In the phase of learning from the real world, the conventional dynamic system method employs the small world method to improve the learning process (Watts, 1998). Nonetheless, in the energy–economic dynamic machine algorithm of this paper, the machine learning algorithm based on sequential pattern data mining is also used in the soft system thinking paradigm or the learning paradigm. Further, in the paradigm of hard system thinking, or the optimization paradigm, this work employs the small world feedback method in the energy–economic dynamic machine algorithm based on the behavior of the predicted variables (Ackoff, 2020) in the data mining-aided business dynamic modeling (DMABDM), which can be matched with package-based time series ARIMA techniques to implement and re-execute the optimal model. As such, the targeted future is live planning (Hyndman, 2018).

2.2. System dynamics method

The system dynamics method is a powerful simulation technique that allows policymakers to model complex systems, predict their behavior, and test various policy scenarios. By capturing feedback loops and time delays, system dynamics models can offer a holistic view of the energy ecosystem and its interdependencies. It is essential to outline limitations such as predicting external shocks like global crises.

Combining data mining and system dynamics offers several advantages in the context of energy policy. First, data mining enables policymakers to enhance the accuracy of their system dynamics models by providing real-world data for calibration and validation (Maede Maftouni, 2023). Second, data mining can identify variables and relationships that might not be readily apparent, enriching the system dynamics model with additional insights (Jennifer Sian Morgan, 2017). Third, the dynamic nature of the energy sector can be better captured by integrating real-time data, allowing for more adaptable and responsive policy frameworks (Sarah Hafner, 2024).

The FOSSIL2 program is one of the oldest successfully implemented models, which has been utilized to analyze the cost-effectiveness of the US energy policies so as to reduce global warming (Energy, 2023). The dynamic machine algorithm starts by collecting the correct statements from specified sources. Conditional statements in DMABDM become cause-and-effect loops of the primary model that can be displayed as a graph based on the propositions extracted from the candidates showing the causes and effects raised at the level of the subject. The extraction of the initial model is the second step of the new method employed herein to reach the final dynamic model. It is equivalent to finding the initial point in the implementation of linear programming.

3. Practical energy policy modeling

This section explores the application of the proposed methodology in practical settings, focusing on integrating data mining and system dynamics to address real-world challenges in energy policy modeling. Here, we expand upon existing frameworks, leveraging empirical data and case studies to strengthen the relevance and applicability of the model.

3.1. Case studies and applications

- The preliminary energy–economy model of Iran (PEEMI) serves as a foundational framework for simulating the interactions between Iran’s energy and economic systems. The PEEMI model has been extended to incorporate advanced dynamic analysis and empirical data to enhance its practical utility:

  - ✓ **Case study:** Iran's energy dynamics under sanctions;
  - ✓ **Objective:** Analyze how the proposed model responds to economic and political uncertainties in Iran, particularly during periods of international sanctions;
  - ✓ **Empirical approach:** The key indices such as the export quality index (EQI), international bargaining power (IBP), and foreign direct investment (FDI) were analyzed using historical data from 1998 to 2022. For instance, during heightened sanctions (2012–2015), the model identified significant shifts in energy exports and investments, demonstrating how adaptive policy measures could mitigate economic vulnerabilities.
  - ✓ **Findings:** The PEEMI model effectively simulated dynamic feedback loops, showing how increased export diversification and reduced reliance on oil revenues enhanced economic resilience.
- Scenario analysis: renewable energy integration
  - ✓ **Objective:** Evaluate the feasibility of transitioning to renewable energy within Iran's policy framework;
  - ✓ **Empirical approach:** Simulated data on renewable energy investments, capacity utilization, and socio-economic impacts were fed into the system dynamics model. The results highlighted critical thresholds where policy interventions (e.g., subsidies for solar energy) yielded optimal outcomes.
  - ✓ **Findings:** The model demonstrated that achieving 30% renewable energy penetration by 2050 required a 2.5% annual increase in investment and a robust international cooperation strategy.

The preliminary energy–economy model of Iran (PEEMI) is an extended version of the Mashaikhi model[†] for simulating Iran's economy–energy system. The energy supply sector is divided into the exploration and production of energy resources, the energy demand sector, energy investment, energy technology, and energy trade; it should be noted that PEEMI only considers oil and gas energy sources (Moradi, M. A., Ahmadi, S., Khorasani, A. H. F., 2015). Since the Mashaikhi model contains most of the main variables of Iran's macroeconomics, PEEMI is an additional model that examines the interactions between the energy sector and other sectors of the economy in the original model (S.pormasomi, 2010). As was already mentioned, PEEMI is composed of eight sections. Here, to develop the above model, we modeled it for ring analysis in DMABDM and for numerical implementation and execution in DMABDM. First, a basic cause-and-effect structure the loops of which have a maximum length of seven network nodes is built based on the literature review and self-evident conditional statements (see Figure 1). As mentioned above, this is similar to generating an initial solution for iterative algorithms. Thus, closed/recursive or cause-and-effect loops as chain conditional statements are added to the model in Figure 1, generalizing the problem space, to extract initial development conditional statements from the previous PEEMI, the Mashaikhi model, and other works (Ivanova, K., 2023; Gauthier, S., 2023; Sandra Maria Correia Loureiro, J. G., 2021; Shaker Mohammadi, A. E., 2019). In other words, all the lines of the cause-and-effect chain are added to the initial model in a research-oriented way (the presence of the elite for extraction). Future research can replace the method used in this section with text-mining artificial intelligence-based extraction to create a suitable virtual machine (Sandra Maria Correia Loureiro, 2021).

[†] Strategy of economic development in Iran: A case of development based on exhaustible resources by Ali Naghi Mashayekhi Submitted to Alfred P. Sloan School of Management March 1978

3.2. Enhancements of PEEMI model

The enhanced PEEMI model incorporates the following:

- **Dynamic feedback analysis:** Identifies emergent properties and stability parameters using sensitivity analysis techniques. For example, the feedback loops associated with international cooperation and trade diversification significantly influenced system stability under volatile conditions.
- **Empirical data integration:** Data from international sources such as the World Bank, IEA, and Organization of Petroleum Exporting Countries (OPEC) supplemented the analysis, ensuring robustness in projections and insights.
- **Generation of big MODEL based on statement-mining:** This part is actually the development of the feasible region and the increase of the dimensions of the problem (Mokhtar S. Bazaraa, 2011). This section presents real-world case studies where data mining and system dynamics have been applied in the energy policy domain. It is inferred from the causes tree report in DMABDM in the basic model of energy policy, which is depicted in Figure 1. The node "International Bargaining Power" (BP) composes the root of the causes tree in the ranking of the problem-solving priority in the final order of the variables of the best starting node selection algorithm in the dynamic equations system. The problem-solving algorithm is explained in the next section. The rest of the variables also have their own causes trees, which are used to form the big model based on the initially extracted propositions. For example, the biggest causal loop of the cause-and-effect diagram discernible in the above structure is that if the acceptability of cooperation and partnership with reputable international companies and enterprises inside (ACPIC) increases, the potential for improving economic conditions (macroeconomics) and growth micro-economy improves, thereby reducing the negative effect of foreign sanctions and subsequently lowering the risk of regional tensions. When the risk of regional tensions decreases, energy security can be accomplished more easily; as a result, the security of foreign investment in the country improves. The improvement of foreign investment security increases international cooperation and subsequently enhances international bargaining power. The higher international bargaining power increases the acceptability of international cooperation from the perspective of political governance in the political realism scenario (S1) and reduces the acceptance of international cooperation from the perspective of political governance in the political absolutism scenario (S2). Each argument of the conditional statement is added as a node to the primary model, and the communication edges are established. The direction of the edges is employed to express the cause-and-effect relationship based on the causality tree of each mother node, modeling experience, and the progressive effect of the variables of a chain. This large model is drawn in DMABDM as presented in Figure 2 for further work. It is essential to outline limitations such as predicting external shocks like global crises.

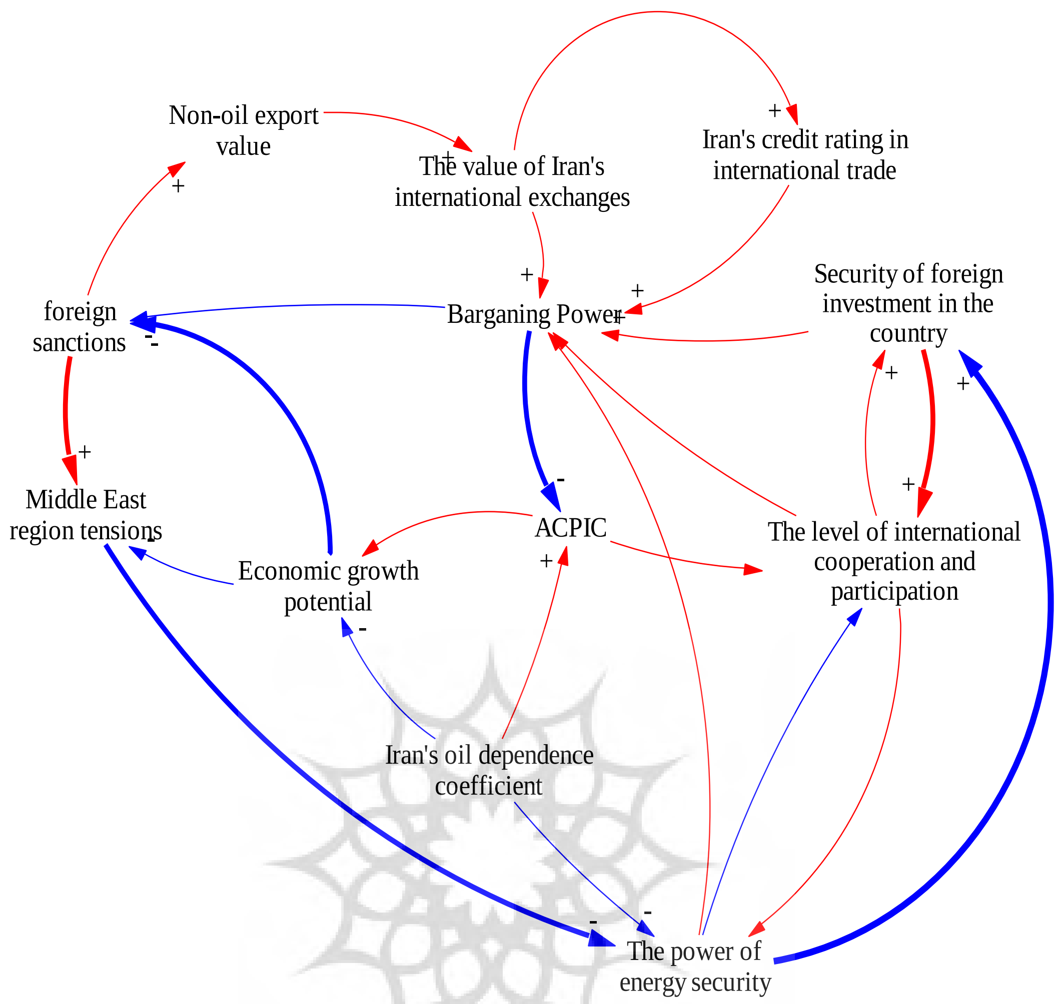

Figure 1

The initial cause-and-effect graph of the energy policy subsection in the model

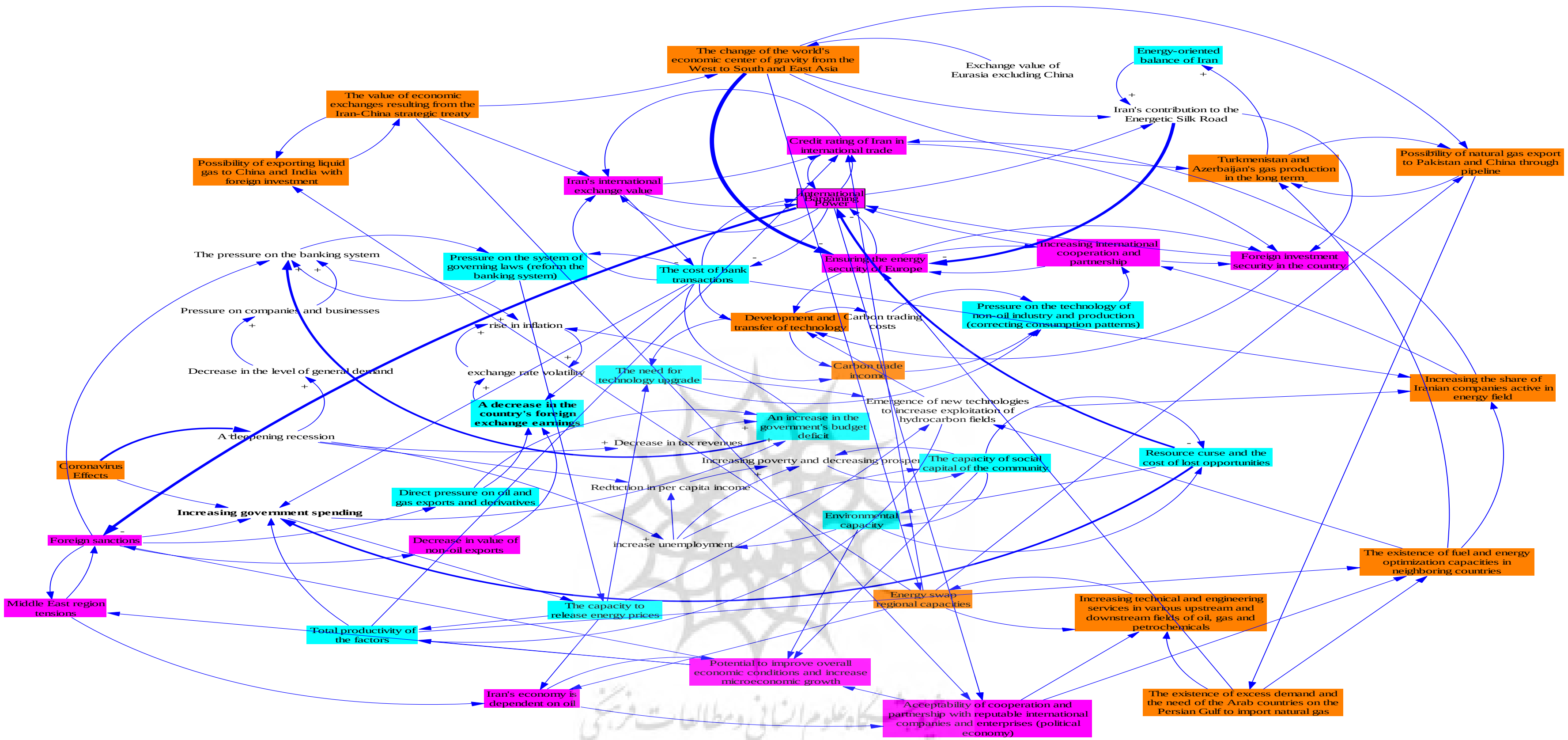

Figure 2

The graph of the big cause-and-effect model of the energy policy subsection

3.3. Model implementation steps

- **Data mining and sequential pattern detection:** The model utilizes historical and real-time data to extract actionable patterns. For example, the analysis of trade (% of GDP) and energy exports revealed recurring dependencies that guided policy prioritization.
- **Dynamic simulation and scenario testing:** Using tools such as ARIMA and Python-based algorithms, dynamic behavior blocks were constructed. For instance, the sensitivity of the global conflict risk index (GCRI) to geopolitical shocks was analyzed under different scenarios, revealing strategies to minimize adverse impacts.
- **Policy recommendations:** Based on the findings, the following strategies are proposed:
  - ✓ **Diversification:** Increase export product diversity to mitigate risks from reliance on single commodities;
  - ✓ **Energy efficiency:** Prioritize technologies that enhance energy efficiency and reduce consumption;
  - ✓ **International cooperation:** Strengthen partnerships to attract foreign investments and bolster economic resilience;
- **Sequential pattern mining from big model loops:** This section demonstrates its potential to inform evidence-based energy policy decisions by applying the proposed model to real-world scenarios. The integration of empirical data and case studies significantly enhances the model's credibility and utility, offering a practical pathway to achieving sustainable energy policy goals in complex and uncertain environments.

Association models find patterns in the input data of processes in which one or more entities (such as events, decisions, or attributes) are related to one or more other entities (Han, 2012). Models create sets of rules that define these relationships. Here, the fields in the data can act as both input and target, and one can find these connections manually. However, associative rule algorithms do it much faster and can discover more complex patterns. A priori and Carma models are examples of the use of such algorithms. Another type of relational model is the sequence detection model that finds sequential patterns in temporally structured data. The advantage of associative rule algorithms over more standard decision tree algorithms (C5.0 and C&RT) is that the algorithms can establish a relationship between all features (Mohammed M. Mazidm, 2009). A decision tree algorithm creates rules with only a single conclusion, while associative algorithms try to find many rules, each of which may lead to a different conclusion. Associative rules link certain outcomes (e.g., making a certain decision) to a set of conditions (e.g., making several other subsequent decisions). For example, increasing exports and improving overall productivity lead to a reduction in the budget deficit, resulting in a triple (173, 17%, 84%). This rule states that the budget deficit often declines when increased exports and increased productivity come together. This rule is 84% reliable and has been applied to 17% of the data, i.e., 173 propositions. The disadvantage of associative algorithms is that they try to find patterns within a very large search space, so their execution takes much longer than the decision tree algorithm.

To implement the algorithm for discovering association rules from propositions extracted from the big model in Figure 2, we first convert the conceptual components of the propositions to simplified coded propositions based on the following transformation matrix for the input of the sequential pattern detection process. Text-mining techniques can be employed to produce coded conceptual propositions. It should be noted that the conceptual components reported in Table 1 can be our final main variables. Another level of transformation is required to convert associative rules into taxonomic rule sets. Hence, the associative rules generated by the associative algorithms are known as unrefined models, which are about 32,766 sequential statements with a maximum length of 32 nodes. This is the reason why we have manually filtered and categorized the rules extracted from the big model based on the combination of support percentage and confidence percentage in a Microsoft Excel file. After four times of filtering items larger than the average Microsoft Excel tool, 17 variables with 24 selected rules were yielded. We re-run the inverse transformation matrix to understand the implemented rules (see Table 2). Then, based on the 24 mined rules, we approached the optimized basic dynamic model.

Table 1

The conceptual components and final main variables mined

Coding	Final main variables mined	Coding	Final main variables mined	Coding	Final main variables mined
A	International bargaining power	N	Possibility of natural gas export to Pakistan and China through pipeline	1	Increasing the share of Iranian companies active in energy field
B	Foreign sanctions	O	The existence of excess demand and the need of the Arab countries on the Persian Gulf to import natural gas	2	Iran’s credit rating in international trade
C	Direct pressure on oil and gas exports and derivatives	P	Increasing technical and engineering services in various upstream and downstream areas of oil, gas, and petrochemicals	3	The value of Iran’s international exchanges
D	Increase in the government budget deficit	Q	Energy swap regional capacities	4	The cost of bank transactions
E	Pressure on banks	R	Possibility of exporting liquid gas to China and India with foreign investment	5	Carbon trading revenue
F	Pressure on the system of ruling laws (amending the banking system)	S	The value of economic exchanges resulting from the Iran–China strategic treaty	6	Pressure on the technology of non-oil industry and production (correction of consumption patterns)
G	The capacity to release energy prices	T	The change of the world’s economic center of gravity from the West to South and East Asia	7	Increasing cooperation and international participation
H	Dependence of Iran’s economy on oil	U	Iran’s share in the energetic the Silk Road	8	Increase in government spending
I	Acceptability of cooperation and partnership with reputable	V	Ensuring the energy security of Europe	9	Tensions in the Middle East region

Coding	Final main variables mined	Coding	Final main variables mined	Coding	Final main variables mined
	international companies and enterprises (political economy)				
J	Potential to improve overall economic conditions and increase microeconomic growth	W	Foreign investment security in the country		
K	Total productivity of the factors	X	Development and transfer of technology		
L	Existence of capacities to optimize fuel and energy consumption in neighboring countries	Y	The need for technology upgrade		
M	Gas production of Turkmenistan and Azerbaijan in the long term	Z	The emergence of new technologies to increase the exploitation of hydrocarbon fields		

3.4. Modification of dynamics model

Now, the dynamic model should be modified logically, so the time series of the extracted variables should first be formulated. The variables the time series extraction of which was not possible were included as a fixed value in a modeling system with sensitivity analysis capability (Francesca Pianosi, 2016). Therefore, we proceed to define the preferably dimensionless variables among the remaining variables to increase the measurability of the decision variables, perform their time series analysis, and finally, create their dynamic blocks. Details on quantifying uncertainties and handling unpredictable factors would enhance this section.

Table 2

The main variables of the optimized model

No.	Index Description	Type	abbreviation	No.	Index Description	Type	abbreviation	No.	Index Description	Type	abbreviation
1	Index of economic freedom	S*	IEF	7	International cooperation	S	ICI	13	Oil revenue reliance (% of GDP)	S	ORR
2	Export quality index	S	EQI	8	Iran's credit rating in international trade	SC	ICRIT	14	Acceptability of cooperation and partnership with reputable international companies and enterprises inside	S	ACPIC
3	Energy security risk	S	ESR	9	Trade (% of GDP)	S	Trade (% of GDP)	15	Ensuring foreign direct investment	S	EFDI
4	Iran foreign direct investment	S	IFDI	10	Export diversification index	S	EDI	16	Bargaining power	S	Bargaining power
5	Sustainable development index	S	SDI	11	Economic resilience index	S	ERI	17	Ensuring energy security	SC	EENS

No.	Index Description	Type	abbreviation	No.	Index Description	Type	abbreviation	No.	Index Description	Type	abbreviation
6	Country and product complexity index	SC**	CPCI	12	Global conflict risk index	S	GCRI	* Stocks ** Standard converter			

3.5. Derivation of mathematical model of time series analysis of main variables

The auto-ARIMA (autoregressive integrated moving average) algorithm uses the SARIMAX (seasonal autoregressive integrated moving average with eXogenous variables) model. As was already mentioned, the criteria for selecting the best model are Akaike information criterion (AIC), corrected Akaike information criterion (AICC), Bayesian information criterion (BIC), Hannan–Quinn information criterion (HQIC), and out-of-bag (OOB); ARIMA returns their minimum values. It should be noted that the auto-ARIMA may not find a suitable model for convergence due to stationarity issues. In this case, a value error message is returned, implying that measures should be taken to recover stationarity or a new range of desired values is selected before re-running the algorithm. Figure 3 displays the steps in running auto-ARIMA in Python coding.

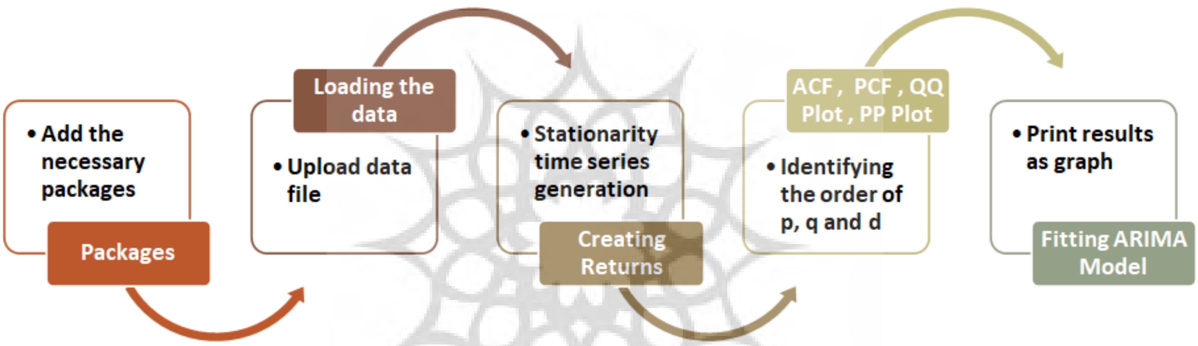

Figure 3

The steps in running auto-ARIMA in Python coding

The mathematical codes of DMABDM blocks for the base models S1 and S2 are provided in Appendix A. The paper presents the first variable based on the solvability algorithm of the dynamic system as an example.

Table 3

The results of confirming the models resulting from the execution of Python codes

Index Description	Best model	log_ret_shift	Lags	Period M	Observations	Log Likelihood	AIC	BIC	HQIC
Index of economic freedom	ARIMA (2,0,1)(0,0,1) [3] intercept	2	6	3	23	30.81	–51.6	–45.9	–50.2

Index Description	Best model	log_ret_shift	Lags	Period M	Observations	Log Likelihood	AIC	BIC	HQIC
Export quality index	ARIMA (0,0,0) (0,1,1) [4]	1	6	4	38	37.3	–70.6	–67.5	–69.6
Energy security risk	ARIMA (1,0,0) (0,0,0) [5]	1	6	5	38	93.58	–183	–180	–182
Iran foreign direct investment	ARIMA (1,0,1) (1,1,0) [2]	2	6	2	20	–24.8	57.55	61.11	58.04
Sustainable development index	ARIMA (0,0,1) (0,1,1) [2] intercept	2	6	2	24	56.1	–106	–103	–105
Country and product complexity index	ARIMA (0,0,1) (0,1,0) [3]	2	6	5	17	–12.9	29.88	31.16	29.76
International cooperation	ARIMA (1,0,1) (0,0,0) [2]	3	3	2	12	1.994	2.012	3.467	1.474
Trade (% of GDP)	ARIMA (2,0,2) (1,0,0) [3] intercept	2	6	3	40	19.76	–27.5	–17.4	–23.9
Export diversification index	ARIMA (1,0,1) (1,1,0) [2]	3	6	2	34	52.55	–97.1	–91.2	–95.2
Global conflict risk index	ARIMA (3,0,0) (3,1,1) [4]	2	6	4	24	–30.9	77.87	85.83	79.42
Oil revenue reliance (% of GDP)	ARIMA (2,0,1) (3,1,1) [3]	4	6	3	36	–20.4	56.88	68.85	60.91

Export quality index is the first starting variable to solve the dynamic system based on the problem solvability algorithm fitted with 38-year data as an ARIMA (0,0,0) (0,1,1) [4] model. Thus, based on the global equation of ARIMA(p,q,d)(P,Q,D)[S] [31], we obtain:

$$\Phi(\beta^S).\emptyset(\beta).\nabla_S^D.\nabla^d.y_t = \Theta_Q(\beta^S).\theta(\beta).\varepsilon_t \tag{1}$$

$$\nabla^d = (1-\beta)^d \qquad \nabla_S^D = (1-\beta^S)^D \tag{2}$$

$$\text{Seasonal AR: } \Phi(\beta^S) = 1 - \Phi_1\beta^S - \cdots \Phi_P\beta^{PS} \tag{3}$$

$$\text{Seasonal MA: } \Theta_Q(\beta^S) = 1 + \Theta_1\beta^S + \cdots \Theta_Q\beta^{QS} \tag{4}$$

$$\text{AR:}\ .\emptyset(\beta) = 1 - \emptyset_1\,\beta - \cdots - \emptyset_p\,\beta^p \tag{5}$$

$$\text{MA:}\ .\theta(\beta) = 1 + \theta_1\,\beta + \cdots + \theta_q\,\beta^q \tag{6}$$

Then, we have for the variable EQI

$$y_t = \frac{(1 - 0.5221 * \beta^4)}{(1 - \beta^4)} \,.\, \varepsilon_t \tag{7}$$

$$\mu_{\varepsilon_t} = 0\ ,\ \ {\sigma^2}_{\mu} = 0.0063 \tag{8}$$

Now, given that $y_{t-1} = \beta.\,y_t$, then $y_t' = y_t - y_{t-1} = (1-\beta)y_t \Rightarrow \beta = 1 - \frac{y_t'}{y_t}$. Therefore, according to Equations 7 and 8, we convert each decision variable or index node to the SD block of the EQI variable in DMABDM using the internal functions of the subnetwork DMABDM codes as follows:

$$B\_of\_EQI = (DELAY\,(EQI,1) – EQI)/EQI \tag{9}$$

$$\begin{aligned} &EQI(t) = EQI\,(t – dt) + (EQI\_Rate) * dt \\ &INIT\ EQI = 0.750 \\ &EQI\_Rate = (DERIVN\,(Ret\_EQI,1) + DERIVN\,(EQI\_HIS,1))/2 \end{aligned} \tag{10}$$

$$EQI\_HIS = GRAPH(TIME) \tag{11}$$

$$\begin{aligned} &EQI\_HIS\_Delay = DELAY(EQI\_HIS, Shift\_EQI) \\ &ERI\_Rate = DERIVN\,(ERI\_HIS,1) + DERIVN\,(SDI,1) + DERIVN\,(ICI,1) \\ &\qquad + DERIVN\,(EQI,1) \end{aligned} \tag{12}$$

$$LAG\_EQI = 6 \tag{13}$$

$$MUT\_EQI = SQRT(1/VAR\_EQI) * LOG10(1/VAR\_EQI) \tag{14}$$

$$Ret\_EQI = EQI\_HIS\_Delay * EXP(Yt\_EQI) \tag{15}$$

$$Shift\_EQI = 3 \tag{16}$$

$$SINW\_EQI = SIN(TIME/LAG\_EQI) \tag{17}$$

$$VAR\_EQI = 0.0063 \tag{18}$$

$$Wnoise\_EQI = NORMAL\,(0, VAR\_EQI, 100) * SINW\_EQI \tag{19}$$

$$Yt\_EQI = ((1 – B\_of\_EQI\char`^4) * (Noisome) * MUT\_EQI)/(1 – 0.5221 * B\_of\_EQI\char`^4) \tag{20}$$

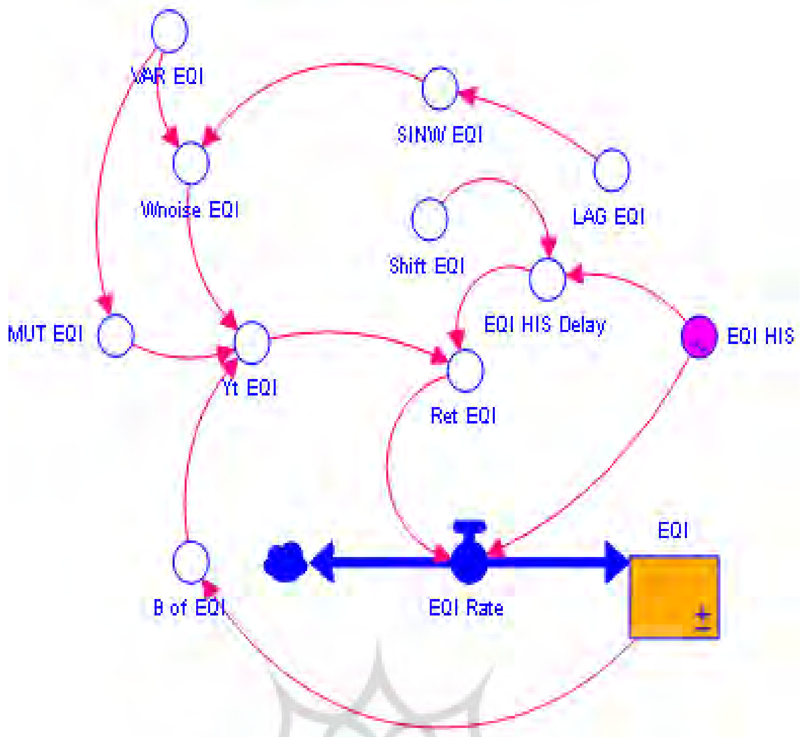

Figure 4

Export quality variable sub-network in SD Simulation software

4. Challenges and limitations

Based on the limit mathematical rules, we herein reached three types of SD blocks in numerical calculations; two types are used in capacity measurement modeling, and the third type is used in scenario modeling. While data mining and system dynamics offer numerous benefits, this section addresses some of the challenges and limitations in their implementation (Emi Iwatani, 2018). Issues related to data quality, model complexity, and the dynamic nature of the energy landscape are explored. It is essential to outline limitations such as predicting external shocks like global crises.

4.1. Characteristics of SD blocks

A) The first type block: The first block in the capacity measurement modeling of ARIMA conversion to DMABDM code is due to Oeder *Yt* of $\beta > 1$. Since there is no division-by-zero error in the dynamic execution stages, we have used *yt* EQI. This behavior has been observed in all variables that have a capacity nature for the socio-economic system, but their white noise variance is close to 1 in the ARIMA simulation. It has been used in the capacity measurement modeling in the reference scenario.

B) The second type block: The first block in the capacity measurement modeling of ARIMA conversion to DMABDM code is not due to Oeder *yt* of $\beta > 1$; since we have a division-by-zero error in the dynamic execution stages, we can use *Yt* EQI/1 block instead of *Yt* EQI. This behavior has basically been observed in all variables that have a capacity nature for the socioeconomic system, but their white noise variance is a very small close to zero in the ARIMA simulation. It has been used in the capacity measurement modeling in the reference scenario.

C) The third type block: The third block in the scenario modeling of ARIMA conversion to DMABDM code by modifying the β implementation formula when using the inverse term 1/*Yt* EQI in the conversion of the equation (by itself due to the compulsion to use the negative term Ret EQI in small noise production variances) has a division-by-zero error; therefore this conversion cannot be used. In this case, the *Yt* EQI sample variable coefficient is used in the vicinity of zero to avoid the error resulting from the variance of white noise as follows:

$$MUT\ EQI\ =\ SQRT(1/VAR\_EQI)\ *LOG10(1/VAR\_EQI) \tag{21}$$

so that

$$Order_{EQI\ Rate}^{EQI\ HIS} \cong\ Order_{EQI\ Rate}^{Ret\ EQI} \tag{22}$$

In other words, the order of EQI HIS effect on EQI rate is equal to the order of Ret EQI effect on EQI rate. Moreover, the weight of these two effects is considered equal to 1⁄2. It will be possible to optimize HIS and RET coefficients; to this end, the first 13 variables of the solution point algorithm of the dynamic device are equipped with their own DMABDM blocks and subnetworks from 17 variables. The remaining four variables are the variables of the connection point of the national network, which are explained further below.

4.2. Connection point variables

The connection point variables of the dynamic system solvability algorithm: The variables of this group include the connection point variables of the subnetworks in addition to the added auxiliary variables such as the variable of rate, the variable of the connection point, or constant value variables, which are placed at the end of the ranking table as discussed below. For example, the construction of the variable dynamic block of the GDP index will be explained further.

Table 4

The characteristics of the variables of the connection points

No.	**Index description**	**Single variable (percent)**	**With initial data series (percent)**	**Degrees of freedom (DF) - interactive relation**	**Rate of DF**	**Ratio of node with initial data to total nodes in relation**	**Ratio of output variables node to total nodes in relation**	**Total score**	**Rank**
		+	+	-	-	+	+	=	
1	Ensuring foreign direct investment	0%	0%	2.00	67%	50%	75%	1.75	15
2	Bargaining power rate	0%	0%	4.00	133%	67%	17%	1.83	14
3	Bargaining power	0%	0%	2.00	67%	50%	75%	1.75	15

4.3. Variable of ensuring foreign direct investment (EFDI)

This index is one of the sub-network connection point indices the time series information of which has not been extracted or is not available. It has two inputs from GCRI and IFDI subnetworks and two outputs to EENS and bargaining power subnetworks, so they are placed at the top of the solvable algorithm. Based on the key propositions, the EFDI variable subnetwork is considered based on the proposition-based differential linear relationships as follows:

(1) Regional tension risk index → (–) foreign direct investment guarantee

(2) Foreign direct investment → (+) foreign direct investment guarantee

$$EFDI\ Rate\ =\ DERIVN\ (IFDI, 1)/IFDI - DERIVN\ (GCRI, 1)/IFDI \tag{23}$$

In other words, the foreign direct investment guarantee the variation rate is equal to the normalized algebraic sum of the differential of the variables of regional tension risk with a negative effect and the volume of foreign direct investment with a positive effect.

(3) Foreign direct investment guarantee → (+) bargaining power

$$\frac{dBarganing\ Power}{dt} = \frac{dERI}{dt} + \frac{dICRIT}{dt} + \frac{dICI}{dt} + \frac{dORR}{dt} + \frac{dEFDI}{dt} \tag{24}$$

(4) Foreign direct investment guarantee → (+) energy security guarantee

$$\frac{dEENS}{dt} = -\frac{dESR}{dt} + \frac{dCPCI}{dt} + \frac{dEFDI}{dt} + \frac{dACPIC}{dt} \tag{25}$$

4.4. Variable of bargaining power

The bargaining power variable typically refers to an indicator used to measure the strength or leverage one party has over another in negotiations or decision-making processes. In the context of energy policy, international relations, or economics, this variable often helps evaluate the power dynamics between countries, companies, or organizations, especially in sectors like energy trade, resource management, or political negotiations (Baldwin, 2013).

The international bargaining power index is also one of the subnetwork connection point indices the time series information of which has not been extracted or is not available. It is one of the variables that has the largest number of inputs and outputs, so it is placed at the top of the solvable algorithm. Now, these nodes are solved by key propositions. We consider the relationships a linear differential for now. This variable is completed by two input and output rate variables; it has three outputs to the three adjacent subnetworks. Thus, in the trade network (% of GDP) of the equations governing the trade rate, one may obtain:

$$\frac{dTrade\ Rate}{dt} = \frac{dBarganing\ Power}{dt} + \frac{dGCRI}{dt} + \frac{dRet\ Trade}{dt} \tag{26}$$

In the GCR network of the equations governing the GCR rate, we have:

$$\frac{dGCR}{dt} = \frac{dBarganing\ Power}{dt} + \frac{dEFDI}{dt} \tag{27}$$

In the ACPIC network of the equations governing the ACPIC rate, one may obtain:

$$\frac{dACPIC}{dt} = -\frac{dBarganing\ Power}{dt} + \frac{dIEF}{dt} \tag{28}$$

Further, its input rate variable (*Bargaining Power Rate In*) has five inputs through the subnetworks of IFDI, ICRIT, ORR, ERI, and ICI with positive polarity as follows:

$$d(Barganing\ Power\ Rate\ In) = \frac{d(ERI)}{ERI} + \frac{d(ICRIT)}{ICRIT} + \frac{d(ICI)}{ICI} + \frac{d(EFDI)}{EFDI} + \frac{d(ORR)}{ORR} \tag{29}$$

$$d(Barganing\ Power\ Rate\ Out) = \frac{d(GCRI)}{GCRI} + \frac{d(ESR)}{ESR} \tag{30}$$

Now, its output rate variable (*Bargaining Power Rate Out*) has two inputs from the subnetworks of ESR and GCRI with negative polarity. Thus, the bargaining power index can be calculated as linear equations.

$$net\ d(Barganing\ Power\ Rate\ In) = \frac{d(ERI)}{ERI} + \frac{d(ICRIT)}{ICRIT} + \frac{d(ICI)}{ICI} + \frac{d(EFDI)}{EFDI} + \frac{d(ORR)}{ORR} - \frac{d(GCRI)}{GCRI} - \frac{d(ESR)}{ESR} \tag{31}$$

The basic point is to normalize the variables related to the nodes of the connection point from the other subnetworks. Therefore, the magnitude of the bargaining power variable is normalized, and its values have been in the range of 10 to 100 over a 70-year period.

All the weight coefficients of the influencing variables are currently considered equal, which will be discussed and investigated in the sensitivity analysis of future research. Details on quantifying uncertainties and handling unpredictable factors would enhance this section.

We will have two types of system modeling here: modeling for determining system capacities in the energy–economy model (with the addition of the energy policy module) and modeling for scenario analysis and sensitivity analysis. The first type of modeling essentially involves extracting system capacity for the analysis of essential capacities in the energy–economy model (with the addition of the energy policy module). The second type of modeling involves absolute realism and political realism for sensitivity analysis and examining the impacts of connection point variables under dynamic conditions. The design and implementation of these primary subnetwork variables are presented in Sections 4.2 and 4.4. Details on quantifying uncertainties and handling unpredictable factors would enhance this section.

First to detect the capacity variables of the system, we have assumed that the output valve of closed resources is closed, just like filling a water reservoir; only the input valve of the resource is embedded, and the input flow is open. In this case, we observed that some variables reached their upper limit near the horizontal line; however, there was no upper limit even within a 72-year range from 1998 to 2070 for some variables.

For the second part, we reached the extraction of signals (time series of main variables of the policy-energy module) vital to the system by utilizing the capacity of extracting key decision-making variables, with the help of data mining. Inspired by the control theory, this led to the construction of dynamic simulation behavior blocks. Here, three types of behavior simulation blocks are introduced. What has led to the creation of dynamic simulation behavior blocks is the solution to the dynamic system of this module, which has been achieved through the solvability algorithm for the dynamic system. Here, we place the origin of uncertainty within the block structure to address the propagation of uncertainty (degree of added freedom in the system) without the fear of result deviation; we assume that the blocks are solvable: individual blocks are placed in the solvable solution space under the block. This is because we ultimately extract what validates the model and removes uncertainties using the dynamic time warping (DTW) analysis mechanism later on.

Subnetworks are transferred to Stata based on the equations in the third-season CP modeling to examine the connection point variables. This is performed to determine the interaction effect of subnetworks with others on the values of the connection point variables.

The most valuable connection point variable is the international bargaining power variable, which in the CP reference model reaches a maximum value of 16.45 from the baseline value of 10.00 based on the effect of changes in international energy security risk (ESR) and regional tension risk (GCRI) on the output rate of its accumulation variable. As mentioned in Section 3.15, this is a dimensionless variable within the range of 10 to 100, which reaches a maximum of 16.45 for Iran in CP modeling until the year 2070.

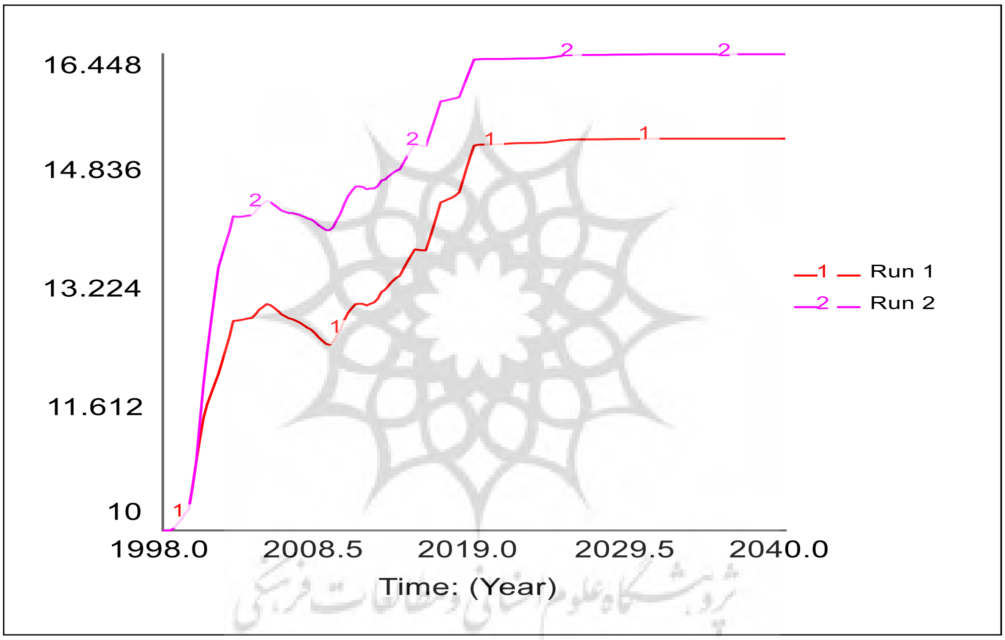

Figure 5

The maximum capacity of the international bargaining power variable in the scenarios of 1) uniflow and 2) biflow.

Figure 5 illustrates the effect of uniflow (considering uncertainty in side effects) on risk and the effect of biflow (without considering uncertainty in side effects) on influential risks. In fact, when determining the ceiling of this variable, it should be noted that the international bargaining power variable increases in the CP reference model by changing the type of variables affecting BP_In and BP_Out to biflow. This creates an effect on the degree of freedom of the accumulation variables of related subnetworks through the accumulation rate variable.

5. Results

Two types of scenarios are employed in the CP reference model biflow: the scenario of political realism versus the second scenario of political absolutism. According to Figure 6, despite the rapid growth of Iran's international bargaining power from 2015 to 2028, the international bargaining power will decrease to less than the value of the second scenario after a 13-year period. This reduction in international bargaining power reaches its inflection point after 2050 (Choucri, 2012).

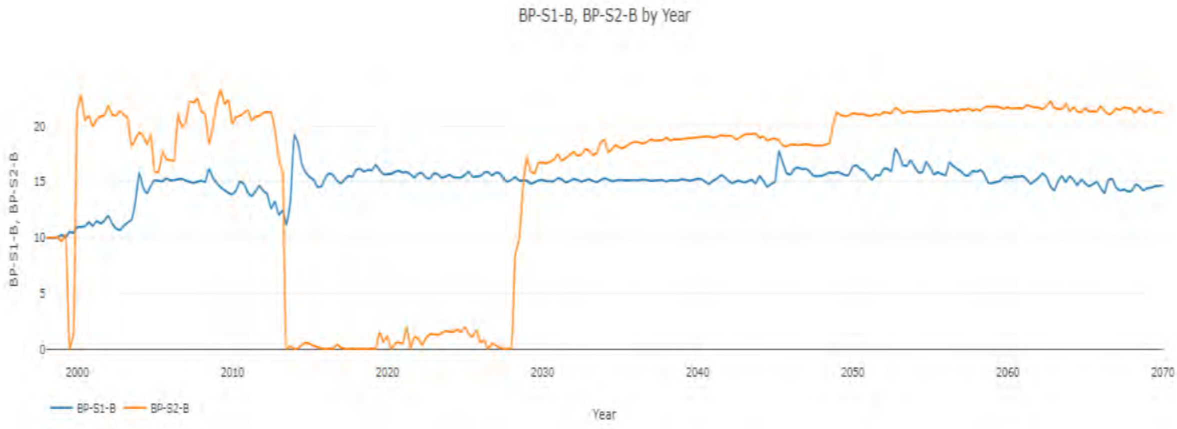

Figure 6

The international bargaining power in scenario 1) political absolutism and 2) political realism

Energy security risk is one of the most significant factors influencing political developments in countries with fossil fuel resources, especially after the discovery of oil. From this perspective, the political changes in fossil fuel-rich countries are affected by the interactions of energy policies and are proportionate to their international mediation power. If we represent international bargaining power in terms of degrees of energy security risk (ESR), it can be observed that there is a transitional period with minimal changes in Iran's international bargaining power [15.5–15.1] between the years 2020 and 2040. However, when years with high ESR levels are predicted, like that between 2024 and 2027, the risk increases again.

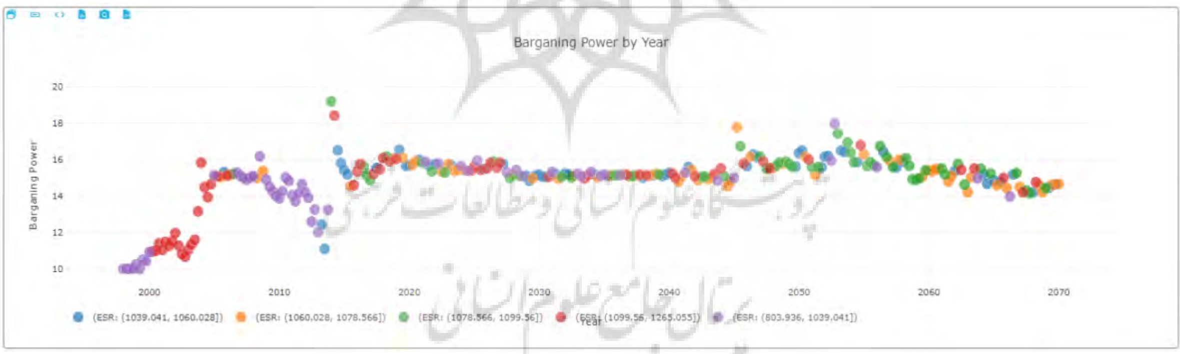

Figure 7

International bargaining power in terms of degrees of energy security risk

Here, we define limit variables as a group of main variables of the dynamic network that have a storage nature over time and reach a limit based on a positive growth rate or a negative fall rate over time. Variables reaching the vicinity of the horizontal line of their upper limit or the ceiling of their system capacity include:

1. The export quality variable reaches a maximum value of 1.68% in 2070 from a value of 0.75% in the base year of 1998, so it can be planned for an average annual rate of 0.02%. This variable is employed to determine the competitive pricing range of industrial and energy products, including petrochemical derivatives, in comparison to regional and global competitors. Export quality, along with the final price, is an interactive tool for maintaining economic and industrial competitiveness.

2. Foreign direct investment increases from 243,750 million IRR to a maximum of 421,613,000 million IRR (approximately equivalent to Iran's budget in 2019) in the 72-year period from the base year of 1998 to 2070, which can be budgeted in scenario S1. Comparing the values of historical data for the foreign direct investment index with the international bargaining power index in a scenario of political realism demonstrates that foreign direct investment is positively associated with international mediation power. This is evident in the upward trend line of foreign direct investment and international bargaining power between the years 1998 to 2019. In other words, it can be inferred that the attraction of foreign direct investment can reach a maximum level equivalent to the country's annual budget.

Therefore, attracting a larger amount leads to economic macro instability, and attracting a smaller amount indicates the underutilization of unused non-national capacities. Here, we employ the ordinary least squares (OLS) linear regression method based on the categorization of bargaining power in the selected scenario via the channel extraction.

3. The variable of technological complexity of domestic products (CPCI) increases from –0.84% to a maximum value of 15.82% in the 70-year period from the base year of 2000 to 2070, which can be planned as an annual average of 0.22%. On the other hand, economic complexity is a novel approach to assessing the commercialization of scientific and technological productions and evaluating the contribution of scientific and technological productions to the economy of selected countries.

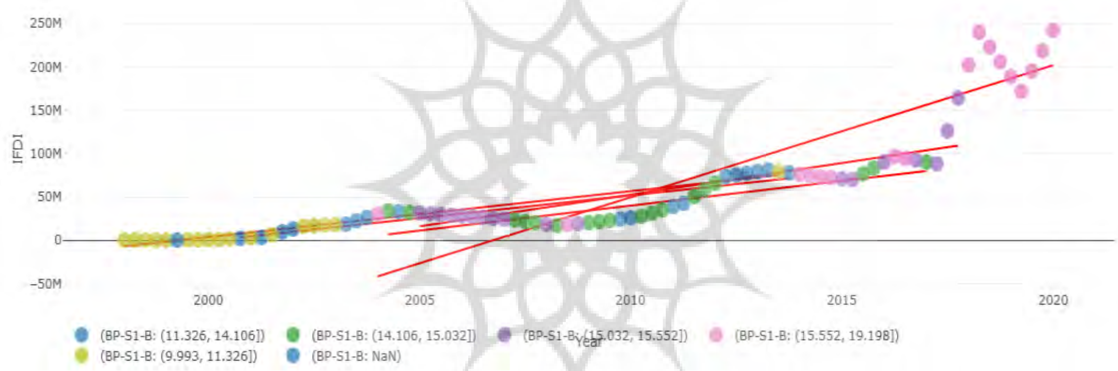

Figure 8

The spectrum chart of the foreign direct investment in the international power structure based on five bargaining power levels

4. The export product diversity variable (EDI) increases from 4.81% to a maximum value of 15.82% in the 108-year period from the base year of 1962 to 2070; an annual average of 0.22% can be considered. Furthermore, when comparing the historical values of the export product diversity index using the measured international bargaining power in the scenario of political realism, the following observation is made: The diversity of high-quality export products has a positive impact on international competitiveness, and the slope of the trend line for the diversity of export products becomes more negative as the ranking of competitiveness decreases. The diversity of top-quality export products positively enhances international competitiveness, and the slope of the trend line for the diversity of export products becomes more negative as the ranking of competitiveness decreases.

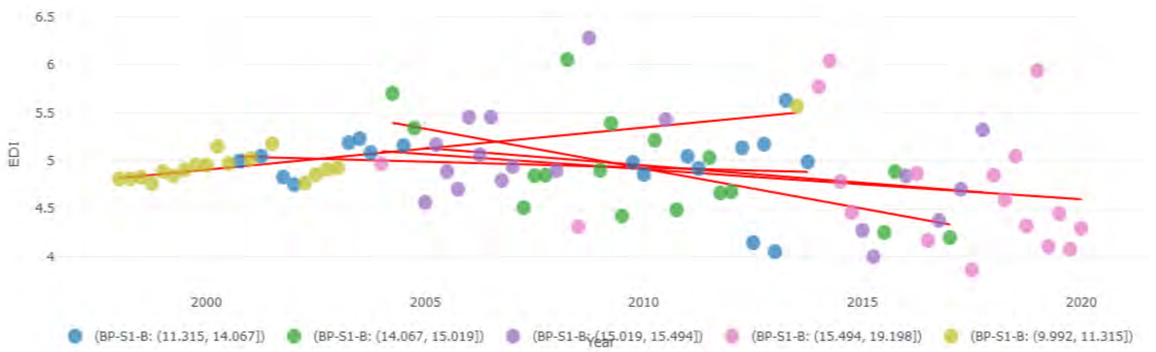

Figure 9

The spectrum chart of the diversity of exported products based on five bargaining power levels

5. The variable reliability of oil revenue (ORR) in terms of the percentage of gross domestic product increases from 13.56% to a maximum value of 67.99% in the 100-year period from the base year of 1970 to 2070, so its annual average growth rate is 0.94%. It can also be concluded at a confidence level of 95% that if we reach an oil revenue dependence rate of 68%, no more dependence will be possible and its downward trend will begin.

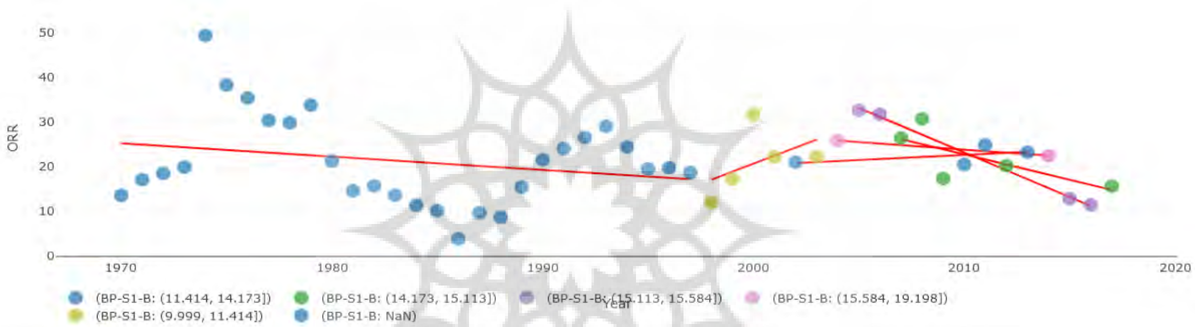

Figure 9

The spectrum chart of the confidence level in oil revenue based on five bargaining power levels

Further, when historical values of the confidence level of oil revenue as a percentage of the gross domestic product are measured using the international power index in the scenario of political realism, we observe that the confidence level of oil revenue as a percentage of gross domestic product has a positive polar orientation with the first-class international power index. As the power class decreases, the slope of the trend line for the confidence level of oil revenue as a percentage of the gross domestic product becomes more negative.

6. The variable of the level of trade exchanges in terms of the gross national income (ORR) shows an increase from 43.19% to a maximum value of 89.18% in the 110-year period from the base year of 1960 to 2070, so its annual average growth rate can be considered 1.24%.

7. The tension risk index (GCRI) rises from 1.65% to a maximum value of 14.35% in the period of 64 years from 2006 to 2070, so it can be planned for an average annual increase rate of 0.20%.

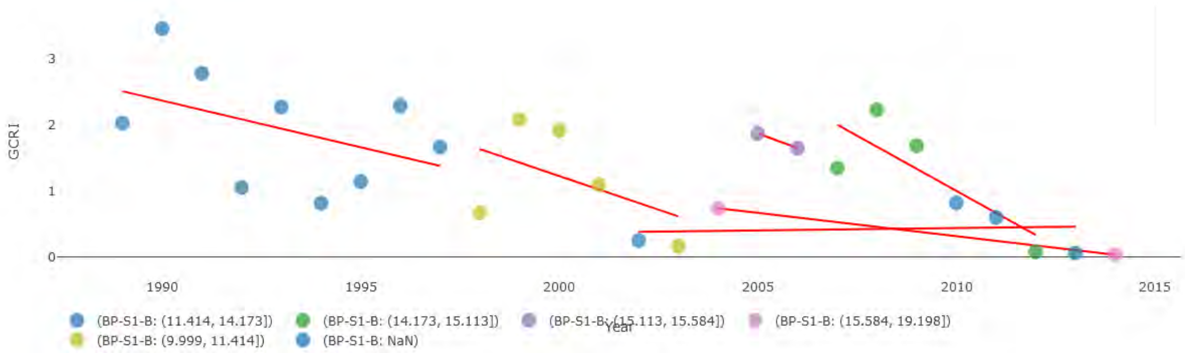

Figure 10

The spectrum chart of risk tensions based on five bargaining power levels

Furthermore, when comparing historical values of the tension risk index using the measured international bargaining power index in the scenario of political realism, in addition to the post-war development years where tension risks have a negative polar orientation with international mediation power, they sometimes exhibit even greater negative polarity with international mediation power in subsequent periods.

8. The economic freedom index (IEE) increases from 36.4% to a maximum value of 63.95% in the 68-year period from the base year of 2002 to 2070, so it can be used for the development of plans by an annual average of 0.89%.

Table 5 presents the maximum variable ceiling limit and the average achievable growth, which is an important factor for planning government projects as strategic goals.

Table 5

The limit variables of the dynamics system

No.	Value	Abbreviations	Circulation of change		System's capacity
1	Export quality index	EQI	1998 0.75%	Maximum until 2070 1.68%	0.02%
2	Iran foreign direct investment	IFDI	1998 243,750	Maximum until 2070 421,613,000	5,855,736
3	Country and product complexity index	CPCI	2000 –0.840	Maximum until 2070 15.82%	0.22%
4	Export diversification index	EDI	1962 4.81%	Maximum until 2070 6.14%	0.09%
5	Oil revenue reliance (% of GDP)	ORR	1970 13.56%	Maximum until 2070 67.99%	0.94%
6	Trade (% of GDP)	Trade (% of GDP)	1960 43.19%	Maximum until 2070 89.18%	1.24%
7	Global conflict risk index	GCRI	2006 1.65%	Maximum until 2070 14.35%	0.20%
8	Index of economic freedom	IEF	2002 36.40%	Maximum until 2070 63.95%	0.89%

6. Conclusions and policy implications

Energy policymakers can make informed decisions that lead to a future with more sustainable, efficient, and resilient energy by harnessing the power of data mining and the system dynamics method. Based on the proposition mining mechanism of the data mining method, this work transformed the initial axiomatic model of the subject dynamics into a large abstract model by the aggregation of articles and sources related to the subject. From the big abstract model, the basic propositions were used to analyze sequential pattern mining in Python to extract valid propositions and rank them. Based on the series of valid propositions, the prominent effective indicators were extracted as main decision variables, which were converted into measurable indicators. The values should be delivered to the ARIMA Python algorithm to analyze the time series and extract the governing equations. Then, based on the mathematical model of ARIMA analysis of the time series of the extracted indicators, dynamic analysis blocks were made and corrections for static modeling were evaluated as separate blocks. The network of blocks for evaluating the behavior of dynamic systems was approved as a new part of the model (under the title of energy policy) and added to the basic model of PEEMI to measure the system capacities of the energy policy apparatus and calculate the indicators of international bargaining power and the acceptability of ACPIC’s international participation in Iran’s energy policy apparatus as the key to the sustainable implementation of energy planning implementation steps and its recursive measurement using the energy–economic dynamic machine algorithm. It is essential to outline limitations such as predicting external shocks like global crises.

The innovation of this work lies in the combined use of two advanced methods of data mining and system dynamics in energy policy analysis. We transformed the initial models into more abstract and comprehensive models using propositional mining, which could play a crucial role in evaluating energy policy decisions and assessing key variables. This paper applied the ARIMA algorithm for time series analysis and used it to create dynamic system analytical blocks, correcting static models and making energy system behavior predictions more accurate. Furthermore, the innovation in using the PEEMI model as a tool for assessing energy system capacities, Iran’s international bargaining power, and ACPIC’s international participation in Iran’s energy policymaking provides novel solutions for improving future sustainable energy policymaking.

Nomenclature

ACPIC	Acceptability of cooperation and partnership with reputable international companies and enterprises inside
ARIMA	Autoregressive integrated moving average
CPCI	Country and product complexity index
EDI	Export diversification index
EENS	Ensuring energy security
EFDI	Ensuring foreign direct investment
EQI	Export quality index
ERI	Economic resilience index
ESR	Energy security risk
GCRI	Global conflict risk index
GDP	Gross domestic product
IBP	International bargaining power
ICI	International cooperation

ICRIT	Iran's credit rating in international trade
IEF	Index of economic freedom
IFDI	Iran foreign direct investment
ORR	Oil revenue reliance (% of GDP)
PEEMI	Preliminary energy–economy model of Iran
SARIMAX	Seasonal autoregressive integrated moving average with exogenous variables
SDI	Sustainable development index

References

Ackoff, R. (2020). The Art of Problem Solving: Accompanied by Ackoff's Fables. Wiley.

Agency I. E, I. E. (2023). World Energy Outlook 2023: Energy Policies and Global Transitions. International Energy Agency.

Auty, R. M. (2001). Resource abundance and economic development. . Oxford University Press.

Baldwin, D. A. (2013). Power and international relations: A conceptual approach. Princeton University Press.

Cashman, K. (2023). Iran's Energy Economy and Sanctions: An In-depth Analysis. Energy Economics Review, 39(2), 120–135.

Choucri, N. (2012). Cyberpolitics in International Relations. MIT Press.

Daniel Maram, S. N. (2022). The Place of Energy Security in the National Security Framework: An Assessment Approach. Energies, 15, 658.

Emi Iwatani, D. P. (2018). Overview of Data Mining's Potential Benefits and Limitations in Education Research. Practical Assessment, Research and Evaluation, ISSN 1531–7714.

Energy, U. D. (2023). Cost-Effectiveness of U.S. Energy Policies: An Analytical Framework. U.S. Department of Energy.

Francesca Pianosi, K. B. (2016). Sensitivity analysis of environmental models: A systematic review with practical workflow. Environmental Modelling and Software, 214–232.

Gauthier, S. (2023). Feedback loops in system dynamics: Applications in energy policy modeling. Energy Policy Journal, 134, 45–58.

Ge Gao, H. L. (2023). Live streaming recommendations based on dynamic representation learning. Decision Support Systems, Volume 169.

Ge Wang, Y. G. (2023). What type of algorithm is perceived as fairer and more acceptable? A comparative analysis of rule-driven versus data-driven algorithmic decision-making in public affairs. Government Information Quarterly, Volume 40, Issue 2.

Han, J. K. (2012). Data Mining: Concepts and Techniques. Elsevier.

Hirshleifer, J. (1988). The theory of cost and the theory of bargaining. Journal of Political Economy, 96(2), 315–336.

Hjorth, P. e. (2023). Decision-making in complex systems: The integration of renewable energy policies in the global economy. Energy Systems Journal, 41(5), 95–112.

Hossein Aghaie Joobani, M. M. (2015). Russia, Turkey, and Iran: Moving Towards Strategic Synergy in the Middle East? Strategic Analysis, 141–155.

Hyndman, R. J. (2018). Forecasting: principles and practice. Monash University, Australia: otexts.

Ivanova, K. (2023). Multi-Method Framework for Development of Systemic, Technology-Driven Capability Concepts. Sydney: UNSW.

James Hendler, A. M. (2016). Social Machines The Coming Collision of Artificial Intelligence, Social Networking, and Humanity. eBook: Apress.

Jennifer Sian Morgan, S. H. (2017). A toolkit of designs for mixing Discrete Event Simulation and System Dynamics. European Journal of Operational Research, 907–918.

Johannes Reissner, E. W. (2004). Iran and Its Neighbors: Diverging Views on a Strategic Region" – Vol. II. Berlin: Stiftung Wissenschaft und Politik.

Kaldor, M. (2007). New and old wars: Organized violence in a global era. . Polity Press.

Katona, V. (2018, September). How Iran Plans To Bypass The World's Main Oil Chokepoint. Retrieved from oilprice.com.

Kesra Nermend, M. Ł. (2016). Neuroeconomic and Behavioral Aspects of Decision Making . Springer.

Konstantin Löffler, K. H.-Y. (2017). Designing a Model for the Global Energy System GENeSYS-MOD: An Application of the Open-Source Energy Modeling System (OSeMOSYS). Energies, 10(10), 1468.

Leo Schrattenholzer, Y. F. (2004). A longer-term outlook on future energy systems. International Journal of Global Energy Issues, 348–373.

Maede Maftouni, N. G. (2023). A Deep Learning Technique for Parameter Estimation in System Dynamics Models. SSRN.

Mashayekhi, A. N. (1978). Strategy of economic development in Iran : a case of development based on exhaustible resources. Massachusetts : MIT.

McKinsey & Company. (2023). Global Energy Perspective 2023: Data-driven insights into the transition to renewable energy. McKinsey & Company. McKinsey & Company.

Mishra, V., Smyth, R. (2020). A recent study in Energy Economics explores how the energy transition impacts global economic structures and the role of renewable energy in fostering sustainable development frameworks. Energy Economics, 92, 104818.

Mohammed M. Mazidm, A. S. (2009). A Comparison Between Rule Based and Association Rule Mining Algorithms. IEEE, DOI: 10.1109/NSS.2009.81.

Mokhtar S. Bazaraa, J. J. (2011). Linear Programming and Network Flows, 3rd Edition. Georgia: Wiley.

Moradi, M. A., Ahmadi, S., – Khorasani, A. H. F. (2015). The impact of energy conservation policies on the projection of future energy demand in Iran. Energy Technology – Policy, 2(1), 104–121.

Navid Ghaffarzadegan, J. L. (2010). How small system dynamics models can help the public policy process. System Dynamics Review, Citations: 230.

Nye, J. S. (2004). Soft power: The means to success in world politics. . Public Affairs.

Papakyriakopoulos, O. (2020). Political machines: machine learning for understanding the politics of social machines. Munchen: Technischen Universit¨at M¨unchen.

Pormasomi, S. (2010). A System Dynamics Model For Analyzing Iran's Energy-Economy System. Tehran: Sharif University of Technology.

Sandra Maria Correia Loureiro, J. G. (2021). Artificial intelligence in business: State of the art and future research agenda. Journal of Business Research, 911–926.

Sarah Hafner, L. G.-B. (2024). Building the Bridge: How System Dynamics Models Operationalize Energy Transitions and Contribute towards Creating an Energy Policy Toolbox. Sustainability, 16, 8326.

Shaker Mohammadi, A. E. (2019). Simulation of Iran’s Energy Balance and Designing Supply and Demand Management Scenarios for 2042 Using LEAP. Iranian Energy Economics, https://doi.org/10.22054/jiee.2019.9918.

Simulation of demand and supply of energy carriers in Iran up to 2035 using LEAP. (2014). Journal of Energy Planning And Policy Research, Iran, http://epprjournal.ir/article-1-46-en.html.

Tanveer Ahmad, D. Z. (2020). A critical review of comparative global historical energy consumption and future demand: The story told so far. Energy Reports, 1973–1991.

Trelstad, B., Varma, P., – Blankinship, B. (2024, April 20). Systems Thinking: A Guide to Decision-Making in Dynamic Environments. Harvard Business School. Retrieved from thoughtexchange.com: https://thoughtexchange.com/blog/the-11-laws-of-systems-thinking-and-stakeholder-engagement/

Wang, H. (2022). Role of environmental degradation and energy use for agricultural economic growth: Sustainable implications based on ARDL estimation. Environmental Technology and Innovation.

Watts, D. J. (1998). Collective dynamics of ‘small-world’ networks. Nature, 393(6684), 440–442.