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Original Article

Artificial intelligence (AI) based analysis for global warming mitigations of non-carbon emitted nuclear energy productions

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A R T I C L E I N F O

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A B S T R A C T

Nuclear energy is estimated by the machine learning method as the mathematical quantifications where neural networking is the major algorithm of the data propagations from input to output. As the aspect of nuclear energy, the other energy sources of the traditional carbon emission-characterized oil and coal are compared. The artificial intelligence (AI) oriented algorithm like the intelligence of a robot is applied to the modeling in which the mimicking of biological neurons is utilized in the mathematical calculations. There are graphs for nuclear priority weighted by climate factor and for carbon dioxide mitigation weighted by climate factor in which the carbon dioxide quantities are divided by the weighting that produces some results. Nuclear Priority and CO2 Mitigation values give the dimensionless values that are the comparative quantities with the normalization in 2010. The values are 1.0 in 2010 of the graphs which are changed to 24.318 and 0.0657 in 2040, respectively. So, the carbon dioxide emissions could be reduced in this study.

1. Introduction

Nuclear energy could be helpful to reduce global warming gas such as carbon dioxide. In this study, nuclear energy is estimated by the machine learning method as the mathematical quantifications where the neural networking is the major algorithm of the data propagations from input to output. As the aspect of nuclear energy, the other energy sources of the traditional carbon emission-characterized oil and coal could be compared. However, there are significant limitations in the decisions by human judgment. Hence, it is applied by the artificial intelligence (AI) oriented algorithm like the robot's algorithm in which the mimicking of biological neurons is utilized in mathematical calculations. There are some papers on applications using machine learning [1–3].

Although it is not easy to estimate the energy demand, the trend of energy could be analyzed by interesting factors such as the carbon emissions to the atmosphere regarding fossil fuels. Renewable energies could be the best choice which doesn't produce the carbons as the global warming gas. However, considering the economic effect, nuclear power would be taken as one of the important energy portions of a nation. Therefore, nuclear energy can be discussed as the possibility of an energy source with its related condition like the populations and governmental services which will be modeled in this study.

The raw data show the trend of the world energy prospect where nuclear and renewable energies are major example sources that can reduce the carbon emission gases such as carbon dioxides. There are the data for the total primary energy demand as the Million Tonnes of Oil Equivalent (Mtoe) by the International Energy Agency (IEA) in Table 1 [4] where the new policies scenario (NPS) incorporates existing energy policies as well as an assessment of the results likely to stem from the implementation of announced policy intentions. The portion of nuclear power decreased in 2017 which is different from other sources where the quantities are increasing continuously. In addition, there is the table for the carbon dioxide emissions in Table 2 [4] in which, as it is expected, it increases smoothly.

With the uncertainties in future estimations, the limitations of the integrity of the modeling could be compensated with the numeric values in which the logical scenarios are necessary. Hence, the future things are regarded as randomly happened cases where the random samplings are used in the modeling of this work. There are previous studies on global warming for nuclear energy with some mathematical manipulations such as AI applications and game algorithms [5]. In the previous studies, it is identified for the research gap of a study attempt to address and motivated the research field in which the study subject expresses the research gap and the references to support the topic [6–10]. In addition, there are some nuclear energy basis studies for global warming [11–15].

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Table 1
Total primary energy demand, Mtoe [4].

	2010	2017	2030	2040
Nuclear	718.8	687.8	847.9	971.1
Coal + Oil	7775.1	8185.4	8613.7	8703.1
Hydro + Bio +Other Renewable	1628.1	1991.6	2885.5	3604.6

Table 2
CO_2 emissions, Mt [4].

	2010	2017	2030	2040
Carbon dioxides	30,331.3	32,580.4	34,575.9	35,881.4

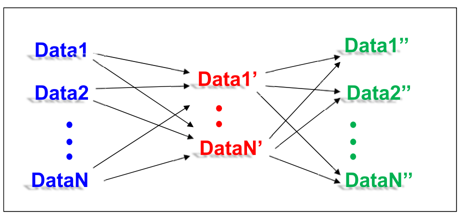

Fig. 1. The typical model for neural networking of machine learning.

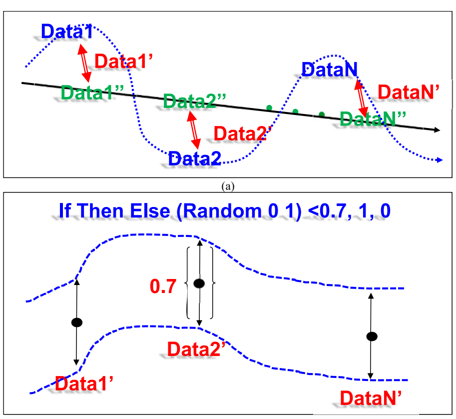

Fig. 2. Data regression analysis based on least squares for machine learning (a) Data set and (b) Modified least-square values.

2. Method

Machine learning is based on neural networking which is the biological process in nerve systems. In this study, the cost of the interested values and their related error-estimations are examined in which the least square method is applied to the random sampling-based method where the minimum value is substituted with the conditional statement choice as the If-Then-Else sentence. That is, the point value of the minimized one is changed to one within the designed range.

2.1. Machine learning

The neural network-based machine learning is applied to the climate change matter in this work which has a three-layers algorithm of input, hidden, and output stages. There is a study for the dynamic neural network identifiers in which the fault detection for the gas turbine engine is analyzed by the dynamic multi-layer perceptron (MLP), a dynamic radial-basis function (RBF) neural network, and a dynamic support vector machine (SVM) [16]. Neural networking is described as,

$$N(x) = C\left(\sum_i h_i p_i(x)\right) \tag{1}$$

where $N(x)$ is the neural network function, $p_i(x)$ is the composition of other functions, h_i is the weighting factor and C is the activation function [17] in which they are dependent on several arrowed variables [18].

2.2. Cost estimation method

To take interesting value, it is regarded that working capital investment is needed to keep the operations of the organization [19]. For the case of the energy industry, machine learning could be one of the solutions where the neural networking algorithm is used to find the optimized values.

2.3. Error-computation

For the integrity of the cost estimations, data manipulations are needed. The error estimation is written as [20],

$$E = \frac{1}{2}\sum_{i=1}^{K}(A_i - B_i)^2 \tag{2}$$

where A_i is the goal value and B_i is the calculated value. So, the differences between the two values are estimated as the machine learning's integrity. That is the minimum values are obtained as,

$$M = min\ (A_i - B_i)^2 \tag{3}$$

The quadratic curve shows the minimum values in the M graph to be obtained for the least-squares.

3. Modeling

The Monte-Carlo method-related random sampling is used for the modeling. Fig. 1 shows the typical model for neural networking of machine learning where there are three steps of input, hidden, and output layers. For the real data in energy sources, the open data to the public are used. Table 1 is the total primary energy demand as the unit of Mtoe [4]. In addition, Table 2 is the CO_2 emissions as the unit of Mt [4]. Fig. 2 shows the data regression analysis based on least squares for machine learning (a) Data set and (b) Modified least-square values where the error-estimations are considered. The minimum value selections are the data selection in the interested range by the conditional statement as the If-Then-Else sentence. So, equation (2) is converted to the modified least square value as,

$$\text{If Then Else (Random 0 1)} < 0.7,\ 1,\ 0 \tag{4}$$

That is, the randomly selected data are compared with the value of 0.7. Then, if the data are lower than 0.7, it is selected as 1.0. Otherwise, it is 0.0. That is, the least squared minimum values are the random number values within the designed range.

Using the above theoretical algorithm, Fig. 3 is the modeling for the Climate where the Vensim code PLE for window version 7.2 single precision is used [21]. This code is originally used for the System Dynamic (SD) analysis where the information originated feedback-based analysis tool where the social humanities, as well as scientific-technological matters, are examined for the quantifications of the designed modeling. In this work, the AI-based algorithm is simulated with a random sampling-equipped quantification method. So, some technical skills of SD are utilized in this study and the modeling goal is fully satisfied. For each value, Table 3 shows the variables for the modeling which is referred from the prevision study [22]. In the case of Age, if the random number is lower than 0.7, the value is 1.0. Otherwise, it is 0.0. Other cases are obtained in similar ways. For CO2,

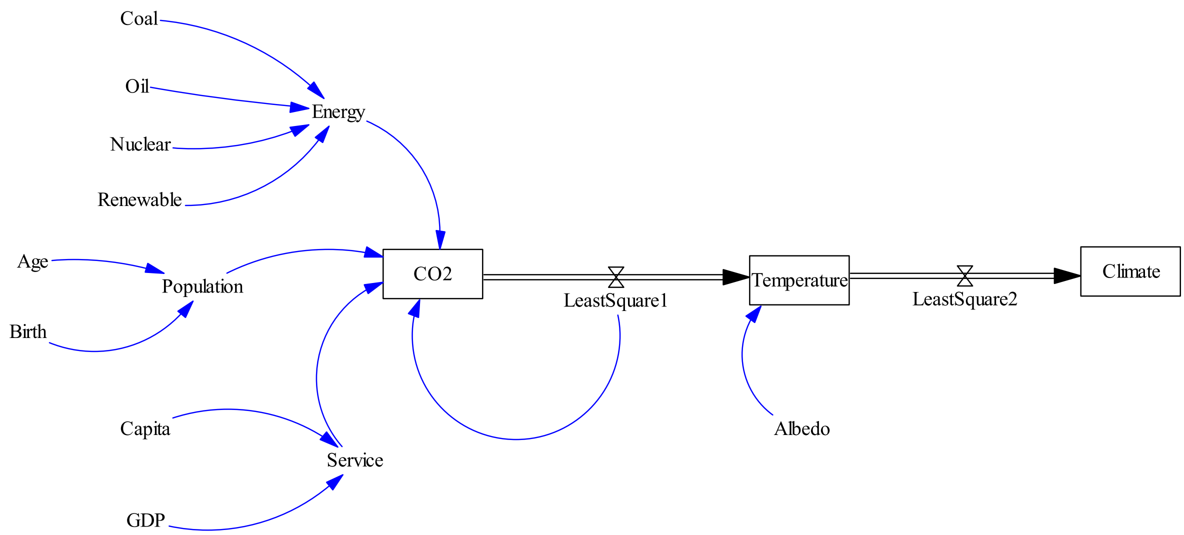

Fig. 3. Modeling for the climate.

Table 3
List of variables [22].

Variable	Value
Age	if then else(random 0 1 () < 0.7, 1, 0)
Birth	if then else(random 0 1 () < 0.8, 1, 0)
Population	Age * Birth
GDP	if then else(random 0 1 () < 0.8, 1, 0)
Capita	if then else(random 0 1 () < 0.9, 1, 0)
Service	Capita * GDP
LeastSquare2	if then else(random 0 1 () < 0.9, 1, 0)
Oil	if then else(random 0 1 () < 0.8, 1, 0)
Coal	if then else(random 0 1 () < 0.6, 1, 0)
Renewable	if then else(random 0 1 () < 0.5, 1, 0)
Nuclear	if then else(random 0 1 () < 0.6, 1, 0)
Albedo	if then else(random 0 1 () < 0.4, 2, 1)
CO2	- LeastSquare1 * if then else(random 0 1 () < 0.4, 1, 0) * CO2 * Energy * Population * LeastSquare1 * Service
Temperature	LeastSquare1 - LeastSquare2 * if then else(random 0 1 () < 0.6, 1, 0)/ (Albedo)
Climate	LeastSquare2 * if then else(random 0 1 () < 0.7, 1, 0)
LeastSquare1	if then else(random 0 1 () < 0.8, 1, 0)

Temperature, Climate, and LeastSquare1, the values are obtained in cumulative ways.

4. Results

There are the simulations for (a) CO2, (b) Temperature, and (c) Climate in Fig. 4 where the Monte-Carlo method-based simulations are performed with the above algorithms. Energy includes Coal, Oil, Nuclear, and Renewable. In addition, Population consists of Age and Birth. Service has Capita and GDP. The single-line arrow shows the typical event flow and the double-line arrow shows the cumulative meaning. In addition, there is the feedback line in LeastSquare1 where the event flows affect the previous task. Fig. 5 is the graph for energy demand in the IEA [4]. Fig. 6 is the graph for nuclear priority weighted by climate weighting. Whereas Fig. 7 shows the graph for carbon dioxide mitigation weighted by climate weighting in which the carbon dioxide quantities are divided by the weighting that produces the results. Nuclear Priority and CO2 Mitigation values give the dimensionless values that are the comparative quantities with the normalization in 2010. The values are 1.0 in 2010 which are changed to 24.318 and 0.0657 in 2040, respectively. So, the carbon dioxide emissions could be reduced in this study.

5. Conclusions

The algorithm of machine learning originated from the biological neurons in which there is stepwise modeling of three layers. However, it is impossible to analyze the task with the exactly same method as the human brain. So, this paper has shown the reasonable logic of the computations. There are some important points in this study as.

- The machine learning is applied to the climate change matter.
- Nuclear energy is considered the major source of global warming mitigations.
- The AI-based quantifications are shown successfully.
- Analysis of energy outlook is constructed.
- Climate-related complex algorithm is achieved successfully.

The limitations of the machine's analysis for the energy prospect are examined by machine learning-based modeling. It is performed for this study to make a better choice for the energy source in the country. There are two choices as nuclear power or renewable energies. Although the results of the modeling show that nuclear energy could enhance the priority in this work, renewable one is also a good candidate in the future, because both sources don't produce carbon gases.

In the endeavor for minimizing the deficiency in the human's ability for the future outlook in energy trends, AI is successfully applied to the designed modeling. By the way, a question could happen that the AI logic can't be wiser than the intelligence of humans because the AI is constructed by mimicking the biological brain. However, there is a big difference between human and AI decisions. When a man thinks about a certain task, all kinds of stuff in the brain area is related to decision-making. Especially, emotion is one good example to make a wrong decision. That is, the prejudice of a human could affect the task. AI is controlled by the operator by a weighting which is used in this modeling of the study. Vensim code modeling is based on random sampling, which means the events in nature are deeply related to the random sampling algorithms.

In future work, the other kind of cases such as the prices in the world market could be modeled which is changed by the weather in a region. The stock market is complicated in the analysis where there are many factors are affected each other. So, the grain prices are estimated by climate change in which the temperature is one of the most important factors to be considered as the latitude of grain cultivation would be changed to the place in northern places. Hence, the climate estimations weighing is very important to make a decision on industrial products including agricultural matters. So, economic and social matters are

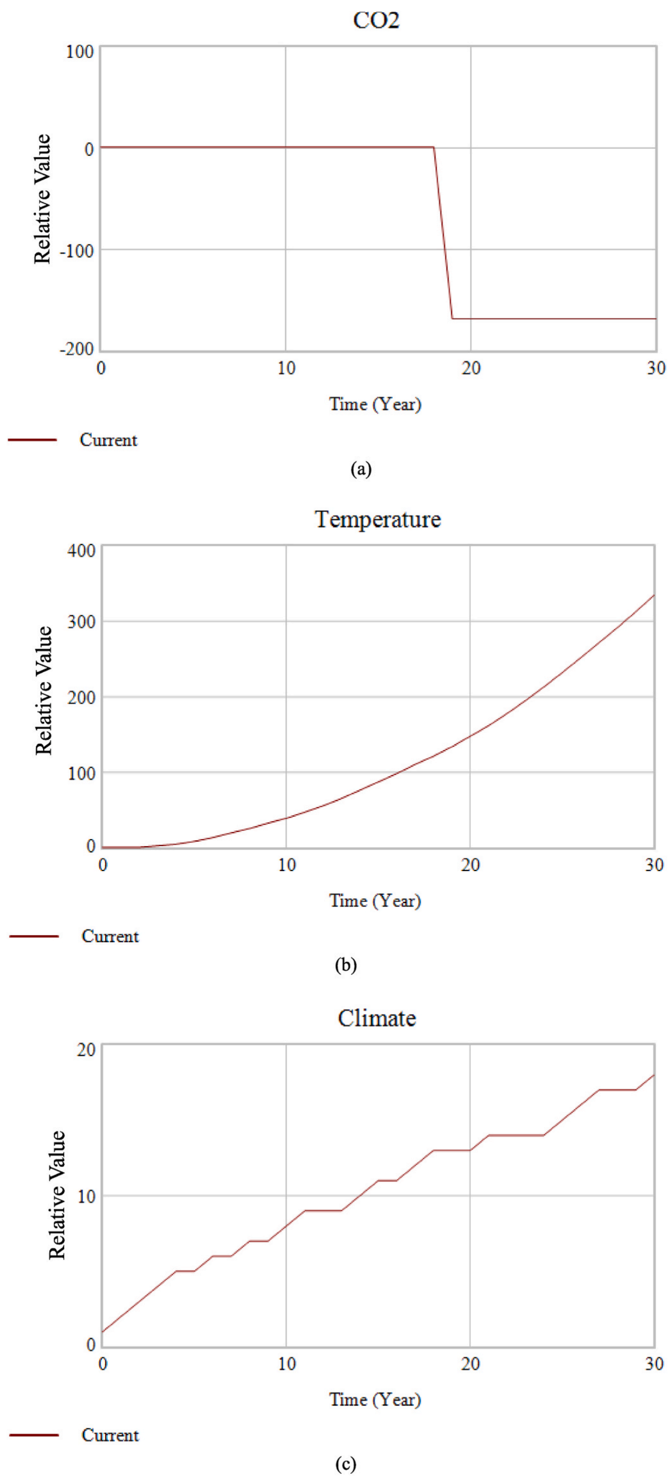

Fig. 4. Simulations for (a) CO2, (b) temperature, and (c) climate.

connected in complicated manners where several complex tasks are connected to find better reasonable solutions.

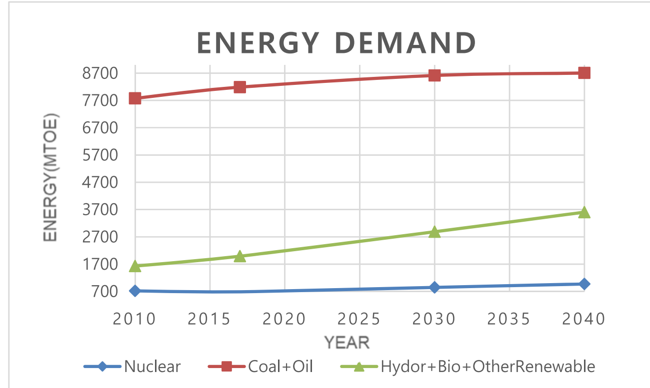

Fig. 5. Graph for energy demand.

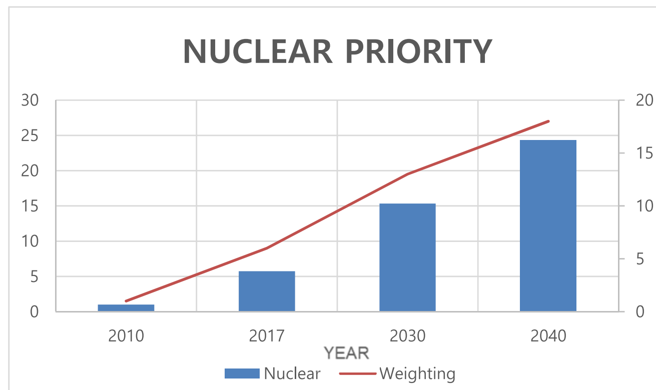

Fig. 6. Graph for nuclear priority weighted by climate weighting.

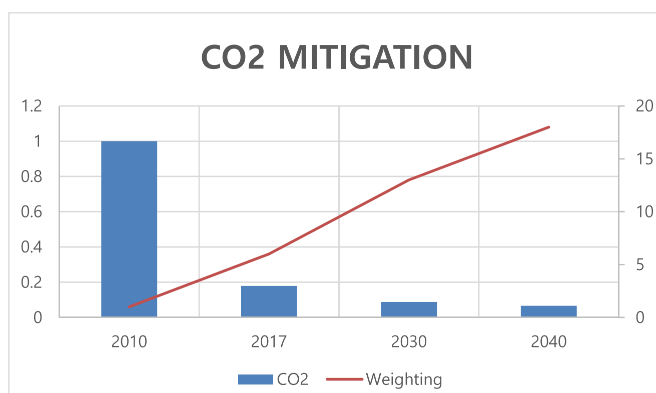

Fig. 7. Graph for carbon dioxide mitigation weighted by climate weighting.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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