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Optimization of Korean energy planning for sustainability considering uncertainties in learning rates and external factors

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ABSTRACT

During the last few decades, energy planning has focused on meeting domestic demand at lower total costs. However, global warming and the shared recognition of it have transformed the problem of energy planning into a more complex task with a greater number of issues to be considered. Since the key issue is to reduce greenhouse effects, governments around the world have begun to make investments in renewable energy systems (e.g., hydro, wind, solar, and/or biomass power). The relatively high costs of renewable energy systems and the uncertain outlook of their rate of diffusion in the market make it difficult to heavily rely on them. The uncertain variations in production cost over time are especially challenging. To handle uncertainties, the concept of the learning rate was adopted in this study so as to compute the costs of energy systems in the future and Monte Carlo simulation was performed.

The aim of this study was to optimize plans of conventional and prospective renewable energy systems with respect to production cost. The production cost included capital, fixed, variable, and external costs. For the case study, the energy situation in South Korea was used. The results of the case study where the proposed methodology was applied could provide useful insights economically and strategies of sustainable energy management for ambiguous environments.

1. Introduction

Although many countries have struggled to decrease their consumption of energy, world consumption of fossil fuels in generating energy has continuously increasing at the rate of 2% per annum [1]. This continual increase has brought about the depletion of natural resources and the emissions of greenhouse gases, which has resulted in environmental problems, including greenhouse effect. By the Kyoto Protocol, Intergovernmental Panel on Climate Change (IPCC) and Copenhagen climate change conference (COP15), many nations have been required to comply with environmental regulations, especially the reduction of CO_2 emissions [2]. Thus renewable energy sources such as hydro, wind, solar and biomass energy have emerged and technologies related to renewable energy systems have been developed. Recently a number of organizations have begun to consider renewable energy systems and their industries as opportunities rather than regulations [3,4]. Korea is no exception; government and companies in Korea have put effort into promoting green technologies [5].

Despite the awareness of renewable energy grows, renewable energy systems make up averagely 7–8% of the entire energy supply in Europe [6], and only 2.2% in Korea [5]. The reasons are that the efficiencies of renewable energy systems are still lower than that of conventional energy systems, and the discontinuity of generation can be occurred. Since the availability of renewable energy sources should be broadened to reduce the emissions of greenhouse gases, it is essential that the planning of energy systems be optimized considering multiple constraints that include satisfying energy demands, minimizing production cost and meeting the required and/or permitted greenhouse gas emission levels [7,8].

Previously, a number of methodologies and schemes for energy planning have been studied and proposed for optimal energy planning. In terms of models, schemes have been introduced by the time-stepped energy system optimization model (TESOM) [9], market allocation model (MARKAL) [10–12], energy flow optimization model (EFOM) [7], and inexact community-scale energy model (ICS-EM) [13]. Each model reflects its own characteristics and optimization techniques but does not incorporate recent changes in nature of renewable energy planning, and overall energy sources in large scale. Krukanont considered various uncertainties to analyze the near-term energy planning and suggested several policy regimes but covered limited renewable

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energy systems [14]. Evaluating feasibility various renewable energy systems have also been introduced. Viebahn compared costs and the contributions of carbon capture and storage (CCS) technologies and renewable energy systems in the long-term [15]. Chatzimouratidis and Kaya evaluated some energy systems under several criteria with weights obtained by an analytical hierarchy process (AHP) [16,17]. Krey incorporated uncertain energy prices into energy systems by including a stochastic risk function [18]. Similarly, Streimikiene conducted a long-term assessment of new electricity generation technologies for CO_2 price scenarios [19], and Koo studied scenario-based economic evaluation of renewable energy systems considering carbon capture and storage (CCS) and varying fuel prices [2]. Despite the recent works, energy planning needs to reflect the integration in terms of uncertainties in prices of fuel price for energy generation, expansion of carbon dioxide trading, and change of learning rates with various models to obtain optimal solution, because the governments which are interested in energy planning want to evaluate energy systems in many ways for robustness. While some previous works provided estimates of variables separately [20,21], we suggest that the proposed method should apply the future prospects on cost and learning effect.

Based on the previous works, a modified model can be introduced with supplementary information. The supplementary information discussed in the proposed method includes not only cost estimates at the present level but also prospects for the future. The uncertainties in the future situations will be considered with respect to the types of energy systems, and the proposed method presents several major uncertainties related to energy systems – the learning rate of the technologies, fuel prices, and carbon prices. The major uncertainties will affect the competitiveness of energy systems. The effects of learning rate and prices of an energy system may be unique attributes; we cannot anticipate exactly [22–24]. Thus, we have to estimate the unpredictable values. This study aims to integrate various uncertainties in growth rate scenarios and apply Monte Carlo simulation for handling uncertainties.

The proposed method constructs the production and CO_2 emission trading costs as an objective function, which allows for economic evaluation of conventional and renewable energy systems taking into consideration the uncertainties. As a result, the optimal capacities of energy systems to be added can be obtained.

The rest of this paper is organized as follows. In Section 2, the brief descriptions on the problem, learning rates, and other uncertainties are provided. Section 3 presents the proposed model including the objective function and constraints. Section 4 discusses the results of the proposed method applied to a Korean case. Section 5 concludes this study.

2. Model formulation

The model is defined to reflect the integration of uncertainties in this section. As mentioned, the previous model needs to be modified by the supplementary information such as learning rate and prices. That makes our model consider the prospect for the future as well as estimation at the present level. The uncertainties are considered by Monte Carlo simulation to achieve robust optimization. Since the using of random input from sampling turns the model into a stochastic model, the inclusion of uncertainties would be reflected to decision-making that decides which energy system should be installed.

2.1. Definition of production costs

In this study, energy system refers to power plants that generate electricity using a certain energy source. The aim of this study was to evaluate the production costs of possible energy supplies and optimize energy planning that included renewable energy systems. According to the method commonly practiced for economic evaluation, the total cost of the production can be expressed as the summation of the capital, fixed, variable, and external costs. Each cost can be calculated as follows [2,7,25,26].

$$\text{Capital cost} = \sum_{t=1}^{N_t} \frac{1}{(1+d)^t} \mathrm{KC}I_t \tag{1}$$

$$\text{Fixed cost} = \sum_{t=1}^{N_t} \frac{1}{(1+d)^t} \mathrm{KFC}_t \tag{2}$$

$$\text{Variable cost} = \sum_{t=1}^{N_t} \frac{1}{(1+d)^t} C_t \mathrm{PF}_t \rho\tau \tag{3}$$

$$\text{External cost} = \sum_{t=1}^{N_t} \frac{1}{(1+d)^t} C_t \mathrm{PC}_t R\tau \tag{4}$$

where N_t denotes the total years from 2011 to 2030; d is the discount rate; KC is the initial unit capital cost of the energy system; I_t is the capacity of the energy system installed in year t; KF is the unit fixed cost of the energy system in 2011; here, the unit fixed cost includes the operation and maintenance cost that are not dependent on the capacities. C_t is the cumulative capacity of the energy system in year t. Variable cost refers to expenses that change in proportion to the activity of a business; here, we assumed that the variable cost is limited to buying fuel. Thus, the variable cost is dependent on fuel price only, and PF_t is the required fuel price to operate the energy system in year t; ρ is the conversion ratio from the TOE to the MWh; τ is the capacity factor for the energy system, which represents the fraction of actual output produced over the maximum output achievable during a period of time. Lastly PC_t is carbon price in year t; R is the emission rate with capacity C_t for the energy system.

2.2. Learning effects

The basic concept of learning is cost reductions as the result of learning-by-doing. It means that the performance improves as capacity or a product expands [22]. Learning can also be regarded as the cost-reducing effect in each energy system that might be used in economics to describe improvement in productivity [27]. The learning process can also be seen as a fundamental human characteristic. A person engaged in a task will improve his/her performance with experience and technological development. Many studies present that the cost reduction is dependent on the industry, region, and time. Especially for renewable system, empirical studies show that learning is influenced by cumulative capacity, C_t [27,28]. The cumulative capacity can be defined as following equation.

$$C_t = C_0 + \sum_{t=1}^{N_t} I_t \tag{5}$$

Reflecting the concept of learning effect, the total cost of each energy system over its life time can be modified as following equation.

$$\text{Total cost} = \sum_{t=1}^{N_t} \left[\frac{1}{(1+d)^t} \left\{ \left(\frac{C_t}{C_0} \right)^{\alpha_t} (\mathrm{KC}I_t) + C_t (\mathrm{KF} + \mathrm{PF}_t \rho \tau_t + \mathrm{PC}_t R \tau_t) \right\} \right] \tag{6}$$

C_0 stands for the initial capacity at the base year, α_t corresponds to learning effect term at year t. The learning effect is restricted to