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The Effect of Ratio-Based Incentive on Wind Capacity Development and Investment Risk of Wind Units: A System Dynamics Approach

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ABSTRACT Different capacity incentives like feed-in-tariff have been considered to encourage companies to invest in wind power units. One of the main challenges of the electricity market policymakers is the determination of this fixed payment based on limited funding in a way that the investment cost of wind units is compensated and the associated investment risk is reduced. The main contribution of this paper is the introduction of a method to manage the amount of payment or incentives during a time horizon to reach the targeted wind capacity and reduce its investment risk. In this regard, the ratio-based incentive is introduced. To study the effects of such a policy, the long-term behavior of the electricity market is simulated by a dynamic model, which is a useful tool for policymakers to analyze the effects of their policies. Then, conditional value at risk and value at risk concepts are used to measure the risk of wind capacity investment. The results illustrate that the ratio-based incentive is more effective than the feed-in-tariff in the context of decreasing the risk of investment, reducing total CO_2 production, electricity price reduction, and speed of providing higher amounts of wind capacity.

INDEX TERMS Capacity investment, electricity market, investment incentive, risk measurement, system dynamics, wind units.

I. INTRODUCTION

In order to decrease the growth rate of global warming, environmental regulations are established by international societies. The main purpose of these policies is the reduction of carbon dioxide emissions along with the consumption of fossil fuels [1]. On the other hand, since the share of thermal power plants in the production of carbon dioxide is considerable, choosing alternative ways to supply sustainable energy is an important challenge for decision-makers [2]. This is because providing sustainable energy resources is an integral part of economic growth in each country [3]. Therefore, the utilization of renewable energies for the production of electrical energy is an attractive way to reduce greenhouse gases and to limit the consumption of fossil fuels. Among various types of renewable energies such as solar energy, wind energy, biomass energy, tidal energy, etc., wind energy is known as a cleaner, more productive, and rapidly growing energy resource that influences solving the problem of energy scarcity [1]. Studies demonstrate that European countries strive for meeting a considerable portion of their demand through wind energy. In this regard, the average annual installed wind capacity in Germany, Spain, and the United Kingdom by 2020 has reached 2952.5 MW, 1224.5 MW, and 1363.8 MW, respectively [4].

In most countries, electricity generation companies work in a restructured environment [5]. The liberalization of the electricity market led to many challenges for investors and market regulators. Meanwhile, high investment costs and uncertain future revenue of wind units have declined the willingness of investors to invest in these units. Therefore, in order to get around this problem, various incentives have been introduced to support wind capacity investment [6]. Although new incentive policies based on supporting research and development activities are introduced [7], most of these incentives revolve around two divisions: feed-in-tariff (FIT) and renewable energy quotas or tradable green certificates [8].

In the common FIT, a fixed payment is considered for renewable energy resources to cover part of their high investment costs. Determination of the amount of this payment is

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an important challenge for market policymakers. This payment can act as a double-edged sword. A low amount of payment cannot motivate companies to invest. Accordingly, wind capacity will not be developed as expected. In contrast, a high amount of payment can waste funding or cause over investment which can endanger the security of weak systems.

An investigation of published works illustrates that a great deal of effort has been put in studying the impact of incentives on the development of distributed energy resources. A dynamic model was used to assess the effect of different wind capacity incentives from the market regulator's viewpoint in [6]. In [9], conventional and wind capacity investment dynamics were modeled and a time series simulation technique for wind speed prediction was proposed. Besides, a subsidy for the construction of wind farms was considered as an incentive. The main shortcoming of the presented case study of [9] is the lack of considering the regional and seasonal correlation of wind speed data with electricity demand profile. In [10], a system dynamic model was utilized to study the effect of different capacity mechanisms on market behavior. The effect of incentives on the development of distributed energy resources in an electricity market was studied by the market dynamic model in [11]. Various dynamic models were proposed to study different countries' electricity market behavior in Colombia [12], Sweden [13], and China [14]. In [15], the supply and demand of electricity were described in the Colombian national market based on the system dynamics approach. Then, the stability of the equilibrium points and non-smooth dynamics of the mentioned model were analyzed. In [15], the capacity to build was defined by a piecewise-smooth function illustrating the magnitude of the investments, and three fixed values were considered for that. Such assumptions in real-world decision-making are not true and the installed capacity cannot be limited to three values. In [16], a system dynamics model was applied to study the effect of various environmental policies on wind power development in China. These policies comprised the air pollution and low-carbon constraint policy, the purchased electricity power policy, and the plan for regional coordinated development. Authors of [17] studied the long-term effect of cautious FIT reduction on photovoltaic generation in the UK. Different investment strategies of the power enterprises considering carbon trading in China were studied in [18] based on system dynamic theory. A new FIT mechanism for wind units based on a regional power grid was proposed in [19]. Different studies were also conducted about renewable energy investment risk through various methods. For instance, the authors of [20] provided a multicriteria decision methodology based on a three-stage decision framework for the identification of risk factors, assessment of them, and the evaluation of strategies to overcome these factors. In [21], the five most relevant renewable energy technology investment risk types (curtailment, policy, price, resource, and technology) were identified and investigated through interview transcripts. In [22], renewable energies investment risk factors in different countries were studied and categorized into five types: economic, technical, environmental, social, and political. Then, the fuzzy-analytic network process was used to weigh and assess these factors. In some papers, system dynamic models were used to investigate the risk of renewable energy investment. For instance, in [23], a system dynamic approach was used to evaluate the investment risk of renewable units considering three categories: Technical risk, Market risk, and Policy risks. In another work, wind power generation investment opportunities and their associated risk in Iran were studied by a system dynamic approach [24]. In another line of research, social benefits due to the integration of large-scale wind units in a deregulated power market were reviewed [25].

To the best of the authors' knowledge, the investment risk of wind units in dynamic models has not been measured through conditional value at risk (CVaR) and value at risk (VaR) methods so far. Moreover, most of the reviewed articles tend to find the optimum amount of fixed payments as an incentive, while they do not answer the following questions. Is it necessary to change the amounts of these payments? If yes, when should it be decreased or increased?

The main contribution of this paper is the introduction of a method for the management of these payments to reach the pre-defined percentage of installed wind capacity in the long-term and reduce the wind capacity investment risk, simultaneously. For this purpose, a ratio-based incentive is introduced. In this incentive model, the amount of payments is not fixed during the time horizon and it decreases as the percentage of wind capacity rises in comparison with predetermined percentage capacity and vice versa. Moreover, this incentive compensates for the low incomes of wind units to mitigate investment risk when prices are low. In this regard, the system dynamic approach is used to study the effect of the proposed incentive on the development of the wind capacity from the market regulator's viewpoint. The procedure of wind capacity investment has a dynamic nature and affects other factors like electricity prices during a long-term period. Therefore, the long-term behavior of the market is simulated by a dynamic model, and important feedbacks on the market and time delays are considered in this study. Furthermore, CVaR and VaR measures are used for investment risk measurement, and the risk of wind capacity investment is analyzed.

The rest of the paper is arranged in the following way: in Section II, the general aspects of the proposed model are introduced. Section III presents the different parts of the dynamics model. Section IV introduces the case studies and analyzes the results of the simulation. Section V is devoted to the sensitivity analysis. Section VI discusses the major conclusions.

II. GENERAL DESCRIPTION OF MODEL

To analyze the effects of the proposed incentive on the electricity market, the main components of the electricity market and their relationship should be recognized by the system dynamics approach. The most important advantages of the system dynamics approach are its simple mathematical

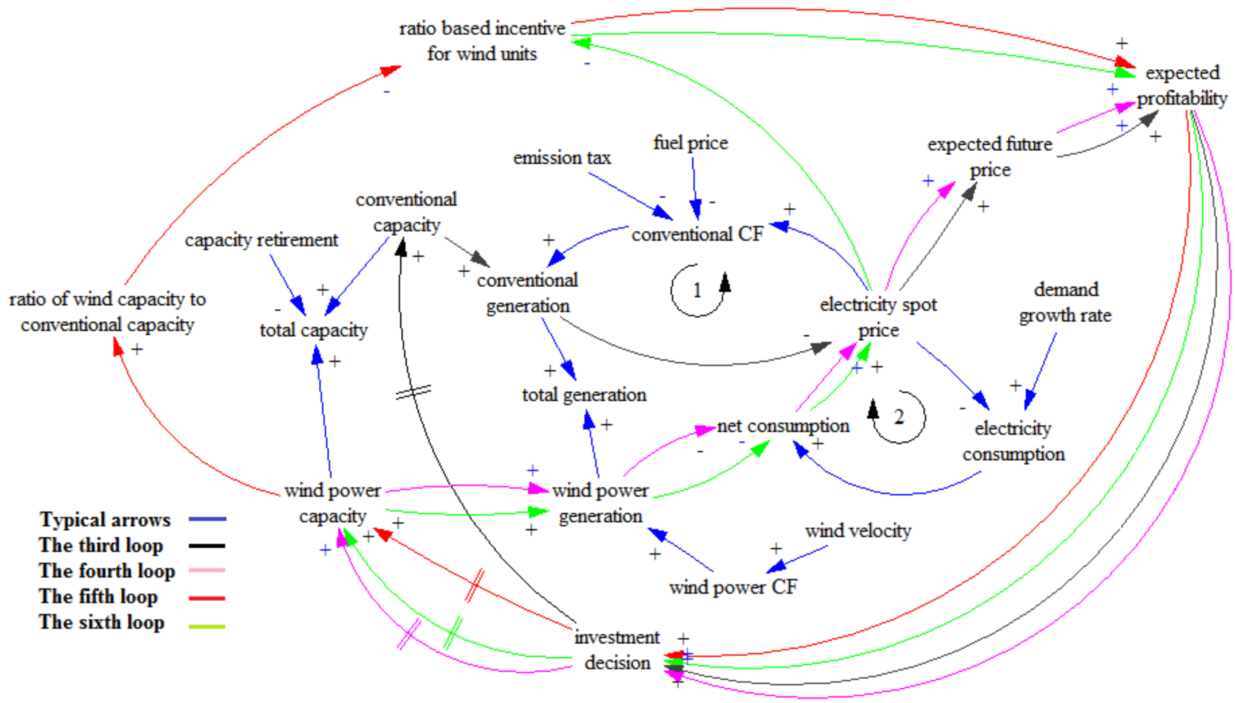

FIGURE 1. The causal loop diagram of an electricity market subjected to ratio-based incentive for wind units.

equations and standard graphical diagrams [26]. The main elements of the dynamic systems comprising feedback loops, delays, causal loop diagrams, stock, and flow variables, can be found in [6] and [27] in detail. Such a system helps market regulators and policymakers investigate the results of different policies. In the current paper, the time step is one week, and simulation is carried out for a time horizon equal to 30 years (1560 weeks). Four different types of technologies comprising hard coal (HC), combined cycle gas turbines (CCGT), gas turbines (GT), and wind technology are utilized to meet the electricity demand. Wind farms participate in the electricity market and due to the stochastic nature of wind speed, their generated power is assumed as a random variable. Part of the load is supplied by wind units as soon as they are available and the rest of the demand which is known as net consumption is supplied by other conventional units. During this process, the price of electricity is determined [28]. Therefore, wind units influence the market price. Consequently, it can be stated that they participate in the market.

Fig. 1 illustrates the causal loop diagram of an electricity market. There are two types of feedback loops in the dynamics of an economic system: positive loops that reinforce changes of the system and negative loops that balance and oppose these changes [29]. Positive (negative) signs show that any increase in the cause or independent variable will lead to an increase (decrease) in the effect or dependent variable [9]. There are five negative and one positive feedback loop in this diagram. Loops number one and two are inner balancing loops that show the price elasticity of fossil fuel units' generation and the price elasticity of electricity demand, respectively [9]. The third loop (black arrows) and the fourth loop (pink arrows) are outer negative feedback loops that control the investments in new conventional fossil fuel units and wind farms, respectively [9]. In this paper, in order to show a causal loop diagram of the proposed ratio-based wind capacity incentive and complete the introduced model in [9], two new loops are considered. The first loop is a negative loop, which is shown by red arrows. Part of the ratio-based incentive that guarantees the installation of a pre-defined percentage of wind units is determined through this loop. As the expected profitability of wind units declines, investment decisions will decrease and this will lead to a reduction of wind power capacity after a time delay. Then, the ratio of wind capacity to conventional capacity decreases. Consequently, the amount of ratio-based incentive for wind units rises and this will lead to an increase in the expected profitability of wind units in a balancing loop. The other loop shown by green arrows is a positive loop that describes part of the ratio-based incentive mechanism that mitigates the investment risk of wind units. As the expected profitability of wind units rises, the tendency of companies to invest in wind capacity increases. This will lead to the rise of wind capacity and wind power generation after a time delay. By increasing the wind power generation, electricity spot price declines after the reduction of net consumption. Then, the rise of the ratio-based wind incentive is the result of price reduction. Finally, expected profitability increases due to the growth of the ratio-based incentive. In another word, based on this loop, when electricity price decreases, the value of ratio-based incentive increases to compensate for the low incomes of wind units and this, in turn, will lead to risk reduction.

The construction time of conventional and wind units is the main time delay in this model [9]. Ancillary services markets, transmission and distribution costs, reactive power markets, and transmission network effects are neglected in this paper. Different parts of the proposed dynamic model are introduced in detail in the following section.

III. DETAILED DESCRIPTION OF MODEL

A. ELECTRICITY DEMAND

A weekly time step is considered in this study denotes that electricity generation and consumption are cleared on a weekly basis. Fig. 2 shows the weekly load coefficients that are used in this paper. This weekly load profile is extracted from the historical data of the USA electricity demand [30]. The first week of January is assumed as the first week of this Figure. The amount of weekly demand changes year by year with respect to a constant value defined as the annual demand growth rate. This value is considered as a random variable and the Gaussian distribution function represents its stochastic nature with standard deviation and expected value equal to 1% and 1.2%, respectively [7].

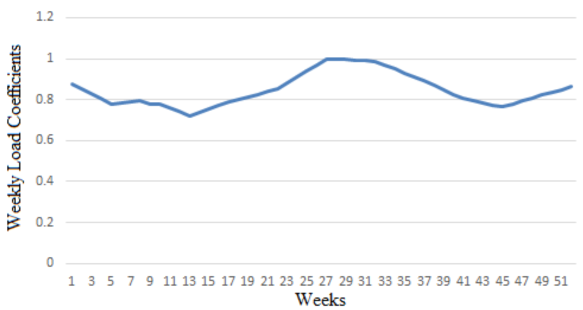

FIGURE 2. Weekly pattern of electricity demand.

In this paper, the weekly demand is calculated by (1) [11].

$$\mathrm{Demand_f}(t+\Delta T) = \mathrm{Demand_f}(t) + \mathrm{Demand_f}(t) \times \int_{t}^{t+\Delta T} \mathrm{AGR}(\tau)\,.d\tau \quad (1)$$

in which, AGR is the annual demand growth rate in (%/yr), $\mathrm{Demand_f}$ is the weekly demand in (MW) and ΔT is one year. It is assumed that the electricity demand (in MW) to be unchanged during each week. Therefore, the electricity consumption (in MWh) in each week can be obtained by the multiplication of electricity demand (in MW) and the hours of a week [9]. The long-term price elasticity of electricity consumption is calculated based on (2).

$$Q(t) = Q_f(t) \times \left(\frac{PR_P(t)}{prav(t)}\right)^{PED} \quad (2)$$

In (2), Q(t) is electricity consumption after price response in week t in (MWh), Q_f is forecasted electricity consumption in (MWh), PR_P is the average of electricity market price in the past year ($/MWh), prav is reference price which is supposed to be the average of prices in five recent years ($/MWh), and PED is the price elasticity of demand [9]. Although the uncertainty in demand growth rate is considered in this paper, for simplicity, the uncertainty in the demand profile is ignored and this profile is modified based on the price elasticity of demand and annual demand growth rate.

B. GENERATION OF CONVENTIONAL FOSSIL FUEL TECHNOLOGIES

Three different types of fossil fuel technologies are considered to meet the net consumption. The marginal cost of generation for each technology consists of fuel price and emission tax. One of the uncertainties related to power plant investments is fuel price uncertainty. There are many sophisticated approaches, such as geometric Brownian motion (GBM) and the mean-reverting process to model the fuel price [31]. Since the focus of this paper is on the development of wind capacity, the fuel price is considered as a fixed value. To indicate the competition between several technologies, all generation units of the same technology are considered as a particular company [9]. Moreover, due to the fact that the effect of incentives on wind capacity development is discussed from the perspective of a system regulator/policymaker, a centralized approach is considered as a better choice. The main strength that can be seen in leveraging a centralized structure is the top-down guidance and focus that can be maintained by the policymaker while working directly with the system/market operators, utilities and generation companies, or power distributors, to establish priorities and employ their knowledge and resources to implement those across the power sector. It should be noted that a decentralized approach could also help drive capacity development and investment plans, however, the lack of a centralized entity providing templates and guidance can often lead to inconsistency across the power sector. More information about the dynamic model of the decentralized system can be found in [32].

Although the decommissioning of equipment (blades, generators, boilers, etc.) and their replacement is not considered, a vintage model is utilized to demonstrate the difference between the efficiency and variable costs of new fossil fuel units and older ones. Fossil fuel technologies include three vintages: new units, middle-aged, and old units [9]. The marginal cost of generation for each vintage of different technologies can be calculated from (3) [7].

$$MC_{ij}(t) = \frac{FP_i(t) \times con_i}{Eff_{ij}} + e_{ij} \times EP_i(t) \quad (3)$$

in which, i is subscript refers to each technology (1:HC, 2:CCGT, 3:GT, 4:wind), j is subscript refers to each vintage, MC is the marginal cost ($/MWh), FP is fuel price ($/MJ), con is conversion factor (MJ/MWh), Eff is efficiency (%), e is emission rate (Ton/MWh), and EP is emission price in ($/Ton). After calculating the ratio of the market price in the previous time step (PR) to the marginal cost of each type of

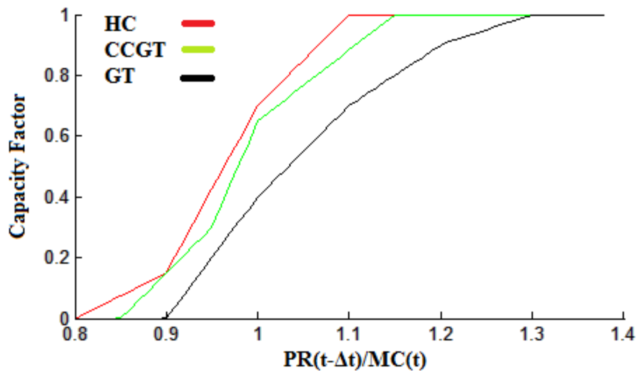

FIGURE 3. Supply curves for each technology [33].

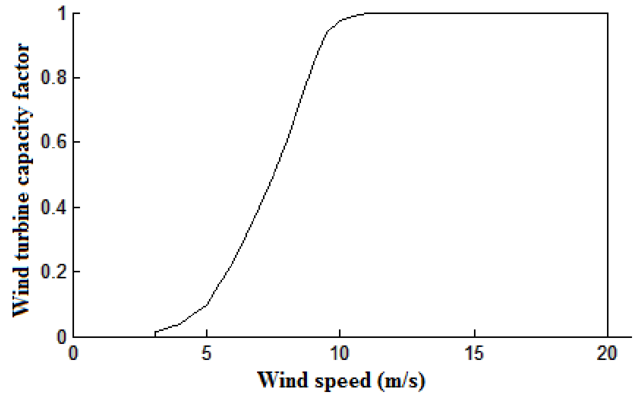

FIGURE 4. Power curve of 87 Siemens SWT 108 2.3 turbine.

technology in the current time step (MC), the capacity factor is extracted from the supply curves of Fig. 3 [33]. Accordingly, based on the capacity factor in each time step and the total installed capacity of each type of technology, the total generation energy by conventional units can be obtained in the mentioned time step [9].

C. WIND TECHNOLOGY GENERATION

Wind power generation depends on the wind velocity and wind velocity is influenced by seasonal variations and geographical characteristics [34]. The behavior of wind speed in most regions is usually fitted by Weibull distribution functions [35]. Since the demand coefficients are gained from historical data of electricity consumption in the USA, the hourly statistical wind speed data in Texas [36] are used to coordinate the wind generation profile with the demand profile from the regional aspect. Then, the Weibull distribution function of wind speed in each season is achieved from the data by the introduced method of [37]. Based on the proposed method in [35], the Monte-Carlo technique is applied to generate different scenarios for weekly wind speed from the Weibull distribution functions. Then, the wind speed time series simulation technique is utilized to consider the chronological characteristics of wind speed. Due to the difference in turbine hub height and height of installed wind speed measurement tools, which is equal to 10 meters [36], the measured wind speed is modified by (4) [38].

$$ws_H(t) = ws_{base}(t) \times \frac{\ln \frac{H}{H_0}}{\ln \frac{H_{base}}{H_0}} \tag{4}$$

in which, ws_H is the wind speed at H (m/s), ws_{base} is the wind speed at H_{base} (m/s), H_0 is terrain characteristics parameter of the region, H is the height of the turbine's hub (m), and H_{base} is the height of measurement tools (m). In order to do the wind speed modification and calculation of the output power of the wind turbines, the technical data associated with Los Vientos Wind Farm in Texas are used. Although there are various types of turbines in this farm, all turbines in wind farms are considered as Siemens SWT 108 2.3 model [39]. The power curve of this type of turbine is depicted in Fig. 4 [40]. In this Fig., the cut-in, rated, cut-off wind speeds are 3, 11, and 20 m/s, respectively, and the rated power of the turbine is 2.3 MW [40]. The height of the turbine's hub is 100 m and the terrain characteristics parameter of the region is 0.01 [39].

Once the wind speed modification is done, the output power of all wind turbines at any time can be obtained from the turbine's output power curve and wind speed.

D. MARKET EQUILIBRIUM AND DYNAMICS

In this paper, the electricity spot price is considered as a stock variable. More information about stock and flow structures in the dynamic system theory can be obtained in [29]. It is assumed that in the electricity market, the price increases if energy demand increases while the opposite happens if the production of electric energy exceeds the consumption. As shown in (5) the changes in electricity prices are calculated in each time interval then, based on (6), the price of electricity at each time step is equal to the sum of the price changes and the price of electricity at the previous time step [10].

$$\Delta PR(t) = PR(t) \times \frac{Q_{net}(t) - TEG(t)}{Q_{net}(t)} \tag{5}$$

$$PR(t + \Delta t) = PR(t) + \int_{t}^{t+\Delta t} \Delta PR(\tau).d\tau \tag{6}$$

where ΔPR is electricity market price changes ($/MWh), PR is electricity market price ($/MWh), Q_{net} is the amount of electricity net consumption (MWh), TEG is total electricity generation of conventional units (MWh), and Δt is one week.

E. PRICE EXPECTATION AND CAPACITY INVESTMENT

For successful investment, correct future price prediction by generation utilities is necessary. In this paper, the trend extrapolation of variables besides the exponential smoothing forecast technique is implemented for the price expectation [29]. The economic assessment of the project is carried out by the net present value (NPV) method [9]. Through this method, cash flows are transferred to a reference time or the time of decision in different years of the project. Then, the profitability of the capacity development can be calculated at time t through the following equation for each type of technology [9].

$$\mathrm{PROF_i}(t) = \sum_{k=1}^{T^a}\left(\mathrm{PROF^e}_i(t) - \mathrm{OMC_i}\right)\times e^{-D_{rate}(k+T^{cons}{}_i)} - \mathrm{IC_i} \quad (7)$$

In (7), i is subscript refers to each technology, PROF is total profit in planning time horizon in (\$/ MW), T^a is amortization period in (yr), $\mathrm{PROF^e}$ is the common expected term of operating profit in (\$/MWyr), OMC is average term of operational and maintenance costs in (\$/MWyr), D_{rate} is the discount rate in (%/yr) which is 9%/yr [7], T^{cons} is the time needed for construction of units (yr), and IC is investment cost in (\$/MW). Based on (8), the expected profit of each technology depends on the expected electricity price and marginal cost in each time step [9].

$$\mathrm{PROF_i^e}(t) = \int_{t-T^p}^{t}\left(\mathrm{PR^e}(\tau) - \mathrm{MC_i}(\tau)\right).d\tau \quad \forall\, \mathrm{PR^e}(t) \geq \mathrm{MC_i}(t) \quad (8)$$

In this equation, $\mathrm{PR^e}$ is the expected price in (\$/MWh), MC is the marginal cost of generation in (\$/MWh), and T^P is perceived time equal to one year. By substituting (8) in (7) and solving the PROF = 0 for D_{rate}, the parameter called investment rate of return (IRR) can be determined. After the calculation of the internal rate of return, profitability index and investment rate are obtained from the following equations [9].

$$\mathrm{PIt_i}(t) = \frac{\mathrm{IRR_i}(t)}{D_{rate}} \quad (9)$$

$$\dot{\mathrm{I}}_i(t) = \frac{\mathrm{SCL}}{1+e^{-(\beta s_i \times \mathrm{PIt_i}(t)+\gamma_i)}} \times (\mathrm{RCR_i}(t) + \mathrm{CAR_i}(t)) \quad (10)$$

$$\mathrm{RCR_i}(t) = \frac{P_i(t)}{T_i^{age}} \quad (11)$$

in which, IRR is the internal rate of return (%/yr), PIt is the profitability index of technology, D_{rate} is adjusted discount rate (%/yr), $\dot{\mathrm{I}}$ is investment rate of technology (MW/yr), RCR is retired capacity rate of technology (MW/yr), P is installed capacity (MW), T^{age} is the lifetime of each unit (yr), and CAR is capacity addition rate of technology to cover the maximum demand (MW/yr). The capacity addition rate of technology for supplying the maximum demand depends on the demand growth rate. In this paper, if the demand growth exceeds the reserve margin, the value of CAR is positive and it is equal to their difference; otherwise, it is equal to zero. This is because most of the companies decide to invest in new capacity in scarcity events and during high prices. Moreover, a fixed pattern for supplying the maximum demand by different generation technologies is considered. It is assumed that 40%, 15%, 35%, and 10% of electricity peak load is supplied by HC, GT, CCGT, and wind technologies, respectively [33]. The reserve margin in each time step is equal to the difference of installed capacity of conventional units and net consumption. In (10), SCL is the saturation capacity level for each technology (unit less); βs and γ are fixed parameters of the S-shaped investment function. The fixed values of SCL, βs, and γ are shown in Table 1 [41], [42].

F. CAPACITY DEVELOPMENT

In this section, the under-construction capacity and installed capacity for electricity generation are considered as stock variables. In the modeling of capacity development, long-term time delays due to the construction of new capacity are considered. Fig. 5 illustrates the stock and flow diagram of capacity development. As shown in this Fig. the investment rate and construction accomplishing rate of technology are inflow and outflow variables of under-construction capacity, respectively. Besides, the construction accomplishing rate and retired capacity rate are inflow and outflow variables of installed capacity, respectively. The amount of installed capacity for each type of technology is determined in each time step from the investment rate, which was calculated in the previous section [9].

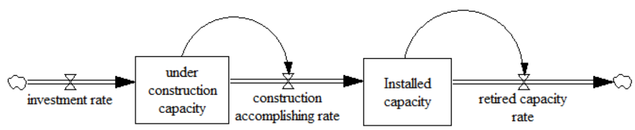

FIGURE 5. The stock and flow diagram of generation capacity development.

G. RATIO BASED INCENTIVE FOR WIND CAPACITY DEVELOPMENT

To encourage the companies to invest in wind capacity, a ratio-based incentive is considered. This incentive consists of two parts. The first part, $\mathrm{incentive^P}$, is calculated based on the percentage of wind capacity compared to the target value and the second part, $\mathrm{incentive^R}$, is calculated to reduce investment risk. The first part provides high amounts of income for wind farms when there is a lack of capacity and the second part guarantees their income when prices are low.

Part of the payments to wind units ($\mathrm{incentive^P}$) changes proportional to the predetermined ratio of wind capacity to the total capacity of the fossil fuel units. This predefined ratio (D) is determined by market policymakers. In this paper, the ratio is assumed to be 15% meaning that policymakers tend to motivate companies to reach the installed wind capacity up to 15% of the installed fossil fuel capacity. To reach this purpose, $\mathrm{incentive^P}$ can be calculated from (12) in each time step.

$$\mathrm{incentive^P}(t) = A(t) \times [B(t) + C(t)] \quad (12)$$

$$A(t) = \max\left[\frac{\mathrm{wct}(t) - \mathrm{pw}(t)}{\mathrm{pw}(t)}, 0\right] \quad (13)$$

$$\begin{aligned} B(t) &= \max\left[(1+D)\times pr(t) - prav(t), 0\right] \\ &\quad\times \max\left[\frac{ADGR(t) - RM(t)}{|ADGR(t)|}, 0\right] \end{aligned} \tag{14}$$

$$C(t) = D \times prav(t) \times \max\left[\frac{TR(t) - RM(t)}{TR(t)}, 0\right] \tag{15}$$

$$wct(t) = D \times ptc(t) \tag{16}$$

$$TR(t) = E\times(ptc(t) + pw(t)) \tag{17}$$

$$ADGR(t) = Demand_f(t) \times \int_t^{t+\Delta T} AGR(\tau).d\tau \tag{18}$$

where pr is electricity spot price (\$/MWh) in time step t, wct is wind capacity target (MW), pw is the installed wind capacity (MW), ptc is the total installed capacity of fossil fuel technologies (MW), E is a fixed value equal to 0.15 [7], TR is targeted reserve margin (MW), D is the predefined ratio of wind capacity to conventional capacity, prav is reference price which is supposed to be the average of prices in five recent years (\$/MWh), RM is reserve margin (MW), AGR is the annual demand growth rate in (%/yr), $Demand_f$ is the weekly demand in (MW), and ADGR is the changes in the average weekly load compared to the same week in the previous year (MW). The term A restricts the amount of incentive when the installed wind capacity is more than the predefined percentage. The term B provides high payments when there is a capacity shortage and term C intensifies these payments as the amount of reserve margin decreases.

After the calculation of $incentive^P$, $incentive^R$ should be obtained. As mentioned before, $incentive^R$ is considered to compensate for the low incomes of wind farms. This type of payment can mitigate investment risk to a high extent. In ratio-based incentive, $incentive^R$ is equal to (19) in time step t.

$$incentive^R(t) = \max\left[(1+D)\times prav(t) - pr(t), 0\right] \tag{19}$$

in which, prav is the reference price (\$/MWh) and pr is the electricity price (\$/MWh). The average price in the recent 5 years can be considered as the reference price [9].

Then, the value of the ratio-based incentive is extracted from $incentive^P$ and $incentive^R$. The term incentive(t) in (20), demonstrates the amounts of ratio-based incentive (\$/MWh) in each time step.

$$incentive(t) = incentive^P(t) + incentive^R(t) \tag{20}$$

H. RISK ASSESSMENT OF MODEL

Although the results of the study in [17] show that reduction in FIT payments reduces the photovoltaic investment in the residential sector, there is no investigation about the effect of fluctuations in FIT payments on installed capacity. In this section, required risk measures to study the wind capacity investment risk influenced by the proposed incentive, are introduced. Risk measures are necessary for the assessment of investment risk. Among different measures such as variance, shortfall probability, expected shortage, value at risk, and conditional value at risk for risk measurement, the last one fulfills the characteristics of desirable risk measures [43], [44]. In this paper, historical VaR and CVaR are applied for risk measurement.

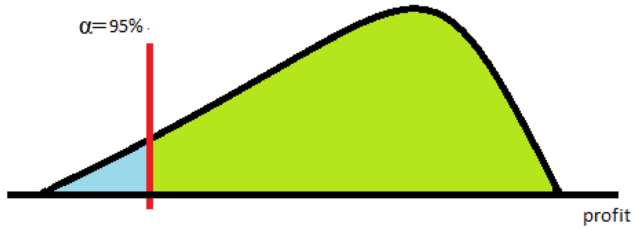

FIGURE 6. Profit-and-loss probability density function.

Fig. 6 illustrates the profit-and-loss probability density function of wind units during the time horizon. For the calculation of historical VaR, historical returns of assets are used. VaR can be depicted in units of the rate of return (%) or profit and loss. First of all, the profit resulting from the generation of wind units (\$/MWh) at each time step is collected over the planning horizon. Then, VaR is obtained from the sorted historical statistical samples [45]. For example, in this study 1560 profit samples are gathered from 1560 time steps. In other words, a unique profit is calculated for each time step. If $profit^1 \leq profit^2 \leq profit^3 \ldots \leq profit^{1560}$ are the sorted profits from per megawatt of wind capacity at each time step, then $VaR_{\alpha=0.95}(profit) = profit^{78}$. The parameter α is known as the confidence level or significance level [46]. In this study, a higher amount of VaR represents lower risk.

The conditional value at risk is defined as the expected value of the wind companies' profit lower than the (1-α)-quantile of the profit distribution [43]. In other words, CVaR is defined as the average profit in the (1-α) × 100% of the worst profits. This measure can be obtained by (21) [47]. In this study, a higher amount of CVaR also illustrates lower risk.

$$CVaR_{1-\alpha}(profit) = \frac{1}{\alpha}\int_0^{\alpha} VaR_{1-t}(profit)\, dt \tag{21}$$

IV. ANALYSIS OF SIMULATION RESULTS

To study the effect of the proposed incentive on wind capacity investment and electricity price, a sample system was used. The characteristics of this system are illustrated in Table 1. The initial peak demand is 15 GW. The planning horizon is 30 years. The elasticity of demand to price is −0.1. The price cap is equal to 300 \$/MWh. Also, simulation is carried out by the MATLAB software.

In this section, three different cases are introduced to simulate market behavior under various conditions. The main features of these cases are indicated below.

- First case: no incentive is considered for wind units.
- Second case: ratio-based incentive is considered for wind units in which parameter D is 0.15.

TABLE 1. **The generation system characteristics.**

Technology	Wind	GT	CCGT	HC
Capacity Under Construction (MW)	500	300	400	500
Initial Installed Capacity (MW) (Vintage 1)	1000	550	1900	4900
Initial Installed Capacity (MW) (Vintage 2)	-	550	1800	4900
Initial Installed Capacity (MW) (Vintage 3)	-	800	100	1300
Average Construction Time (Yr)	1	1	1.5	3
Lifetime (Yr)	20	20	30	40
Investment Cost ($/kW)	1500	500	600	1000
Fuel Price× Conversion Factor ($/MWh)	0	10.5	10.5	3.6
Emission Price ($/Ton of CO2)	0	26	26	26
Maintenance Cost ($/kW/yr)	12	16	16	16
Recourse Efficiency (%) (Vintage 1)	-	0.35	0.6	0.455
Recourse Efficiency (%) (Vintage 2)	-	0.32	0.57	0.425
Recourse Efficiency (%) (Vintage 3)	-	0.27	0.54	0.39
Emission Rate (Ton/MWh) (Vintage 1)	-	0.29	0.33	0.87
Emission Rate (Ton/MWh) (Vintage 2)	-	0.31	0.35	0.9
Emission Rate (Ton/MWh) (Vintage 3)	-	0.37	0.4	0.95
SCL	3.3	2	3	1.5
βs	1.8	2.5	2	3.5
γ	-2.7	-2.5	-2.6932	-2.8069
Amortization Period (Yr)	15	15	20	25

- Third case: a fixed payment is considered for wind units in each time step, which is equal to the average of the ratio-based incentive in the second case.

The main purpose of selecting these cases is to provide a better insight into the effect of different incentive schemes exercised by the market regulator on wind capacity development and the investment risk of wind units.

A. CASE 1

Fig. 7 (a) illustrates the weekly average spot electricity price in case 1. High prices in each time step show that the electricity demand exceeds the generation, and low prices are seen as the demand becomes lower than the generation. Fig. 7 (b) demonstrates the demand, the total installed capacity of fossil fuel units, and reserve margin during the time horizon. The electricity demand rises in proportion to the annual demand growth rate and changes because of the price response. Fig. 7 (c) and Fig. 7 (d) illustrate the installed capacity and investment rates for each technology, respectively. By decreasing the reserve margin, price increases. Therefore, as depicted in Fig. 7 (b) and (c), when reserve margin decreases, wind and conventional fossil fuel capacity rise after a time delay due to the high tendency of investors to acquire benefits. As shown in Fig. 7 (d), due to the high investment cost and emission penalty of hard coal units, their investment rate is lower than the investment

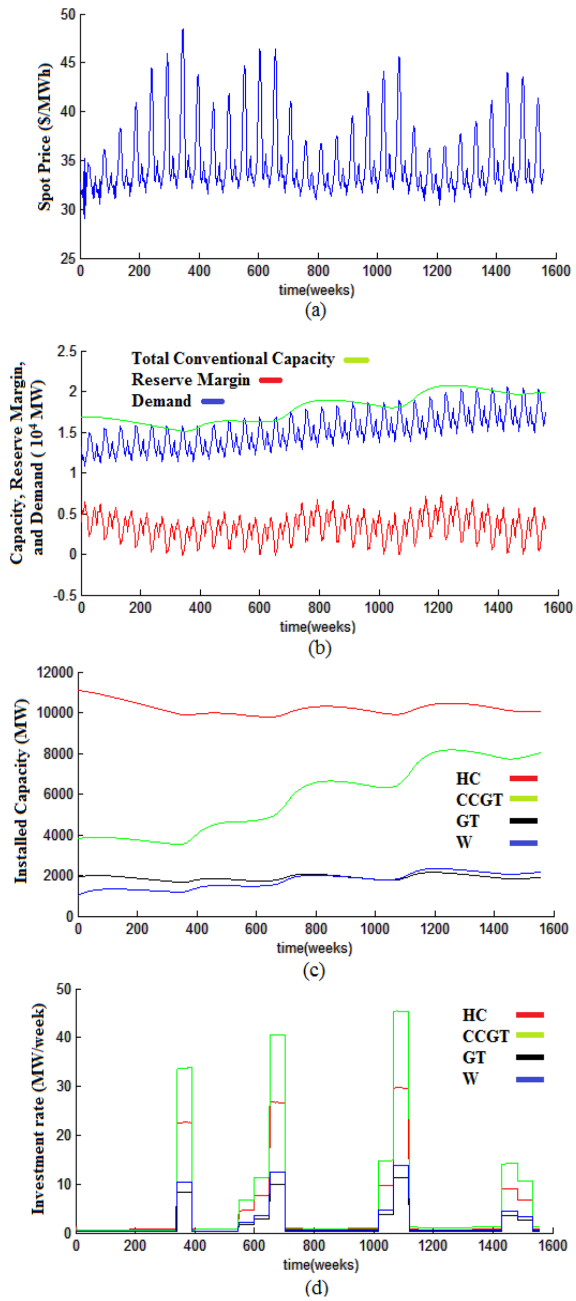

FIGURE 7. **Simulation results of case 1.**

rate of CCGT units. The fluctuations of the reserve margin in Fig. 7 (b) indicate the business cycles. Over and under-investment will lead to long-time boom and bust cycles in the investment wave in Fig. 7 (c). The variety in construction time, the lifetime of units, incentives, and retired capacity rate of technologies affect these cycles. Because of the high investment cost of wind units, the investment in this technology is not remarkable and there is more tendency to invest in CCGT units. Therefore, an incentive is necessary for the development of wind units. Since the results of this paper are in agreement with the findings of [9], the similarity in the general results of this paper and [9] can be considered

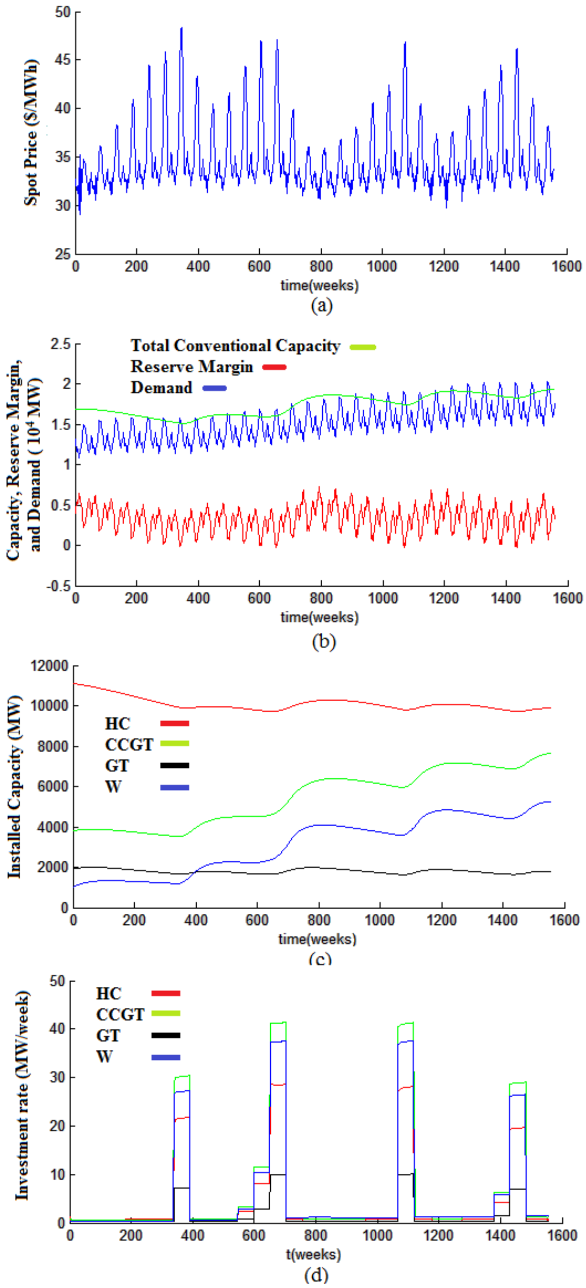

FIGURE 8. Simulation results of case 2.

as the validation of the dynamic model. For instance, in both papers, as the reserve margin decreases (increases), electricity price increases (decreases), or a few years after the price jump new installed capacity is added to the system. In other words, booms (busts) are revealed on the investment wave a few years after the price rise (reduction).

B. CASE 2

In case 2, the ratio-based incentive was considered in the system of case 1 to reduce the investment risk of wind technology and increase the ratio of installed wind capacity up to 15% of total fossil fuel installed capacity (D = 0.15). Fig. 8 (a) illustrates the weekly average spot electricity price in case 2. The average price increased from 34.79 in case 1 to 34.82 in case 2, and its standard deviation increased from 3.32 to 3.40. This happened because of fossil fuel capacity reduction and increasing installed wind capacity in case 2 compared to case 1. The total installed fossil fuel capacity at the end of the time horizon is 19928.3 MW in case 1, while it is 19339.6 MW in case 2. The uncertainty in electricity generation by wind units increases the prices and its fluctuations in case 2. Fig. 8 (b) demonstrates the demand, the total installed capacity of fossil fuel units, and reserve margin during the time horizon. Fig. 8 (c) and Fig. 8 (d) illustrate the installed capacity and investment rates for each technology, respectively. As shown in Fig. 8 (c) and Fig. 8 (d), due to the implementation of the ratio-based incentive for wind units, an incentive which was calculated by (20) was paid to wind units when prices were low or the ratio of wind capacity to conventional capacity was lower than 15%.

Accordingly, the investment rate of wind units increased compared to case 1, and after a time delay, more wind capacity was added to the system. In addition, the investment rate of conventional units decreased compared to case 1, since most of the companies invest in wind technology. In this case, the total amount of wind incentive during the time horizon was 8618.68 $/MWh and the weekly average of wind incentive was 5.5248 $/MWh. In the third case, a fixed payment equal to 5.5248 $/MWh was considered for wind units in each time step, to compare market behavior under an equal budget which was spent for wind capacity development.

C. CASE 3

In case 3, fixed payments equal to 5.5248 $/MWh were considered as an incentive for wind units in the system of case 1. Fig. 9 (a) illustrates the weekly average spot electricity price in case 3. Fig. 9 (b) demonstrates the demand, the total installed capacity of fossil fuel units, and reserve margin during the time horizon. Fig. 9 (c) and Fig. 9 (d) illustrate the installed capacity and investment rates for each technology, respectively. The average price in case 2 increased from 34.82 to 35.13 in case 3, and the standard deviation increased from 3.40 in case 2 to 3.52 in case 3.

In case 2, the installed wind capacity and conventional capacity at the end of the time horizon are 5241.8 MW and 19339.6 MW, respectively, while they are 4127.2 MW and 17324 MW in case 3. Less installed capacity in case 3 is the main reason for higher average prices and higher price fluctuation in this case. Numerous price jumps in case 3, which are the result of the capacity shortage, will increase the iteration of the investment but with lower intensity. As a result, as shown in Fig. 9 (d), the number of investment decisions for wind capacity in case 3 is more than case 2, but because of the inefficiency of fixed payments in case 3, the amount of investment rate is lower than case 2. Therefore, the intensity of boom and bust cycles in case 3 is lower than in case 2. Supporting wind units during low prices and providing a high amount of incentive during capacity shortage periods is the effective feature of the ratio-based

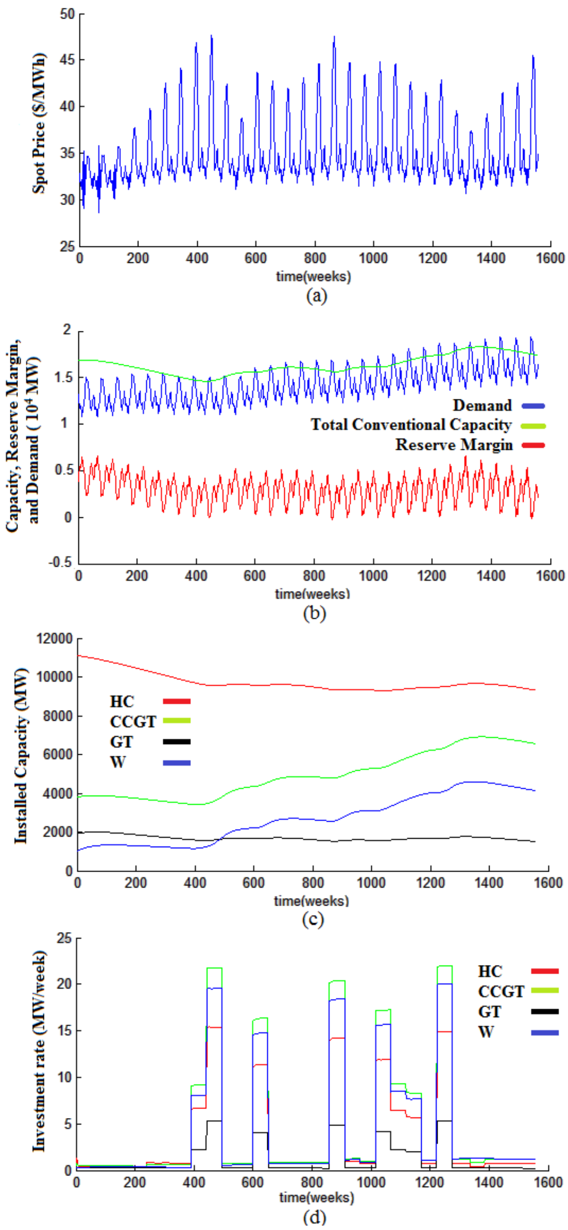

FIGURE 9. Simulation results of case 3.

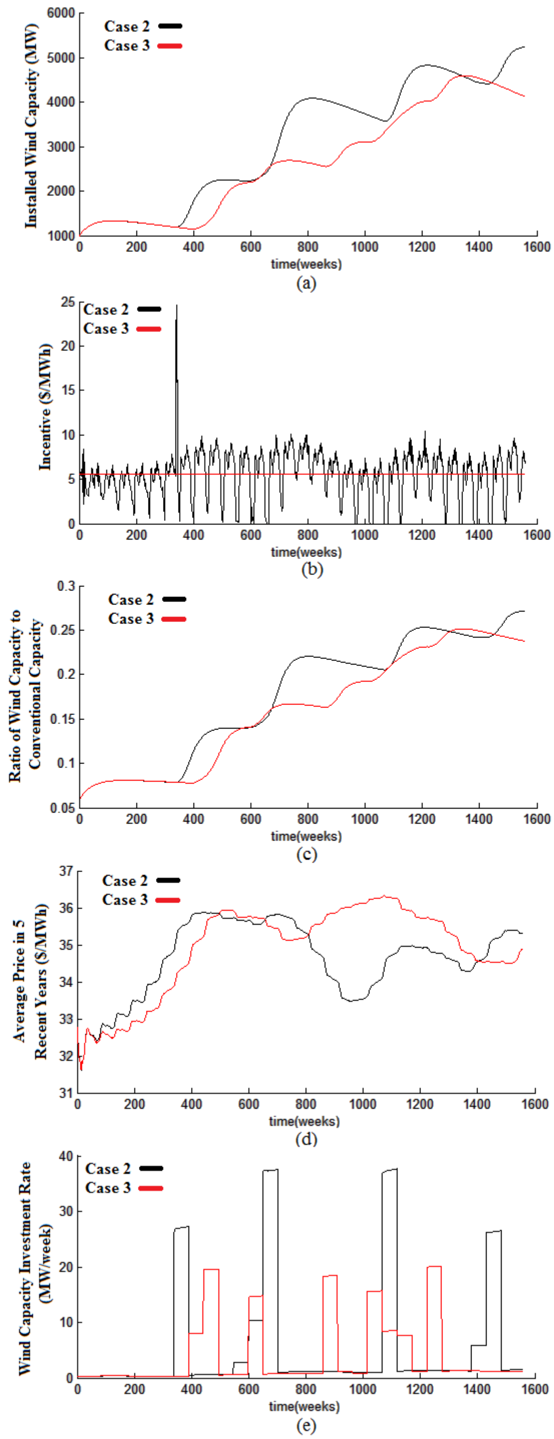

FIGURE 10. Comparison of cases 2 and 3.

incentive. This feature is the main reason for high capacity addition after the capacity shortcomings. In case 3, the total amount of fixed payments during the time horizon was the same as case 2 (8618.68 $/MWh). Some important simulation results of cases 2 and 3 are depicted simultaneously in Fig. 10 and Table 2.

Installed wind capacity, the incentive for wind units, the ratio of wind capacity to conventional capacity, the average of price in 5 recent years, and the investment rate of wind technology in cases 2 and 3 are compared in Fig. 10 (a), 10 (b), 10 (c), 10 (d), and 10 (e), respectively. As shown in Fig. 10 (a) and Fig. 10 (c), more wind capacity was installed by the implementation of the ratio-based incentive, and most portion of this capacity was installed at the beginning and middle of the time horizon. As shown in Fig. 10 (d), this will lead to the price reduction in case 2 compared to case 3. Fig. 10 (b) and Fig. 10 (c) illustrate that the amount of ratio-based incentive increased to 25 $/MWh when the ratio of wind capacity to conventional capacity is lower than 15%, and when this ratio reached over 15%,

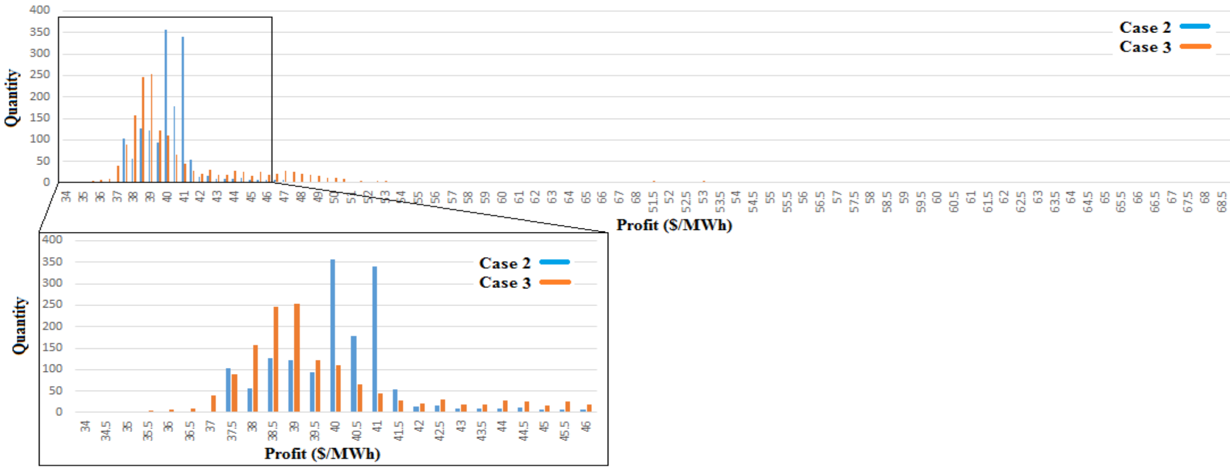

FIGURE 11. Profit distribution function for cases 2 and 3.

the amount of intentive^{P} will be zero and just a payment equal to incentive^{R} will be paid to wind units. For this reason, the rising percentage of installed wind capacity will not stop and reaches up to 25% at the end of the time horizon in case 2. The diagram of case 2 in Fig. 10 (e) shows that despite the accelerating of the wind capacity investment in the beginning and middle of the time horizon, the investment will not be postponed at the end of the time horizon.

TABLE 2. Data for comprising cases 2 and 3.

	Case 2	Case 3
Total Amount of Wind Incentive ($/MWh)	8618.68	8618.68
Average of Wind Incentive ($/MWh)	5.5248	5.5248
Average of Prices ($/MWh)	34.8256	35.1354
Standard Deviation of Prices ($/MWh)	3.4099	3.5277
Average of Wind Units' Profits ($/MWh)	40.3504	40.6602
Standard Deviation of Wind Units' Profits ($/MWh)	2.3707	3.5277
Wind Capacity at the End of the Time Horizon (MW)	5241.8	4127.2
VaR (95)	37.6571	37.3455
VaR (99)	37.3741	36.5574
CVaR (95)	37.3876	36.7649
CVaR (99)	37.3015	35.6125
Total Generation (MWh)	3.9598×10^{9}	3.739×10^{9}
Total CO_2 Production (Ton)	2.5097×10^{9}	2.4218×10^{9}
Ratio of CO2 Production to Total Generation (Ton/ MWh)	0.6338	0.6477
Total Generation of Wind Units(MWh)	2.7034×10^{8}	2.3199×10^{8}

Table 2 shows that by spending 8618.68 $/MWh as fixed payments in case 3, 4127.2 MW wind capacity can be installed by the end of the horizon, while by managing the same funding through ratio-based incentive, more wind capacity can be reached (5241.8 MW) and most of this capacity is installed at the beginning and middle of the time horizon. Moreover, comparing the standard deviation of prices in cases 2 and 3 reveals that the implementation of the ratio-based incentive decreased price fluctuation. The average price of electricity in cases 2 and 3 were 34.8256 and 35.1354, respectively. Therefore, it can be stated that the ratio-based incentive not only benefits the wind power companies with payments but also profits the consumers through low prices. In addition, the ratio-based incentive is effective from the environmental aspect. Although the total energy generation and consequently the total CO_2 production in case 2 is more than in case 3, the ratio of CO_2 production to total energy generation in case 2 is lower than in case 3. This happens because of the more generation of wind units, in case 2. The average profit of wind units in cases 2 and 3 were 40.3504 and 40.6602, respectively. Furthermore, the standard deviation of wind units' profits in cases 2 and 3 were 2.3707 and 3.5277, respectively. The lower standard deviations and the average profit of wind units in case 2 reveal that for motivating the companies toward investment in wind capacity, there is no need to provide high payments. Instead, by managing the timing of payments through ratio-based incentive better results can be achieved.

In order to validate the performance of the ratio-based incentive model, the investment risk of wind units was measured. For this purpose, VaR and CVaR were calculated for the profit of wind units in cases 2 and 3. In case 2, VaR(95) and VaR(99) were 37.65 and 37.37, respectively. It means that in 5% of the worst cases, profits were lower than 37.65, and in 1% of them, profits were lower than 37.37. The amounts of VaR(95) and VaR(99) were 37.34 and 36.55 in case 3. This is depicted in the distribution function of wind units' profit in Fig. 11. In case 2, CVaR(95) and CVaR(99) were 37.38 and 37.30, respectively. These values show that the expected value of profit in 5% of the worst cases was 37.38 and it was 37.30 in 1% of the worst cases. The amounts of CVaR(95) and CVaR(99) were 36.76 and 35.61 in case 3. The values of VaR and CVaR demonstrate that investment risk in case 2 is lower than in case 3. Higher installed wind capacity in case 2 compared to case 3 confirms this claim. The approximate values of VaR and CVaR can be estimated from Fig. 11. The range of profits for wind units of case 3 varied from 34.06 to 53.17, while in case 2, it varied from 37.26 to 68.7. Therefore, the values of VaR and CVaR in case 2 are more than those

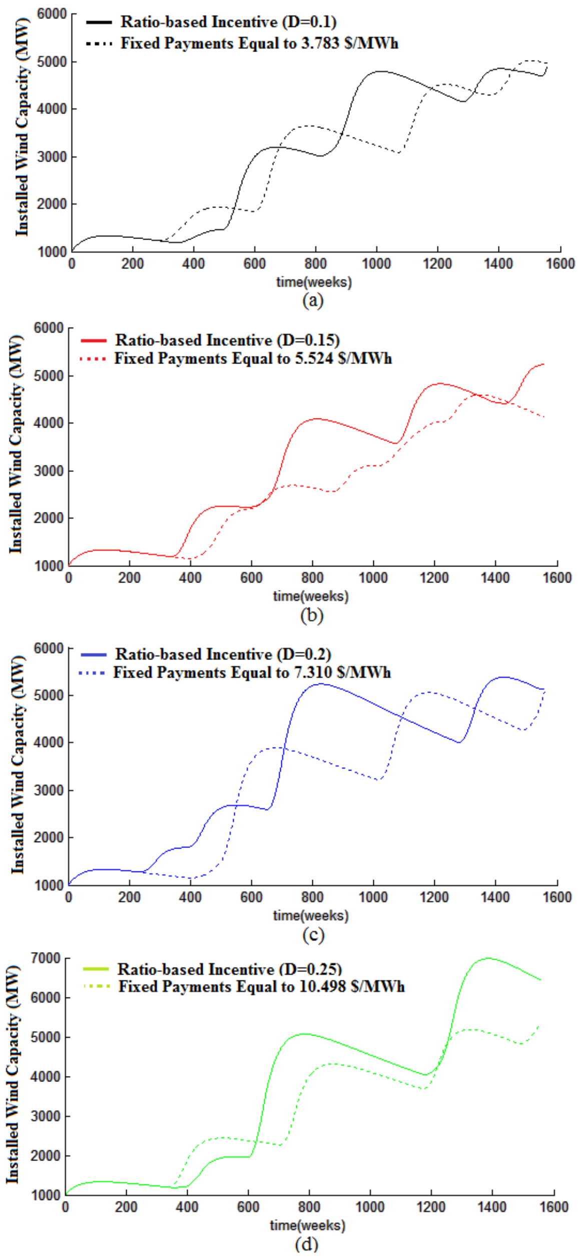

FIGURE 12. Installed wind capacity resulting from the implementation of Ratio-based incentive and fixed payment incentive.

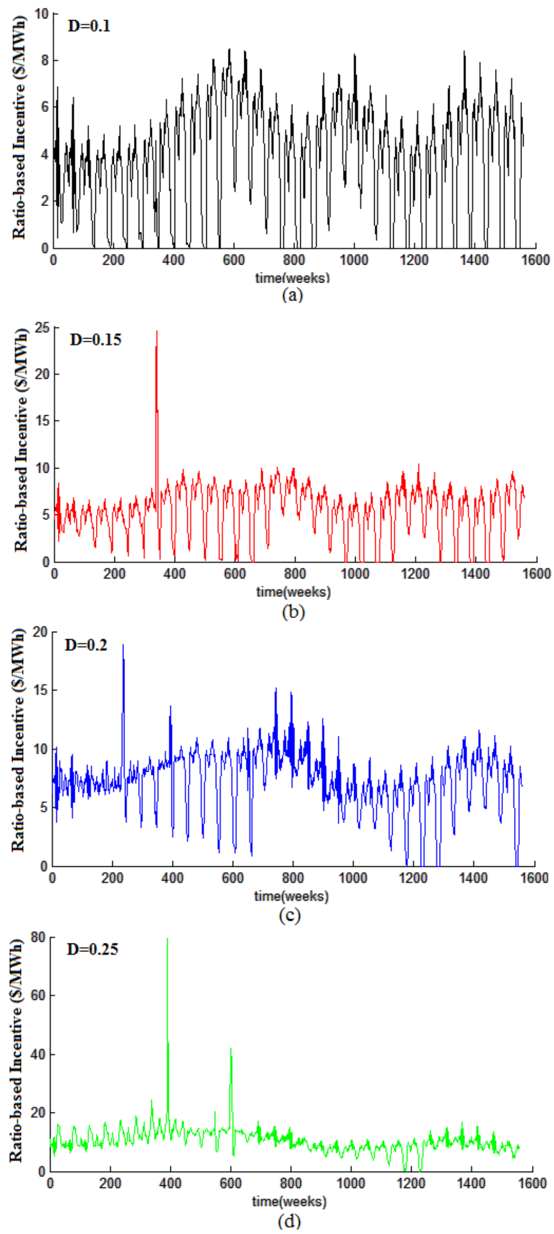

FIGURE 13. The amount of ratio-based incentive for different values of D.

of case 3. Accordingly, the risk of wind capacity investment in case 3 is higher than in case 2.

V. SENSITIVITY ANALYSIS

To investigate the impact of the policymaker's decision on wind power investment, a sensitivity analysis was conducted. For this purpose, four values of 10%, 15%, 20%, and 25% were selected for the targeted ratio of wind to conventional capacity (parameter D in (16)). It means that the payments are managed in a way that the ratio of wind capacity to conventional capacity rises more than the mentioned percentages. To simulate this part, case 2 was used.

To encourage the companies to invest in wind units and achieve predetermined wind capacity ratios of 10%, 15%, 20%, and 25%, the total amount of wind incentive during 30 years was 5901.94, 8618.68, 11404.69, and 16377.04 $/MWh, respectively. In other words, the weekly average of wind payments was 3.783, 5.524, 7.310, and 10.498 $/MWh, respectively. Therefore, to have a better picture for the sake of comparison, the fixed payments equal to 3.783, 5.524, 7.310, and 10.498 $/MWh were considered for wind units in case 3. Fig. 12 compares the results of the implementation of the FIT and ratio-based incentive. In both cases, the total amount of payments during the time interval was the same.

TABLE 3. Comparing data for different values of D.

	Case 2	Case 3	Case 2	Case 3	Case 2	Case 3
The predefined ratio of wind capacity to conventional capacity (D)	0.1	-	0.2	-	0.25	-
Total Amount of Wind Incentive ($/MWh)	5901.94	5901.94	11404.69	11404.69	16377.04	16377.04
Average of Wind Incentive ($/MWh)	3.7833	3.7833	7.3107	7.3107	10.4981	10.4981
Average of Prices ($/MWh)	34.7123	34.7438	34.0731	34.2549	33.8092	34.4952
VaR (95)	35.764	35.367	38.477	38.373	40.346	40.215
VaR (99)	35.691	34.147	38.364	36.737	40.217	39.189
CVaR (95)	35.726	34.705	38.404	37.420	40.255	39.617
CVaR (99)	35.640	33.610	38.361	35.963	40.210	38.329
Total CO_2 Production (Ton)	2.4855×10^9	2.4380×10^9	2.4935×10^9	2.4186×10^9	2.3475×10^9	2.3754×10^9
Ratio of CO_2 Production to Total Generation (Ton/ MWh)	0.6339	0.6375	0.6181	0.6287	0.6195	0.6398
Total Generation of Wind Units(MWh)	2.6661×10^8	2.5578×10^8	3.0341×10^8	2.7154×10^8	3.1698×10^8	2.7178×10^8

As shown in Fig. 12 when the same amount of funding was distributed between wind units through ratio-based incentive, more wind capacity was installed compared to the case that this funding was distributed as equal fixed payments. This shows that not only the amount of incentives is important to encourage companies to invest in wind units but also the timing of their allocation to these units is remarkable. Fig. 13 illustrates the amount of the ratio-based incentive for different values of the parameter D. Based on this Fig., as the value of D increases, the amount of incentive rises. Despite reaching the targeted wind capacity, the amount of incentive will not become zero. This is because the investment risk of wind units should be mitigated in each time step through this incentive. Therefore, at the end of the time horizon, the installed wind capacity reaches over the predefined percentage.

Table 3 shows some useful data for different values of parameter D. When the specific funding is distributed through ratio-based incentive, the average price becomes lower compared to the case that the same funding is paid through fixed payments. The more the value of D increases, the more the average price declines. By implementing this incentive, the ratio of CO_2 production to total energy production will decrease compared to the cases with fixed payments. Moreover, ratio-based incentive provides more energy from wind units for the power system. Comparing the VaR and CVaR values in cases 2 and 3 for different values of parameter D depicts that the proposed incentive decreases the investment risk of wind capacity.

VI. CONCLUSION AND POLICY IMPLICATIONS

The main goal of the present study was to demonstrate that by applying a new type of incentive and utilizing the same amount of funding that is spent in feed-in-tariff, electricity market policymakers could reduce the investment risk of wind units to reach more installed wind capacity and lower electricity prices. In this respect, the ratio-based incentive for wind capacity was introduced and a model was presented to simulate the dynamic behavior of the electricity market to analyze the investment in wind and fossil fuel units and investigate the impact of the mentioned incentive. Two positive and negative feedback loops were added to the former causal loop diagram of the electricity market. These loops helped get a better insight into the performance of the ratio-based incentive. The mechanism of the ratio-based incentive was described in detail. The first part of this incentive was calculated to reach a predetermined targeted wind capacity and the second part of that was obtained to mitigate the risk of investment. Then, these two values were integrated for achieving the value of the incentive. Moreover, the value at risk and conditional value at risk measures were used to measure the risk of wind capacity investment.

The results of simulations conducted for three different cases depicted that the ratio-based incentive is more effective than the feed-in-tariff in the context of decreasing the risk of investment, reducing electricity price, reduction of CO_2 production, and speed of providing higher amounts of wind capacity. In other words, by distributing the same budget for the promotion of wind capacity through ratio-based incentive, the growth rate of wind capacity increased more, compared to the case that this budget was distributed under the feed-in-tariff policy. This is because the timing of the payments gained importance in addition to the amount of payments. Furthermore, the ratio-based incentive did not slow the growth of wind capacity investment towards the end of the time horizon. Also, the ratio-based incentive benefited both the wind power producers and the consumers. It means that not only the producers' associated VaR and CVaR lower significantly with this incentive, but also the average electricity prices decreased during the 30 years-period.

Although the presented incentive model provides a better picture for the policymakers to encourage the investors, it is not enough to accelerate the development of wind capacity. There are still important concerns, which need to be addressed with appropriate policies. Therefore, a more comprehensive policy is needed to consider other factors which affect the development of wind capacity. Such an incentive policy model should take into account the issues raised by the communities. For instance, a comprehensive policy should address environmental impacts, enhance social welfare, provide awareness on the positive aspects of wind technology, compensate land usage appropriately, and consider the public consultation during the planning process.

In this paper, it was assumed that the price of natural gas is fixed. Therefore, in future research the behavior of the natural gas market can be simulated by a dynamic model and the gas price can be determined from the interaction of electricity and natural gas markets. Moreover, the performance of the ratio-based incentive model in the electricity market can be examined by other dynamic models in future works.

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