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Introduction of an efficient incentive for investment in wind turbines based on system dynamics modelling approach

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Abstract
Due to the stochastic nature of wind energy, allocating an appropriate investment incentive for wind generation technology (WGT) is a complicated issue. We propose an improvement on the traditional incentive, known as capacity payment mechanism (CPM), to reward the wind generators based on their performance exogenously affected by the wind energy potential of the location where the turbines are installed, and therefore, lead the investments towards locations with more generation potential. In CPM, a part of investment cost of each generator is recovered through fixed payments. However, in our proposal, wind generators are rewarded according to dynamic forecasts of the wind energy potential of the wind farm where they are located. We use an auto-regressive moving average (ARMA) model to forecast the wind speed fluctuations in long-term while capturing the auto-correlation of wind velocity variation in consecutive time intervals. Using the system dynamics (SD) modelling approach a competitive electricity market is designed to examine the efficiency of the proposed incentive. Performing a simulation analysis, we conclude that while a fixed CPM for wind generation can decrease the loss of load durations and average prices in long-term, the proposed improvement can provide quite similar results more efficiently.

Keywords
Wind turbine, restructured power systems, electricity market, capacity payment, system dynamics.

Introduction

Liberalization has restructured the power generation industry by privatizing the utilization of its different sections. Unlike the traditional power industry where planning for investment in new generation capacity was developed centrally to minimize the total cost, in the restructured power industry, decisions for generation capacity expansion are made by competing individual generation firms trying to achieve the maximum profit. This has reformed the previous electricity markets from a monopoly structure to a dynamic and behavioural environment in which generation capacity and the electricity demand do not maintain their long-run equilibrium state [1]. Allowing generation companies to compete independently motivates them to improve their technologies and services. Hence, with increase of the generation efficiency, consumers benefit from the competition [2]. However, in a competitive environment, financial uncertainties adversely affect the investment decisions. In consequence of experiencing time cycles of over-capacity and under-capacity caused by investment fluctuations in several countries, it has been suggested that allowing the generation capacity to develop by the invisible hand of the electrical energy market may not continuously provide the sufficient generation capacity for the electricity market [3]. On the other hand, the intrinsic variability and uncertainty of the renewable generation create a major challenge for investment planning in such energy sources [4].

Capacity payment mechanism (CPM) is a method which by providing a stream of constant revenues, separated from what is earned within the electrical energy market, creates a stable income to cover a part of the fixed costs of the generators keeping their capacity available during the market intervals. The impact of employing a fixed CPM on damping the investment fluctuations has been investigated by [5]. Since design of the CPM significantly affects the generation system [6], there have always been attempts to carry out improvements on designing the mechanism. Authors in [7] propose a variable CPM to make the capacity installation comply with the market’s future demand. Authors of [8] propose a new framework for assessing the impact of firm contracts and capacity payments in the restructured power systems considering uncertainties.

However, among the studies examining the investment fluctuations within the power generation industry and mechanisms to improve the generation adequacy, the subject of capacity payment (CP) for renewable energy sources with intrinsic uncertainty such as the wind generation technology (WGT) has not been given the proper attention. Due to the intrinsic uncertainty and rapid fluctuation of the wind speed, wind energy penetration and integration are critical issues in the modern power systems [9]. The uncertainty of wind power generation causes the investors to face financial risks while considering investment in this technology. Thus, to improve the expansion of the WGT, employing incentive mechanisms can be functional [10]. Due to the aforementioned uncertainty, wind generators cannot make the same contribution to the generation adequacy of the power system as well as the thermal generation technologies [11], therefore, they should be awarded with different approaches.

Investigating the long-term development and investment fluctuations in the restructured power generation industry, the static viewpoints and presuming equilibrium conditions in calculations seem to be inadequate due to the behavioural and dynamic environment of the deregulated industry [12]. Thus, in addition to the traditional approaches, employing complementary modelling methods such as system dynamics (SD), agent-based models and etc. has become necessary to assess the deregulated power industry. The dynamic viewpoint on power generation industry has been firstly adopted by [13] investigating England's power market, and later by [5], assessing the western United States' power market. Afterwards, the SD modelling approach has been widely used to investigate the effects of different issues on the power generation industry. Using the SD modelling approach, the impact of electricity market design on investment under uncertainty has been assessed by [14]. Using dynamic simulations, authors in [15] investigate the impact of capacity mechanisms on generation adequacy. Authors in [16] analyse the capacity adequacy in power markets facing energy transition by using the SD model.

This paper addresses designing a new incentive mechanism matching the intrinsic uncertainty and rapid fluctuation of the WGT. The proposed capacity payment mechanism considers not only the capacity that the wind generators keep available during market intervals but also the wind energy potential of the wind farm where generation units are located.

A SD model is developed based on the knowledge of designing capacity payment mechanisms in the electricity generation industry. The causal loop diagram of the proposed SD modelling plays the key role, which captures the relation between wind speed variation and their quantified impact on the capacity payment allocated to each wind generation facility. The proposed system dynamics modelling provides insight in the way that the impact of an implemented incentive mechanism is composed combining several dynamic interactions and intrinsic delays.

The main objective of the proposed incentive mechanism is to improve the installation of wind turbines and increase the reliability of the generation system while decreasing the average prices.

The rest of this paper is organized as follows: In Section 2, general framework of the proposed model is described. In Section 3, different sections of the model are explained in details. Finally, a simulation analysis is performed in Section 4, the results and conclusions of which are discussed in Section 5.

Model description

The purpose of this study is to investigate the long-term development of a competitive and behavioural power market under different supporting policies. Thus, the system dynamics (SD) modelling method has been employed to reflect the interactions between the components of the market and the delays involved in the process of its generation capacity development. SD is a mathematical framework with the ability of suitably capturing such complexities. SD is a branch of control engineering and system theory applied predominantly to economical, business and managerial systems. In the SD modelling approach, causal loop diagrams present a useful tool for the feedback structure of systems, capturing hypothesis about the cause of dynamics. Causal diagrams are composed of variables connected by arrows denoting causal influence among variables. Variables and arrows can be arranged to represent either a balancing or a reinforcing loop. In a balancing loop, the variables neutralize each other's effect after a specific period of time causing a balance in the system. However, in a reinforcing loop the variables tend to magnify each other's effect leading the system to divergence [17].

In Fig. 1, causal loop diagram of the presented electricity market model is illustrated. In this diagram, two balancing loops are designed to show the participation of WGT and thermal generation technologies in the electricity market, as well as their capacity development in long-term. Due to the stochastic nature of the wind speed, wind generation is an uncertain variable, therefore, it is not applicable to dispatch it like thermal generation units. On that account, as it is observed in the first loop, net consumption, the difference between electricity consumption and total wind generation, is the criterion for determining the unit commitment of the thermal generators. Consequently, as the net consumption is responded with the thermal generation, the market spot price for electricity (marginal cost of the most expensive running generation unit) is determined. This is the price that is paid to the generators for each MWh of generation. However, it is not what the consumers pay for their consumption. Total electricity price, the price which is claimed for each MWh of consumption, is calculated by summing the spot price and the value of CPs corresponding to each market interval.

As shown in loops 1 and 2 of Fig. 1, investors use the spot price signal to form expectation of their future profitability. This is done by comparing the expected revenues with the expected costs. CP restores a share of the investment costs to investors, and therefore, increases the profitability of the investments. As illustrated in loop 1, the wind speed condition is considered to allocate an efficient CP to wind generation units. Details of the implemented payment method are explained in Section 3.5. Furthermore, as the investors perceive possible profitability in their assessments, due to electricity consumption increment or generation capacity retirement,

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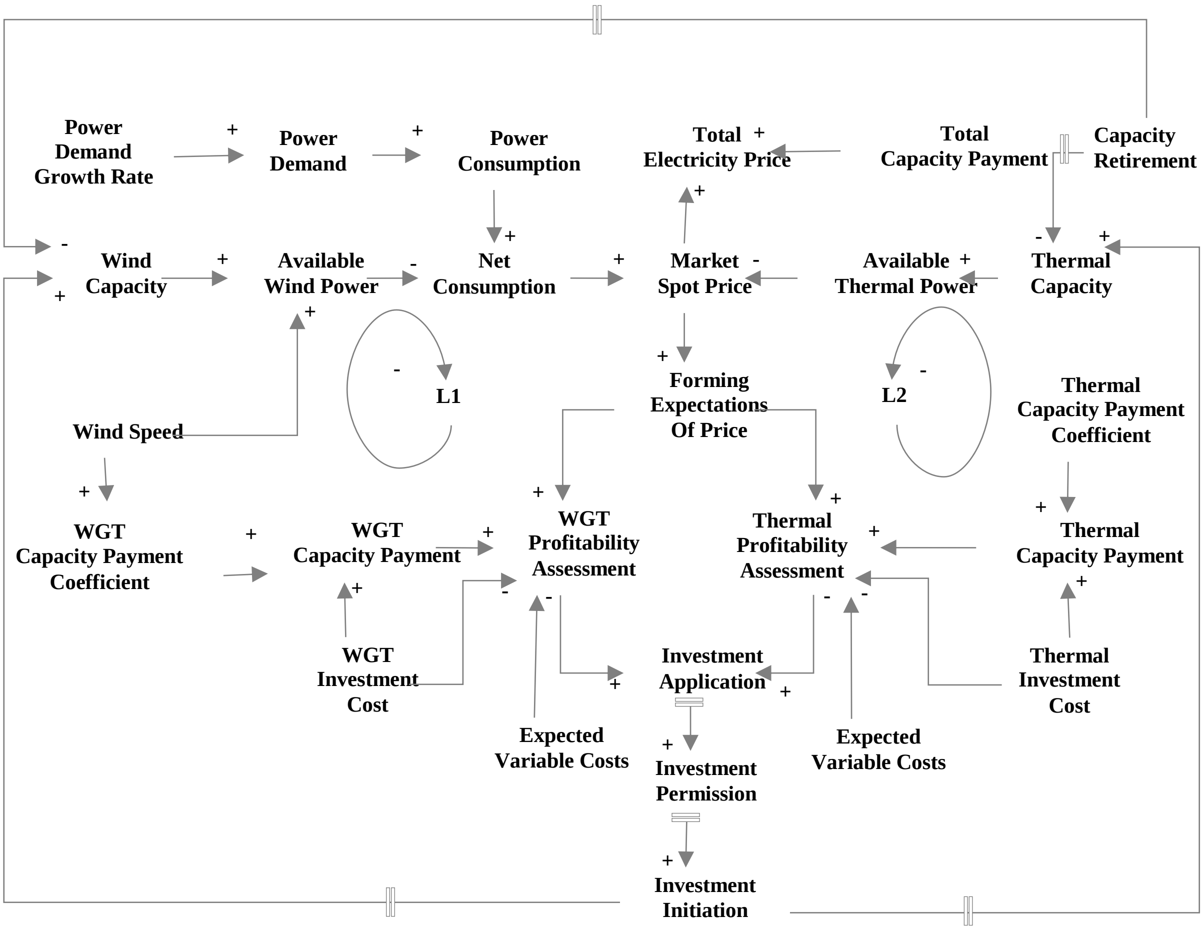

Fig. 1. Causal loop diagram of the designed model.

they discover investment opportunity, and therefore, start sending investment applications. After spending the required time, authorities give their approval to the new investments if they see it necessary. Investors start constructing after receiving permissions, and when the construction is completed, the overall installed capacity increases, and consequently, as the generation capacity increases, the electricity spot price falls. Decrease in electricity price will decrease the expected profitability, and therefore, less investment proposals will be sent, and less constructions will be initiated. Moreover, finding the investments economically irreversible, investors can defer or cancel the projects.

The presented diagram is an appropriate tool to offer an overview of the interactions between components of the model. However, to present a model which is able to explain issues such as delays, SD method offers the stock and flow model [17]. Stock and flow structures, along with feedbacks, play a key role in dynamic system theory. Stocks are accumulations, characterizing the state variables of the system and generating information upon which decisions and actions are based. The delays of the system can be modelled by stocks by accumulating the difference between the inflow to a process and its outflow. Under the system dynamics approach, with a set of nonlinear differential equations that account for existing system feedbacks, delays, stock-and-flow structures and nonlinearities, the dynamics of power markets can be described. Eq. (1) presents the stock and flow equation which is extensively used in SD models, where $S(t)$ is the stock variable, with $IF(t)$ and $OF(t)$ as its inflow and outflow rates respectively.

$$S(t+dt) = S(t) + \int_t^{t+dt} (IF(\tau) - OF(\tau)) \cdot d\tau \qquad (1)$$

The system illustrated in Fig. 1 is combined of several stock and flow equations similar to Eq. (1) which are connected to each other by feedbacks. Hence, the dynamics of the electricity market are represented with a number of nonlinear dynamic differential equations [1], which are solved by using the Euler algorithms in the desired time steps.

SD model components

1.1. Electricity demand

Considering the long-term time horizon of the study, hourly variations of electricity demand $D(t)$ don't have a significant effect on the results. Therefore, depending on frequencies chosen to clear the electricity market, the corresponding average demand can be used. Sorting the acquired demands during a year in a descending order submits an annual load duration curve (ALDC), from which different load levels (base, middle, and peak) can be recognized. At each market interval $T = [t, t + dt]$, the power consumption $C(T)$ in MWh is calculated by multiplying the average demand by the interval's duration dt as given below:

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$$C(T) = D(t) \cdot dt \quad (2)$$

1.2. Wind generation

Investigating the impacts of implementing an improved CP for WGT on the long-term development of an electricity market requires long-term simulation of wind velocity to model the wind generation. On that account, the wind speed is simulated based on the ARMA models to capture the auto-correlation of wind velocity variation pattern in consecutive time intervals, and include in the seasonal and local effects of each wind farm in the model. To create an initial time series of the wind velocity, real historical records of wind velocity variations in real sites are gathered. The average wind velocity corresponding to each market interval is calculated to have the data complying with the study's time resolution. To describe the data statistically, it is fitted by a Weibull sampling expression where the probability density function (PDF) of the wind velocity $WV(t)$ (km/h), with the shape parameter λ and the scale parameter s (km/h), is given by:

$$f(WV(t);\lambda,s) = \frac{\lambda}{s} \cdot \left(\frac{WV(t)}{s}\right)^{\lambda-1} \cdot e^{-\left(\frac{WV(t)}{s}\right)^{\lambda}} \quad (3)$$

and the cumulative distribution function (CDF) is obtained as follows:

$$F(WV(t);\lambda,s) = 1 - e^{-\left(\frac{WV(t)}{s}\right)^{\lambda}} \quad (4)$$

The initial time series of the wind velocity is calculated as follows:

$$Z(t) = \big(WV(t) - \mu(t)\big)/\sigma(t) \quad (5)$$

where $WV(t)$ in km/h represents the observed wind velocity at each step, with $\mu(t)$ and $\sigma(t)$ representing its mean value and standard deviation respectively. Having the initial time series, the ARMA model can be obtained as below [18]:

$$Z(t) = \sum_{p=1}^{P} \Phi_p \cdot Z(t-p) + M - \sum_{q=1}^{Q} \Theta_q \cdot M(t-q) \quad (6)$$

As Eq. (6) depicts, ARMA models are generally consisted of an auto-regressive and a moving average part. $\mathrm{M}(t)$ is a normal white noise process. Φ_p and Θ_q are the auto-regressive and moving average coefficients respectively, which are obtained by applying the least square of errors criterion. P and Q are the ARMA orders which can be set by trial and error.

After creating the appropriate ARMA time series, the simulated wind velocity for the entire time horizon of the study can be obtained by employing the created time series as follows:

$$SWV(t) = \mu(t) + \sigma(t) \cdot Z(t) \quad (7)$$

At each time, constrained by the wind speed, the maximum generation capacity that each wind generation facility w with the total installed capacity $Ca_w(t)$ can provide in MW is reflected in the wind turbines' nonlinear power output curve as follows:

$$ACa_w(t) = \begin{cases} 0, \\ Ca_w(t) \cdot (\alpha + \beta \cdot SWV(t) + \gamma \cdot SWV(t)^2), \\ Ca_w(t), \\ 0, \end{cases} \quad (8)$$

where α, β and γ are the wind generation coefficients which can be estimated as functions of Vci and Vr, which are the wind turbine's cut-in and rated velocities respectively [19]. When the wind velocity is more than turbine's cut-out velocity Vco or less than Vci, it cannot be utilized, and its output power equals zero.

Assuming that the time interval of power market $T = [t, t+dt]$ is short enough that the installed capacity of each generation technology remains fixed, by using the average wind speed for each interval, the maximum electricity that each wind generation facility w can generate in MWh can be calculated from multiplying its actual generation capacity by its total production time within a market interval AD_w as follows:

$$P_w(T) = ACa_w(t) \cdot AD_w \quad (9)$$

Total production time in hour is estimated by multiplying the availability factor of each technology by the duration of any given time step. The availability factor reflects the effects of technical contingencies and other planned maintenances on the availability of each generating unit. Other parameters involving in wind generation can vary significantly in long-term, and therefore, due to purpose of the study and avoid computational complexities they are neglected.

1.3. Thermal generation

Unlike the wind generation, considering operational contingencies which are reflected in the total production time, thermal generation units usually produce electricity as much as their rated capacity at the time $Ca_x(t)$ allows them. Hence, Eq. (10) indicates the maximum electricity which can be committed by each thermal generator x in MWh, and it is obtained by multiplying its total installed capacity by the total production time AD_x.

$$P_x(T) = Ca_x(t) \cdot AD_x \quad (10)$$

1.4. Power market

In a perfectly competitive power market, no generation company can strategically influence the market price and all the competitors are price takers. It can be proven that in such condition, each unit offers electricity by its marginal cost of generation, and the optimal combination of the generating units is committed to respond to the electricity demand [1]. In this model, it is assumed that thermal generation units with the same technology and wind generators installed in the same location use the same fuel and have the same generation pattern respectively. Therefore, instead of considering each generator separately, the aggregated supply curve and the total installed capacity of the generators with similar generation characteristics are considered in computations and analysis. Accordingly, at each market of this model, each thermal generator offers its production based on the marginal cost, which for each technology x it can be obtained by Eq. (11):

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$$SC_x(t) = FC_x/\eta_x + ET \cdot (EI_x/\eta_x) \tag{11}$$

where, FC_x, EI_x and η_x are the fuel costs (€/MWh), emission intensity (ton/MWh), and thermal efficiency of technology x respectively. ET represents the tax imposed on the greenhouse gas emission in €/ton. Other variable costs are neglected.

Assuming no price sensitivity for electricity consumption, the spot market price for electricity $MP(t)$ equals the marginal generation cost of the most expensive committed unit. This is what is paid to generators for any MWh of energy they produce. However, WGT can provide electricity at a marginal cost low enough to be neglected. Thus, it is committed to the system whenever available. Since its availability is not certain, at each interval of the market $T = [t, t + dt]$, it can be seen as a negative consumption, reducing the actual power consumption. A new variable called the net consumption $NC(T)$ can be defined, which is the difference between the electricity consumption $C(T)$ and total wind generation $\sum_{w=1}^{W} P_w(T)$. This variable determines the level of unit commitment for the thermal generators with marginal costs more than zero. Moreover, in case the electricity generation is not sufficient to cover the consumption, electricity price equals the value of lost load (VOLL) which is the maximum price of electricity of this model.

1.5. Capacity payment

A perfectly competitive market may not always be in the best interest of all generators. Given that the power demand is not always at its peak, a peak time generation technology such as GT may barely recover its operational costs [1]. Moreover, investment in generation technologies with uncertain production and high capital costs such as WGT may seem very risky to the investors. CPM is established to provide the generators with a fixed income separated from the energy market; hence, by providing a level of financial certainty it can prevent the long-term investment fluctuations [20]. The payments are usually paid to generators proportional to the level of capacity they offer to the market, and the total amount of payments has to be high enough to cover at least a share of the capital cost of generation units to motivate new investments and keep the existing ones from going out of business [21].

3.5.1 Capacity payment coefficient

According to the basic principle of CP, a fraction of the investment cost of each generator should be paid proportional to the capacity that they provide for the market. Therefore, we introduce an improved CP coefficient for the WGT considering the wind energy potential of the location in which the turbines are installed to motivate the investors to install wind generators in locations with high generation potential. We present a dynamic method to annually decide the share of the investment cost of the wind generators which is to be paid. In Fig. 2, the process of selecting an efficient CP coefficient for each wind generation facility is illustrated. The proposed CP coefficient is dynamic and it changes every year with respect to the wind speed variation of the recent years. The coefficient is selected in 5 steps: First, the recent records of the wind speed in the selected location is gathered. Second, by using the ARMA method discussed in Section 3.2, several scenarios of wind speed variation forecasts are created.

After simulating enough scenarios, in step 3, to make the forecasting robust, the expected value of average wind speed at each time interval of the market is calculated as follows:

$$EXP\big(SWV(t)\big) = \textstyle\sum_{i=1}^{I} SWV_i(t) \cdot f\big(SWV_i(t)\big) \tag{12}$$

where for I simulated wind speed variation samples, $SWV_i(t)$ in km/h is the simulated wind velocity at time t in the simulated sample i with probability of occurrence $f(SWV_i(t))$. After calculating the expected value of the average wind velocity at each desired time interval within a year, in step 4, assuming that the wind speed variation within a year fits a Weibull distribution with PDF and CDF as Eq. (3) and Eq. (4), the Weibull parameters can be estimated using the maximum likelihood method. Accordingly, assuming WV_n in km/h as the wind velocity at the center of each bin n, and $P(WV_n)$ the frequency of the wind velocity falling within the speed range of the bin n, the likelihood of a chosen sample being within the velocity range of a class is proportional to the probability density function at its centre. Eq. (13) shows the likelihood of having observations settled in n independent ranges [22]:

$$L(WV_1 \dots WV_N; \lambda, s) = \prod_{n=1}^{N} f(WV_n; \lambda, s)^{P(WV_n)} \tag{13}$$

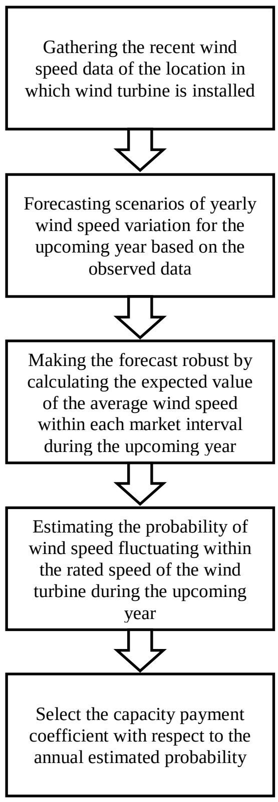

Fig. 2. Process of selecting capacity payment coefficient for WGT.

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To obtain the maximum likelihood, the shape and the scale parameters should be determined in a way that L is maximized. Since L is multiplicative, its logarithm could be maximized instead [23]. Therefore, solving $\frac{\partial \ln L}{\partial \lambda} = 0$ and $\frac{\partial \ln L}{\partial s} = 0$ submits Eq. (14) and Eq. (15) respectively:

$$\lambda = \left(\frac{\sum_{n=1}^{N} WV_n^{\lambda}\, ln(WV_n) P(WV_n)}{\sum_{n=1}^{N} WV_n^{\lambda} P(WV_n)} - \frac{\sum_{n=1}^{N} ln(WV_n) P(WV_n)}{P(WV>0)}\right)^{-1} \tag{14}$$

$$s = \left(\frac{\sum_{n=1}^{N} WV_n^{\lambda} P(WV_n)}{P(WV>0)}\right)^{\frac{1}{\lambda}} \tag{15}$$

Eq. (14) is solved irrelatively, until λ converges to the desired value; then, by placing it in Eq. (15) scale parameter s is acquired. $P(WV > 0)$ indicates the frequency of wind velocity exceeding zero.

After estimating λ and s, the probability of the wind velocity residing within the range of the turbine's nominal velocity during a year is estimated as follows:

$$P\big(Vr < EXP(SWV(t)) < Vco\big) = F(Vco; \lambda, s) - F(Vr; \lambda, s) \tag{16}$$

By using the Eq. (16), the probable hours during a year within which a wind farm can produce electricity is obtained, and the CP coefficient of WGT, CPF_w at each year is selected with respect to this probability and a control parameter g used for setting a wider or a narrower range for the coefficient based on the situation. Moreover, since the focus of this study is to investigate the improvement on CP to WGT in a competitive electricity market, to filter the results from the interference of other varying parameters, a fixed CP coefficient CPF_x is assumed for each thermal generation technology.

3.5.2 Total capacity payment price

Presenting the electricity spot price and the total CP price $TCP(t)$, total electricity price $TEP(t)$ in €/MWh is the cost of consuming a MWh of electricity at each time step:

$$TEP(t) = MP(t) + TCP(t) \tag{17}$$

Assuming that the CPs are given annually from the year when the generation capacity is brought online until when it is retired, for each MW of each generation technology, the annual value of the investment during its lifetime can calculated as below [24]:

$$AIC = IC \cdot \frac{r(1+r)^{TL}}{(1+r)^{TL}-1} \tag{18}$$

where, IC stands for the investment cost (€/MW), r is the required rate of return (%/yr), and TL presents lifetime duration of the generator in yr.

Considering the capacity that was offered to the system by the generators in each market, the payment allocated to each generation unit at each time interval $T = [t, t + dt]$ is obtained as follows:

$$CP_w(T) = P_w(T) \cdot CPF_w \cdot dIC_w(t) \tag{19}$$

$$CP_x(T) = P_x(T) \cdot CPF_x \cdot dIC_x(t) \tag{20}$$

where $dIC_w(t)$ and $dIC_x(t)$ represent the hourly segments of annual investment costs of wind and thermal generation technologies in €/MWh respectively ($dIC(t) = \frac{AIC(t)}{8760}$).

Assuming W and X the total number of wind generation and thermal generation units respectively, total CP price at each market is obtained by summing all of the relevant CPs. At each market, the € value of the payable CP must equal the value that should be given to the generators. Accordingly, total CP price (€/MWh) at each market can be obtained by Eq. (21) and Eq. (22):

$$C(t) \cdot TCP(t) = \sum_{w=1}^{W} P_w(t) \cdot CPF_w \cdot dIC_w(t) + \sum_{x=1}^{X} P_x(t) \cdot CPF_x \cdot dIC_x(t) \tag{21}$$

$$TCP(t) = \frac{1}{C(t)} \cdot \left(\sum_{w=1}^{W} P_w(t) \cdot CPF_w \cdot dIC_w(t) + \sum_{x=1}^{X} P_x(t) \cdot CPF_x \cdot dIC_x(t)\right) \tag{22}$$

1.6. Profitability assessment and capacity development

3.6.1 Operational profit

Before initiating any investment project, investors firstly analyse its future profitability. The evaluation is based on the expectations which are established upon the recent price signals. Therefore, using a proper forecasting method can help the investment plans in contrast with financial uncertainties. Accordingly, in this study, a bounded rationality approach described by [25] is employed to predict future prices. Indicating each generation technology by j, to model the process of profitability assessment, the annual operational profit (€/MW/yr) is introduced by [1], by which we describe the expected future profitability of installing any extra MW of each wind or thermal generation technology during a one year period respectively:

$$EOP_j(t) = \int_{t0}^{t0+Top} \big(EMP(\tau) - ESC_j(\tau)\big) \cdot d\tau \quad \forall\, EMP(t) \geq ESC_j(t) \tag{23}$$

where $t0$ is the time when utilization of a capacity begins, and Top is the operation time duration which is one year. $EMP(t)$ presents the expected market price of electricity, and $ESC_j(t)$ shows the expected marginal cost of each generation technology.

3.6.2 Economical profit

To examine the project economics, cash-flows of different years within the amortization period of each technology TA should be brought to a common reference time (the time of profitability assessment). The process can be performed by using the net present value (NPV) method. Applying the NPV method, we can calculate the entire economic profit of investment in one MW of each generation technology, the construction of which begins at time t as below:

$$EP_j(t) = \sum_{m=1+TC_j}^{TA_j+TC_j} \big(EOP_{j,m}(t) + ECP_{j,m}(t)\big) \cdot e^{-\rho(m)} - IC_j(t) \tag{24}$$

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In Eq. (24), for wind and thermal generation technologies respectively, $ECP_{j,m}(t)$ is the expected CP, $IC_j(t)$is the investment cost, j is the amortization period, and TC_j is the time needed for construction. Moreover, ρ presents the adjusted discount rate.

3.6.3 Profitability index

Solving $EP_j(t) = 0$ for ρ yields another parameter known as the internal rate of return (IRR). Dividing this parameter by ρ, yields an index called the profitability as below:

$$PI_j(t) = IRR_j(t)/\rho \tag{25}$$

Profitability index is a criterion to determine if the situation is suitable for investments. In the long-run equilibrium this index equals 1, suggesting that the operational profit of any investment will only cover its capital costs. Therefore, there is no incentive for new investments. However, greater profitability index indicates more investment opportunity.

3.6.4 Investment application

In a real power system, profitability index is not the only reason for investments. The retired units need be replaced by the new ones, and the generation capacity is expanded proportional to the demand growth. To reflect the effect of profitability index in capacity development process of different generation technologies, [1] offered an S-shaped as below:

$$SF_j\left(PI_j(t)\right) = MSF_j\left(1 + e^{-(\Psi_j PI_j(t)+\Omega_j)}\right)^{-1} \tag{26}$$

In Eq. (26), MSF_j is the saturation level of the S-shaped function. Ψ_j and Ω_j can be obtained by solving the equation $SF_j(1) = 1$. Using Eq. (26), the profitability index is converted to a factor by which the investor's behaviour is influenced. Investors start their job by sending investment application to the authorities. The rate at which the investment application process of each technology j in MW/yr starts is given by:

$$dIA_j(t) = SF_j\left(PI_j(t)\right)\cdot\left(dR_j(t) + dG_j(t)\right) \tag{27}$$

where in MW/yr, $dR_j(t)$ and $dG_j(t)$ are the retirement rate and the capacity addition rate to respond to the maximum demand respectively. The procedure of sending application is delayed since it takes some time for them to be processed completely. Therefore, by using the stock and flow concept, at each time step, the investment application under process of each technology j in MW is obtained by:

$$IA_j(t + dt) = IA_j(t) + \int_t^{t+dt}\left(dIA_j(\tau) - dPR_j(\tau)\right)\cdot d\tau \tag{28}$$

Eq. (28) implies that at time $t + dt$ the value of the investment application under process corresponding to each technlogy j is obtained by summing its value at the former time step and the accumulation of the difference between its inflow $dIA_j(t)$ and outflow $dPR_j(t)$ during the new interval. $dPR_j(t)$ represents the application processing rate in MW/yr and it is calculated by dividing the initial investment application $IA_j(t)$ by processing time TP_j.

3.6.5 Application evaluation

Authorities receive the investment applications with the same rate by which they are processed. They take their time to assess the applications, and then decide whether to approve them or not. This time delay can also be modelled by Eq. (1) as follows:

$$EV_j(t + dt) = EV_j(t) + \int_t^{t+dt}\left(dPR_j(\tau) - dEC_j(\tau) - dRJ_j(\tau)\right)\cdot d\tau \tag{29}$$

where $EV_j(t)$ in MW represents each technology j's investment application under the evaluation of authorities. $dEC_j(t)$ in MW/yr describes the application's evaluation completion rate and it is obtained from dividing $EV_j(t)$ by evaluation time TE_j minus the rejection rate. The rejection rate $dRJ_j(t)$ is the rate by which the applications are rejected, and its value in MW/yr is achieved by multiplying $EV_j(t)$ by the rejection fraction RJ_j (%/yr).

3.6.6 Acquired permission and investment initiation

After receiving the required permissions, investors use the permissions to initiate their investments. However, this procedure does not happen instantly. Due to some slow investment initiation rates, the investors may find the need to use their acquired permission so late that they expire. These conditions need to be properly modeled in a long-term model of the power market. Eq. (30) expresses this procedure mathematically:

$$ACQ_j(t + dt) = ACQ_j(t) + \int_t^{t+dt}\left(dEC_j(\tau) - dXP_j(\tau) - dI_j(\tau)\right)\cdot d\tau \tag{30}$$

where for each technology j, $ACQ_j(t)$ represents the acquired investment permission in MW, $dXP_j(\tau)$ in MW/yr is the permission expiration rate, and $dI_j(t)$ stands for the investment initiation rate (MW/yr). Considering TXP_j and TI_j as the expiration time and the investment initiation time respectively, the expiration rate and the investment initiation rate are given by:

$$dXP_j(t) = ACQ_j(t)/TXP_j \tag{31}$$

$$dI_j(t) = min\left[IA_j(t)\,, ACQ_j(t)/TI_j\right] \tag{32}$$

3.6.7 Capacity construction and retirement

The capacity construction of each generation technology j is started with the investment initiation rate explained in former section. To model the delay in capacity construction, another stock and flow equation based on Eq. (1) is presented as below:

$$UC_j(t + dt) = UC_j(t) + \int_t^{t+dt}\left(dI_j(\tau) - dCC_j(\tau)\right)\cdot d\tau \tag{33}$$

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where $UC_j(t)$ in MW represents the capacity under construction of each technology j, and considering TC_j as the construction completion time for each technology j, the construction completion rate $dCC_j(t)$ in MW/yr is given by:

$$dCC_j(t) = UC_j(t)/TC_j \tag{34}$$

Each constructed capacity is assumed as the installed capacity of each technology, and it remains in the system until its retirement. Therefore, the total installed capacity of each technology in MW can be given by:

$$Ca_j(t+dt) = Ca_j(t) + \int_t^{t+dt} \big(dCC_j(\tau) - dR_j(\tau)\big) \cdot d\tau \tag{35}$$

$$dR_j(t) = Ca_j(t)/TL_j \tag{36}$$

where TL_j represents the life time of each generation technology j.

Simulation and results

In this section we present a simulation analysis to show the benefits of the proposed incentive for the wind turbines in generation system improvement and average prices decrease. Four generation technologies are considered for the study. Namely, hard coal power plants (HC), combined cycle gas turbines (CCGT), gas turbines (GT) and wind turbine generators (WGT). In Table 1, the data is presented to define the initial generation capacity of the system. This table provides the input data for the simulation analysis.

Table 1. Generation system description.

	HC	CCGT	GT	WGT loc. A	WGT loc. B
Investment application (MW)	500	500	500	200	200
Application under evaluation (MW)	200	200	200	200	200
Acquired permission (MW)	100	100	100	100	100
Capacity under construction (MW)	400	400	400	200	200
Installed capacity (MW)	12500	3500	1500	1100	1100
Application rejection fraction (%/year)	1	1	1	1	1
Efficiency (%)	40	60	30	NA	NA
Availability factor (%)	98	98	98	98	98
Emission intensity (ton/MWh)	80	50	50	NA	NA
Emission tax (€/ton)	5	5	5	NA	NA
Fuel cost (€/MWh)	1.5	12	12	NA	NA
Investment cost (€/KW)	1000	600	400	1250	1250
Life time (year)	40	30	20	20	20
Amortization period (year)	25	20	15	15	15
Processing time (year)	0.75	0.75	0.75	0.75	0.75
Evaluation time (year)	0.75	0.75	0.75	0.75	0.75
Construction time (year)	3	2	1	1	1
Permission expiration time (year)	3	3	3	3	3
Investment initiation time (week)	2	2	2	2	2

The simulation analysis is over a hypothetical power system with competitive electricity market. A time horizon of 25 years is selected for the study. Considering this long-term time horizon, and the slight effect of hourly price changes in investment decisions, to avoid computational difficulties, the simulation time resolution is set to one week, which is also chosen to be the frequency of holding the electricity market. Accordingly, instead of hourly load profiles, weekly averaged load profiles are employed in the simulation. Moreover, to include the effects of seasonal weather variations on the electricity consumption, a predefined pattern for load fluctuations is presumed, which is initially varying between a base and peak of 6800 MW and 13000MW respectively. The ALDC is assumed to remain fixed during every year; however, the load levels grow annually by a constant rate of 3%/yr, reflecting the effects industrial development and population growth on the electricity demand. Market is initially at long-run equilibrium. The value of lost load (VOLL) is set at 1000 €/MW which is the electricity price cap. An adjusted discount rate of 9%/yr is assumed for the study. No short-term and long-term price elasticity is assumed for electricity demand, and no auxiliary market is presumed in the model. Moreover, the purpose of our proposed incentive is to direct the WGT investment towards more efficient wind fields. Given that, two wind generation facilities with different wind speed potentials are presumed in the generation system under study. Finally, CP coefficients of thermal generation technologies are set in a way that they do not encourage technologies with low efficiency or high rate of pollution [7]. The simulation results are presented in three subsections.

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4.1 Simulation analysis results

To have a comparative analysis over the effects of applying the proposed incentive, the presumed power system is analysed under three different incentive scenarios. Scenario 1 refers to a case where thermal technologies receive CPs while no CP is given to the wind turbines. This case is designed to answer the question of whether it is sensible to give CP to wind turbines. In Scenario 2, CP is given to the wind turbines with the same approach it is given to the thermal technologies. Eventually, in Scenario 3, an incentive according to what is proposed in this study is given to the WGT. Comparing the total installed capacity of the market under different scenarios during the simulation horizon in Fig. 3, shows that although in scenarios 2 and 3, payments to WGT start from the first day of simulation, their total installed capacity graphs do not vary significantly before the year 4, indicating that the inherent time delays prevent incentive policies from influencing the generation capacity immediately.

Moreover, comparing graph of scenario 1 with other scenarios reveals that without incentive for WGT, boom and bust cycles in total installed capacity are stronger, indicating that CP to WGT has been effective in decreasing the capacity investment fluctuations. Furthermore, acquiring total average reserve margins of 30.69%, 33.69% and 33.01% for scenarios 1, 2 and 3 shows that incentive for WGT has been effective in improving the generation adequacy.

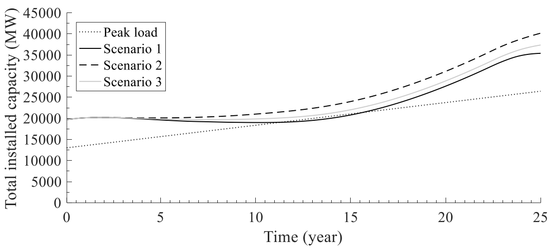

Fig. 3. Total installed capacity and peak load.

In Table 2, the simulation results of different scenarios namely, the defined capacity payment factors of different generation technologies with the corresponding average price of electricity and loss of load duration are listed.

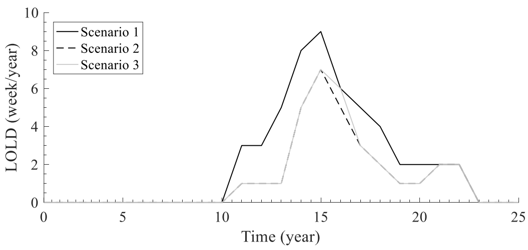

Fig. 4. Loss of load duration.

Comparing generation adequacy which is caused by each incentive policy, Fig. 4 and Table 2 shows that in comparison with scenario one, CP for WGT has decreased the loss of load durations which occurred from year 11 to 22 (from a total average of 2.04 week/yr to 1.24 and 1.28 week/yr in scenarios 2 and 3 respectively).

However, there is a slight difference between the outcomes of incentives used in scenarios 2 and 3, as equal CPs to both locations, has resulted in 1 week lesser of LOLD in year 16. On the other hand, while multiple occurrences of LOLD followed by VOLL has increased the average electricity price in scenario 1 (with total average electricity price of 66.50 $/MWh), comparing the average electricity price graphs relevant to scenarios 2 and 3 in Fig. 5 shows that even with more occurrence of LOLD, the least average price has occurred in the case, where the incentive has been given by our proposed method (with total average electricity price of 52.52 $/MWh).

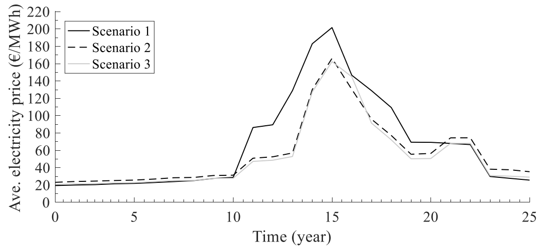

Fig. 5. Yearly average electricity price.

4.2 Sensitivity analysis

As it is in observed Fig. 6, thermal technologies are not significantly affected by implementing different CPs for WGT.

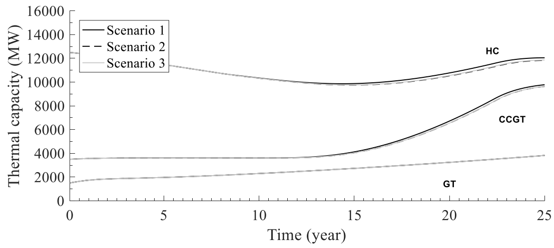

Fig. 6. Total installed capacity of thermal generation technologies.

However, after 10 years of payment to WGT, a slight reduction occurs in HC and CCGT installation (on average about 103.58 MW for HC and 68.17 MW for CCGT in scenario 2 and 90.70 MW for HC and 66.12 MW for CCGT in scenario 3). This is because, in scenarios with payment to WGT, there are more wind turbines to respond to the electricity demand, and therefore, less electricity price reduces the motivation to invest in thermal technologies. As Table 1 shows, since GT technology has very low efficiency and investors mostly acquire their expenses by the CPs that they receive. Therefore, it does not show the sensitivity that other thermal technologies do. Figs. 7a and 7b display the capacity development of wind generation units installed in two locations. The installed capacity of facility A, which has a more preferable wind energy potential than location B, has considerably increased under any type of CP allocation (up to 7450 MW and 7200 MW by year 25 in scenarios 2 and 3 respectively).

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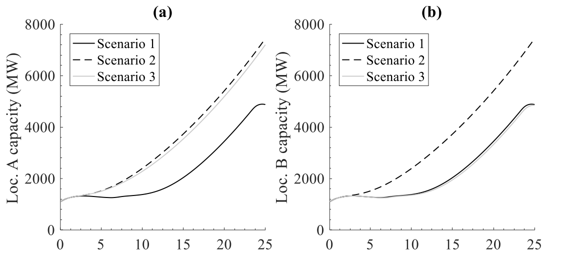

Fig. 7. Total installed capacity of WGT in (a) location A, (b) location B.

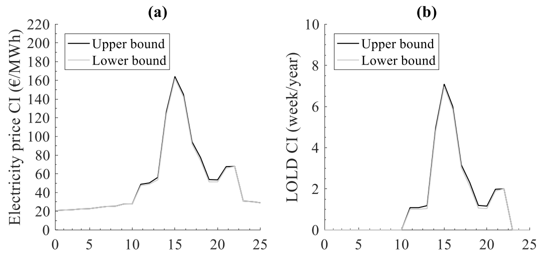

Fig. 8. Confidence interval of (a) yearly average electricity price, (b) LOLD.

In case of, paying equal payments to both locations, although the installed capacity of both locations significantly increases (up to 7450 MW by year 25), the contribution of WGT to the generation adequacy of the system does not greatly differ from scenario 3 (which is reflected in LOLD graphs). However, in scenario 3, our proposed incentive, by increasing the Location B's WGT capacity up to 4850 MW (2600 MW less than scenario 2), provides a quite similar generation adequacy at lower prices (see Fig. 5).

Table 2. Simulation results in different scenarios.

scenario	CP F_{HC} (%)	CPF_{CCGT} (%)	CP F_{GT} (%)	CP F_A (%)	CP F_B (%)	Ave. EP (€/MW)	Ave. LOLD (week/year)
1	25	70	100	0	0	66.50	2.04
2	25	70	100	100	100	56.06	1.24
3	25	70	100	Var	Var	52.52	1.28

4.3 Uncertainty analysis

Stochastic simulation is performed to analyse the effect of wind speed uncertainty on the simulation outcomes. Over 1000 cases of wind velocity variation during the simulation time horizon are created by using ARMA method. Initial samples of the ARMA model are created by using the Weibull distribution of the historic data and Monte Carlo technique. Each simulated wind speed variation is implemented in the model. The expected value of the output and its narrow band of variations, named confidence intervals, are usually assessed for better clarification. Confidence intervals of yearly average electricity price, LOLD, and total installed capacity are presented in Figs. 8 and 9 respectively. The low intervals imply that the uncertainty of wind velocity has no major effect on these variables. Also, occurrence of high prices and LOLDs in years 11, 15, and 22 correspond to the simulation results of Section 4.1, and the upper band of the confidence interval is pretty close to the actual results of Fig. 5. This agreement is due to using the expected value of wind speed to set the CP coefficients in each year.

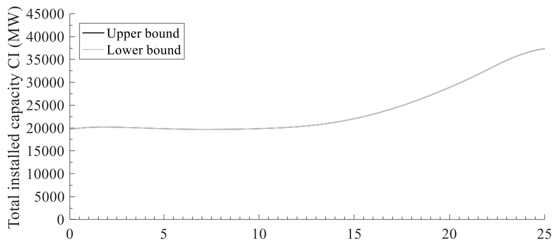

Fig. 9. Confidence interval of total installed capacity.

Discussion and conclusion

In prior studies related to improving the generation adequacy by allocating incentives, CPM for WGT has not been a subject of any significant study. To compare the contribution of this paper with the existing literature addressing the subject, a critical survey has been presented in Table 3. However, in the presented study the previous works have been promoted by proposing an investment incentive mechanism based on the former CP mechanism for improving the integration of WGT and increasing the generation adequacy while decreasing the average electricity prices.

Our proposed CP is allocated to each wind turbine considering not only its offering generation capacity, but also the dynamic predictions of production potential related to the wind farm where it's installed. Employing an SD modelling approach, a simulation analysis is carried out by which the impact of our proposal on different aspects of a restructured generation system with competitive electricity market is analysed. The analysis has shown that the statement established by [3] also applies to the integration of WGT, as we observe that without incentives for WGT, in several time intervals, there is no sufficient generation capacity in the network, and the results confirm the statements of [9] and [10] in the introduction section as the generation capacity improves by employing the investment incentives. Moreover, confirming the statement of [11], our analysis shows that a simply designed investment incentive for WGT cannot effectively fulfil the incentive policy targets since this technology, due to its intrinsic uncertainty, does not make the same contribution to the generation adequacy of the system as thermal technologies. Therefore, as our proposal, a CP for WGT needs to be dynamic and adaptive to the specific nature of wind energy of the associated wind farm.

Table 3. A critical survey of existing literature methods.

Ref.	Research Question	Approach	Advantageous	Defect
[5]	Construction cycles in a restructured electricity industry.	Introducing a constant capacity payment to damp the construction cycles.	Lower energy prices would nullify the impact of capacity payments in the long run.	The introduced capacity payment is constant and not flexible.
[7]	Long-term investment planning under uncertain conditions.	Presenting a variable mechanism for capacity payment.	Having a variable capacity payment, the investment fluctuations are not of high amplitude, and the reserve and available capacity can efficiently be controlled.	The stochastic nature of energy sources such as wind is not considered in the study.
[8]	The generation capacity expansion in restructured power systems considering uncertainties.	Assessing investment incentives such as firm contracts and capacity payments.	Presence of firm contracts and capacity payment increase generation investment in different technologies and improve long-term stability of the market.	The investment problem is solved as an optimization problem. Thus, dynamic viewpoints and the stochastic nature of energy sources such as wind are not considered in the study.
[14]	Investment cycle in the electricity markets due to their capital-intensiveness and the long lead time of new generation facilities.	Testing the stability of different capacity mechanisms in the presence of uncertainty regarding the demand growth rate with a stochastic dynamic model.	Benefits of such mechanism for the generating companies is that it would motivate new market entrants and reduce the shortages and price spikes.	Consumers are compromised by the lack of economic efficiency.
[16]	How a capacity mechanism can address security of supply objectives in a power market undergoing an energy transition.	Developing a system dynamics model, the energy-only market design with a price cap, with and without a capacity mechanism, is compared to scarcity pricing in two investment behaviour scenarios with and without risk aversion.	The results highlight the advantage of the capacity mechanism over scarcity pricing under the hypothesis of risk aversion.	The stochastic nature of energy sources such as wind is not considered in designing of the capacity mechanism.

Eventually, the results of our simulation analysis reveal that incentive for WGT can decrease the investment fluctuations in generation capacity. It can also improve the generation adequacy and decrease the average electricity price of the market. However, our results show that integrating the installation of wind turbines does not mean more generation adequacy. Incentives for integration wind generation capacity is efficient when it is placed smartly. Our proposed CPM can fulfil these expectations by dynamically lead the investments of WGT to the efficient wind farms. Furthermore, the results also state that the integration of the wind turbines by employing the proposed incentive does not significantly influence the investments of thermal generation technologies which are considered as the reliable reserve sources. At last, our analysis over the influence of the wind uncertainty on the simulation results denies any significant effect on the efficiency of our proposed incentive. In the current from, the proposed incentive mechanism for wind generation technology uses the wind speed variation as the major criterion for allocating payments to the wind generators. Considering the future desired capacity of each generation technology, defining the incentive mechanism can be taken as future works.

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