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On the Role of Renewable Energy Policies and Electric Vehicle Deployment Incentives for a Greener Sector Coupling

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ABSTRACT Various incentives are introduced for the expansion of electric vehicle fleets and electricity generation from renewable energy resources. Although many researchers studied the effect of these policies on the related sector, there is no study investigating the indirect effect of renewable energy incentives on the deployment of electric vehicles or the indirect effect of electric vehicle adoption policies on the long-term integration of renewable energy resources. The main contribution of this paper is to analyze the impact of the specific incentives on both deployment of electric vehicles in the transportation system and investment in capacity generation in the electricity market. For this purpose, a new framework was designed to analyze the effect of policies on the electric vehicle deployment and development of DC charging stations based on the system dynamics approach. Then, this framework was combined with the existing dynamic models of the electricity market to study the interaction and behavior of both coupled systems from the policymakers' perspective. The effect of policies implementation was interpreted in a mathematical framework and the Net Present Value method was used for assessing the investment in charging infrastructures. Simulation results of a case study in the United States and sensitivity analysis illustrate that increasing the wind capacity incentives accelerated the electrification of the transportation system and increasing the incentives for electrification of transportation system influences wind capacity positively. Moreover, the sensitivity of the electric vehicle adoption to gas price is more than the sensitivity of the wind capacity penetration to gas price.

INDEX TERMS DC charging stations, electricity market, electric vehicles deployment policies, plug-in electric vehicles, renewable capacity incentive, system dynamics, wind capacity investment.

NOMENCLATURE

A. ABBREVIATIONS

ESS	Energy storage system.
RES	Renewable energy source.
PEV	Plug-in electric vehicle.
EVSE	Electric vehicle supply equipment.
HC	Hard coal units.
CCGT	Combined cycle gas turbines.
GT	Gas turbines.
NPV	Net Present Value.

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B. VARIABLES

DUCH	Number of PEVs that are supplied in DC charging station.
d	Time step (day).
TNPEV	Total number of plug-in electric vehicles.
DCEVC	Daily consumption of electric vehicles that use DC charging stations (kWh/day).
MAGE	Average daily driving distance of electric vehicles (km/day).
ACEV	Average daily consumption of electric vehicles (kWh/km).
TCEV	Total electricity consumption of all PEVs each day (kWh/day).

TCESC	Stored energy in ESSs of charging stations (kWh/day).
TCS	Total number of DC charging stations.
EE	Excess energy sold to the grid by ESSs.
ESG	Energy of PEVs that is not supplied from ESSs of DC charging stations (kWh/day).
WDF	Electricity demand in each week (MW).
ADGR	Growth rate of demand in each year (%/year).
ΔT	Time step changes equal to one year (year).
WD	Weekly demand after price response (MW).
t	Time step (week).
AP	Average price in the previous year ($/MWh).
RP	Average of prices in five recent years ($/MWh).
PED	Long-term price elasticity of demand.
i	Indices of each technology (HC, CCGT, GT, and wind).
h	Time step (hour).
WSH	Weekly average wind speed at H (m/s).
WSB	Average weekly wind speed at HB (m/s).
TCPR	Terrain characteristics of the area.
H	Height of the turbine's hub (m).
HB	Height of measurement tools (m).
ΔPR	Hourly electricity price changes ($/MWh).
PR	Electricity price ($/MWh).
QNET	Electricity net demand (MWh).
TEGC	Total electricity generation of fossil fuel units (MWh).
Δh	Time step changes equal to one hour (hour).
TAM	Amortization time (year).
DR	Discount rate (%/year).
TPE	Perceived time (year).
PROFC	Total profit of DC charging stations ($/MW).
EPROFC	Common expected term of operating profit for DC charging stations ($/MWyear).
OMCC	Average operational and maintenance costs of DC charging stations ($/MWyear).
TCONSC	Construction time of DC charging stations (year).
ICC	Investment cost of DC charging stations ($/MW).
REV	Average weekly revenue of DC charging stations ($/MWh).
EXP	Average weekly expenditure of DC charging stations ($/MWh).
IRRC	Investment rate of return for DC charging stations (%/year).
PITC	Profitability index of charging stations.
SSFDC	S-shaped function of DC charging stations.
ADC	Saturation capacity for DC charging stations.
BDC and CDC	Fixed values of the S-shaped investment function for DC charging stations.
IRCS	Investment rate of charging stations (number/year).
RRC	Retired rate of charging stations (number/year).
NNCS	Needed number of fast DC charging stations (number/year).
TAGEC	Lifetime of DC charging stations (year).
TEV	Total number of PEVs.
CST	Targeted ratio of plug-in electric vehicles to DC charging station.
PROB	Probability of purchasing new PEVs.
Z	Factors that affect the probability of purchasing a new electric vehicle.
COVA	Constant value related to the purchasing a new electric vehicle.
LCOE	Logit coefficient correspond to Z.
CSPC	DC charging stations per capita (charging stations per 10,000 capita).
POP	Population of the United States.
PROBA	Probability of purchasing new PEVs after implementing incentives.
ICI	Individual credit for purchasing a new vehicle ($).
HOV	HOV lane access incentive (vehicles per HOV lane per hour).
EVSES	Electric vehicle supply equipment (EVSE) Subsidy ($).
ALDV	Added number of light-duty vehicles (number/year).
GRLDV	Growth rate of light-duty vehicles production (%/year).
TLDV	Total number of light-duty vehicles.
AEV	Added number of PEVs.
RREV	Depreciating rate of PEVs (number/year).
TREV	Lifetime of PEVs (year).
TCV	Total number of conventional vehicles.
ACV	Added number of conventional vehicles.
RRCV	Depreciating rate of conventional vehicles (number/year).
TRCV	Lifetime of conventional vehicles (year).
Δt	Time step changes equal to one week (week).
SCDR	Development rate of DC charging stations (number/year).
UCCS	Number of under-construction charging stations.
TDEV	Time needed for construction of each charging station.

I. INTRODUCTION

Due to the finite fossil fuel supplies, growing energy demand, and environmental issues, the utilization of RESs has become an attractive alternative for electricity generation [1]. Meanwhile, the combination of RESs with PEVs plays an important role in emissions reduction [2]. As the replacement of electric vehicle batteries has an expensive process and may cause environmental problems, there are still challenges regarding the cost of acquisition and maintenance of batteries, their recycling [3], performance, life, and required protection devices [4]. Nevertheless, due to the benefits of the electrification of the transportation system regarding fossil fuel consumption and air pollution, the number of electric vehicles is expected to rise rapidly in the near future [5]. At present, one of the main barriers to the large-scale deployment of electric vehicles is the shortage of charging infrastructures [6]. Although fast-charging stations reduce the time of charging, uncoordinated charging of a high number of PEVs in charging stations can cause some problems for the power grid operators [7]. It is common that RESs and ESSs to be utilized along with charging stations. Therefore, ESSs can mitigate the intermittent nature of RESs, provide load-leveling functions and reduce the charging time [6]. The ESSs are charged when demand is low, supply PEVs, and the remaining stored energy is discharged to the grid when demand is high [8].

As mentioned above, the interaction of fast charging stations equipped with ESSs and renewable energy resources is inevitable. One of the main concerns of the policymakers and regulators is the investigation of the interaction of different components of the power systems, such as renewable energy resources and fast charging stations. To reach this purpose, they can utilize the system dynamics approach as a beneficial instrument to study the interaction and behavior of these components and orient planning decisions and strategies [9].

There have been various dynamic models studying the behavior of energy systems and electricity markets over the last few years. For instance, in [10], the dynamics of investment in fossil fuel and wind capacity in the electricity market were studied considering the stochastic characteristics of wind speed. A dynamic model was introduced in [11] to investigate the effect of the renewable portfolio standard policy on the strategy of stakeholders in the retail electricity market in China. In [12], a system dynamics approach was used to investigate the implementation of island operation capability in the Colombian electricity market. A new dynamic model was proposed in [13] to consider the peak shaving and frequency control reserve constraints in addition to power generation planning. In [14], the effect of the transmission and distribution tariff policy on electricity network investment was studied and a novel investment optimization decision-making model based on system dynamics theory was introduced and applied in the case study of a city in China. The integration of renewable energy resources has been investigated through the system dynamics approach in many countries such as Sweden [15], Iran [16], China [17], and Australia [18]. The authors of [19] introduced a system dynamic model to analyze the development of electric vehicles under direct and indirect policies in China. A system-dynamics model of Iceland's energy and transport systems was established in [20] and different strategies for hydrogen and electricity transitions toward a greener transportation system were compared. To obtain the evolution pattern of electric vehicles, a system dynamics approach was represented in [21] to simulate and forecast the scale of the PEVs. This forecasting helps accelerate PEVs' deployment. As far as we know, many papers study the renewable resources investment problems in electricity markets and deployment of electric vehicles via the system dynamic approach, separately. Nevertheless, there is no comprehensive dynamic model that studies the integration of renewable energy resources in power systems and electrification of the transportation system simultaneously and accounts for their interaction.

The main purpose of this paper is to study the effect of the penetration of renewable energy resources on the development of fast-charging stations or deployment of electric vehicle fleets and vice versa. In other words, the effect of renewable energy incentive policies on electrification of the transportation system is analyzed and the effect of policies for electrification of the transportation system on the investments in the electricity market is studied.

In this regard, the main contributions of this paper are listed below:

- A dynamic model is designed to model the purchasing behavior of PEV drivers as well as the behavior of companies in the investment in DC charging infrastructures. Then, this model is combined with the proposed dynamic model of the electricity market in [22] to achieve a comprehensive model to study the behavior of the coupled electricity market and electrified transportation system. Such models draw a better picture of the whole system for policymakers and help them provide planning strategies and policies effectively.
- New stock and flow variables, feedback loop, and causal loop diagrams of the transportation system are designed.
- The implementation of policies for the electrification of the transportation system is described in a new mathematical framework.
- The NPV method is used to assess the economic aspects of investment in DC charging infrastructures.
- Different criteria are introduced to evaluate the social benefit resulting from the implementation of incentive policies.

It is expected that this model answers the following questions. What is the effect of the renewable energy incentive policies on the development of fast charging stations and consequently on the deployment of electric vehicles? What is the effect of PEV deployment policies on the penetration of renewable energy resources? Does the rising utilization of fast charging stations encourage companies to invest in renewable energies? Does the rising penetration of renewable energy resources encourage people to purchase electric vehicles? How does the utilization of fast charging stations influence

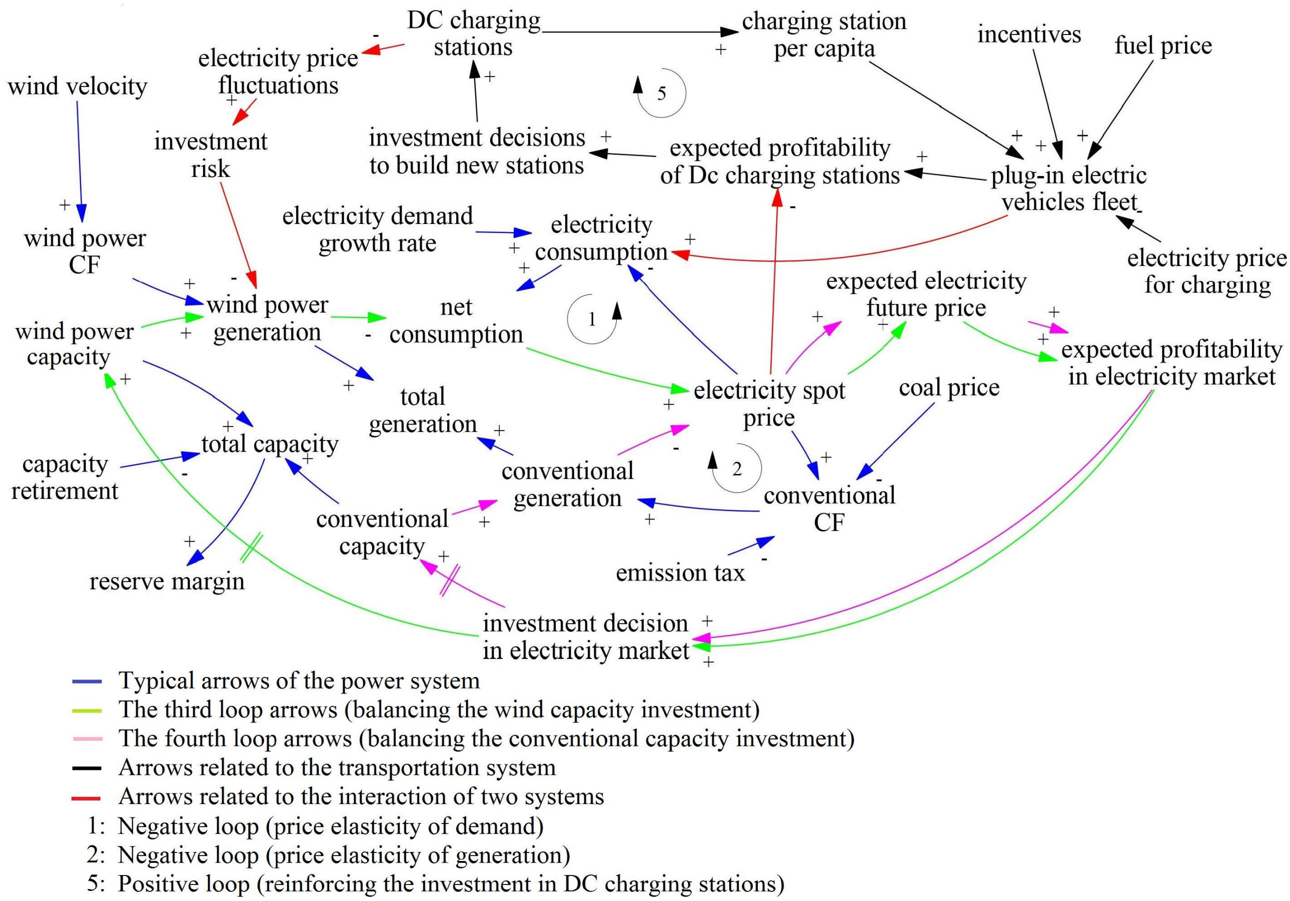

FIGURE 1. Causal loop diagram of the coupled electricity market and transportation system.

the investment in fossil fuel generation units in the electricity market?

The rest of this paper is arranged as follows. Section II depicts the overall features of the presented model. Section III discusses the details of the proposed dynamic model. Section IV illustrates the simulation results. Section V is devoted to sensitivity analysis. The validation process is clarified in Section VI. The main conclusions are provided in Section VII.

II. GENERAL ASPECTS OF THE MODEL

System dynamics has a wide range of use in modeling the behavior of electricity networks. It is applicable for evaluating the regulation policies, generation expansion planning, investment in renewable energy resources, demand-side management models, etc. [23]. To achieve the dynamic model of the coupled electricity market and transportation system, the main components of both systems should be simulated by the system dynamics approach. The details of the feedback loops, stock and flow diagram, auxiliary, inflow, outflow variables, connectors, and causal loop diagram as the main elements of the system dynamics approach were described in [23].

The causal loop diagram of the coupled electricity market and transportation system is illustrated in Fig. 1. The black arrows in this Figure show the relation of variables in the transportation system and pink, blue, and green arrows represent the relation of variables in the electricity market. Red arrows depict the link of the transportation system with the electricity market. Positive (negative) signs illustrate that as the independent variable rises, the dependent variable increases (decreases) [10]. In the dynamics of an economical system, positive loops reinforce changes in the system, and negative ones balance changes [24]. One positive and four negative feedback loops are seen in Fig. 1. The details of two inner negative loops (loops 1 and 2) in the market can be found in [10] and [22]. Loops 1 and 2 show the price elasticity of demand and the price elasticity of conventional units' generation, respectively. Green arrows form the third negative loop and pink arrows construct the fourth one. The investments in new wind farms and fossil fuel power plants are balanced through the third and the fourth loops, respectively [22]. In order to show the causal loop diagram of the transportation system and complete the proposed models of [10] and [22], a positive loop is added.

The fifth loop in Fig. 1 represents the investment in fast DC charging stations. As the number of PEVs increases, the number of drivers that refer to the charging station increases and this will lead to the rise of the expected profitability of charging stations. Accordingly, the investment decisions for building new stations will increase and after a time delay, more charging stations will be added to the system. The more the number of fast DC charging stations increases, the more the charging station per capita will rise. By rising the charging station per capita, citizens will be encouraged to purchase electric vehicles. Consequently, the total number of electric vehicles grows. The deployment of PEVs influences the electricity market from two aspects. Firstly, as the number of PEVs increases, the consumption of electricity rises. Secondly, ESSs of charging stations can change the load profile since they are used for load leveling purposes. Load leveling can prevent low prices and consequently provide higher benefits for wind units. On the other hand, the behavior of the electricity market affects PEVs adoption. The arrangement of generation technologies alters the electricity price and any price fluctuation can change the profit of charging stations and the investment in this context.

Indeed, any incentive for accelerating the deployment of PEVs influences the electricity market and vice versa, wind capacity incentives affect the deployment of PEVs indirectly. It seems that by subsidizing wind units and their penetration, the electricity price will decrease and this encourages the deployment of PEVs, but it should be noted that when the electricity price decreases, the electricity demand in the transportation system and other sectors increases and this increases the electricity price after a short time delay. Moreover, decreasing the electricity price prevents investment in the electricity market. Therefore, the variables and behavior of actors in the system is changing constantly. To study the behavior of the components of complex systems, the effect of all factors should be considered simultaneously and one of the positive features of the system dynamics approach is its ability to study the effects of all factors simultaneously.

In this paper, ancillary services markets, distribution costs, and the effects of transmission and distribution lines are neglected for simplicity.

III. DETAILED DESCRIPTION OF THE MODEL

In order to reach the dynamic model of the electricity market, fast-charging stations, and electric vehicles deployment, the whole system is divided into several subsystems. Each subsystem receives the input data and produces output data as input data for other subsystems. The policymakers can investigate each output data as the outcome of the problem. The detailed description of each subsystem is clarified in the next sections.

A. ELECTRICITY CONSUMPTION OF PLUG-IN ELECTRIC VEHICLES

In this paper, it is assumed that PEVs can be charged at home, public charging stations, and DC charging stations. DC charging stations provide energy for 5% of the electric vehicles in the United States [25] and the rest of those are supplied by level 1 and 2 chargers. Therefore, the following equation calculates the number of PEVs that are supplied at

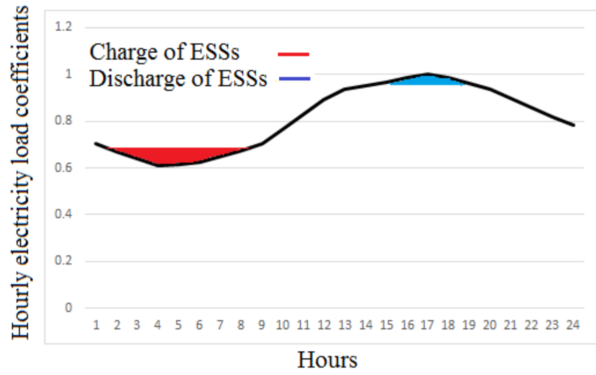

FIGURE 2. Valley filling and peak load shaving using ESS.

DC charging stations.

$$\mathrm{DUCH}\,(d) = 0.05 \times \mathrm{TNPEV}\,(d) \tag{1}$$

Then the energy that the PEVs get from DC charging stations and the total consumption of electric vehicles each day can be obtained from (2) and (3), respectively, as follows:

$$\mathrm{DCEVC}\,(d) = \mathrm{MAGE} \times \mathrm{ACEV} \times \mathrm{DUCH}\,(d) \tag{2}$$

$$\mathrm{TCEV}\,(d) = \mathrm{MAGE} \times \mathrm{ACEV} \times \mathrm{TNPEV}\,(d) \tag{3}$$

All PEVs in this paper are assumed Tesla model 3, as it is the most popular electric vehicle in the United States [26]. Although in some papers, average daily driving distance is a function of driving time and fitted by Normal distribution [27], for simplicity, the average daily driving distance was used in this paper because the focus of this paper is on the performance of incentives. Moreover, it is assumed that the efficiency of the old and new PEVs are the same and their average daily consumption would not change during the time horizon. All charging stations are equipped with ESSs with a capacity equal to 500 kWh [5]. The total storage capacity of charging stations is calculated from the following equation.

$$\mathrm{TCESC}\,(d) = \mathrm{TCS}\,(d) \times 500 \tag{4}$$

The charging strategy at the DC charging stations is in a way that electricity demand of PEVs is first supplied by the ESSs, and when ESSs are exhausted, the grid starts to supply their demand [28]. Therefore, it is assumed that ESSs are charged completely based on Fig. 2 in each day. Then, they supply the needed energy of the vehicles that are charged in DC fast charging stations and sell the excess energy to the grid in peak hours for peak shaving purposes [8]. The excess energy that the ESSs deliver to the grid in peak hours is obtained from the following equation.

$$\mathrm{EE}\,(d) = \mathrm{TCESC}\,(d) - \mathrm{DCEVC}\,(d) \tag{5}$$

Then, the electric consumption of EVs which are charged by level 1 and level 2 chargers can be obtained by (6).

$$\mathrm{ESG}\,(d) = \mathrm{TCEV}\,(d) - \mathrm{DCEVC}\,(d) \tag{6}$$

In Fig. 2, the difference of the red and blue areas is equal to the daily consumption of electric vehicles that use fast DC charging stations.

Hourly load profile of electric vehicles that are supplied directly from the grid (not from ESSs) can be obtained from ESG and the hourly charging coefficients of EVs. The output of this block is the hourly load profile of electric vehicles that are supplied directly from the grid and the needed energy of PEVs that is supplied from ESSs. The needed coefficients can be found in the Appendix.

B. ELECTRICITY DEMAND

It is assumed that the electricity market is run on an hourly basis and total demand and generation are balanced in each hour. Therefore, the hourly total electricity demand should be calculated. For this purpose, the average weekly load is determined from weekly load coefficients and yearly peak value. The weekly load coefficients are obtained from the past year's data of the electricity consumption (which is the electricity demand of the USA in this case) [29]. The same weekly pattern will be used for all years of time horizon but the average weekly demand alters in each year proportional to the annual demand growth rate. In this paper, it is a random variable so the normal distribution function with the standard deviation equal to 0.01 and expected value equal to 0.011 shows its random behavior [30]. Therefore, the weekly demand is determined from (7) [22].

$$\mathrm{WDF}\,(\mathrm{t}+\Delta\mathrm{T}) = \mathrm{WDF}\,(\mathrm{t}) + \mathrm{WDF}\,(\mathrm{t}) \times \mathrm{ADGR}\,(\mathrm{t}) \tag{7}$$

It is assumed that consumers can modify their demand proportional to the long-term price signals that they receive. Such assumption can be modeled by (8) [22].

$$\mathrm{WD}\,(\mathrm{t}) = \mathrm{WDF}\,(\mathrm{t}) \times \left(\frac{\mathrm{AP}\,(\mathrm{t})}{\mathrm{RP}\,(\mathrm{t})}\right)^{\mathrm{PED}} \tag{8}$$

After calculation of the weekly average load, the hourly demand in each day can be calculated. Although the peak value of demand on the weekends is lower than those of common weekdays [31], for the sake of simplicity, the peak value of all days and their hourly load profile are considered the same in each week. In this paper, the hourly electricity load coefficients in Texas are used. It is assumed that the hourly coefficients of all days of each season are the same and their peak values change. These coefficients are represented in the Appendix.

The total hourly load profile can be achieved by adding the hourly load profile of electric vehicles, which was obtained in section A, and the hourly load profile which is obtained in this section.

C. GENERATION OF FOSSIL FUEL UNITS

The three main energy sources for electricity generation in the United States are fossil fuels (coal, natural gas, and petroleum), nuclear energy, and RESs [32]. The HCs and nuclear power plants are responsible to meet the baseload. Although these units have different costs, for simplicity, it is assumed that the baseload is supplied just by HCs. Therefore, three technologies comprised of HC, CCGT, and GT are considered as the conventional technologies to supply base, middle, and peak loads, respectively [10]. A centralized approach is considered in this paper to investigate the interaction of investment decisions in the electricity market and the deployment of electric vehicles from the perspective of policymakers [22]. In addition, all units with similar technology were considered as one company to form a competition between various technologies [9].

The gas and coal prices and pollution penalty are the main elements of the marginal cost of conventional technologies. The uncertainty in fuel price is neglected and a fixed value is considered for that. As the efficiency and performance of the old units are different from middle-aged and new ones, the vintage model is utilized to show the different variable costs of these fossil fuel units [10]. Since the demand and generation are cleared on an hourly basis, the generation of fossil fuel units is calculated each hour [10], [22]. In order to obtain the generation, the capacity factor of these units is acquired from the supply curves (see the Appendix) [33]. Then, the hourly generation of each fossil fuel technology is calculated from the installed capacity and capacity factor of that technology in that specific hour.

D. GENERATION OF WIND UNITS

In the United States, about 21% of the total electricity is generated from renewable energy resources. In this regard, the production of 8.61% of the total power by wind technology makes this technology the most popular renewable energy resource in this country [30]. Since one of the goals of this paper is to study the effect of renewable energy incentive policies on the electrification of transportation systems, for the sake of simplicity, other types of renewable energies are not included in this paper. Therefore, wind technology is considered as the representative of renewable energy resources and it will supply the baseload once wind power is available. The remaining load that is called net demand is supplied by fossil fuel units [10]. The generation of wind units highly depends on wind speed and the behavior of wind speed depends on the regional, seasonal features, and short-term variations [10]. The iteration of wind speed occurrence usually matches with Weibull distribution functions [10]. In this paper, the hourly wind speed data in each month is obtained from the historical data of wind speed in Texas [34] and [35]. These data are properly fitted by the Weibull distribution function. The different scenarios of hourly wind speed are produced from the Weibull distribution functions by using the Monte-Carlo technique. By utilizing the wind speed time series simulation technique, the chronological characteristics of wind speed are considered in created scenarios. Then, the average wind speed in each week is calculated from these data [10]. The created average weekly wind speed scenarios are authentic in the height that measurement tools are installed (10 m) [35]. Accordingly, the calculated average weekly wind speeds scenarios are modified for the height of the turbine's hub, by the following equation [22].

$$\mathrm{WSH}\ (\mathrm{t}) = \mathrm{WSB}\ (\mathrm{t}) \times \frac{\ln \frac{\mathrm{H}}{\mathrm{TCPR}}}{\ln \frac{\mathrm{HB}}{\mathrm{TCPR}}} \tag{9}$$

It is assumed that the height of the turbines is fixed during the time horizon. After obtaining the modified average weekly wind speed data at the height of the turbine hub, hourly wind speed is obtained from this modified data and the hourly profile of wind speed in each season. For simplicity, it is assumed that the hourly wind speed profile on all days of one week is the same. Then, the capacity factor of wind turbines in each hour can be obtained from the hourly wind speed profile and output power curve of wind turbines. Finally, the output power of wind turbines is calculated from the capacity factor of wind turbines and total installed wind capacity.

Many factors such as distance from the coast [36], features of the regions, and learning effects [37] influence the capital costs of farms over time. Therefore, to reach a precise estimation of the investment cost of wind units, a wide range of factors should be considered. For simplicity, an average investment cost is considered for all of the wind units in this paper.

E. MARKET EQUILIBRIUM AND PRICE DETERMINATION

To investigate the effect of ESSs of DC charging stations on the market behavior, it is assumed that generation and net demand are cleared on an hourly basis. For this purpose, the hourly net demand is leveled based on the capacity of ESSs and the utilization of PEVs from DC charging stations. Then it is embedded in the following equations to calculate the electricity price [10].

$$\Delta PR\ (\mathrm{h}) = \mathrm{PR}\ (\mathrm{h}) \times \frac{\mathrm{QNET}\ (\mathrm{h}) - \mathrm{TEGC}\ (\mathrm{h})}{\mathrm{QNET}\ (\mathrm{h})} \tag{10}$$

$$\mathrm{PR}\ (\mathrm{h} + \Delta\mathrm{h}) = \mathrm{PR}\ (\mathrm{h}) + \Delta\mathrm{PR}\ (\mathrm{h}) \tag{11}$$

The electricity generation companies use weekly average price for investment decision making which can be determined from hourly electricity market price.

F. GENERATION CAPACITY INVESTMENT

In this paper, investment in all sectors is done on a weekly basis. Generation companies should predict the future market price precisely to reach a successful investment. For this purpose, the trend extrapolation of variables and the exponential smoothing forecast methods are used in this paper for the price expectation [24]. The NPV method is used for the economic evaluation of the capacity investment [10] [22].

In the United States, wind capacity investment is supported by various policies at the state and national levels. These policies consisted of the production tax credit, renewable portfolio standards, mandatory green power options, clean energy funds, state government green power purchasing, etc. [38]. The production tax credit was assumed as the only wind capacity supporting policy, which is 20 \$/MWh [38].

G. INVESTMENT IN DC CHARGING INFRASTRUCTURES

For the economic evaluation of the investment in DC charging stations, the NPV method is utilized similar to section F. The gained profit of the DC charging stations is calculated at week t by (12).

$$\mathrm{PROFC}\ (\mathrm{t}) = \sum_{\mathrm{k}=1}^{\mathrm{TAM}} (\mathrm{EPROFC}\ (\mathrm{t}) - \mathrm{OMCC}) \times \mathrm{e}^{-\mathrm{DR}\times(\mathrm{k}+\mathrm{TCONSC})} - \mathrm{ICC} \tag{12}$$

The expected operating profit of charging stations is determined from (13).

$$\mathrm{EPROFC}\ (\mathrm{t}) = \sum_{\mathrm{s}=\mathrm{t}-\mathrm{TPE}}^{\mathrm{t}} (\mathrm{REV}\ (\mathrm{s}) - \mathrm{EXP}\ (\mathrm{s})) \quad \forall \mathrm{REV}\ (\mathrm{t}) \geq EXP\ (\mathrm{t}) \tag{13}$$

The weekly revenue of DC charging stations highly depends on the hourly price of energy that is sold to PEVs and to the grid during peak demands. Moreover, the average weekly expenditure is a function of hourly electricity price during low demands when DC charging stations charge their ESSs with lower prices. To find the investment rate of return for DC charging stations (IRRC), (13) is substituted in (12) and the PROFC=0 is solved for DR. Then the profitability index of DC charging stations is achieved from the following equation.

$$\mathrm{PITC}\ (\mathrm{t}) = \frac{\mathrm{IRRC}\ (\mathrm{t})}{\mathrm{DR}} \tag{14}$$

Then, by substituting the profitability index in (15), the S-shaped function of DC charging stations and consequently their investment rate is obtained.

$$\mathrm{SSFDC}\ (\mathrm{t}) = \frac{\mathrm{ADC}}{1 + \mathrm{e}^{-(\mathrm{BDC}\times\mathrm{PITC}(\mathrm{t})+\mathrm{CDC})}} \tag{15}$$

$$\mathrm{IRCS}\ (\mathrm{t}) = \mathrm{SSFDC}\ (\mathrm{t}) \times (\mathrm{RRC}\ (\mathrm{t}) + \mathrm{NNCS}\ (\mathrm{t})) \tag{16}$$

To calculate the investment rate of DC charging stations, the needed number of DC charging stations and retired rate of charging stations are required, which can be obtained through the following equations.

$$\mathrm{RRC}\ (\mathrm{t}) = \frac{\mathrm{TCS}\ (\mathrm{t})}{\mathrm{TAGEC}} \tag{17}$$

$$\mathrm{NNCS}\ (\mathrm{t}) = \max\left[0, \frac{\mathrm{TEV}\ (\mathrm{t})}{\mathrm{CST}} - \mathrm{TCS}\ (\mathrm{t})\right] \tag{18}$$

In 2020, the number of connectors in DC charging stations of the United States was 13627 [39] and the total number of DC charging stations in this country was 5263 [39], [40]. Moreover, it is estimated that there will be 15 million active light-duty PEVs in this country by 2030 and 27500 DC connectors are needed to meet the demand for charging (about 10621 DC charging stations) [39]. Therefore, it can be stated that the fixed value of CST is one station for 1412 light-duty PEVs.

Equation (15) depicts the S-shaped investment function for DC charging stations. The features of this function depend on saturation level (ADC) and its other fixed parameters (BDC and CDC). Parameters ADC, BDC, and CDC should satisfy the following condition [10].

$$1 = \frac{\mathrm{ADC}}{1 + e^{-(\mathrm{BDC}+\mathrm{CDC})}} \tag{19}$$

The investment behavior of companies in DC charging stations is similar to the investment behavior in wind units to a high extend. Due to the small size of DC charging stations and their environmental advantages, the permission and construction of these stations do not have a long process compared to the technologies such as HC units. Since companies plan to construct or get permits in a short period, other companies do not access information of competitors timely. Therefore, some investment over-reaction in charging stations is inevitable similar to the wind units. Secondly, in addition to well-experienced companies that are constructing DC charging stations, there are small and inexperienced companies that are active in this field. These small companies are influenced by the decisions of well-known companies. In this situation, a herding behavior may be seen. Thirdly, the short construction times and the incentives for building charging infrastructures encourage companies to begin new projects or be involved in several projects, simultaneously [41]. Based on these facts, the saturation level (ADC) for DC charging stations is set approximately high, similar to the wind units. Therefore, by choosing the value of 3.3 for ADC, the values equal to 1.8 and -2.7 for BDC and CDC, satisfy the condition of (19) [22].

H. EXPANSION OF ELECTRIC VEHICLES FLEET

Many factors affect the purchasing of electric vehicles. The effect of some of these factors on purchasing behavior and adoption of electric vehicles in California were studied in [42] through the logit regression model. These factors are depicted in Table 2 (see the Appendix), and (20) represents the probability of purchasing new electric vehicles by customers each week.

$$\mathrm{PROB}\,(t) = \frac{1}{1 + e^{-(\mathrm{COVA}+\sum_{k}\mathrm{LCOE}_k Z_k)}} \tag{20}$$

Since our focus is on investigating the effect of DC charging stations on the investment decisions in the electricity market, the average values that are shown in Table 2 were used for most of the factors (except charging station per capita, gas, and electricity price). More details about these average amounts, their range, and the associated interpretations are provided in [42].

The amount of DC charging stations per capita is described through (21) [42].

$$\mathrm{CSPC}\,(t) = \frac{10000 \times \mathrm{TCS}(t)}{\mathrm{POP}(t)} \tag{21}$$

The initial population is 331002651 and its annual growth rate is 0.5 %/year [43]. Gas and electricity prices are considered as the random variables with the expected values equal to 3.832 $/gallon and 14.6 cents/kWh; and standard deviations equal to 0.069 and 1.5, respectively [42].

There are various incentives to accelerate the deployment of electric vehicles in the United States. The effect of three types of them comprised of individual credit, high-occupancy vehicle (HOV) lane access, and electric vehicle supply equipment (EVSE) subsidies are considered in this paper. The individual credit policy is a tax credit or rebate that is considered for purchasing a new vehicle. It varies at federal and state levels [44]. In this paper, the amount of this incentive is 7500 $ at the federal level and 2500 $ at the state level (totally 10000 $) [45]. By implementation of the HOV lane access incentive, electric vehicles receive permission that allows them to drive in carpool lanes even if they do not carry the required minimum number of passengers. The HOV lane access is based on the density of traffic in vehicles per lane per hour and it is assumed that the average vehicle density is 983 vehicles per HOV lane per hour [44]. Another incentive is EVSE Subsidies for electric vehicle charging infrastructures that are installed in private or public places [44]. A rebate equal to 6000 $ and a subsidy up to 60000 $ were considered for Level 2 EVSEs and for the investment cost of DC charging stations, respectively [46]. As the output power of most of the installed DC charging stations in the United States is 50 kW [39], it is assumed that the output power of all installed DC charging stations is 50 kW. Hence, there is a rebate equal to 1200 $/kW for the investment cost of DC charging stations in (12). The results of [44] present that by increasing 1000$ in individual credit, the registration of electric vehicles will rise 2.6% and by increasing 1000 $ in EVSE Subsidies, the registration will increase 1.9%. For the rise per unit of HOV, the registration will increase by 0.04%. Therefore, the probability of purchasing new electric vehicles after implementing incentives is obtained from the following equation.

$$\begin{aligned} &\mathrm{PROBA}\,(t) \\ &\quad = \mathrm{PROB}\,(t) \times (1 + 0.0259 \times \frac{\mathrm{ICI}}{1000} + 0.000473 \\ &\qquad \times \mathrm{HOV} + 0.0196 \times \frac{\mathrm{EVSES}}{1000}) \end{aligned} \tag{22}$$

The total number of light-duty vehicles, number of PEVs, and fossil fuel electric vehicles (conventional vehicles) are considered as the stock variables. The growth rate of light-duty vehicles production is obtained from historical data. It can be extracted from a normal distribution function. The standard deviation and expected value of this function are 10% and 11%, respectively. The initial number of light-duty vehicles is 194,348,815 [47] and the initial number of PEVs is 1,700,000 [48]. The production rate of light-duty vehicles is obtained from the following equation.

$$\mathrm{ALDV}\,(t) = \mathrm{GRLDV}\,(t) \times \mathrm{TLDV}\,(t) \tag{23}$$

Then, the total number of PEVs is calculated through the following equation.

$$\mathrm{TEV}(t+\Delta t) = \mathrm{TEV}(t) + \mathrm{AEV}(t) - \mathrm{RREV}(t) \quad (24)$$

$$\mathrm{AEV}(t) = \mathrm{PROBA}(t) \times \mathit{ALDV}(t) \quad (25)$$

$$\mathrm{RREV}(t) = \frac{\mathrm{TEV}(t)}{\mathrm{TREV}} \quad (26)$$

Then, the total number of conventional vehicles is calculated through the following equations.

$$\mathrm{TCV}(t+\Delta t) = \mathrm{TCV}(t) + \mathrm{ACV}(t) - \mathrm{RRCV}(t) \quad (27)$$

$$\mathrm{ACV}(t) = (1 - \mathrm{PROBA}(t)) \times \mathit{ALDV}(t) \quad (28)$$

$$\mathrm{RRCV}(t) = \frac{\mathrm{TCV}(t)}{\mathrm{TRCV}} \quad (29)$$

Then, the total number of light-duty vehicles is calculated through the following equation.

$$\mathrm{TLDV}(t+\Delta t) = \mathrm{TCV}(t+\Delta t) + \mathrm{TEV}(t+\Delta t) \quad (30)$$

I. DEVELOPMENT OF DC CHARGING STATIONS

In this paper, it is assumed that the number of DC charging stations and PEVs varies weekly. To model the development of DC charging stations stock and flow structure is used. In the system dynamics approach, different time delays can be modeled by cumulating the difference between inflow and outflow of a process in the related stock variables [10]. The time required for the construction of generation units and installation of charging stations are the main time delays in this paper. the under-construction DC charging stations and the number of installed charging stations were considered as the stock variables. The relation between the number of under-construction DC charging stations and its flow variables is depicted below.

$$\mathrm{SCDR}(t) = \frac{\mathrm{UCCS}(t)}{\mathrm{TDEV}} \quad (31)$$

$$\mathrm{UCCS}(t+\Delta t) = \mathrm{UCCS}(t) + \mathrm{IRCS}(t) - \mathrm{SCDR}(t) \quad (32)$$

$$\mathrm{RRC}(t) = \frac{\mathrm{TCS}(t)}{\mathrm{TAGEC}} \quad (33)$$

$$\mathrm{TCS}(t+\Delta t) = \mathrm{TCS}(t) + \mathrm{SCDR}(t) - \mathrm{RRC}(t) \quad (34)$$

J. DEVELOPMENT OF GENERATION CAPACITY

The modeling of the development of generation units is similar to the development of DC charging stations. The under-construction and installed generation capacity are considered as stock variables in MW. The investment rate that was calculated in section F, the construction rate of technology, and the retired rate of capacity are flow variables. A detailed description of generation capacity development can be found in [10].

IV. SIMULATION RESULTS

The data of the United States' power system and transportation system was used as a case study to assess the introduced model. In addition, through this model, the effects of incentives on the deployment of PEVs and investment decisions in the electricity market can be studied from the policymaker's perspective. The features of the electric power system are illustrated in Table 3 and the characteristics of the DC charging stations and Tesla model 3 are shown in Table 4 (see the Appendix). The generation of electricity by hydroelectric power plants in the United States is about 7% of the total generation. This percentage has a falling trend and will reach 5% by 2050 [30]. Since this technology is not the dominant renewable technology by 2050 compared to the wind and solar technologies, the generation of this type of technology was neglected in this paper. Secondly, their operation is subjected to different scheduling processes, and investment in this technology depends on many sophisticated rules. By ignoring this type of technology, the model is simplified without the loss of its general features. The time horizon is 30 years and begins from 2020. Furthermore, MATLAB software was utilized for the simulations. In order to simulate and analyze the behavior of the electricity market and PEV adoption under various conditions, three different cases are introduced as follows.

1. Wind capacity incentive and PEVs deployment incentives are implemented in the system.
2. Wind capacity incentive in the first case increases but PEV deployment incentives are not changed compared to case 1.
3. Wind capacity incentive in the first case is not changed but PEV deployment incentives are increased compared to case one.

A. CASE 1

In this case study, the production tax credit for wind units is 20 \$/MWh. Due to the planning of the European Union and developed countries to reach carbon neutrality by 2050, the incentive is just considered for wind units. Because of the environmental reasons and zero marginal costs, these units are attractive choices for investors and policy-makers. The amount of incentive for purchasing a new PEV is 10000 \$, the HOV lane access is 983 vehicles per HOV lane per hour. The rebate for Level 2 charging stations is 6000 \$ and a rebate equal to 1200 \$/kW is considered for the investment cost of DC charging stations.

Fig. 3 (a) shows the average electricity price in each week in the first case. Fig. 3 (b) shows the installed conventional capacity, reserve margin, and weekly electricity demand. As shown in Fig. 3, electricity price increases when reserve margin decreases and it declines when reserve margin rises. In other words, as the electricity generation exceeds the consumption, there will be a falling trend for the price, and the rising trend of price is revealed in reverse situations. Fig. 3 (c) shows the installed capacity of each technology. Due to the lower investment cost of CCGTs compared to HC units and their lower emission, companies tend to invest in these units more than HCs. Accordingly, in contrast to HCs; the installed capacity of CCGTs has a rising trend by 2050. Although the investment cost of wind units is comparatively high, they are desirable for investors. This is because; these units do not have any pollution, their marginal cost is zero and the

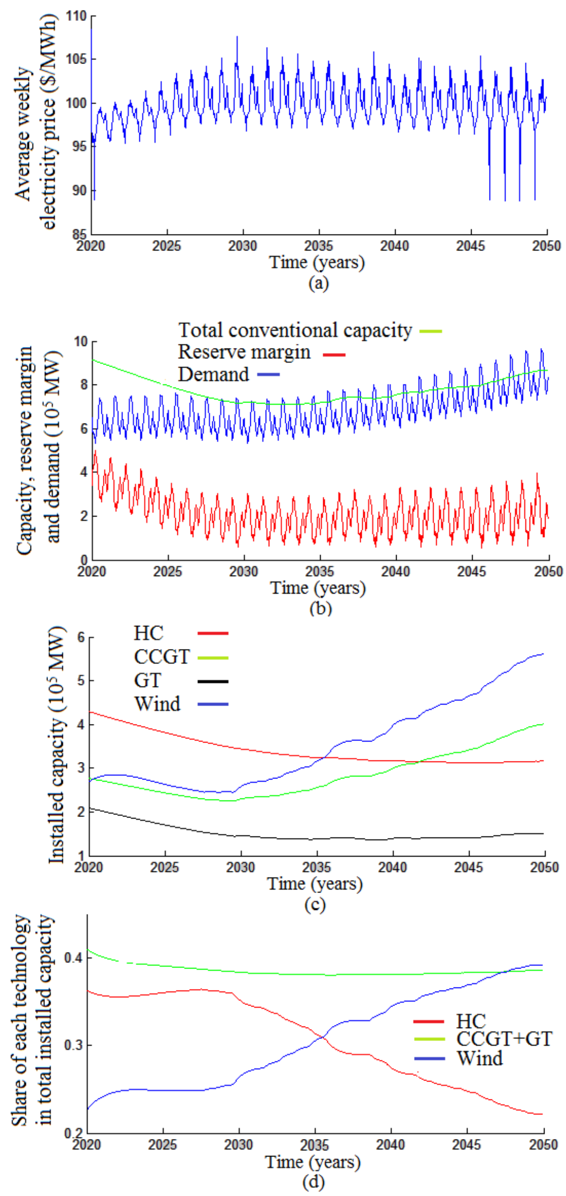

FIGURE 3. Behavior of the electricity market in case 1. (a) Electricity price. (b) Capacity, reserve margin, and demand. (c) Installed capacity (d) Share of each technology in total capacity.

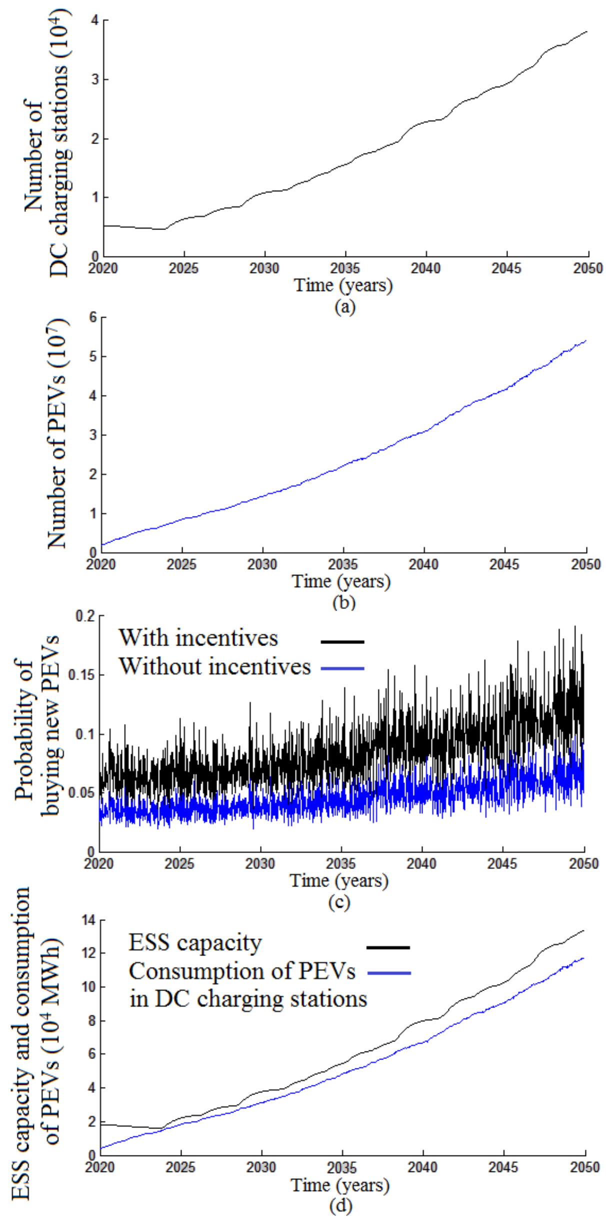

FIGURE 4. Electric vehicle adoption in case 1. (a) Number of DC charging stations. (b) Number of PEVs. (c) Probability of buying PEVs. (d) ESS capacity and consumption of PEVs.

considered incentive guarantees part of their revenue. Since GTs cover their costs during the peak load, companies usually invest in this technology during scarcity events. Therefore, the investment in these units is low. Fig. 3 (d) shows the portion of installed capacity of each technology to the total installed capacity. Based on this Fig. wind technology will be the most popular technology in the United States by 2050. By comparing Fig. 3 (a) and 3 (d), as the percentage of installed wind capacity increases, due to the stochastic nature of these units, the fluctuation of electricity price increases, while due to their negligible marginal cost, the weekly average price decreases.

Fig. 4 (a) and 4 (b) illustrate the total number of installed DC charging stations and the total number of PEVs in the United States, respectively in case 1. Fig. 4 (a) and 4 (b) reveal the rising trend of PEV and DC charging stations' growth. Due to (16) and (18), the number of PEVs influences the investment rate of DC charging stations. Since the number of PEVs was low from 2020 to 2024, the investment in DC was not considerable. Therefore, the number of DC charging stations had a falling trend. As the number of PEVs increased after 2024, the investment in the DC charging station increased. Moreover, the targeted ratio of plug-in electric vehicles to DC charging station is another factor that influences the investment in DC charging stations. Fig. 4 (c) shows the probability of purchasing new PEVs. As shown in this Fig., the implementation of state and federal incentives for the electrification of the transportation system has a remarkable effect on purchasing behavior of people. By increasing the gas price and DC charging station per capita, the willingness to buy PEVs increases. The increase in the price of electricity that is sold to drivers by DC charging stations has a negative effect on the adoption of PEVs.

On the other hand, when the price of electricity (Fig. 3 (a)) which is sold to DC charging stations by the grid increases, the profit of DC charging stations decreases and this will lead to lower investment in DC charging infrastructures which in turn reduces the DC charging station per capita and reduces the willingness of purchasing PEVs. Fig. 4 (d) depicts the weekly capacity of ESSs in charging stations and the weekly consumption of PEVs that are charged in DC charging stations. The first one is a function of the number of DC charging stations, and the second one depends on the number of PEVs.

B. CASE 2

In this case, all incentives of the first case are implemented but the wind capacity incentive increase to 30 \$/MWh. Fig. 5 (a) shows the average electricity price in each week in the second case. Fig. 5 (b) shows the installed conventional capacity, reserve margin, and weekly electricity demand. Fig. 5 (c) illustrates the installed capacity of each technology. Fig. 5 (d) shows the share of each type of technology.

Since the amount of wind incentive increased, companies were encouraged to invest in wind capacity more than in case 1. In 2050, the installed wind capacity in cases 1 and 2 was about 560 GW (39.2%) and 662 GW (43.9%), respectively. As the installed wind capacity rises, the average price decreases, and its fluctuations increase. The average price in case 1 was 99.77 \$/MWh and it decreased to 99.57 \$/MWh in case 2. The standard deviation of the price reached from 2.06 \$/MWh in case 1 to 2.34 \$/MWh in case 2.

Fig. 6 (a) and 6 (b) illustrate the total number of installed DC charging stations and the total number of PEVs in the United States, respectively in case 2. By increasing the amount of wind capacity incentive in case 2, the total number of installed DC charging stations and the total number of PEVs at the end of time horizon grew from 38227 and 53.7 million in case 1 to 41477 and 57.84 million in case 2. By raising the percentage of wind capacity, electricity price declines and this will lead to amplifying the gained profit of DC charging stations. Therefore, the expansion of this type of station will be accelerated, and by increasing the charging station per capita, the probability of purchasing PEVs rises. The average probability of purchasing PEVs (after the implementation of PEV deployment incentives) during 30 years in cases 1 and 2 was 8.11% and 8.17%, respectively. Fig. 6 (c) shows the probability of purchasing new PEVs. Fig. 6 (d) depicts the weekly capacity of ESS in charging stations and the weekly consumption of PEVs that are charged in DC charging stations. The capacity of ESSs influences the load leveling and this can mitigate the price fluctuations but since the capacity of ESSs, in this case, is not considerable compared to the generation of wind units, the effect of load-leveling is not tangible compared to case 1.

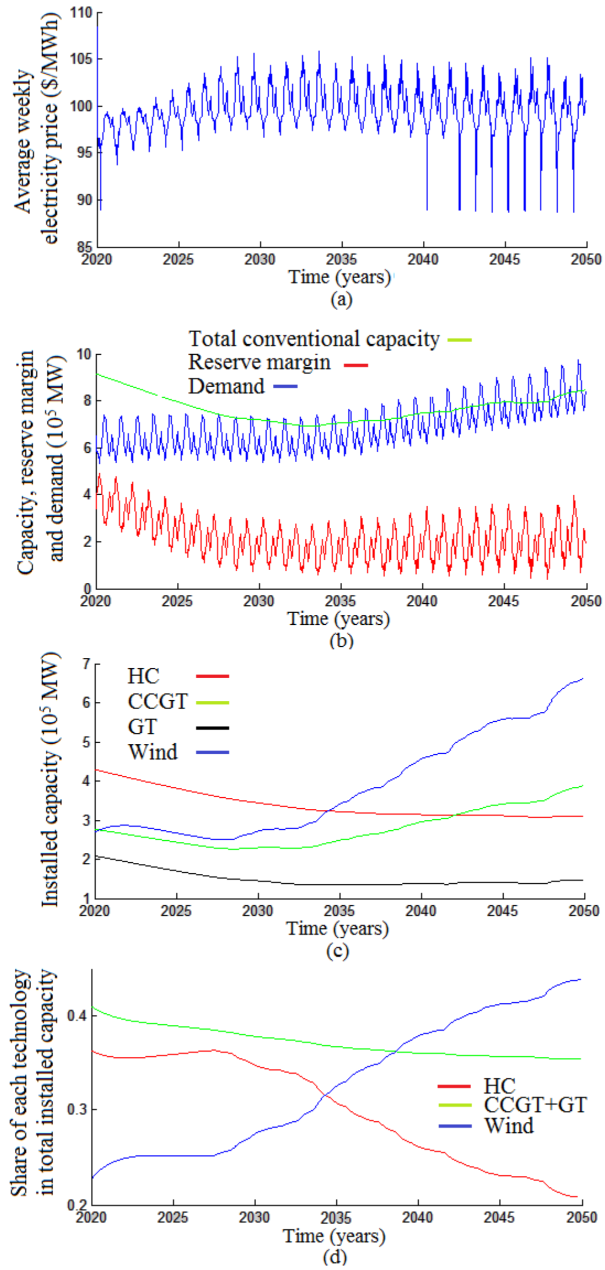

FIGURE 5. **Behavior of the electricity market in case 2. (a) Electricity price. (b) Capacity, reserve margin, and demand. (c) Installed capacity. (d) Share of each technology in total capacity.**

C. CASE 3

In this case, wind capacity is the same as case 1, but all of the incentives for deployment of PEVs increased 10%. Fig. 7 (a) and 7 (b) illustrate the total number of installed DC charging stations and the total number of PEVs in the United States, respectively in case 3. Fig. 7 (c) shows the probability of purchasing new PEVs. Fig. 7 (d) depicts the weekly capacity of ESS in charging stations, and the weekly consumption of PEVs that are charged in DC charging stations. By growing the incentives, in this case, the average probability of purchasing PEVs during 30 years rose to 9.22%. Accordingly, the total number of installed DC charging stations and the

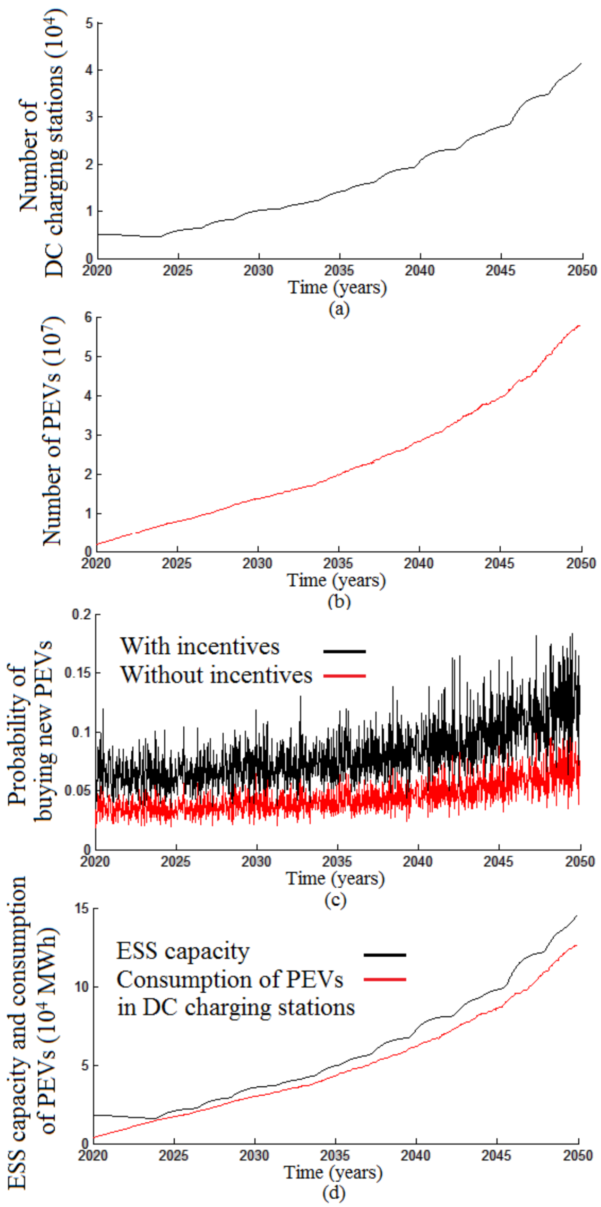

FIGURE 6. **Electric vehicle adoption in case 2. (a) Number of DC charging stations. (b) Number of PEVs (c) Probability of buying PEVs. (d) ESS capacity and consumption of PEVs.**

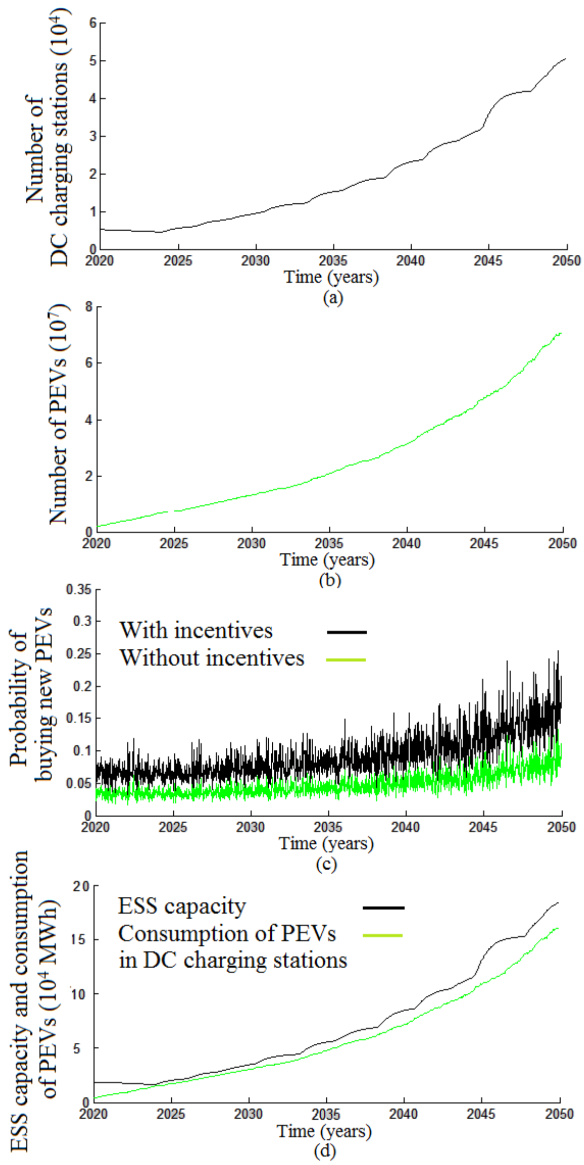

FIGURE 7. **Electric vehicle adoption in case 3. (a) Number of DC charging stations. (b) Number of PEVs. (c) Probability of buying PEVs. (d) ESS capacity and consumption of PEVs.**

total number of PEVs increased compared to case 1 and reached 50485 and 70.96 million, respectively by 2050. As a result, the capacity of ESSs and the weekly consumption of PEVs at DC charging stations increased from 133 and 117 GWh in 2050 in case 1 to almost 176 and 154 GWh in case 3, respectively. Therefore, as the capacity of ESSs has a considerable effect on load leveling, the hourly load profile was leveled in case 3 more than in case one. In case 3, the standard deviation of the hourly load profile before and after load-leveling was 129.3 and 97.53 GW during the time horizon, while in case 1, it was 124.31 and 93.95 GW before and after load leveling.

Fig. 8 (a) shows the average electricity price in each week in the third case. Fig. 8 (b) shows the installed conventional capacity, reserve margin, and weekly electricity demand. Fig. 8 (c) and 8 (d) illustrate the installed capacity and percentage of each technology, respectively. The average electricity price during the time horizon in cases 1 and 3 was 99.77 \$/MWh and 99.65 \$/MWh, respectively. As the installed wind capacity in case 3 is more than in case 1, the average electricity price, in this case, is lower than in case 1 too.

The intensity of valley filling in hourly load profile highly depends on the capacity of ESSs (the black curve in Fig. 7 (d)) and the intensity of peak shaving depends on the remaining energy of ESSs that is not consumed (difference of the black and green curves in Fig. 7 (d)). The valley filling feature of ESSs prevents price fluctuations and decreases the benefit fluctuations. Between 2020 to 2040, the standard deviation of

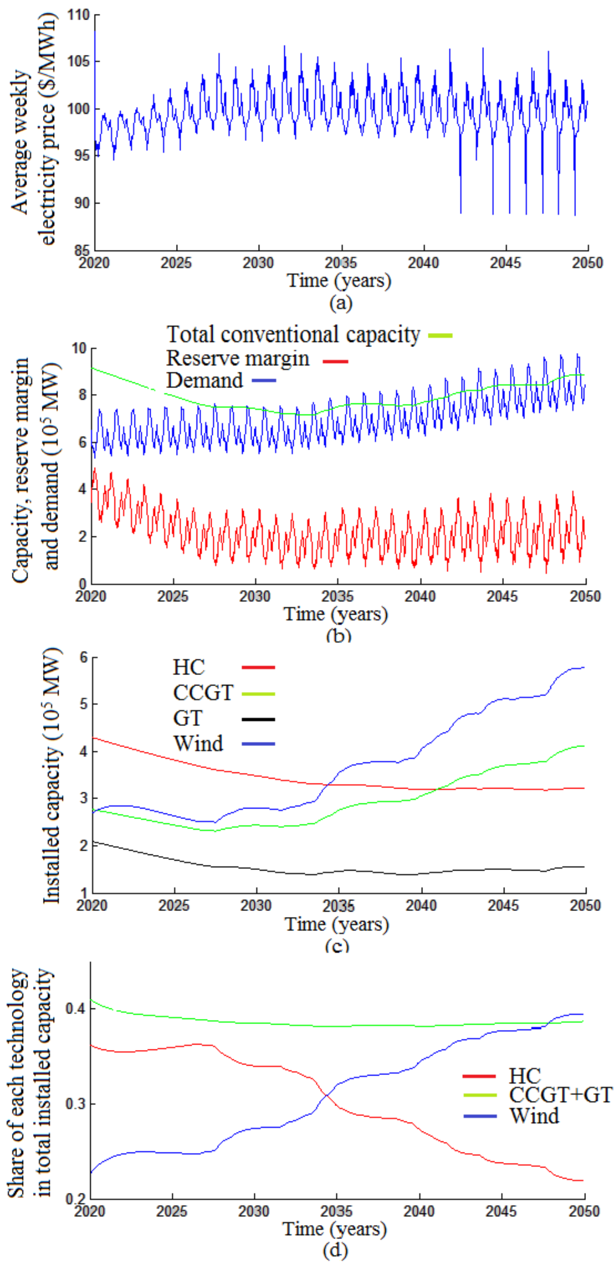

FIGURE 8. Behavior of the electricity market in case 3 (a) Electricity price (b) Capacity, reserve margin, and demand (c) Installed capacity (d) Share of each technology in total capacity.

price is 2.01 in case 3, which is lower than the price standard deviation in case 1 in a similar period (2.08). This reduces the investment risk of wind units and motivates companies to invest in this technology. As a result, in case 3, installed wind capacity increases between 2040 to 2050 more than in case1. This leads to lower prices in case 3 compared to case 1 from 2040 to 2050 (compare Fig. 3 (a) and Fig. 8 (a)). Although reducing the investment risk motivates the investors to invest in conventional units too, these technologies cannot compete with wind technology. Therefore, the growth rate of wind units will be more than that of conventional units.

TABLE 1. Factors affecting social welfare in each case.

Item	Case 1	Case 2	Case 3
1- Average difference between the benefit of electricity generating companies and electricity price in each week ($/MWh)	5.1361	7.6370	5.1373
2- Expected demand not supplied (MW)	0	8955.7	0
3- Ratio of the produced CO2 in the electricity market to total electricity generation (Ton/MWh)	0.4229	0.4077	0.4169
4- Average ratio of the produced CO2 in the transportation system in each week to the number of total vehicles (Ton per vehicle per week)	0.0328	0.0328	0.0327

In case 3, the installed wind capacity by 2050 was about 576 GW (39.4%), while it was 560 GW (39.2%) in case 1.

The social benefit resulting from the implementation of policies was assessed in these three cases. There are different criteria for evaluating the social benefit. Some of these criteria were used in this paper to measure the social benefits. One of these criteria is the difference between the benefit of consumer and generation cost or the difference between the benefit of electricity generating companies and electricity market price [49]. The second measure is the variable called the expected demand not supplied. It happens when the generation capacity is lower than electricity demand [50]. Furthermore, the environmental benefits were assessed by defining two variables. The first one is the ratio of the produced CO2 in the electricity market to total electricity generation and the second one is the ratio of the produced CO2 in the transportation system to the number of total vehicles comprised of electric and fuel-based vehicles. It is assumed that the average emission of fuel-based vehicles is 130 gr CO2 per kilometer [51]. Table 1 depicts the related data for each case.

The first item is the average difference between the benefit of electricity generating companies (wind and conventional units) and electricity price each week. The higher value of this item shows higher social benefit. More benefits for generation companies along with low electricity prices for consumers guarantee the benefit of both sides of the market. Since the percentage of wind capacity in case 2 is higher, cheaper electricity is provided for consumers. By comparing this value in case 3 (5.1373) with its value in case 1 (5.1361), it can be stated that the policy actions in the transportation system can influence the social benefits in the electricity market.

The expected demand not supplied in case 2 is higher than the two other cases because of the intermittent behavior of wind units. Based on the data of the third item, the ratio of CO_2 production to total generated electricity has a reverse relation with the penetration of wind units. In addition, the data of the fourth item for case 3 shows that more deployment of EVs in the transportation system reduces the emission in this sector. The data relating to CO_2 emission in Table 1 shows that any incentive policy for wind capacity in the electricity market or electrification of the transportation system influences the emission in other sectors.

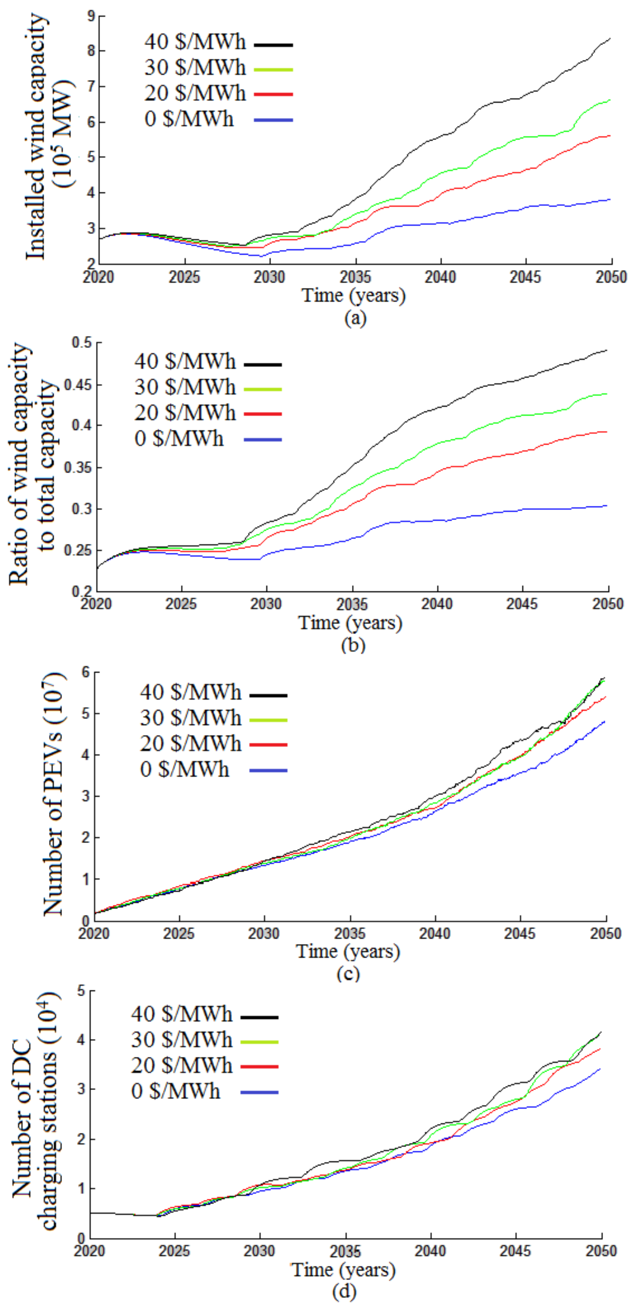

FIGURE 9. **Simulation results for different values of wind capacity incentive. (a) Wind capacity. (b) Share of wind capacity. (c) Number of PEVs. (d) Number of DC charging stations.**

V. SENSITIVITY ANALYSIS

To analyze the effect of wind capacity incentive on PEV deployment and the effect of incentives related to the electrification of the transportation system on decision making in the electricity market, the sensitivity analysis was conducted. In addition, the effect of gas price as an external factor was studied.

In the first analysis, the development of wind capacity, installed DC charging stations, and PEV adoption were investigated under three different values of wind capacity incentive equal to 0, 20, 30, and 40 $/MWh. Fig. 9 (a), 9 (b), 9 (c), and 9 (d) illustrate the installed wind capacity, portion of wind capacity, total number of active PEVs on roads, and total number of active DC charging stations, respectively.

Based on Fig. 9, as the amount of wind capacity incentive increased the tendency for investment in this technology increased. By rising the share of wind units in the generation, the benefits of companies for installation of DC charging stations grew and this led to the rising of the charging stations per capita. Consequently, this will encourage people to purchase new PEVs. It can be stated that any incentive for encouraging the development of wind capacity can accelerate the deployment of PEVs indirectly.

In the second analysis, the development of wind capacity, installed DC charging stations, and PEV adoption were investigated under different values of PEVs deployment incentives. If it is assumed that the total PEVs deployment incentive in the first case was equal to X, the effect of incentives equal to $1.1\times X$ and $1.2\times X$ were investigated. Fig. 10 (a), 10 (b), 10 (c), and 10 (d) illustrate the installed wind capacity, portion of wind capacity, total number of active PEVs on roads, and total number of active DC charging stations, respectively. By rising the number of PEVs and DC charging stations, the capacity of ESSs increased. ESSs play an important role in valley filling of hourly load profile and therefore prevent the reduction of electricity market prices. This led to more profits for wind units. Consequently, it can be claimed that any incentive for deployment of PEVs or expansion of DC charging stations can encourage companies to invest in wind capacity, indirectly.

In the third analysis, the effect of gas price was investigated on simulation results. Unlike our assumption, gas price varies over time and it is not fixed. The gas price not only affects the marginal cost of CCGTs and GTs but also influences the purchasing behavior of the masses regarding PEVs. In the first case, the gas price of conventional vehicles was different from the gas price of generation units. In this section, it is assumed that gas prices increase up to 5% and 10% compared to the price in the first case. Fig. 11 shows the simulation results for this analysis. As shown in this Fig., by rising gas prices, the tendency for investment in wind capacity and purchasing PEVs increased. The sensitivity of PEVs deployment to gas price is much higher than the sensitivity of wind capacity investment to gas price.

VI. VALIDATION

In this paper, to assess the validity of the presented model, the obtained results were compared with the result of other papers and authentic existing reports. Fig. 12 shows the capacity factor of wind units and their average each week. The first week of this Fig. corresponds to the first week of January. The historical data related to the capacity factor of the Los Vientos wind farm reveals that the capacity factor varied approximately between 0.2 and 0.6 [52]. These statistical data confirm the findings of this paper.

In this paper, the existing models of [10] and [22] were extended and completed. The general aspects of the market

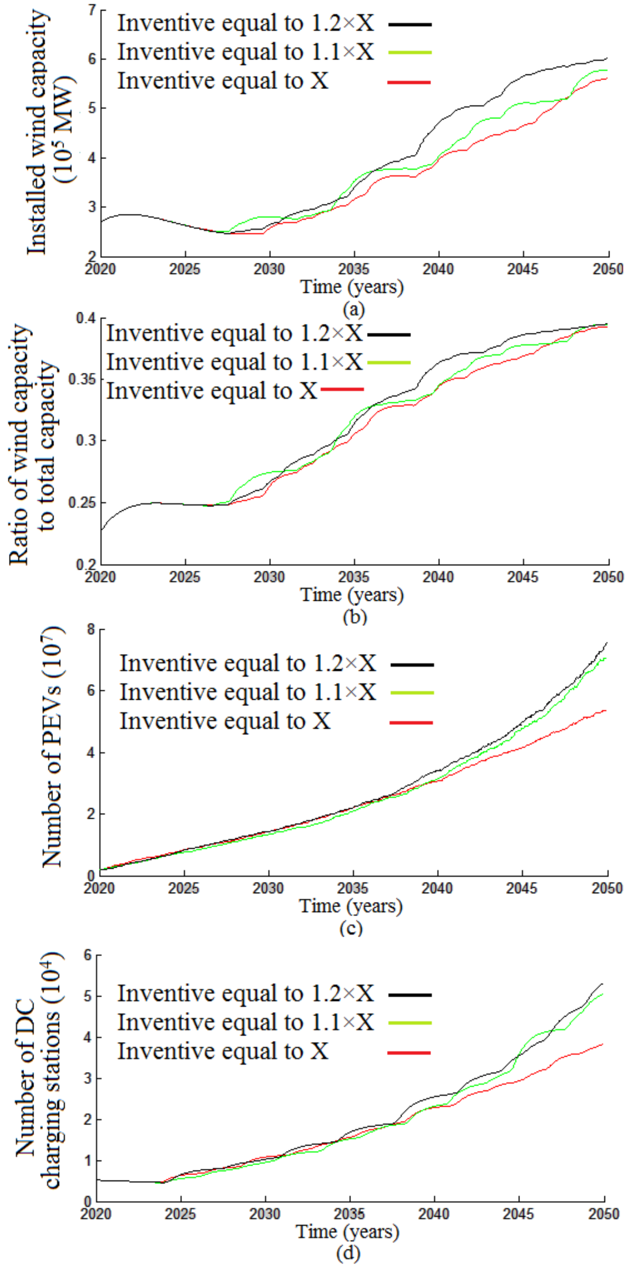

FIGURE 10. Simulation results for different values of PEV deployment incentive. (a) Wind capacity. (b) Share of wind capacity. (c) Number of PEVs. (d) Number of DC charging stations.

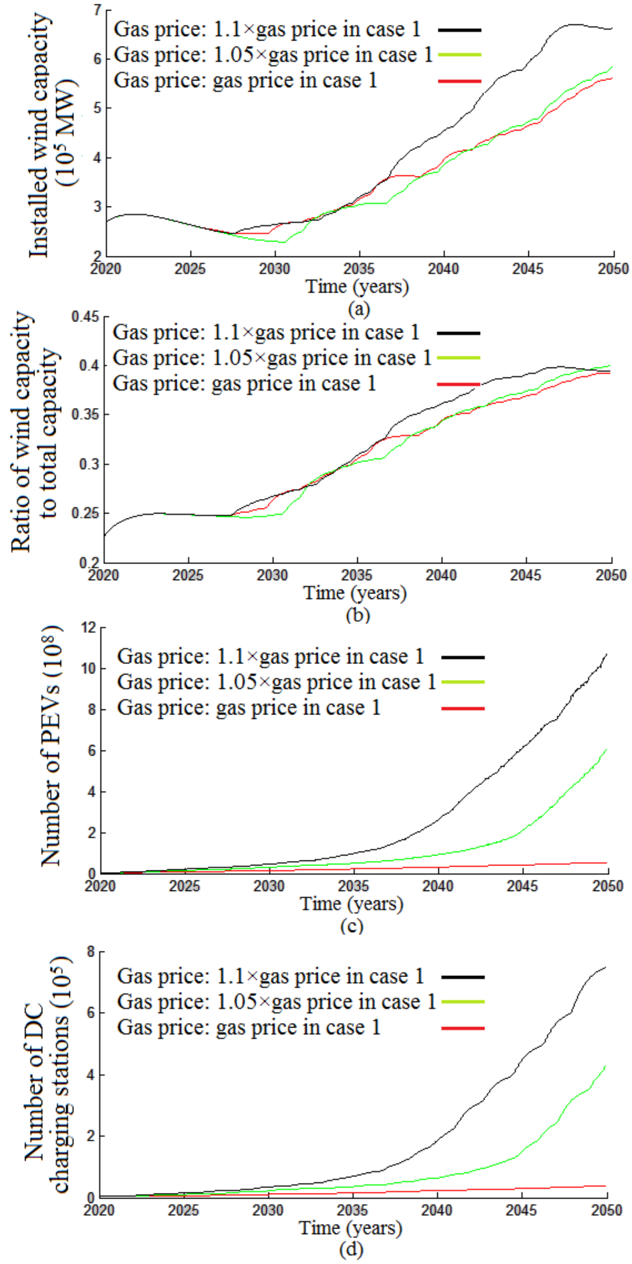

FIGURE 11. Simulation results for different values of gas price. (a) Wind capacity. (b) Share of wind capacity. (c) Number of PEVs. (d) Number of DC charging stations.

behavior in the mentioned papers are in agreement with the market behavior in the proposed model of this paper. For example, there is an inverse relationship between electricity price and reserve margin. In addition, a few months after each price jump, a new boom cycle is seen on the investment wave of technologies. Moreover, CCGTs are the dominant conventional technology in these papers since they have lower costs and higher profitability. To assess the validity of the simulation results of this paper, they can be compared with the annual energy outlook in 2021 that explores long-term energy trends in the United States by 2050 [30]. It is estimated that gas-based generation technologies comprised 36% of the total generation in the United States by 2050. In this regard, the share of renewable energy resources, nuclear power plants, and HC units reaches 42%, 11%, and 11%, respectively [30]. The findings of this paper (Fig. 3 (d)) show that gas-based technologies comprise about 38.7% of the total generation capacity by 2050. The share of renewable energies at the end of 2050 is approximately 39.2% and the percentage of units that supply the baseload (HCs) is almost 22.1%. The percentage of wind capacity does not reach the expected amount (42%); this is because all federal and state renewable incentives were not considered in our model.

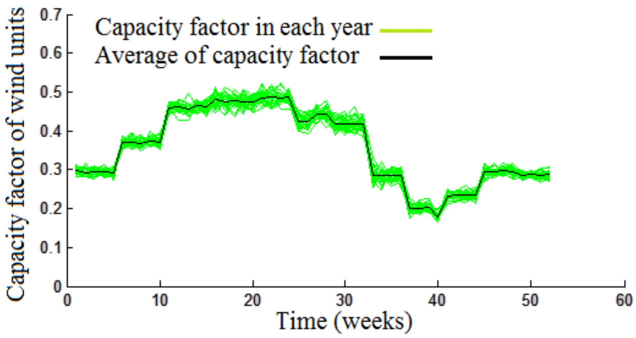

FIGURE 12. Capacity factor of wind units in case 1.

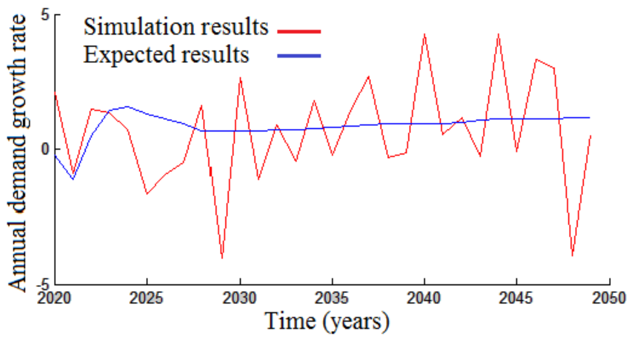

FIGURE 13. Annual demand growth rate.

Fig. 13 shows the annual electricity demand growth rate during the time horizon. The red curve represents the calculated demand growth rate in this model and the blue curve shows the forecasted demand growth rate by the annual energy outlook report [30].

Moreover, it is forecasted that the total number of PEVs will reach 15 million by 2030 [39] and 50 million by 2050 [53]. The estimated number of DC connectors to meet the charging demand of 15 million PEVs in 2030 is almost 13627 (10621 DC charging stations) [39]. The simulation results in this paper show that the total number of PEVs reached about 14.2 million by 2030 and 53.7 million by 2050. To meet the charging demand 10766 and 38227 DC charging stations were installed by 2030 and 2050, respectively.

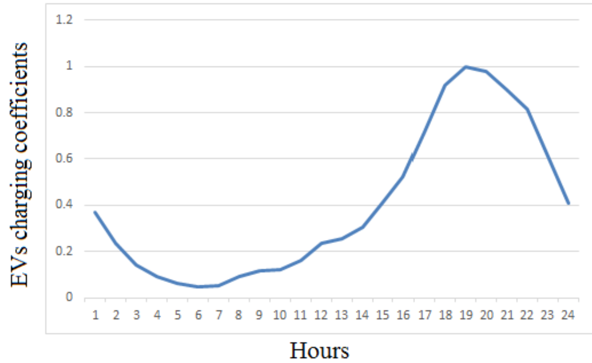

FIGURE 14. Hourly PEVs charging coefficients [54].

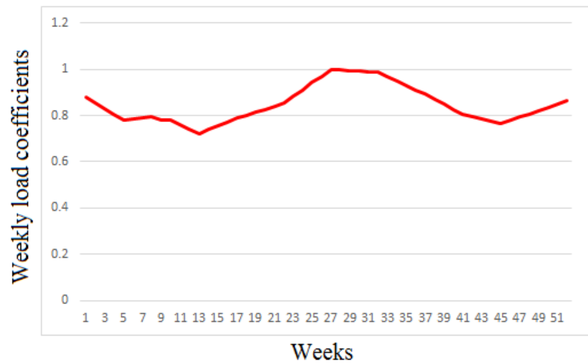

FIGURE 15. Load coefficients in each week.

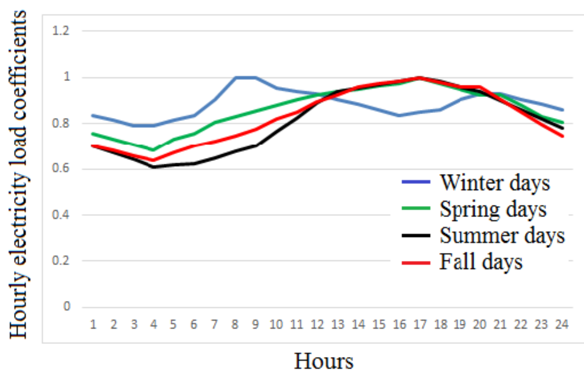

FIGURE 16. Average hourly electricity load coefficients for days of each season in Texas [31].

VII. CONCLUSION

The main contribution of this paper was to demonstrate that any incentive policy to accelerate the deployment of PEVs or expansion of DC charging stations influences the wind capacity investment in the electricity market. Furthermore, the implementation of incentive policies for the development of wind capacity affects the deployment of PEVs. To reach this goal, the system dynamic approach was used to model the purchasing behavior of EV consumers and the behavior of companies in the investment in DC charging stations. Then this proposed model was combined with the previous model of the electricity market to study the coupled electricity market and transportation system. The mathematical formulation of various federal and state incentive policies was embedded in the proposed model. In addition, the economic evaluation of DC charging stations development was conducted by the NPV method. A positive feedback loop was added to the former dynamic models of the electricity market to show the relation of cause and effect variables in the causal loop diagram of investment in DC charging stations and purchasing behavior of drivers.

The data of the transportation system and electricity market in the United States was used as a case study and three scenarios were examined. In order to assess the validation of the model, the simulation results of this paper were compared with the information of authentic reports and results of other

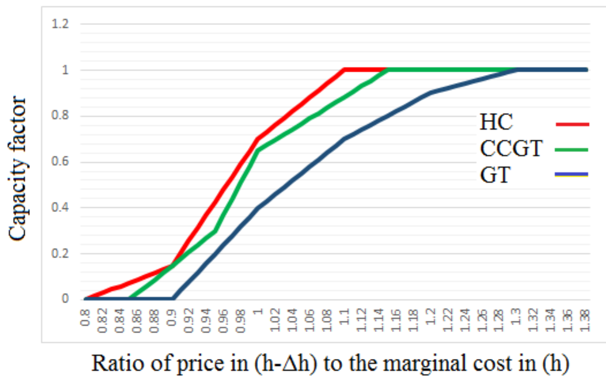

FIGURE 17. Supply curves of technologies [33].

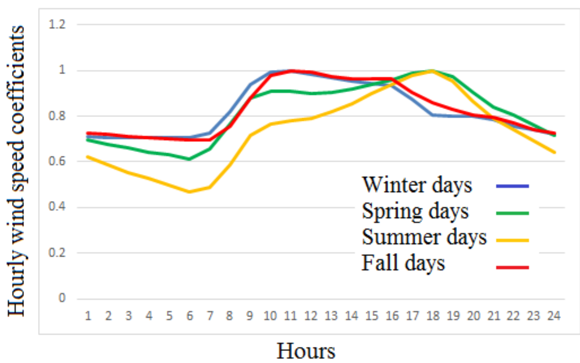

FIGURE 18. Hourly coefficients of wind speed for each season [35].

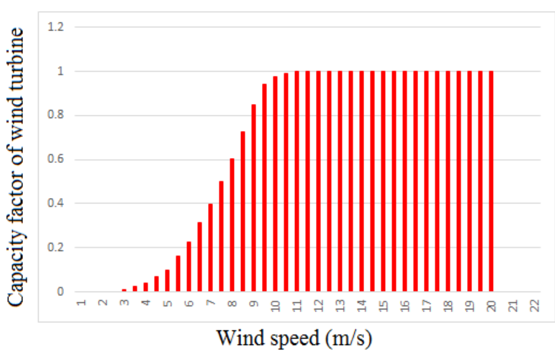

FIGURE 19. The output power curve of 87 Siemens SWT 108 2.3 turbines [56].

TABLE 2. Factors affecting the purchasing of electric vehicles in California [42].

Factor	Logit Coefficient (LCOE)	Average
Age	0.008	52.18
Gender	−0.001	0.559
Employment status	0.111	0.740
Multiple jobs	−0.018	0.207
Car sharing	0.922	0.011
Trip duration	0.001	52.38
Income	0.443	3.728
Home ownership	0.176	0.822
Residence type	−0.076	1.347
Number of vehicles in family	−0.055	2.090
Household size	−0.067	2.781
Maximum education	0.269	4.756
Manufacturer density	−0.006	0.391
Population density	−0.0000	1481.2
Gas price	2.885	-
Electricity price for PEVs	−0.070	-
DC Charging station per capita	0.832	-
Constant value (COVA)	−19.788	-

TABLE 3. The electric power system characteristics.

Technology	Wind	GT	CCGT	HC
Under construction capacity (MW) [30]	24810	2633	4000	17
Initial installed capacity (MW) (First vintage) [57] [30]	268000	69000	92000	143000
Initial installed capacity (MW) (Second vintage) [57] [30]	-	70000	92000	143000
Initial installed capacity (MW) (Third vintage) [57] [30]	-	70000	93000	143000
Average time needed for construction (year) [22]	1	1	1.5	3
Lifetime (year) [22]	20	20	30	40
Investment cost ($/kW) [22]	1500	500	600	1000
Fuel price × conversion factor ($/MWh) [58]	0	8.15	8.15	6.55
Emission penalty ($/Ton of CO2) [59]	0	7.6	7.6	7.6
Maintenance cost ($/kWyear) [22]	12	16	16	16
Efficiency (%) (vintage 1) [22]	-	0.35	0.60	0.45
Efficiency (%) (vintage 2) [22]	-	0.32	0.57	0.42
Efficiency (%) (vintage 3) [22]	-	0.27	0.54	0.39
Emission factor (Ton/MWh) (First vintage) [22]	-	0.29	0.33	0.87
Emission factor (Ton/MWh) (Second vintage) [22]	-	0.31	0.35	0.90
Emission factor (Ton/MWh) (Third vintage) [22]	-	0.37	0.40	0.95
Amortization period (year) [22]	15	15	20	25

papers. The simulation results revealed that the implementation of wind capacity incentive policies accelerated the deployment of PEVs and investment in DC charging stations. On the other hand, incentives that were considered to encourage drivers to purchase PEVs or the development of charging infrastructures had a positive effect on the development of wind capacity too. The sensitivity analysis depicted that by increasing the gas price, companies were encouraged to invest in wind capacity. This even extremely affected the purchasing behavior of drivers. Generally, it can be stated that the EV adoption and development of DC charging stations highly depend on some parameters and assumptions such as gas price and the targeted ratio of PEVs to DC charging station.

For future works, the effect of development in the technology of PEVs, batteries, charging stations, and the maturity of their technology on the whole system can be investigated. Secondly, the effect of the rising share of RES and electric vehicle adoption on the ESS market can be studied. Thirdly, some of the generation technologies were neglected in the electricity market such as photovoltaic panels, nuclear power plants, hydroelectric power plants, and pumped storage power plants, which could have a considerable effect on

TABLE 4. The fast DC charging station and tesla Model 3 characteristics.

Item	Quantity
Investment cost of charging station ($/kW) [60]	2110
Maintenance cost of charging station ($/kWyear) [60]	76
Lifetime of charging station (years) [60]	15
Construction time of charging stations (year) [61]	1
Amortization period of charging station (years) [62]	10
Average daily consumption of EV (ACEV) (kWh/km) [63]	0.1616
Passenger volume of EV (ft^3) [63]	97
Luggage volume of EV (ft^3) [63]	15
Electric motor/battery (AC 3-Phase) (kW) [63]	147 / 211
Time to charge battery of EV at 240V (hours) [63]	10
Lifetime of PEVs (year) [64]	15

TABLE 5. Constant values.

Item	Quantity
MAGE (km) [65]	38.6
PED (unitless) [22]	-0.3
TCPR (unitless) [52]	0.01
H (m) [52]	100
TPE (year) [22]	1
TRCV (year) [66]	12

TABLE 6. Hourly load data set.

Hours	EVs charging coefficients	Hourly electricity load coefficients			
		Winter	Spring	Summer	Fall
1	0.367	0.837	0.756	0.703	0.702
2	0.235	0.814	0.732	0.672	0.681
3	0.143	0.791	0.707	0.641	0.660
4	0.092	0.791	0.683	0.609	0.638
5	0.061	0.814	0.732	0.617	0.670
6	0.046	0.837	0.756	0.625	0.702
7	0.051	0.907	0.805	0.648	0.723
8	0.092	1.000	0.829	0.675	0.745
9	0.117	1.000	0.854	0.703	0.777
10	0.122	0.953	0.878	0.766	0.819
11	0.163	0.942	0.902	0.828	0.851
12	0.235	0.930	0.927	0.891	0.894
13	0.255	0.907	0.939	0.938	0.926
14	0.306	0.884	0.951	0.953	0.957
15	0.408	0.860	0.963	0.969	0.974
16	0.520	0.837	0.976	0.984	0.985
17	0.714	0.849	1.000	1.000	1.000
18	0.918	0.860	0.976	0.984	0.979
19	1.000	0.907	0.951	0.961	0.957
20	0.980	0.930	0.927	0.938	0.957
21	0.898	0.930	0.927	0.898	0.904
22	0.816	0.907	0.878	0.859	0.851
23	0.612	0.884	0.829	0.820	0.798
24	0.408	0.860	0.805	0.781	0.745

price and load profile. Fourthly, different pricing strategies and charging strategies in DC charging stations influence simulation results, which can be studied in future works. Finally, the expansion of transmission lines and distribution systems can be included in future works to provide a more comprehensive model for policymakers.

APPENDIX

The hourly and weekly coefficients, functions, and data sets are represented in this section.

TABLE 7. Hourly wind speed data set.

Hours	Hourly coefficients of wind speed			
	Winter	Spring	Summer	Fall
1	0.710	0.694	0.621	0.724
2	0.708	0.675	0.588	0.720
3	0.704	0.660	0.554	0.711
4	0.708	0.641	0.527	0.706
5	0.708	0.631	0.497	0.702
6	0.708	0.614	0.469	0.694
7	0.725	0.655	0.489	0.694
8	0.818	0.763	0.588	0.754
9	0.936	0.877	0.717	0.881
10	0.992	0.910	0.766	0.979
11	1.000	0.907	0.779	1.000
12	0.982	0.901	0.788	0.991
13	0.968	0.903	0.818	0.974
14	0.954	0.919	0.857	0.964
15	0.943	0.941	0.897	0.966
16	0.935	0.959	0.938	0.964
17	0.875	0.987	0.978	0.906
18	0.806	1.000	1.000	0.857
19	0.801	0.972	0.953	0.829
20	0.802	0.905	0.866	0.806
21	0.787	0.840	0.789	0.793
22	0.757	0.806	0.743	0.768
23	0.738	0.762	0.691	0.743
24	0.721	0.718	0.644	0.728

TABLE 8. Weekly load data set.

weeks	Weekly electricity load coefficients	weeks	Weekly electricity load coefficients	weeks	Weekly electricity load coefficients
1	0.878	19	0.813	36	0.911
2	0.853	20	0.826	37	0.892
3	0.829	21	0.839	38	0.87
4	0.804	22	0.852	39	0.848
5	0.779	23	0.882	40	0.826
6	0.784	24	0.911	41	0.804
7	0.789	25	0.941	42	0.794
8	0.794	26	0.97	43	0.784
9	0.779	27	1	44	0.774
10	0.779	28	0.997	45	0.764
11	0.76	29	0.995	46	0.778
12	0.741	30	0.992	47	0.793
13	0.722	31	0.99	48	0.807
14	0.738	32	0.987	49	0.822
15	0.755	33	0.968	50	0.836
16	0.771	34	0.949	51	0.85
17	0.788	35	0.93	52	0.864
18	0.8				

The first week in Fig. 15 is the first week of January and the amount of peak value in the first year is 740 GW [55]. The consumption of the transportation system was not considered in the first year peak value and load profile of Fig.15.

In this paper, the technical data of Siemens turbines (model SWT 108 2.3) of Los Vientos Wind Farm in Texas are considered [52].

The initial values, coefficients, constant values and data set that were used in the paper are provided in the following tables.

TABLE 9. Wind turbine capacity factor data set.

Wind speed	Capacity factor of wind turbine	Wind speed	Capacity factor of wind turbine
1	0	9	0.8465
1.5	0	9.5	0.9404
2	0	10	0.9752
2.5	0	10.5	0.9883
3	0.0117	11	1
3.5	0.0252	12	1
4	0.04	13	1
4.5	0.0683	14	1
5	0.0978	15	1
5.5	0.1626	16	1
6	0.2278	17	1
6.5	0.3139	18	1
7	0.3996	19	1
7.5	0.5022	20	1
8	0.6039	20.5	0
8.5	0.7261	21	0

TABLE 10. Fossil fuel units capacity factor data set.

PR(h-Δh)/MC(h)	HC	CC GT	GT	PR(h-Δh)/MC(h)	HC	CC GT	GT
0.8	0	0	0	1.06	0.88	0.79	0.58
0.81	0.01	0	0	1.07	0.91	0.81	0.61
0.82	0.03	0	0	1.08	0.94	0.83	0.64
0.83	0.04	0	0	1.09	0.97	0.86	0.67
0.84	0.06	0	0	1.1	1	0.88	0.7
0.85	0.07	0	0	1.11	1	0.90	0.72
0.86	0.09	0.03	0	1.12	1	0.93	0.74
0.87	0.10	0.06	0	1.13	1	0.95	0.76
0.88	0.12	0.09	0	1.14	1	0.97	0.78
0.89	0.13	0.12	0	1.15	1	1	0.8
0.9	0.15	0.15	0	1.16	1	1	0.82
0.91	0.20	0.18	0.04	1.17	1	1	0.84
0.92	0.26	0.21	0.08	1.18	1	1	0.86
0.93	0.31	0.24	0.12	1.19	1	1	0.88
0.94	0.37	0.27	0.16	1.2	1	1	0.9
0.95	0.42	0.3	0.2	1.21	1	1	0.91
0.96	0.48	0.37	0.24	1.22	1	1	0.92
0.97	0.53	0.44	0.28	1.23	1	1	0.93
0.98	0.59	0.51	0.32	1.24	1	1	0.94
0.99	0.64	0.58	0.36	1.25	1	1	0.95
1	0.7	0.65	0.4	1.26	1	1	0.96
1.01	0.73	0.67	0.43	1.27	1	1	0.97
1.02	0.76	0.69	0.46	1.28	1	1	0.98
1.03	0.79	0.72	0.49	1.29	1	1	0.99
1.04	0.82	0.74	0.52	1.3	1	1	1
1.05	0.85	0.76	0.55				

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