The experience curve effect on renewable energy penetration

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***Abstract* —** The experience curve effect has always challenged technology-related decisions. In the electricity sector, new renewable electricity generation technologies have shown a considerably high learning rate up to now, which could differentiate the profitability of energy generation technologies in the near future. The scope of this work is to investigate the effect that the Experience Curve of the renewable energy technologies may have on the orders for new electricity generation technologies and therefore, on the future electricity generation mix of Greece. The official renewable energy generation targets are considered as a constraint of the system, and the learning rates of the various technologies are included in the calculations. Three scenarios of learning rates have been applied, to examine the experience curve effect on renewable energy penetration. The national electricity generation system is modeled for long-term analysis and a linear programming method is applied, in order to come up with the optimal generating mix that minimizes electricity generation cost, while satisfying the national emissions reduction targets. In addition, two scenarios for future emission allowance prices are considered, in order to examine the effect of changes in this very volatile parameter. Furthermore, an investigation is made to identify if a point should be expected when renewable energy will be more profitable than conventional fuel electricity generation.

***Keywords*—**energy policy, experience curve, optimization, renewable energy economics.

I. Introduction

Strategic planning for the medium- to long-term expansion of the electricity generating capacity of a specific country has been an important issue in the past, when electricity markets were regulated. The major concerns in regulated markets were mainly the dependence from imported fuels, stability and reliability of the transmission grid, as well as quality and security of supply. In recent years, the deregulation of the electricity sector as well as the introduction of environmental constraints, such as the reduction of greenhouse gas emissions and targets for penetration of Renewable Energy Sources (RES) in the electricity generating mix, have added additional constraints that complicate further the procedure of planning. Furthermore, the rapid evolution of new technologies, especially renewables, has resulted in significant generation cost reduction. The main result of the market deregulation is that the major focus of the private investors is the generation cost, since in a competitive market it is much more probable to survive and achieve higher yields if one has lower generation cost than his competitors. Therefore, technologies with the lowest generation cost are the most advantageous for private investors. The main result of the RES introduction and the CO2 emissions trading system is the complication of the investment decision as well as the addition of an extra expense stream for electricity generators based on conventional fuel sources, as they have to purchase the emission allowances they require.

The scope of this work is to investigate the effect that the Experience Curve of the renewable energy technologies may have on the orders for new electricity generation technologies and therefore, on the future electricity generation mix of Greece. The renewable energy generation targets are taken into consideration as a constraint of the system, and the learning rates of the various technologies are included in the calculations. The methodology presented may be used for the electricity system of any country.

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TABLE I
NOMENCLATURE

Indices	**Description**
i	Technologies included in the study
t	Years *[2010,2050]*
Sets	**Description**
REN	Renewable technologies
$CONV$	Conventional technologies
Parameters	**Description**
$AI_{i,t}$	Investment annuities (€/MWel/year)
$Cf_{i,t}$	Fuel cost (€/MWh fuel)
$Cco2_t$	Forecasted CO2 price in year t (€/tn CO2)
$CO2_{i,t}$	Total emissions allowance cost for year t and conventional tech. i (€/MWel)
E_i	Energy generated yearly from unitary capacity of technology i (MWh/MWel)
$Edem_t$	Energy demand in year t (MWh)
$EGC_{i,t}$	Average levelised lifetime electricity generation cost (€/MWh)
$Emco2_i$	CO2 emissions of technology i (tnCO2/MWh electr.)
$F_{i,t}$	Total fuel cost for year t and technology i (€/MWel)
$I_{i,t}$	Investment cost per unit of capacity installed (€/MWel)
$OMf_{i,t}$	Fixed Operational & Maintenance costs (€/kWel)
$OMv_{i,t}$	Variable Operational & Maintenance costs (€/MWel)
$Pcl_{i,t}$	Capacity of tech. i scheduled to be decommissioned in year t (MWel)
$Pdem_t$	Peak-load demand in year t (MWel)
$Pmax_i$	Maximum resource potential of technology i (MWel)

$Ptot_{i,t}$	Installed capacity of technology i in year t (MWel)
$Q_{i,t}$	Projected global installed capacity of technology i in year t (GW)
Top_i	Operational lifetime of technology i (Years)
b_i	Learning rate of technology i
fav_i	Availability factor of technology i
$fcap_i$	Capacity factor of technology i
n_i	Efficiency factor of technology i
r	Interest rate

II. LITERATURE REVIEW

Researchers have dealt for a long time with the issue of the optimum electricity generating portfolio. Among the first to introduce the portfolio analysis in the Power Sector were Bar-Lev and Katz [1]. Other researchers [2]-[4] have extended the analysis to various power expansion mixes. Furthermore, mean-variance portfolio techniques have been applied in various instances, presenting also various risk measures [5],[6].

In the literature there are two predominant approaches, when dealing with energy portfolios and the future optimum power generation mix. The first approach mainly aims at maximizing the Net Present Value (NPV) of the entire system investigated, which is usually the electricity generation sector. The NPV comprises the objective function of an optimization problem, which is subject to an appropriate set of constraints, depending on the case examined. The optimum point determined by the optimization problem is the power generation mix for which the system NPV is maximized, thus indicating the optimum investing timing, such as in the works [7]-[9]. Inevitably, this approach entails forecasting of the future electricity prices.

The second main approach of optimizing energy portfolios concerns works focusing on minimizing the electricity generation cost [10]. This approach has the advantage that no assumption over the future electricity prices has to be made. Focusing on minimum generation cost may imply maximizing the potential for positive financial yields, irrespective of the electricity price. Equivalently, attempting to minimize the generation cost may be considered equivalent to minimizing the cost to be passed on to the energy consumers [11]. For example, in [12], medium-range planning economics of alternative fuel options for electrical-power generation systems in Jordan is discussed, for a 15 year period. The options examined in this work were natural gas, heavy fuel oil, coal and local oil shale, which were compared using the levelised generation cost methodology. In [13], the electricity generation cost in Turkey has been investigated, focusing mainly on determining economy of scale, overcapitalisation, and technological progress for past years.

Mean-variance frameworks have also been proposed to address the energy portfolio planning and the optimal allocation of positions in peak and off-peak forward contracts [14]. It has been shown that optimal allocations are based on the risk premium differences per unit of day-ahead risk as a measure of relative costs of hedging risk in the day-ahead markets. In a case study [15], multiple objectives are confronted in portfolios under demand uncertainty in order to lead to optimal expansion solutions while including environmental and demand constraints. The influence of the risk management has been analyzed in different studies concerning either solely electricity production or multi-objective functions comprising of combined heat and power production [16],[17]. Decision support tools have been also developed [18] seeking for globally optimal solutions, taking into account financial and economical conditions and constraints imposed at an international level.

The experience curves have been acknowledged as a significant method of analyzing the dynamics of technical change and cost development. The experience curve is constructed using historical data, and it is the extrapolated to predict future cost development [19]. Especially in the electricity generation sector, the new renewable electricity generation technologies have shown a very high learning rate, which leads to significant cost reduction. It is therefore interesting to examine how this would change the relative competitiveness of the various energy sources in the future. As the various researchers of the experience curves for renewable energy technologies have not reached a consensus over the exact values, a scenario analysis is performed in this work, to include the full range of learning rate values found in the relevant literature. The interested reader may refer to [20] for a thorough analysis on experience curves for various renewable energy sources.

III. METHODOLOGY

In this work, ten different electricity generation methods have been examined, using different fuel sources (as seen in Table III). The currently best available technology has been selected in all cases. The rationale behind this choice is that all available conventional and renewable energy sources should be included in the work. Nuclear power is omitted, as it is strategically excluded from the electricity generation mix of Greece since many years. The electricity generating cost is calculated for each year and each technology using the Levelised Lifetime Cost Estimation Methodology [21]. According to this methodology, the levelised lifetime cost per unit of electricity generated is the ratio of total lifetime expenses versus total expected outputs, both expressed in terms of present value equivalent. The original methodology has been expanded to match the specific requirements of this work. Thus, the average levelised lifetime electricity generation cost is

$$EGC_{i,t} = \sum_{n=t}^{T}[(AI_{i,t} + OMf_{i,n} + OMv_{i,n} + F_{i,n} + CO2_{i,n})(1+r)^{-t}] / \sum_{n=t}^{T}[E_i(1+r)^{-t}] \qquad (1)$$

$\forall i,\ \mathrm{t} \in [2010,2050],$

where

$T = \min(t + Top_i, 2050).$

The investment cost is calculated as a series of equal annuities, spread over the entire lifetime of the specific technology, in order to be able to perform reliable calculations also for the time t where the operational lifetime of a specific technology is longer than the remaining time period for examination:

$$AI_{i,t} = \frac{I_{i,t} r}{(1-(1+r)^{-Top_i})} \qquad \forall i,\ \mathrm{t} \in [2010, 2050], \qquad (2)$$

where the investment cost $I_{i,t}$ is calculated using the learning rate, to take into account the experience curve effect stemming from the projected increase in global installed capacity for each specific technology:

$$I_{i,t} = I_{i,t0} \cdot \left[\frac{Q_{i,t}}{Q_{i,t0}} \right]^{\log_2[1-b_i]} \qquad \forall i,\ \mathrm{t} \in [2010,2050], \quad (3)$$

where *t0* is the reference year, equal to year 2010. In order to examine the effect of learning rates on the competitiveness of renewable energy generation, three scenarios of learning rate values have been examined. The learning rates used for the base scenario of this work may be seen in Table III (*Medium LR*). The scenario *Low LR* assumes the learning rates are half than those of the base scenario, and the *High LR* assumes the learning rates are double than those of the base scenario.

The fuel cost per unit of capacity of each technology is calculated as

$$F_{i,t} = \frac{E_i}{n_i} Cf_{i,t} \qquad \forall i,\ \mathrm{t} \in [2010, 2050], \quad (4)$$

where the energy generated from a unit of capacity of each technology is

$$E_i = 8760\, fav_i\ fcap_i \qquad \forall i. \quad (5)$$

The cost of obtaining the emission allowances for the power plants using conventional fuel sources is calculated as

$$CO2_{i,t} = E_i Emco2_i Cco2_t \qquad \forall i \in CONV. \quad (6)$$

The Operational and Maintenance cost (O&M) is distinguished into variable (OMv - proportional to the energy generated) and fixed costs (OMf).

A. *The optimization model.*

The optimization problem is formed as a linear programming model, modeling a series of yearly decisions. Each yearly decision concerns the capacity of each one of the examined electricity generation technologies to be added to the current generation mix, in order to meet the electricity demand increase. The objective function to be minimised is the cost of generating the excess energy required in the year examined.

$$f(x) = \min \sum_i E_i EGC_{i,t} X_{\mathrm{i}} \qquad \forall t \quad (7)$$

s.t.

$$Ptot_{i,t} \le P\max_i \qquad i \in (wind, hydro, geothermal) \quad (8)$$

$$130\% Pdem_t \le \sum_i Ptot_{i,t} \quad (9)$$

$$Edem_t \le \sum_i E_i Ptot_{i,t} \quad (10)$$

$$\sum_{i \in REN} E_i Ptot_{i,t} \le 50\% \sum_i E_i Ptot_{i,t} \quad (11)$$

$$\sum_{i \in REN} E_i Ptot_{i,t} \ge 35\% \sum_i E_i Ptot_{i,t} \quad t \in [2020,2050] \quad (12)$$

where the total installed capacity for each technology and year is provided by a recursive formula, taking into account the new generation capacity installed each year and subtracting the old generation capacity that has reached its operational lifetime during the year under examination:

$$Ptot_{i,t} = Ptot_{i,t\text{-}1} + X_i - Pcl_{i,t} \qquad \forall i. \quad (13)$$

The first set of constraints (8) states the maximum potential of some renewable energy sources. In this work it has been assumed that the maximum installed capacity of wind, hydro and geothermal power must be less than the respective national potential, conservatively estimated, at all times.

Constraints (9) and (10) refer to the power and energy demand. (9) ensures that the total installed generating capacity will be at least 30% greater than the peak-load demand, in order to secure uninterrupted supply of demand, even in peak-load periods. (10) requires that the energy produced will be enough to satisfy energy demand.

Constraint (11) takes into account grid stability issues. The fact that most renewable energy sources cannot be dispatched when required, prevents them from constituting a reliable base-load solution in the long term (mainly applicable to wind parks and photovoltaics, and to some extent for hydro and biomass). Despite their short setup periods and zero fuel requirements, they often suffer from resource unavailability. Thus, unpredictable conditions might impact the stability of the national grid and the reliability of power supply. Despite the fact that there is no consensus on the maximum allowable percentage of renewable energy to secure the grid stability, scientists agree that there is currently an upper limit on renewable power penetration to the grid [23]. For this reason a constraint is imposed ensuring that the total energy production from RES may not exceed 50% of the total energy demand.

Constraint (12) reflects the current national renewable energy targets, which require that 35% of the total electricity from year 2020 onwards will be generated by renewable energy sources. In order to facilitate the model operation, this target has been linearly shared to the years until 2020, starting from a 10% RES share for the year 2010.

Furthermore, an arbitrary upper limit equal to 1500 MW/year for every conventional power technology and 1000 MW/year for every RES has been applied, in order to avoid the unnatural case where only one power source is installed during one year.

The CO2 allowance price uncertainty has been included in the work by analyzing two scenarios of price evolution. Both scenarios use as starting value the prevailing CO2 price at the end of the year 2009, which was around 15 €/tn CO2. The first one (scenario 1) assumes a very low increase in future emission allowance prices, whereas scenario 2 models a medium-to-high price increase (2,5% yearly).

TABLE II
CO2 PRICE SCENARIOS

Year	Scenario 1: Low CO2 price (€/tn CO2)	Scenario 2: Medium CO2 price (€/tn CO2)
2010	15,00	15,00
2015	15,17	16,97
2020	15,17	19,20
2025	15,29	21,72
2030	15,45	24,58
2035	15,59	27,81
2040	15,79	31,46
2045	15,90	35,60
2050	16,10	40,28

The model formulation is based on several assumptions. Firstly, it has been assumed that conventional-fuel electricity generators will have to purchase the full amount of the emission allowances they require for electricity generation. Secondly, it is assumed that the renewable energy generators will not be able to trade the green certificates from the energy they generate. The potential income from trading emission allowances or green certificates has not been included in the cost estimation method used. Another assumption is that the inflation rate has not been included in the analysis, which means that all future values used are deflated to real values. The interest rate has been assumed equal to 8%. It should be noted also that no public subsidy has been assumed for the renewable energy sources, as subsidies are policies varying for each country and also within the same country with time. Therefore, this work takes into account the real electricity generation cost of all technologies, with either conventional or renewable fuel sources, as any type of subsidies are ultimately passed on to the final consumers (directly or indirectly) and finally increase the generation cost. The main inputs of the model are presented in Table III.

TABLE III
MAIN INPUTS OF THE MODEL (SOURCE: [9],[21])

	Hard-coal	Oil	Natural Gas	Lignite	Biomass	Solar PV	Wind turbines	Hydro-electric	Hydro pumped storage	Geothermal
Investment cost (€/ KW_{el}) year 2010	1250	1150	440	1050	2200	2770	1100	1300	3400	1800
Fixed cost (€/kW_{el})	56,4	38	18,8	35	19	30	18	3	50	32
Variable cost (€ / MWh_{el})	3,2	1,6	1,6	1	0	0	0	1,5	1,5	18
Availability factor	0,75	0,7	0,75	0,75	0,75	0,98	0,96	0,97	0,92	0,7
Capacity factor	0,85	0,8	0,85	0,85	0,8	0,15	0,35	0,25	0,4	0,9
Learning rate (Low)	0,005	0,005	0,005	0,005	0,05	0,1	0,05	0	0	0
Learning rate (Medium)	0,01	0,01	0,01	0,01	0,1	0,2	0,1	0	0	0
Learning rate (High)	0,02	0,02	0,02	0,02	0,2	0,4	0,2	0	0	0
Efficiency Factor	0,51	0,45	0,54	0,41	0,3	1	1	1	1	1
CO2 emissions (tnCO2 / MWh_{el})	0,66	0,62	0,38	1,027	0	0	0	0	0	0
Operational Life-Time (Years)	40	40	30	40	40	25	20	40	40	40

IV. RESULTS & DISCUSSION

In Fig. 1 – 3, the calculated optimum generation mix, energy mix and renewable energy penetration level are presented, for the *Low Learning Rate* scenario. It is interesting to note that with low future CO2 prices, lignite is the base-load conventional fuel source to dominate, while with higher CO2 prices the base-load fuel chosen is Natural Gas, due to reduced emissions-related cost. Furthermore, increased CO2 prices lead to higher RES penetration in the electricity generation system. Actually, low CO2 prices lead to marginally satisfying the official RES penetration targets, whereas high CO2 prices lead to the maximum allowable RES penetration in the system (50% of the electricity generated yearly), after the year 2027. This fact implies that from this time onward, RES become more competitive than the cheapest conventional power source. In the high CO2 price case, a significant part of base-load generation is replaced by biomass.

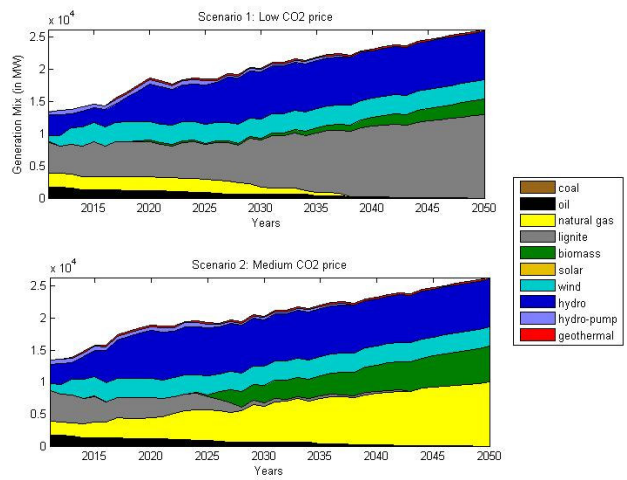

Fig. 1 Generation Mix - Scenario Low LR

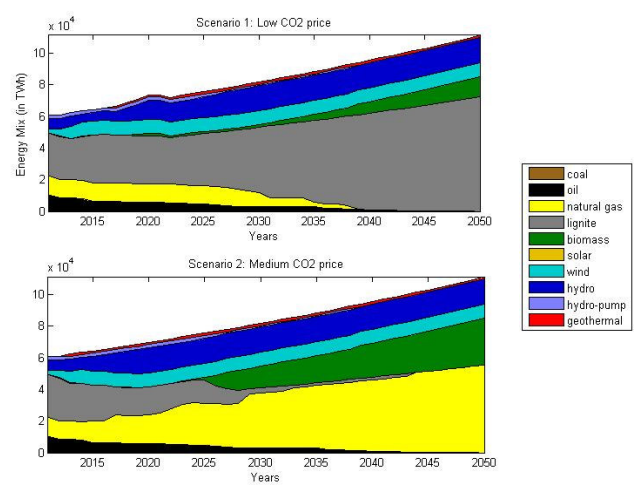

Fig. 2 Energy Mix - Scenario Low LR

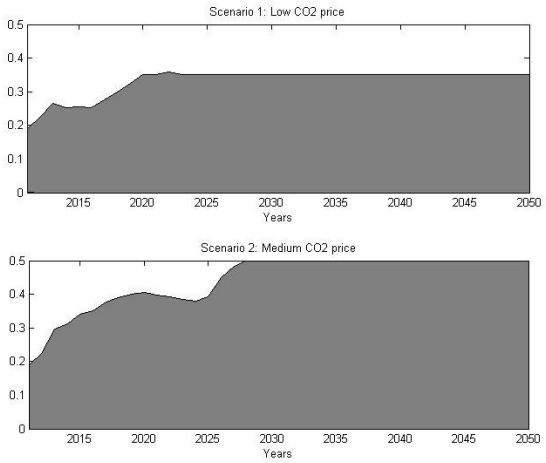

Fig. 3 Renewable energy penetration - Scenario Low LR

For the *Medium Learning Rate* scenario (base scenario), the results are very similar to the ones of the *Low Learning Rate* scenario (Fig. 1 – 3), and are therefore not presented. The main difference lies in the fact that with higher CO2 prices, the maximum allowable RES penetration level is achieved earlier, in year 2025 (Fig. 4). It is therefore concluded that with lower Learning Rate values (compared to the base case), the relative competitiveness of the electricity generation technologies examined does not change significantly.

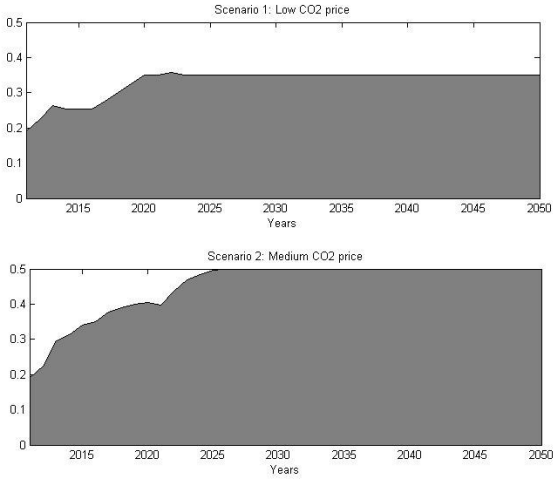

Fig. 4 Renewable energy penetration - Scenario Medium LR

For the *High Learning Rate* scenario the results are presented in Fig. 5 – 7. It is interesting to note that in this scenario, solar PV is used significantly after the year 2027, which means that it becomes the most competitive RES after this time. In this case, a very large PV capacity has to be installed, leading to an increase on the total system installed capacity, due to the low capacity factor of solar PV technology. It should also be noted that in this scenario, even with low future CO2 prices, the RES penetration level gradually increases to 50% until the year 2048.

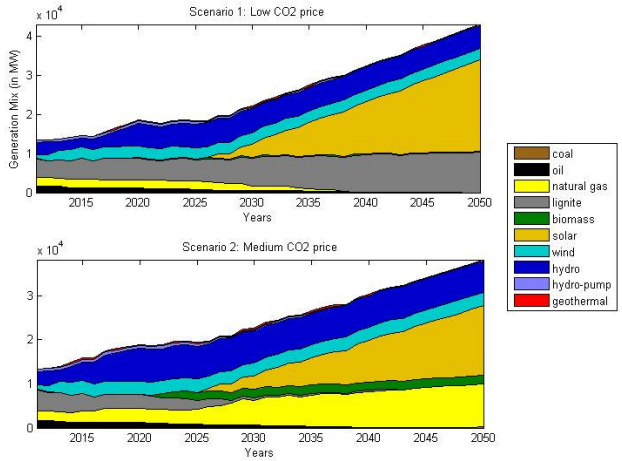

Fig. 5 Generation Mix - Scenario High LR

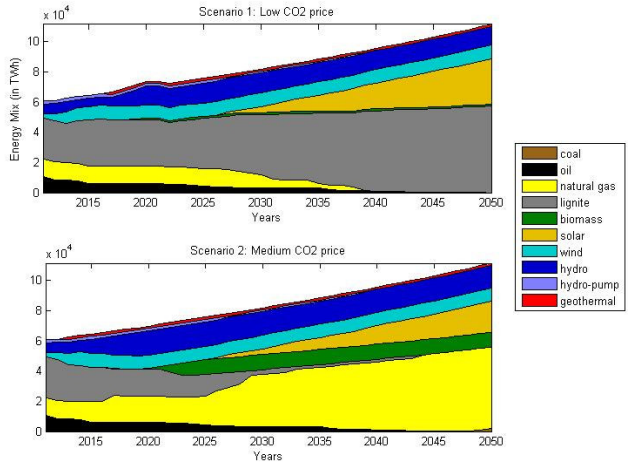

Fig. 6 Energy Mix - Scenario High LR

The reason for this result may be better explained by Fig. 8, where the generation cost for all RES is presented, for the High LR scenario. It is obvious that after the year 2027, solar PV becomes the most competitive RES option, as the other competitive options have already exhausted their yearly capacity potential (wind, hydro and geothermal). There exists also a time frame, between years 2021 and 2027, where biomass is the most competitive RES, after wind, hydro and geothermal have exhausted their potential. The very high learning rate of solar PV assumed for this scenario is responsible for the very steep cost reduction. The generation cost of the RES is the same for scenarios 1 & 2, as the CO2 price does not affect this cost, under the assumptions made for this work.

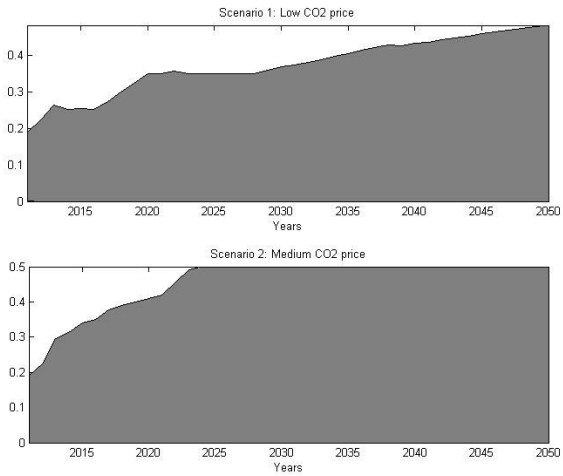

Fig. 7 Renewable energy penetration - Scenario High LR

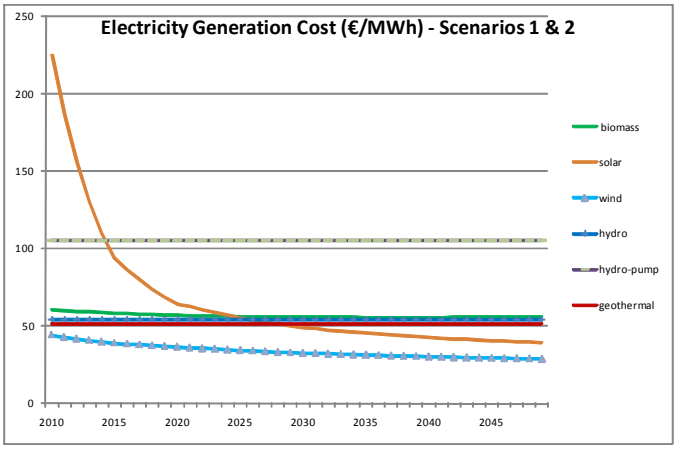

Fig. 8 Renewable energy generation cost evolution-Scenario High LR

V. Conclusion

To conclude, this work has attempted to investigate the effect of experience curve to the penetration of renewable energy on the future electricity generating mix of Greece. The methodology presented may be applied in any other case, and is mainly comprised of a linear programming model.

The results of this work show that the experience curve effect may result in some renewable energy sources becoming even more competitive than conventional power sources, without any form of subsidy, if CO2 prices follow a medium increase trend in the future. RES could become more competitive than conventional power sources even with current CO2 prices, only if the most optimistic scenario for learning rates is assumed, which is however highly unlikely to be realized. Furthermore, it is shown that solar PV electricity will not be able to become more cost competitive than wind power, even if the most optimistic assumptions for future learning rates are realized.

Finally, the reader should be aware that the learning rate values assumed are unfortunately characterized by uncertainty, and therefore the results should be treated as indications of future trends, and not as absolute values.

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