Learning by doing for Renewables Energy Technologies:
Empirical Evidence from Iran

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Abstract:

The concept of learning curve reflects the fact that technologies may experience decreasing costs as a result of increasing adoption into the society due to the accumulation of knowledge through, among others, processes of learning-by-doing. Studies show that while the mature technologies such as coal, oil and lignite conventional technologies present relatively low learning rates, the new renewable energy technologies such as solar photovoltaic energy exhibit high rates. The introduction of learning curves for different energy technologies in many bottom-up energy system models has become common. The introduction of learning rate in bottom-up energy models has an important implication for the investment timing in the energy technologies. When endogenous learning is introduced in the model, empirical outcomes are significantly different from those obtained by static or exogenous cost trends. This paper investigates technological learning implications for the long run capacity of renewable energy technologies as well as CO_2 *emission reductions. Results show that although learning by doing has positive impact on renewable share in electricity generation capacity but the existence of energy carriers price distortions alters this result significantly*

Key Words: Progress Ratio, Endogenous technological learning (ETL), Price distortions, Iran.

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1. Introduction

Technology constitutes one of the main driving forces of economic growth and has become an important factor in shaping our lives. Technical change is a gradual process that evolves through different stages of economic development. Sustainable development depends, among other factors, of cost-effective, safe, and environmentally robust energy systems (Brundtland Commission, 1987). Technological advance is a key factor in this process as it enables a more productive use of energy resources. Since 1990, learning curves literature has caused considerable interest in energy technology investment timing and energy policy analysis (Papineau, 2006).

The idea of learning by doing as a distinct source of technical change was pioneered by Wright (1936) and Arrow (1963). Since that time, there have been considerable developments in both theoretical and empirical aspects of technical change. However, the focus of the literature has shifted to the role of economic factors on technical change (Thirtle and Ruttan, 1987). The learning effect is measured in terms of reduction in the unit cost (or price) of a product as a function of experience gained from an increase in its cumulative capacity or output. The main contribution of this research is the impact analysis of energy carriers price distortions on the trend of renewable energy technologies in Iran using endogenoue learning curve approach.

2. Endogenous Learning Curve in renewable energy technologies

The most common forms of learning curves specify improvement in the cost of a given technology by a power function (e.g. cumulative installed capacity or output) (Eq. 1). The learning effect of cumulative capacity or output on cost improvement is then, generally, expressed as a learning rate measured in terms of percentage cost reduction for each doubling of the cumulative generation capacity or production (Eq. 2).

$$SC(C) = a \cdot C^{-b} \qquad (1)$$

where

SC: Specific cost (e.g. US$/kW for electricity generation technologies)

C: Cumulative capacity

b: Learning index

a: Specific cost of the first unit

The learning index ***b*** defines the effectiveness with which the learning process takes place. It constitutes one of the key parameters in the expression above. Usually, its value is not given but the progress ratio (PR)) is specified instead. Kaholi-Brahmi (2008) show that the relation between progress ratio and learning index can be expressed as below:

$$PR = 2^{-b} \qquad (2)$$

Different contributions have estimated learning rates for various renewable energy technologies. The variabilities of these learning rates (progress ratios) are shown in Figs 1 and 2, which show the range of estimated progress ratios for wind and solar photovoltaic (PV) energy technologies. The variability of wind energy technology and PV learning rates may depend mainly on the data point and the time span of various studies. Although different researchers distinguished some other causes for this variability such as various estimation methodologies (Kohler et al. 2006).

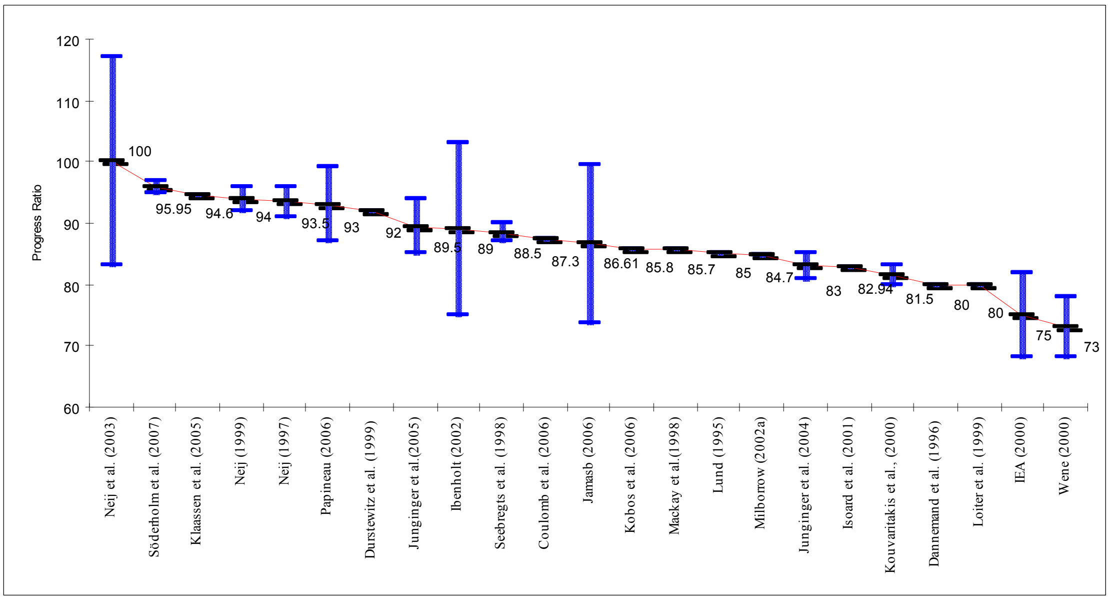


Figure 1. Estimated wind energy technologies progress ratios

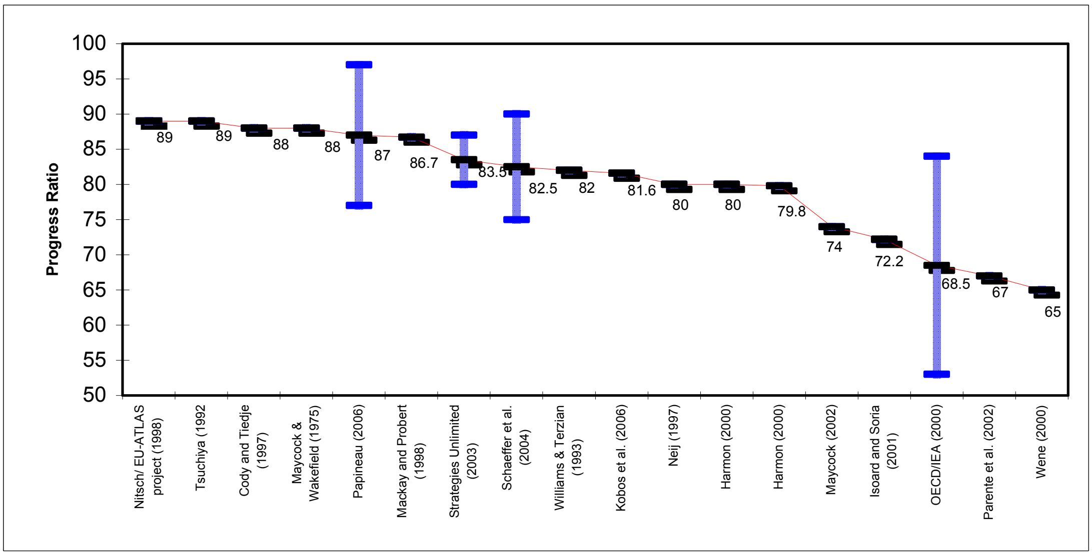


Figure 2. Estimated solar photovoltaic progress ratios

As Fig. 1 indicates progress ratios for wind energy technology, estimated in various studies, ranges down from 117% to 65% which means the learning rates of -17% to +35%. However, learning curves developed for PV technology indicate a learning rate from 11% to 35%.

The functional form of learning curves described in equation (1 or 2) is not used directly when endogenising them in a Bottom-Up model, because it would lead to a severe non-linearity in the objective function. Therefore, the total cumulative cost is used as an alternative as is mentioned by Barreto (2001). The total cumulative cost ($TC_{k'',t}$) is expressed as the integral of the specific cost curve (Fig. 3)

$$TC_{k'',t} = \int_0^C SC_{k'',t}(C) \cdot dC = \int_0^C aC_{k'',t}^{-b} \cdot dC = \frac{a}{1-b} C_{k'',t}^{1-b} \qquad (3)$$

where k'' represents the set of learning technologies and $C_{k'',t}$ is a non-decreasing variable and can be expressed as:

$$C_{k'',t} = C_{k'',o} + \sum_{\tau=1}^{t} INV_{k'',\tau} \qquad (4)$$

where

$C_{k'',t}$: Initial cumulative capacity (parameter)

$INV_{k'',t}$: Investments made on this technology in a particular period t (variable)

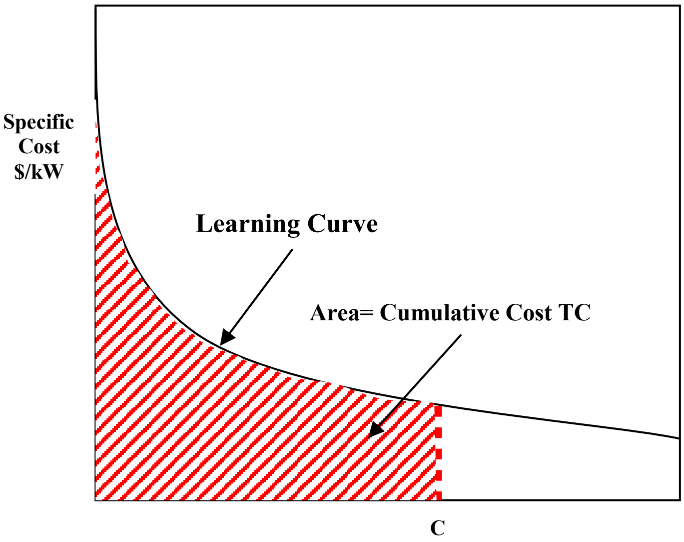


Figure 3. Cumulative

Figure 3. Cumulative cost curve as the area below the learning Curve

`The investment cost $IC_{k'',t}$ associated with the investments in a given learning technology k'' in the period t, is computed as the subtraction of two consecutive values of the cumulative cost:

$$IC_{k'',t} = TC_{k'',t} - TC_{k'',t-1} \tag{5}$$

These investment costs are discounted and included in the objective function. In the NLP formulation, equation (3) presented above is substitutes directly into equation (5) in order to compute the investment costs per period for a given technology:

$$IC_{k'',t} = \frac{a(C_{k'',t}^{1-b} - C_{k'',t-1}^{1-b})}{1-b} \tag{6}$$

Such investment costs are discounted and directly incorporated in the objective function and the corresponding $IC_{k'',t}$ terms is computed using equation (6) as a constraint in the model. So the objective function (Z) comprises the usual computation of all the costs for the other non-learning technologies (k'), plus the discounted investment costs for the k'' learning technologies:

$$Z = \sum_{t=1}^{\pi} (1+d)^{1-t} \cdot ANC(k',d,p,f)_t \cdot (1+(1+d)^{-1}+(1+d)^{-2}+\ldots+(1+d)^{1-\tau}) + \sum_{k'}\sum_{t} d \cdot IC_{k'',t} \quad (7)$$

where:
Z is the net present value of the total cost of the electricity system
d is the general discount rate
τ is the number of periods in the planning horizon
π is the number of years in each period t
$ANC(k', d, p, f)_t$ is the annual cost for period t, which is the sum over all (non learning) technologies k', all demand segments ***d*****,** all pollutants ***p***, and all input fuels ***f*** of the various costs incurred, namely: annualized investments, annual operating costs (including fixed and variable technology costs, fuel delivery costs, costs of extracting and importing energy carriers), minus revenue from exported energy carriers, plus taxes on emissions, plus cost of demand losses.

In order to specify the learning curve to be interpolated, a maximum capacity $C_{k'',\max}$ must be defined. $C_{k'',\max}$ implies an upper bound for the capacity of the technology and will affect the segmentation. The corresponding maximum cumulative cost is given by:

$$TC_{k'',\max} = \frac{a}{1-b}(C_{k'',\max})^{1-b} \quad (8)$$

Besides the maximum cumulative cost, the number of segments N for the cumulative cost curve must be specified. Using the initial and final points of the curve and according to the number of segments previously defined, the breakpoints are computed. Taking into account that a faster decrease of costs occurs in the first region of the curve, in this particular formulation, shorter segments are at the beginning and then increasingly longer segments is used to obtain a better representation for the first region of the curve. The segments are defined as follows:

$$TC_{i,k} = TC_{0,k} + \frac{\frac{1}{2^{N-i}}(TC_{k,\max} - TC_{0,k})}{\sum_{i=0}^{N-1}\frac{1}{2^{N-i}}} \quad (9)$$

And the corresponding cumulative capacities:

$$C_{i,k} = \left(\frac{(1-b)}{a} (TC_{i,k}) \right)^{\frac{1}{1-b}} \tag{10}$$

3- The main characteristics of the Iranian electricity market

3.1- Vast Oil and gas reserves: Based on official statistics proven oil and natural gas reserves in Iran are 138.22 billion barrels and 28.13 trillion cubic meters, respectively (MOE, 2008). Fig. 4 shows the relative share of different energy carriers in the primary energy supply. Oil and natural gas provide more than 98% of country's primary energy supply.

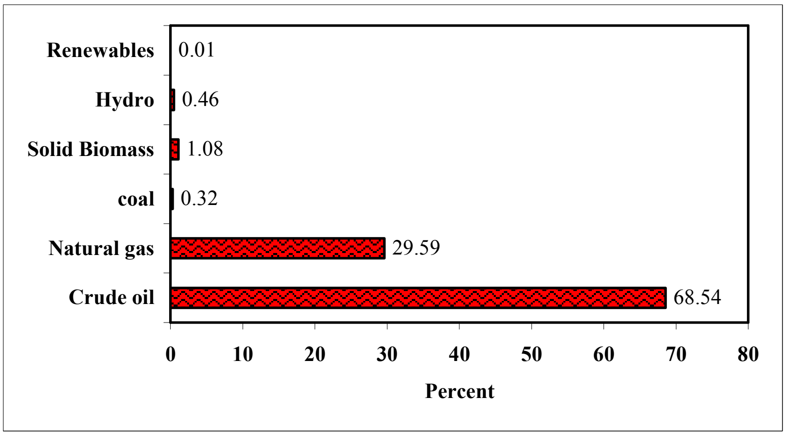


Figure 4. The share of energy carriers in final energy consumption

3.2- Increasing electricity demand: The demographic trend and intensified industrial growth have emerged in electricity demand growth by 8% annually. Accordingly, the Iranian energy sector has focused its efforts on meeting this continuous demand. Therefore, the electric power capacity expansion plans are provided to utilize oil efficient power plants as well as an emphasis on natural gas production.

3.3- The dominant share of gas fired power plants: Having the second estimated large gas reserves in the world, Iran has already imposed a comprehensive fuel-substitution policy to change the pattern of domestic energy consumption toward larger share of natural gas among other energy carriers and to promote its position in international gas markets. As Fig. 5 shows, during the last years, the share of gas fired technologies including gas turbine and combined cycle technologies has increased. Total nominal installed capacity of electricity generation in

Iran reached over 49.53 GW in 2007, showing a growth of 13% compared to 2006. At the same year, share of different types of power plants were as steam turbines 31.5%, combined cycles and gas turbines 52.6%, hydro turbines 15.0%, diesel 0.9%, and finally solar and wind power plants 0.1%.

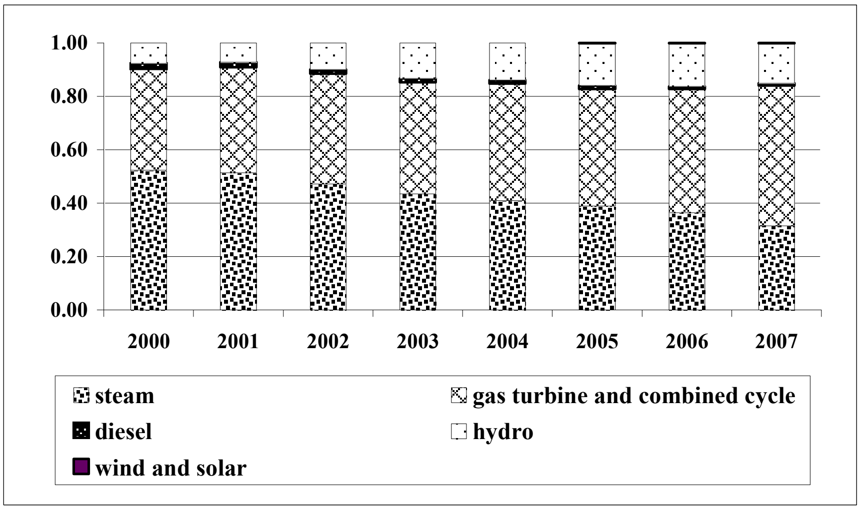


Figure 5. Share of different technologies in total installed capacity

6.4. Energy subsidzation: The energy market in Iran is almost a natural monopoly. The government, as the major supplier, sets the domestic prices of energy carriers which are much lower than their border prices (Fig. 6). Due to the large gap between domestic and border prices, total amount of implicit energy subsidy has reached to US$ 41.56 billion in 2006 out of which the share of electricity subsidies was 19.7% (MOE, 2008).

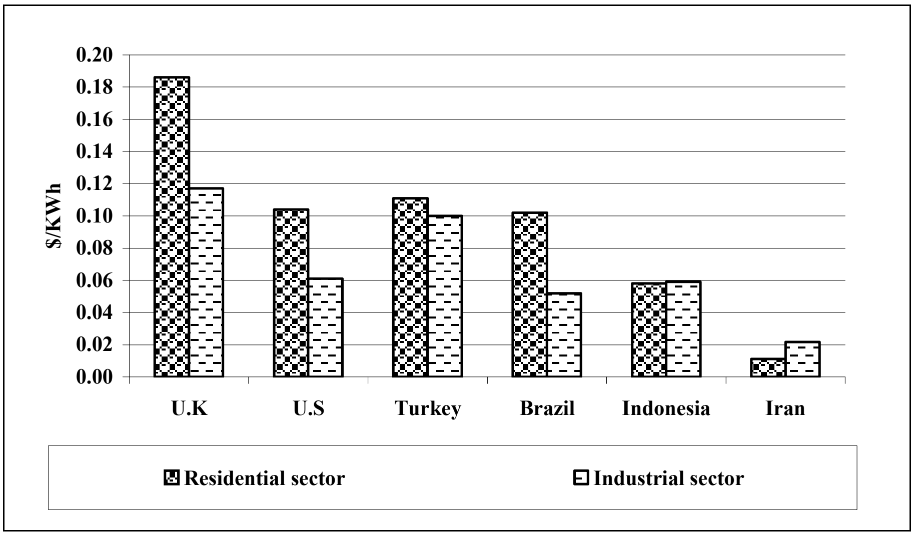


Figure 6. Industrial and residential electricity prices in different countries

6.5. High rate of GHGs emissions: Since 1990, GHG emission in Iran has risen dramatically by more than 147%. In the same period, per capita CO_2 emission has increased from 3046 Kg to 5972.6 Kg in 2006. Among all sectors, energy and transport sectors are playing crucial role in CO_2 emission. In 2006, highest emissions were caused by CO_2 emission in the power sector amounting 572.6 g/KWh. Among the thermal power plants, the lowest emissions were those of combined cycle and the highest were of gas fired power plants. Table 1, shows CO_2 emissions by different thermal power plants in 2006. (MOE, 2008)

Table 1. CO2 emissions by different thermal power plants in 2006

Power Plant	CO_2 **emission Million tones**	**Share in total power sector** CO_2 **emission**
Steam	58.11	52.67
Gas Turbine	32.25	29.23
Combined Cycle	19.68	17.84
Diesel	0.17	0.16

Considering that Iran has ratified the Kyoto Protocol, it will be very difficult to reduce GHGs emissions to 1990 baseline as a prerequisite of the convention. Mitigation policies in the energy sector are crucial to the Iranian energy and economic policies.

6.6. Renewable resources utilization: Total potential of hydro electricity generation in Iran is estimated to be 50 TWh annually while total potential wind power of the country is 12 to 15 GW (Atabi, 2004; Karbassi et al., 2007). The average annual solar radiation is estimated up to 5 KWh per square meter and the average sunny hours reaches to 2800 hours per year. In some regions such as inner deserts and their surrounding cities (e.g. Khour-o-Biabanak and Yazd), the average sunny hours even reach above 3200 hours in a year. In general, regions with annual direct solar radiation of at least 1800 KWh/m^2 will be preferable sites to build solar power plants (SAUNA, 2006). Fig. 7 shows total energy production of wind and photovoltaic (PV) technologies during the time span 1998-2007.

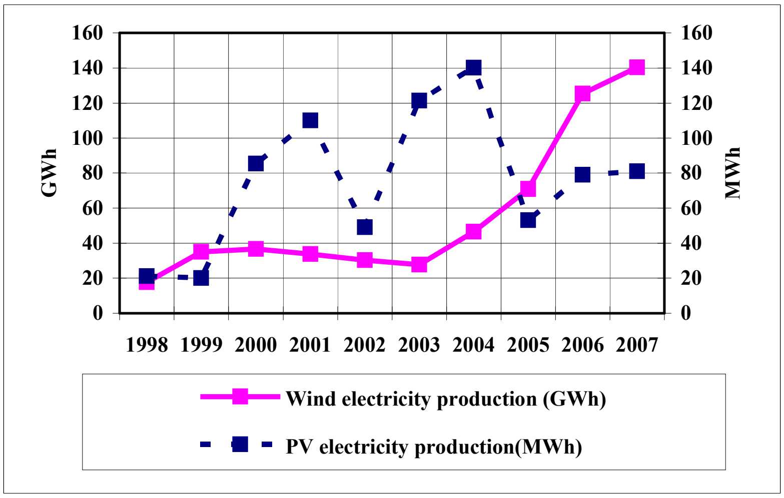


Figure 7. Total wind and PV power production during 1998-2007

Regarding renewable energy development in Iran, different policies has been pursued such as: encouraging private sector to invest in renewable energies, preparing power purchase agreements for all renewable energy sources, providing subsidies and supporting manufacturers and design companies for technology development and transfer for competitive technologies in mid-term like wind and PV power plants etc. Meanwhile, the fundamental factor for a successful development and utilization of renewable energy is the possibility of competition with other forms of energy regarding the cost and the price. This is more pronounced in Iran and other developing countries where financial resources are decisive.

7. Empirical results

The optimization model was run under 24 different scenarios as described in Table 2. The business-as-usual (BAU) scenario, namely B1, characterized as follows: all power generation technologies are non-learning technology and there is not any advantage for renewable energy technologicy learning because of subsidized fossil fuels and no environmental taxation. The remaining scenarios can be divided into non-learning and learning scenarios. To show whether "learning by doing" has any impact on the status of renewable energy utilization or not, it seems reasonable to use the expected value of these almost evenly distributed PRs as the most probable case. The expected values of PV and wind turbines PR are 86% and 80% respectively. To have an optimistic view, the maximum reported PR for both wind and PV technologies were considered 73% and 65%, respectively. Finally WP scenarios expect wind and PV technologies simultaneous learning.

Some important questions are the impact of fuel price distortions on the technology learning process and consequently, the share of renewable energy sources in future power supply; or whether imposing a CO_2 emission tax -in the case of subsidized fuel prices- can have any effect on renewable energy utilization assuming technological learning? To answer the above questions, different learning scenarios with the assumption of subsidized fuel prices are introduced.

Table 2. Scenarios description

Scenario	**Learning Technology**	**Progress Ratio %**	CO_2 **Emission taxation**	**Subsidy Removal**
B1 (BAU)	--	--	-	-
B2	--	--	+	-
B3	--	--	-	+
B4	--	--	+	+
W1	Wind	86	-	+
W2	Wind	86	+	+
W3	Wind	86	-	-
W4	Wind	86	+	-
W5	Wind	73	-	+
W6	Wind	73	+	+
W7	Wind	73	-	-
W8	Wind	73	+	-
P1	PV	80	-	+
P2	PV	80	+	+
P3	PV	80	-	-
P4	PV	80	+	-
P5	PV	65	-	+
P6	PV	65	+	+
P7	PV	65	-	-
P8	PV	65	+	-
WP1	Wind & PV	Wind(86) & PV(80)	-	+
WP2	Wind & PV	Wind(86) & PV(80)	+	+
WP3	Wind & PV	Wind(86) & PV(80)	-	-
WP4	Wind & PV	Wind(86) & PV(80)	+	-

7.1. Non-learning scenarios: As Fig. 8 shows, under BAU scenario, thermal power plants including gas turbine, steam and combined cycle power plants continues to have the dominant share in total power production capacity. The share of these technologies declines slightly in early periods but increases from 76.41% in 2015 to 87.27% in 2030. The initial decline in the share of conventional thermal plants is mainly because of the long-term government plan to promote the share of hydro energy. Although the installed capacity of large hydro power plants increases from 5.77 in 2005 to 15 GW in 2015, the share of this technology in electricity supply declines from 15.62% in 2005 to 11.86% in 2030. Therefore, the status of hydro energy in power production capacity mix will decline which indicates the government policy failure to promote renewable energy utilization. On the other hand, subsidy phase-out or CO_2 emission taxation policies have clear impacts on the power production capacity mix. By removing subsidies, the share of conventional thermal plants declines suddenly and remains below 75% during the planning period.

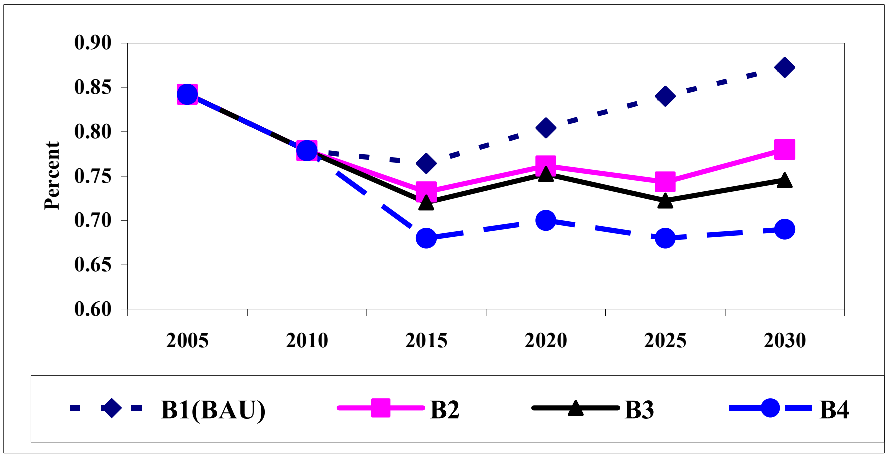


Figure 8. The share of thermal power plants under different non-learning scenarios

The results of different non-learning scenarios concerning RETs cumulative capacity are summarized in Table 3 which encompass the effects of subsidy removal and/or emission taxation on RETs status in the Iranian power sector. Two above mentioned policies only affect small hydro and to a lesser extent geothermal power generation technologies. This result has a clear implication: the government policy to promote the share of hydro energy in total installed capacity and to promote private sector participation in small hydro power plants utilization specially in rural and discrete areas, will be successful provided that the energy prices are rationalized and/or CO_2 emissions are taxed.

Table 3. RETs optimal cumulative capacity under different non-learning scenarios

	Small hydro	**Wind**	**PV**	**Solar thermal**	**Geothermal**
B1	0.00	0.56	0.00	0.00	0.00
B2	3.05	0.56	0.00	0.00	0.00
B3	7.25	0.56	0.00	0.00	2.30
B4	7.75	0.56	0.00	0.00	2.50

7.2. Learning scenarios: Fig. 9 shows the effect of endogenous technological leaning on wind energy technology installed capacity in the long run assuming two progress ratio (PR) ratios. The results show that considering PR=86%, if fuel prices are subsidized (scenarios W1 and W2) the optimal wind power installed capacity remains unchanged compared to the base scenario. While if subsidies are removed, cumulative wind power capacity increases to 2.61 GW (25.1 times more than the cumulative capacity in BAU scenario). This implies that, current slow path towards utilization of wind energy potential is mainly due to incorrect energy pricing policies. The results are highly sensitive to the level of PR ratio. **In an optimistic view of PR=73%, the cumulative capacity increases even when fuel prices are subsidized**.

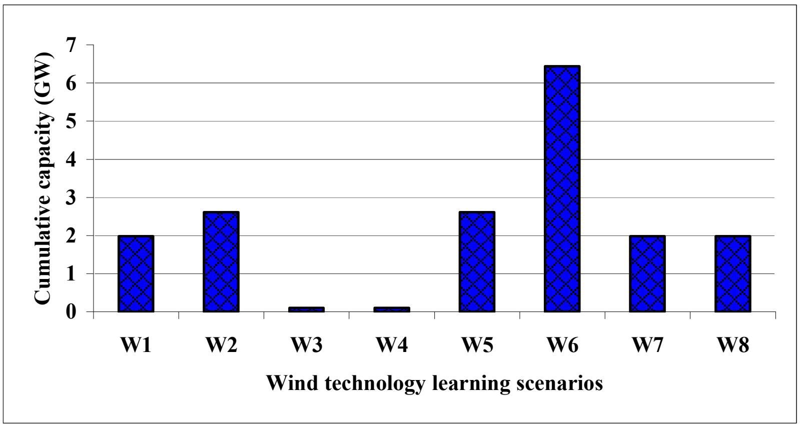


Figure 9. The effect of learning by doing on the wind energy technology installed capacity

A similar pattern can be witnessed in Fig. 10. As the figure shows, ETL can affect PV energy utilization only if government stops controlling fuel prices. In this case, PV technological learning causes a considerable increase in the share of PV units in the power supply. Assuming a PR=80%, the cumulative PV capacity reaches about 5 GW in 2030. Similar to wind technology learning scenarios, results of PV learning scenarios are, although to a lesser extent, sensitive to the level of PR. So, the results of PV learning scenarios also verify the fact that, ETL does affect the level of PV technology utilization only when energy subsidies are removed. For PV learning scenarios, an environmental tax accompanied by subsidy removal does not have considerable impact on the level of PV capacity. But CO_2 emission taxation can bring required money for research and development activities related to RETs.

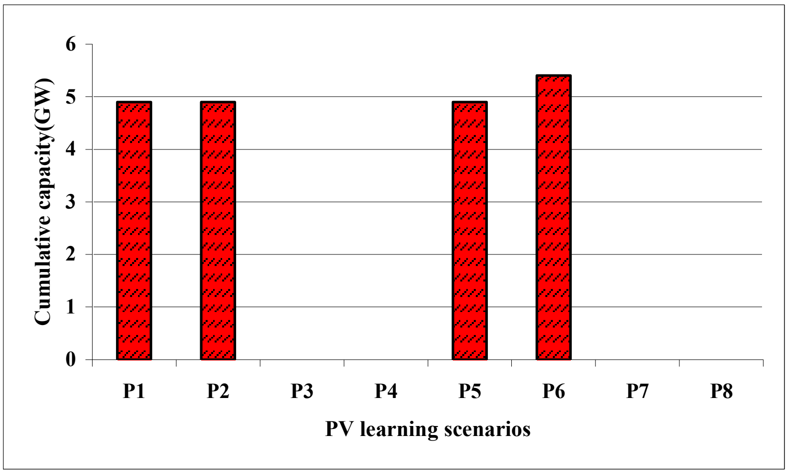
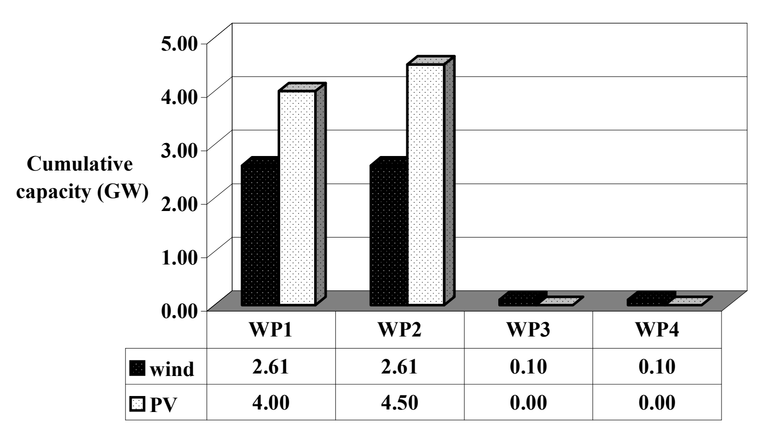


Figure 10. The effect of learning by doing on the PV technology installed capacity

WP scenarios expect simultaneous learning for wind and PV technologies with a PR of 86% and 80%, respectively. Results are shown in Fig. 11. Similar to wind and PV learning scenarios, ETL does not has any effect on wind and PV optimal capacities under subsidized fuel price assumption. Under both WP1 and WP2 scenarios, wind power cumulative capacity rises to 2.61 GW, while PV optimal cumulative capacity amounts to 4.00 and 4.50 GW under two above scenarios respectively.



	WP1	WP2	WP3	WP4
■ wind	2.61	2.61	0.10	0.10
☐ PV	4.00	4.50	0.00	0.00

Figure 11. Wind and PV technologies optimal cumulative capacities under WP scenarios

Fig. 12. also shows the effect of ETL on the share of various renewable technologies in total optimal RETs capacity. As the figure shows, wind and PV technological learning, strengthen the share of renewable technologies other than large hydro power plant in total renewable capacities. In other terms wind and PV ETL results in more diversified renewable capacity mix and consequently, more diversified power production system. Power capacity diversification in its terms makes the system more reliable and secure.

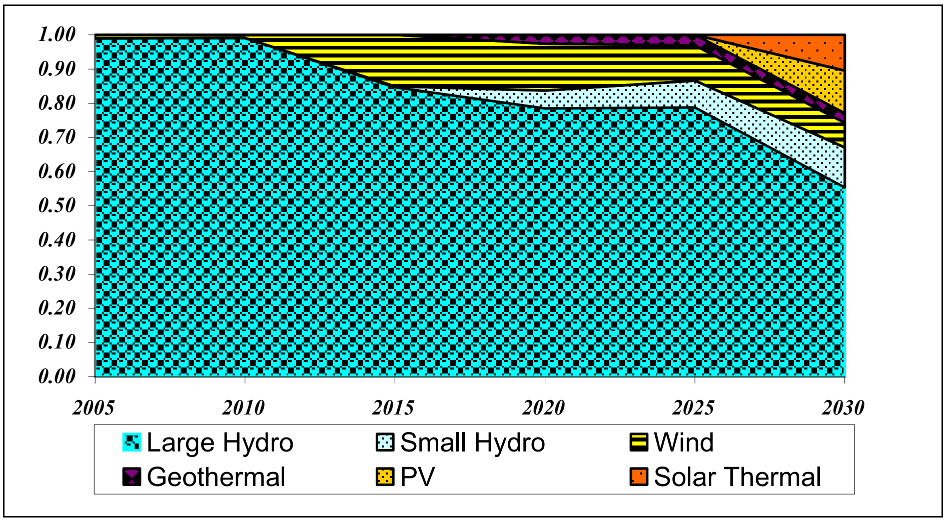


Figure 12. Share of different technologies in total RE installed capacity under joint learning scenario

7.3. The effect of technological learning on power sector CO_2 emission: As it is expected by increasing the share of renewables in total power production capacity, the level of CO_2 emission declines compared to BAU and other non-learning scenarios. Fig. 13 shows the anticipated total CO_2 emission in the Iranian power sector during 2005-2030 under BAU and other non-learning scenarios. Fossil fuels subsidy removal causes a considerable decline in total power industry CO_2 emission. Actually the negative effect of B3 scenario on accumulated emission is more than twice the effect of B2 scenario. An environmental tax imposed after subsidy removal policy can also decrease the accumulated emission slightly.

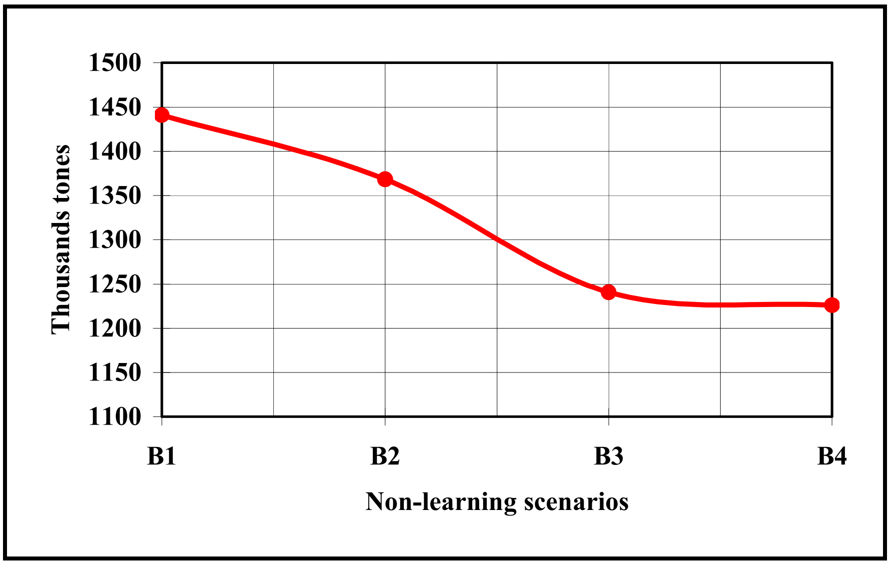


Fig 13. Power sector accumulated CO_2 emission under non-learning scenarios

Figs. 14 and 15 show the accumulated CO_2 emissions under different wind and PV ETL scenarios. The dashed line shows the level of accumulated power system CO_2 emission under BAU scenario. The results indicate a direct relation between renewable energies capacities expansion and emission reduction. As figures show, if an environmental tax is imposed, wind technological learning causes a reduction in CO_2 emission even without subsidy removal. A similar pattern can be observed PV.

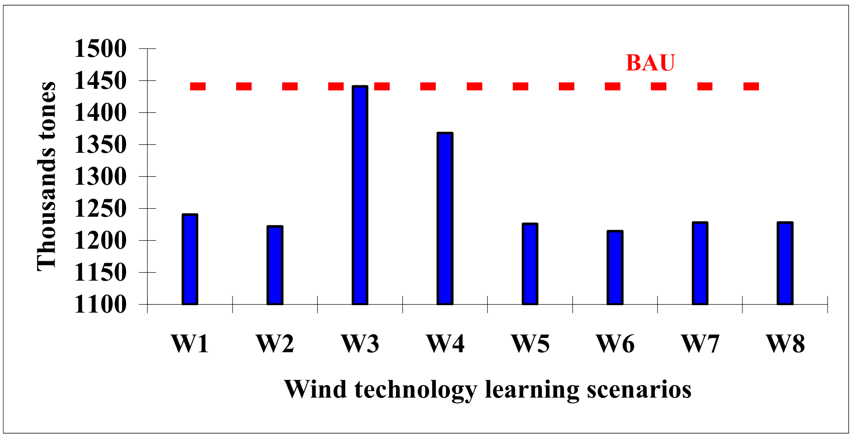


Fig. 14. Power sector accumulated CO_2 emission under wind technology learning scenarios

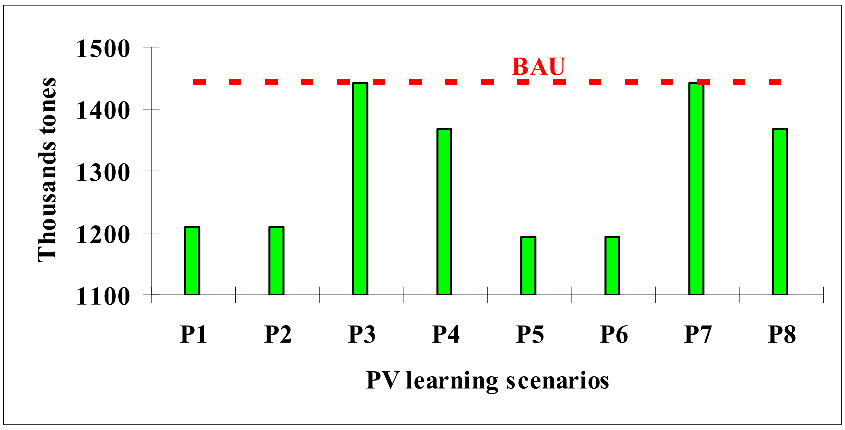


Figure 15. Power sector accumulated CO2 emission under PV technology learning scenarios

8.Concluding Remarks

This paper has surveyed the potential effect of technological learning on RETs share and also power sector CO_2 emission in the Iranian power sector. The results show that:

1- Considering a PR of 86%, if subsidies are removed, cumulative wind power capacity increases to 2.61 GW (25.1 times more than the cumulative capacity in BAU scenario). This implies that, current slow path towards utilization of wind energy potential in the country is mainly due to incorrect energy pricing policies. The results are highly sensitive to the level of PR ratio. In an optimistic view, if PR=73%, the cumulative capacity increases even when fuel prices are subsidized.

2- PV technological learning causes a considerable increase in the share of PV units in the country's power supply. Assuming a PR of 80%, the cumulative PV capacity reaches about 5 GW in 2030. Similar to wind technology learning scenarios, results of PV learning scenarios are, although to a lesser extent, sensitive to the level of PR.

3- Price distortion alters the expected positive effect of technological learning on the share of renewable energy. So apart from various inefficiencies of government intervention in market mechanism, the "crowding-out" effect of government direct (through thermal power plants capacity building) and indirect (through paying fossil fuels subsidies) expenditures in conventional thermal power capacity building, exacerbates the current situation in which steam and gas turbine power plants, mostly with small fuel efficiencies and high CO_2 emissions, play the dominant role in the power market.

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