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Computing optimal subsidies for Iranian renewable energy investments using real options

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Abstract

For the valuation of the renewable energy investments, providing private investors with a financial incentive to accelerate their investment is a very significant issue. Financial subsidies are known by the majority of the people to be one of the most important drivers in renewable energy expansion and one of the main reasons which result in the development of any industry. In this paper, we present a new approach to compute the optimal subsidies over a specific time period by using the Binomial model for the Valuation of Real Options for Iranian renewable energy investments adjusted with Tax rate. We also apply linear regression method for predicting energy prices in order to allow an investor to exercise the relevant option over the timeline of the project at the optimal price. To evaluate our proposed approach, we apply it using predicted electricity prices for the next 16 years and electricity generation cost for Seid Abad, Damghan solar power plant. Our results in comparison of the base paper show that our proposed approach improves the error of subsidy's computation by 1.57 percent since we used the predicted energy prices rather than the spot price as used before in real options' valuation.

Keywords: Real options, subsidy, renewable energy investment, binomial method

1- Introduction

Iran is currently producing only 0.2% of its energy from renewable sources. The renewable energy sector mainly comprises of wind (53.88 MW), biomass (13.56 MW), solar (0.51 MW) and hydropower (0.44 MW). Iran has 80 thousand MW capacity for all installed power plants and it has the first rank of electricity generation in the Middle East and fourteenth rank in the entire world (Fazelpour et al. 2015).

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There is an aggressive forecast that says Iran could achieve a renewable energy share of 75% to its neighboring countries because of the vast deserts and 66% renewable electricity by 2050. Iran is going to implement several measures to reach its goals, including a national carbon cap-and-trade program, a green dispatch policy, and a cap on coal consumption for 2022 to 2026 (Tofigh and Abedian, 2016). In addition, Iran has made efforts for electricity market reform, including launching carbon market, issuing green certificates and setting provincial renewables portfolio standards (RPS). As the second largest clean energy investor in Middle East after Saudi Arabia, Iran invested $100 billion for the next four years in clean energy and also plans to increase installed capacity of wind and solar power to around 45 GW and 30 GW respectively by 2030. These ambitious targets bring tremendous business opportunities to renewable power investors, manufacturers and developers.

Iran has a unique geographical position so that 90% of the country has enough sunlight to generate solar power 300 days a year. According to Press TV Iran has 520 watts per hour per square meter of solar radiation every day. Other sources give an average of 2,200 kilowatt-hour solar radiation per square meter. Energy generated by solar power reached 53 MW in 2005 and 67 MW in 2011. Iran has the potential to generate 20 to 30 GW of wind energy. That is half of the total energy consumption needs of the country. As of 2012 Iran had 163 wind turbines with an installed capacity of 92470 kWh.

Financial subsidies are important drivers in renewable energy expansion and one of the main reasons which leads to socio-economic development (Zhao et al. 2016). And also it is believed by the economists that the subsidies will increase the social welfare and external incentives are required to make up for the long payback period (Gatzert and Kosub, 2016). Renewable energy subsidies include feed-in tariff (FIT), rebates, renewable energy credits (REC) and premiums (Zhang et al., 2014). Various previous researches have mentioned the valuation of subsidies, most of them using quantitative analysis, cost-benefit and net present value (NPV) (Zhang et al., 2017). They used the real-options method to calculate the optimal level of subsidy for renewable energy investors in China, and how the government should adjust policies to absorb more renewable energy investments to improve electricity production and keeping the climate clean (Zhang et al., 2016). Real option is a method available for financial managers of a firm who consider the opportunities in a business investment. The reason that it is referred as "real" is because it usually references projects involving a tangible asset instead of a financial instrument. Tangible assets are physical assets such as buildings, land, machinery or an inventory. The managers can use them to make a better decision about expanding, abandoning, or curtail projects based on changing economic, technological, or market conditions by using real option value analysis (ROV) and estimating the opportunity cost of continuing or abandoning a project.

There are several methods to price the real options. Zhang et al. (2017) used the Longstaff-Schwartz Monte Carlo simulation least squares method (Schwartz, 2001) to value real options and solve the model. But in this paper, we use the binomial model which requires fewer calculations, converges faster and is more facile to implement. In this paper, we also focus on methods and results comparison between the Zhang et al. (2017) paper and our applied binomial model. In this paper, we use an American call option as a real option with a maturity of 15 years in order to compute our given subsidy by the government to our renewable energy plant by valuing the project during the next 15 years. More details will be explained in section of modeling method. Since investors can operate the project any time before the maturity, here we use an American style option. This paper aims at computing the optimal subsidy for the option's life time using valuation of real options by predicting the price of electricity rather than using the spot price of energy.

This paper is organized as follows. Next section is an introduction to real options method and summarizes past research regarding its application to renewable energy investments. Section 3 is about the data which we collected from a renewable energy plant in Tehran and then it proceeds with the details of our valuation model. Section 4 presents implementation of our option valuation model including computation of relevant parameters as well as the option value and the value of 15-year subsidies. This section also includes analysis of results. Finally, section 5 summarizes the outcomes of this research and gives some suggestions for improvement of our real option valuation model.

Real option valuation applies option pricing methods to capital budgeting decisions. Real option analysis are usually derived from conventional financial options in which they are not typically traded as securities (Zhang et al., 2014). Another difference between real options and financial options is that real option holders can directly affect the value of option's underlying projects. Furthermore, management is not able to measure uncertainty in terms of volatility and he can only depend on realization of uncertainty. Real options are more valuable when uncertainty is high so the option holder has such flexibility to change the path of project line in a favorable direction or exercise the options (Liu and Ronn, 2018). The development of real options usually needs decision support systems, because of the complexity of real options is sometimes so high to be handled easily. This approach is an advanced valuation technique, enabling the investors to take advantage of market opportunities and at the same time avoiding or reducing losses if future conditions evolve adversely (Pringles et al., 2015). The power of option theory applied to this arena permits the optimization and valuation of the flexibilities embedded in the operation of energy assets owners (Zhang et al., 2014).

There are significant studies that applied real option method to the oil field. McDonald and Siegel (1986) and Paddock, Seigel and Smith (Page, 1988) established the comparison among such a decision and the literature on the pricing of financial options. Schwartz (1997) and Schwartz and Smith (2000) addressed the significant matter of the number of factors about "sources of uncertainty" prevalent in the oil futures markets. In another study, Routledge, Seppi and Spatt (2001) derive equilibrium results for forward rates that they relate risk premia to the volatility of price changes and uncertainty in quantity demanded. At the end, in the field of renewable energy investments, Fleten, Linnerud, Moln´ar and Nygard (2016) compared two methods which are the real options and net present value in green electricity investments. Yang et al. (2007) assessed the power investment options by bringing and computing the uncertainties in weather policy. Boomsma et al. (2012) pursued a real options approach to analyse investment timing and capacity choice for renewable energy projects. Pringles, Olsina and Garc´es (2014) valued power transmission investments by stochastic simulation by real option analysis.

They are also some other option pricing methods using the same underlying stochastic process such as Geometric Brownian Motion (GBM). The most popular methods are Black-Scholes, binomial model and Monte Carlo simulation. We can conclude that these methods should produce the same values. Though the values of both Monte Carlo and binomial model should be the same, but the binomial value converges faster (Fleten et al., 2016). Longstaff and Schwartz (2001) derived a Monte Carlo simulation-based method that has been suggested in the past decade. Ronn (2004) used the binomial method to determine the optimal time to extract oil from a particular oil field. In this paper, we use the binomial method in order to value the real option which in this case is a 15-year to maturity American call option.

In the next section, we discuss about some basic and fundamental concept of the model and also we will explain the model used for valuation. And we will make some changes in model to make it batter by predicting the energy prices for the next 15 years and also adjusting the different tax rates, we will see that the optimal subsidy would be changed and become closer to the real one.

2- Modeling method

In this section, we explain our valuation model which we use for pricing the American-style option in order to achieve the optimal subsidy for a renewable energy plant in Iran. We also describe the fundamental concepts of model and also the changes that we have applied to our new model in order to consider the tax rates. First we need to have some data to make our valuation model (factors and parameters used in the model) which you can see in the following section. Our data belongs to Seid Abad solar energy power plant in Damghan, Iran which has a generating capacity of 1500 kW/h.

2-1- Data

The data that we used are shown tables 1 and 2 which were adopted from Zhang et al. (2017) in order to ensure comparability of results across our two different methodologies. Whereas they used three sources of uncertainty in a Monte Carlo model, we demonstrate below how we reduced uncertainty into a one-factor model and then employ the binomial model. Most of the data have been taken from ministry of energy of Iran (MOE) and Government law and value-added tax organization (EVAT).

Table 1. Main Stochastic Factors

Parameters	Variable	Initial Value	Drift Rate	Volatility	Source
Market Price of Electricity	$S_0 = F_0$	383311 IR/kWh	0.02	0.02	MOE of Iran
CO_2 Price	P_0	738.31 IR/kWh	0.02	0.03	MOE of Iran
Unit Investment Cost	K_0	73831680 IR/kW	-0.06	0.04	R&D section of PV power plant

Table 2. Other Parameters Used in the Model

Parameters	Variable	Value	Source
Unit Operation and Maintenance Cost	uomc	1230.52 IR/kWh	R&D section of PV power plant
Unit Generating Capacity	ugc	1500 kWh	R&D section of PV power plant
The Rate of Corporate Income Tax	τ	25%	Government law
Rate of Value-Added Tax	π	9%	EVAT
Magnitude of Installed Capacity	IC	1 kW	R&D section of PV power plant
Discount Rate	r	8%	Zhang et al. (2016a, 2016b)
Annual Decline Rate of the Unit Generating Capacity	N/A	2%	R&D section of PV power plant
Lifetime of Power Generating Project	N/A	25 years	R&D section of PV power plant

2-2- Valuation model

We used the same model as Zhang et al. (2017) model for using subsidy but we added the two tax rates to section of carbon credit and also we use the future prices of electricity for computing the project value for each year[9],

$$C = C\ (V, K, r, \sigma, T, N) \tag{1}$$

In equation (1),

C = Value of American-style call option on a futures contract
V = After-tax value of the project, including electricity generation, subsidy and carbon credits
K = Investment Cost of the project
r = Risk free rate, r = 8%
σ = Embedded volatility of project value
T = Time to maturity (length of option, 16 years)
N = No. of Time Steps in valuation

To implement this model, we need to determine the values of the futures prices for the next 16 years and the corresponding volatility for these maturities. The following two subsections explain essential parameters in order to use the binomial model for option valuation.

2-2-1- Electricity Production Value P_0

As the first step, we should calculate the electricity production value which is shown here as P_0. We consider 2% drift rate in electricity price. In order to obtain the present value of electricity.. Since the future price is the risk-neutral forecast of the spot price, which indicates $F=E^*(F_t)$ (Insley, 2002). F is the price of electricity which has been used in model and it is achieved by linear regression method

actually this is the prediction of spot price energy and we have obtained it for the next 25 years(lifetime of power generating project) regarding the historical data of energy price which we took from DOE (Insley, 2002). S_0 is 383311 IR/kWh. With drift rate $\mu_S = 2\%$, we have:
$E^*(Ft) = F_0 \exp\{.02 t\}$.

In this section, we need to calculate the value of electricity production for the whole lifetime of power generating project which is 25 years, which is unit generating capacity multiplied by installed capacity multiplied by the differences between the future price of electricity in that specific year (calculated by linear regression using historical data) and unit operation and maintenance cost, and then discount them back to today and sum up all the present values. Income tax applies to value of electricity production but in fact the operating and maintenance costs are exempted from income tax and only taxed for the value-add tax. Then the value of expected electricity production P_0 is calculated using equation (2):

$$p_0 = E^*\left[(1-\pi)\sum_{t=1}^{25}\frac{IC\ ugc\ (F_t - umoc)\exp\{-0.02t\}}{(1+\mathrm{r})^t} - \pi\sum_{t=1}^{25}\frac{IC\ ugc\ F_t \exp\{-0.02t\}}{(1+\mathrm{r})^t}\right] \quad (2)$$

$$= IC\ ugc\ F_0\frac{1}{\mathrm{r}}\left[1-\frac{1}{(1+\mathrm{r})^{25}}\right](1-\mathrm{r}-\pi) - \mathrm{IC\ ugc}\ (1-\mathrm{r})uomc\ \frac{1}{r+0.02}\left[1-\frac{1}{(1+\mathrm{r})^{25}}\right]$$

And also the price of CO2 is p_0 = 735.018 IR/kW, multiplied by installed capacity and unit generating capacity. Then we should discount all 25 years' values to today. V_0 (credit) notifies the present value of CO_2 credit at time t_0, which is calculated yearly. Carbon credit is actually a permit which let a country or a company to produce a certain amount (one tone of carbon dioxide or equivalent amount of a different greenhouse gas) of carbon emissions. The different work that we added to the base paper is that we also calculate the different tax to the carbon credit and then we adjust it so it would be much more precise[14], which is brought as shown in equation (3):

$$V_0(Credit) = IC\ ugc\ P_0\frac{1}{r}\left[1-\frac{1}{(1+\mathrm{r})^{25}}\right] + ugc\ (r+\pi) \quad (3)$$

k_0 = 73831680 IR/kW is the exercise today if there is no option to wait. K_T represents the exercise today, T years to maturity.

$$K_T = k_0 \exp\{-0.06T\} \quad (4)$$

2.2.2 Project Value V and Volatility $\boldsymbol{\sigma}$

In this part, we calculate V which is total value of project today when there is an option in it, 15 years to maturity which encompasses subsidy, carbon credits and production value. Also $\boldsymbol{\sigma}$ should be computed which represents volatility of project value.

$$V = D + P_0 + V_0(Credit) \quad (5)$$

Now we should calculate the derivative of V because joint volatility for V reflects every volatility component, and it will evolve from the given value today.

$$dV = dD + dP_0 + dV_0(Credit) \quad (6)$$

Since the D is constant then derivative of it is 0, dD=0, and volatility of the subsidy is zero, σ(dD/D) = 0 :

$$\frac{\mathrm{dV}}{\mathrm{V}} = \frac{\mathrm{P_0}}{\mathrm{V}}\frac{\mathrm{dp_0}}{\mathrm{p_0}} + \frac{\mathrm{V_0(Credit)}}{\mathrm{V}}\frac{\mathrm{dV_0(Credit)}}{\mathrm{V_0(Credit)}} \quad (7)$$

The second part we require to derive is the σ to apply in the call-option formula (1), we obtain the following formula by using (4) and (7):

$$\left\{\frac{P_o}{V}\right\}^2 \sigma^2 \left\{\frac{dp_0}{p_0}\right\} + \left[\frac{V_0(Credit)}{V}\right]^2 \sigma^2 \left[\frac{dV_0(Credit)}{V_0(Credit)}\right] + \sigma^2 \left\{\frac{dK}{K}\right\} \tag{8}$$

We recognize $\sigma\left\{\frac{dp_0}{p_0}\right\} = \sigma\left\{\frac{ds_0}{s_0}\right\} = 2\%$ and the volatility is given by the square-root of (8). In fact, we need to know for optimal early exercise is the volatility of the asset and how much in-the money we are.

D is part of V in equation (5), applying the American call option formula (C) for the whole option's life T=1 to T=16 for each year date that satisfies the two equivalent conditions for early-exercise. The first one is:

$$V - K_T = C(V, K_T, r, \sigma, T, N) \tag{9}$$

This equation shows that early exercise happens when the difference between project value and exercise value is equal to option's intrinsic value, also it means that option's time value is disappeared[15].

An equivalent condition is when $\Delta = 1.0$, where $\Delta \equiv \partial C/\partial V$is the partial derivative of the option with respect to value V. After that we can get all the subsidies from T=1 to T=16. The subsidy that incentivizes investors to exercise immediately the option is the maximum value of all subsidies, also it is the minimum subsidy that the government should pay to the renewable power plant (Zeng et al., 2012).

Since we have American-style call option, so we use the upper-case C:

$C = \max_T C$ (P0 + V0 (Credit) + DT, KT, r, σ, T)

Then we should solve for each D_T by satisfying the condition previously presented in equation (9):

P0 + V0 (Credit) + DT − KT = C (P0 + V0 (Credit) + D_T, K_T, r, σ, T) (10)

T = 0 is the first of the T's being considered, we must note that we are also satisfying the condition that the option value is greater than or equal to the following relation:

P_0+V_0 (Credit)+D_0–K_0:

$$C = \max C (P_0 + V_0 (Credit) + D_T, K_T, T) = P_0 + V_0 (Credit) + D_T - K_T \geq P_0 + V_0 (Credit) + D_0 - K_0.$$

For being sure that early exercise occurs, the following condition must be satisfied:

D = max {D1, . . . , D16} (11)

If we select a D value less than the maximum, the condition which we have in equation (10) will be violated for at least one T. Therefore, all the conditions must be met in order to early exercise.

3- Analysis of results

First we need to calculate electricity production price P_0 and also V_0 (credit) from equations (2) and (3),

$$P_0 = \mathrm{IC\ ugc\ S_0}\frac{1}{r}\left[1-\frac{1}{(1+r)^{25}}\right](1-\tau-\pi) - \mathrm{IC\ ugc}\ (1-\tau)\mathrm{umoc}\frac{1}{r+0.02}\left[1-\frac{1}{(1.02+r)^{25}}\right] = 21739642.76$$

$$V_0(\mathrm{Credit}) = \mathrm{IC\ ugc\ p_0}\frac{1}{r}\left[1-\frac{1}{(1+r)^{25}}\right] + \mathrm{ugc}(\tau+\pi) = 11770197.52 + 510 = 11770707$$

In order to compute the value of option, our inputs are strike price, volatility, risk-free interest rate, time to expiration and also future prices. As a fact, the subsidy will be calculated iteratively by solving equation (9) and satisfying the early exercise condition which is $\Delta \rightarrow 1.0$. We have the equations for strike price and also the option's futures price which is V in the previous section. The number of steps that has been considered is N=200. Since the V_T encompasses the value of subsidy in itself, we fix the subsidy at some value, calculating the V_T and the volatility, and then iterate to compute the subsidy at which the early-exercise happens. Then feed that back into the volatility computation and see if the process converges (Liu and Ronn, 2018).
For instance, for T=1:

$$K_1 = 73831680\,\exp(-0.06 \times 1) = 69532057.68$$

$$V_1 = D + P_0 + V_0(Credit) = D + 21739642.76 + 11770707 = D + 33510349.76$$

For that V_1 be at least as large as K_1, D should at least be 36021707.92. Now assume that:

D =36021707.92, then V_1 = 63216618.84, and set V_1 =63216618.84 into the equation (8),
Now we calculate the volatility as below:

$$\sigma_1 = \sqrt{\left(\frac{P}{V_1}\right)^2 \sigma^2 \left(\frac{dP_0}{P_0}\right) + \left[\frac{V_{0(Credit)}}{V_1}\right]^2 \sigma^2 \left[\frac{dV_{0(Credit)}}{V_0(Credit)}\right] + \sigma^2 \left\{\frac{dK}{K}\right\}} = 6.02\%$$

We should note that whenever V_1 changes, σ will be automatically changed. When the early exercise condition is met, V_1 =67439488.98, and thus D_1 =40020117.50 . Now consider for the last year of option's life T=16:

$$K_{16} = 73831680\,\exp(-0.06 \times 16) = 28269625.03$$

$$V_{16} = D + P_0 + V_0(Credit) = D + 27419371.48$$

For that V_{16} be at least as large as K_{16}, D should at least be 850253.55. Again assume that:
D = 850253.55, then V_{16} =28270135.03, and put V_{16} = 28270135.03 into the volatility equation

$$\sigma_{16} = \sqrt{\left(\frac{P}{V_{16}}\right)^2 \sigma^2 \left(\frac{dP_0}{P_0}\right) + \left[\frac{V_{0(\mathrm{Credit})}}{V_{16}}\right]^2 \sigma^2 \left[\frac{dV_{0(\mathrm{Credit})}}{V_0(\mathrm{Credit})}\right] + \sigma^2 \left\{\frac{dK}{K}\right\}} = 6.3\%$$

In this step we should repeat the iteration process, and try larger D until $V_{16} - K_{16}$ will be equal to the option value $\Delta = 1$ and we calculate that, When the early exercise condition is met, V_{16} =31586221.87, and thus D_{16} =4166850.39. By using the same method, we can obtain all the subsidies from T = 1 to T = 16, and the optimal subsidy level will be found and it is the maximum subsidy among all these years.

At the end we consider two scenarios, one with carbon credit existing and one without the carbon. For the one without carbon credits, we just need to put V_0 (Credit) = 0 in the model. The results for two scenarios are summarized as following table:

Table 3. Results of Subsidy by Time to Expiration T

T	Strike Price (K)	With Carbon Credit	Without Carbon Credit
16	28269625.03	4166850.39	15813244.44
15	30017721.02	6125270.07	17756388.45
14	31873913.22	8207861.89	19822736.06
13	33844885.94	10054630.00	21655100.19
12	35937736.80	12006233.68	23591480.55
11	38160002.34	14077308.99	25646401.47
10	40519685.10	16267738.27	27819745.40
9	43025282.49	18582637.43	30116588.34
8	45685817.37	21026254.25	32541144.95
7	48510870.55	23599867.77	35094684.29
6	51510615.25	26297332.66	37771108.95
5	54695853.81	29119036.45	40570803.46
4	58078056.52	32030940.10	43459994.25
3	61669402.96	34977786.59	46383855.34
2	65482825.87	37765516.18	49149840.64
1	69532057.68	40020117.50	51386856.06

Because of the fact that we can indicate the American-style option as a European option plus the early exercise premium, the American option is likely to inherit many of properties of the European option [Liu et al]. Therefore, we need to compute all D_T's from T = 1 to T = 16 in order to find the optimal subsidy. It is told that increasing the number of steps up to 500 will increase accuracy and as we discussed before we should consider the maximum subsidy as the optimal one, so according to table 3, with carbon trading, the investors need 40020117.50 IR/kW and without carbon trading, they need 51386856.06 IR/kW. For purpose of comparing results with the base paper, the following table represents the differences between our approach and previous one (Liu and Ronn, 2018)).

Table 4. Real subsidy vs. subsidies calculated from two different methods

(T) year	Real subsidy(without carbon credit) by the government (IRR)	Subsidy calculated from the forecasted electricity prices (IRR)	Subsidy calculated in basis of paper of Liu et al (spot prices of energy) (IRR)
16	15981924.78	15813244.44	15750604.80
15	17913299.23	17756388.45	17670209.76
14	19961648.52	19822736.06	19700561.16
13	21707608.37	21655100.19	21860116.74
12	23767102.36	23591480.55	24142723.92
11	25806620.87	25646401.47	26566840.44
10	28276105.85	27819745.40	29132466.30
9	30278094.92	30116588.34	31839601.50
8	33223924.26	32541144.95	34706703.78
7	36114228.58	35094684.29	37733773.14
6	39145959.17	37771198.95	40920809.58
5	42216231.87	40570803.46	44261660.52
4	45205083.56	43459994.25	47750173.38
3	48172796.63	46383855.34	51361737.84
2	51980029.32	49149840.64	55010217.78
1	54124335.71	51386856.06	58461815.16

In the second column of table (4), the subsidy given by the government to the solar power plant for

16 years have been listed. We can obviously see that these amounts are much closer to our proposed approach and we can conclude that when we use the forecasted electricity prices rather than taking the spot price into the account in computation of subsidy, the amount of subsidy will get closer to the reality.

Now we show that our method has superiority in comparison with the pervious paper by computing the errors between the real value and the two methods using two approaches. First we validate our work by calculating the MAPE, which is known as mean average absolute error. This method in statistic is a measure of prediction accuracy of a forecasting method. It is defined by the following formula:

$$M = \frac{100\%}{n} \sum_{t=1}^{n} \left|\frac{A_t - F_t}{A_t}\right| \tag{12}$$

Where A_t is the actual value and F_t is the forecasted value of methods. N is the number of the years starting from 1 to 16.

Now calculate the MAPE for column 2(actual value) and column 3(subsidy by using forecasted electricity prices) which is:

$$\text{MAPE} = \frac{0.3667}{16} \times 100\% = 2.2918\ \%$$

Second we calculate the MAPE for column 2(actual value) and column 4(subsidy by paper of Liu et al) which is:

$$MAPE = \frac{0.6186}{16} \times 100\% = 3.8662\ \%$$

It is clear that the first error is less than the second one by 1.5744% therefor we would better to use the forecasted price of energy in subsidy's calculations (McDonald and Siegel, 1986). Furthermore, due to comparison of predictability of approaches, the analysis of variance (ANOVA) utilized on data of table (5). The basis of F test in one-way ANOVA, k populations, each denoting one level of factor, could be considered with repetitions as shown in table(5) (Hossain et al., 2019). Since each repetition would be returned to the population and measured an infinite number of repetition would be taken on each population. So, the mean of Y_{i1} is $E(Y_{i1}) = \mu_1$, $E(Y_{i2}) = \mu_2$ and so on. The parameter μ denotes an overall model parameter. The factor effect in the model is $\tau_j = \mu_j - \mu$, the random error is $\varepsilon_{ij} = Y_{ij} - \mu_j$ and the model is either:

$$Y_{ij} = \mu + \tau_j + \varepsilon_{ij} \tag{13}$$

$$Y_{ij} = \mu + (\mu_j - \mu) + (Y_{ij} - \mu_j) \tag{14}$$

Because these averages are unknown, random samples are drawn from each population and estimation can be made of the factor means and the grand mean. Here the ''dot notation'' indicates a summing over all repetition in the sample. The $T_{.j}$ represents the total of repetition taken under factor j, n_j represents the number of repetition taken for factor j and $\bar{Y}_{.j}$ is the sample mean for factor j. Also not that the grand total of all observation taken is:

$$T_{..} = \sum_{j=1}^{K} \sum_{i=1}^{n_j} Y_{ij} = \sum_{j=1}^{k} T_{.j} \tag{15}$$

The total number of observation is:

$$N = \sum_{j=1}^{k} n_j \tag{16}$$

And the mean of all N observation is:

$$Y_{..} = \sum_{j=1}^{k} \frac{n_j \bar{Y}_{.j}}{N} = \frac{T_{..}}{N} \tag{17}$$

In this sample which we mentioned, statistics are substituted for their corresponding population parameters in equation (17), we obtain the sample equation of the form as following equation:

$$Y_{ij} - \bar{Y}_{..} \equiv \left(\bar{Y}_{.j} - \bar{Y}_{..}\right) + (Y_{ij} - \bar{Y}_{.j}) \tag{18}$$

This equation denotes that the deviation of an observation from the grand mean can be separated into two parts: the deviation of the observation from its own treatment mean plus the deviation of the treatment mean from the grand mean.
If both sides of equation (18) will be squared and then added over i and j, it is summarized as bellow:

$$\sum_{j=1}^{k}\sum_{i=1}^{n_j}\left(Y_{ij} - \bar{Y}_{..}\right)^2 = \sum_{j=1}^{k}\sum_{i=1}^{n_j}\left(\bar{Y}_{.j} - \bar{Y}_{..}\right)^2 + \sum_{j=1}^{k}\sum_{i=1}^{n_j}\left(Y_{ij} - \bar{Y}_{.j}\right)^2 + 2\sum_{j=1}^{k}\sum_{i=1}^{n_j}(\bar{Y}_{.j} - \bar{Y}_{..})(Y_{ij} - \bar{Y}_{.j})$$

By examine the last expression on the right, we have:

$$2\sum_{j=1}^{k}\sum_{i=1}^{n_j}(\bar{Y}_{.j} - \bar{Y}_{..})(Y_{ij} - \bar{Y}_{.j}) = 2\sum_{j=1}^{k}(\bar{Y}_{.j} - \bar{Y}_{..})\left[\sum_{i=1}^{n_j}(Y_{ij} - \bar{Y}_{.j})\right]$$

The term in brackets is equal zero, since the sum of the deviation about the mean within a given treatment equal zero. Therefore:

$$\sum_{j=1}^{k}\sum_{i=1}^{n_j}\left(Y_{ij} - \bar{Y}_{..}\right)^2 = \sum_{j=1}^{k}\sum_{i=1}^{n_j}\left(\bar{Y}_{.j} - \bar{Y}_{..}\right)^2 + \sum_{j=1}^{k}\sum_{i=1}^{n_j}\left(Y_{ij} - \bar{Y}_{.j}\right)^2 \tag{19}$$

In equation (19) could be referred as the base equation of analysis of variance. It defines the concept that the sum of the squares of the deviations from the grand mean is equal to the sum of the squares of the deviations between treatment means and the grand mean plus the sum of the squares of the deviations within treatments (Rouder et al., 2016). This is,

$$SS_{total} = SS_{between} + SS_{within} \tag{20}$$

Also it is expressed as:

(21)

Table 5. Real subsidy vs. subsidies calculated from two different methods

	treatment		
Years	Real subsidy	Subsidy calculated	Liu et al (spot prices of energy)
16	15981924.78	15813244.44	15750604.80
15	17913299.23	17756388.45	17670209.76
14	19961648.52	19822736.06	19700561.16
13	21707608.37	21655100.19	21860116.74
12	23767102.36	23591480.55	24142723.92
11	25806620.87	25646401.47	26566840.44
10	28276105.85	27819745.40	29132466.30
9	30278094.92	30116588.34	31839601.50
8	33223924.26	32541144.95	34706703.78
7	36114228.58	35094684.29	37733773.14
6	39145959.17	37771198.95	40920809.58
5	42216231.87	40570803.46	44261660.52
4	45205083.56	43459994.25	47750173.38
3	48172796.63	46383855.34	51361737.84
2	51980029.32	49149840.64	55010217.78
1	54124335.71	51386856.06	58461815.16
Total	533874994.00	518580062.84	556870015.80
Number	16	16	16
Means	33367187.13	32411253.93	34804375.99

Table (6) demonstrates the result of ANOVA for two approaches with a confidence level of 95%.

Table 6. ANOVA analysis of the relevant data with a confidence level of 95%

source	***SS***	***d.f***	***MS***	***F***	***F Crit***
Between	46433884259400.00	2	23216942129700.00	0.09	19.50
Within	7091751260958280.00	27	262657454109566.00		
Total	7138185145217680.00	29			

According to the result of ANOVA test, calculated F is less than the critical F value with confidence level of 95% and degree of freedom (2-27). This means there is no significant differences between Factors. In another word values of two approaches are valid .in addition, since by the view of statistical matter there is no significant differences between approaches, by estimating the error percentage of both approaches, the predictability of them has been assessed. The results of error's estimation are summarized as bellow:

Table 7. Computation of error of two methods

Years	|Error%| (our method)	|Error%| previous method
16	1.06	1.45
15	0.88	1.36
14	0.70	1.31
13	0.24	0.70
12	0.74	1.58
11	0.62	2.95
10	1.61	3.03
9	0.53	5.16
8	2.06	4.46
7	2.82	4.48
6	3.51	4.53
5	3.90	4.85
4	3.86	5.63
3	3.71	6.62
2	5.44	5.83
1	5.06	8.01
Means	2.30	3.36

According to the obtained results from computation of errors, we conclude that the proposed approach is able to predict the subsidies better in comparison with the previous one.

4- Discussion

In conclusion, we take the benefits of the binomial model to implement the valuation of the required subsidy in Iranian renewable energy investment. This paper provides Iranian government with resources of subsidy setting and provides Iranian energy investors with references to select the proper timing about when it is suitable to operate the project. For option valuation, the binomial model is more effective, practical, and simpler than Monte Carlo method used in the previous studies. As we have seen before for the American style option, the Monte Carlo simulation needs effortful Longstaff-Schwartz model. Quite the contrary, the binomial model merely necessitates the implementation of a binomial network. Since we have added the different tax rates to our price of carbon credit we conclude that the project value has been achieved precisely.

Considering that in this work as a new study, we did not consider the spot price as the price that should be used in our model (we just wrote the spot electricity price S_0 over and over in the equations but that was actually the predicted electricity price for the next 16 years). In the base paper it is said "Since the future price is the risk-neutral forecast of the spot price, so we replace this price by the predicted one for the next 16 years. We also showed by two different methods that our approach had better result by 1.574% Mean Absolute Percentage Error (MAPE) in comparison with the base paper and also by analysis of variance we represented that by using the future prices for electricity we can have a better estimation of the subsidy.

The limitation of the linear regression model can be that, this only is able to model the relationships between dependent and independent variables that are linear. Another disadvantage is that if we have a number of parameters than the number of samples available then the model begins to model the noise rather than the relationship between the variables.

This work can also be conducted and developed to other regions for future analysis by the data for three main parameters and adjusting the tax rates for that specific country.

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