

An Optimal Feed-In-Tariff Policy for Renewable Energies Using A Markov Model

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Abstract

Recent developments in renewable energy generation make it possible for renewable sectors to supply considerable share of electricity all around the world. As these sectors get larger, more attention is paid to the implementation of supportive strategies with the aim of motivating renewable energy (RE) developers. At present, Feed-In-Tariff (FIT) policies are regarded as one of the efficient strategies in stimulating renewable energy development and as such, designing approaches and controlling options of these policies are of utmost important. This paper presents a method based on a Markov chain model to investigate the economic benefits associated with the FIT policies. The proposed technique is used to study different aspects of FIT policies by dividing electricity prices, generation conditions and developer's cost-benefits into distinct states. Simulations are performed on a sample wind turbine to examine various features of designing premium price FIT policy.

Keywords

Feed-In-Tariff, Markov Chain Model, Premium Price FIT, Renewable Energy

Received: March 23, 2015 / Accepted: April 5, 2015 / Published online: April 10, 2015

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1. Introduction

Renewable energy technologies (RET) play a significant role in electricity generation; and thus, more efforts are made to expand these eco-friendly energies [1]. The reasons for supporting RET vary from one country to another and are strongly dependent on the overall situation from the environmental phases to the economic and social aspects. Commonly, the main reasons for supporting renewable energies (RE) are the global warming, fuel depletion, security of supply, expansion of distributed generations (DGs) [2], and expansion of plug-in hybrid vehicles [3].

Experiences around the world have shown that the strategies devised to support RE developers play an undeniable role in developing RETs [4]. Based on such experiences, various schemes have been developed and successfully implemented to reassure the RE sectors, such as Renewable Obligation Certificate (ROC) [5], Non-Fossil Fuels

Obligation (NFFO) [6], Renewable Energy Certificates (REC) [7], and Feed-In-Tariffs (FIT) [8].

Among the above policies, FIT is known as the one of the successful strategies [9]. FIT refers to an above market energy payment for the electricity fed into power grid generated by a renewable energy resource. Under this strategy, the government guarantees to purchase all the electricity generated by renewable generations according to a certain remuneration model [9], [10].

FIT policies are categorized into two main groups as shown in Fig. 1: market independent (fixed price) policy and market dependent (premium price) policy [11]. As shown in this figure, in the market independent FIT, the producer sells electricity on higher rate (solid line) as compared with the market price (dashed line) in the initial years of the project as an incentive. This rate is fixed through the project period. However, the market price may increase annually and after a few years, the producer may receive less as

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compared with the market price. On account of this fact, the RE developer is motivated to expand its facilities and generate as much electricity as possible in the initial years of the project [11].

In the market dependent FIT policy, the RE developer receives a certain premium on top of the market price as an incentive for the whole duration of the project period. However, the developer might face more difficulties in the beginning of the project as compared with the fixed price policy since less incentive is given to the RE developer [11]. In both policy models, incentive payments are determined with respect to some critical parameters such as the technology aspects (type, maturity, generation cost, etc.), the environmental conditions (wind speed, sunshine radiation), the project size, the plant sites and the electricity application (base or peak load) [12]. Details of the differences between these two types of policies are discussed in [13]. Policy makers analyze several designing factors in order to employ the mentioned policies [12]. Not only do they need accurate information about current and near-future markets, but also they must be able to accurately predict the long-term market and technological trends [13]. A number of approaches have been proposed to analyze FIT models. Muhammad-Sukki in [14] have studied general financial aspects of FIT in Malaysia and compared the results with the other countries. Dusonchet and Telaretti [15] have investigated different incentive policies in Western European countries and performed economic analyses on various aspects of these policies. Lesser and Su [16] have overviewed the performance of some current FIT policies in different countries and modeled a two-part FIT on a forward capacity market to ensure security of development and stability of the whole market. Shrimali and Baker [17] have derived an optimal FIT schedule under production-based learning. They have performed two dynamic approaches, the learning-by-doing (LBD) and the economies of scale (EOS) method to investigate how the levelized cost of renewable technologies can be reduced.

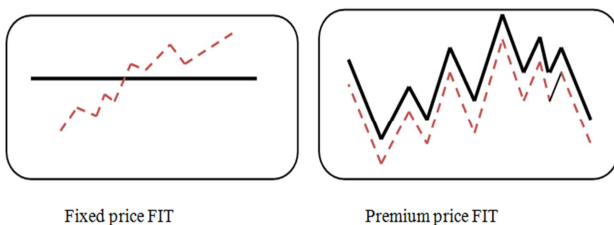


Figure 1. Market dependent and independent FIT Policies (the dashed line is the market price and the solid line is the FIT price [11]).

In [18], the impact of regulatory uncertainty induced by regulators considering moves from a FIT scheme to a more market-oriented regulatory regime is studied. Besides,

numerical solutions reflecting current and expected future revisions in FIT levels is developed to show the potential changes in regulatory regimes. In [19], different FIT policies is studied for Photovoltaic systems. The advantages and disadvantages of each policy is investigated and compared. Lack of a comprehensive method with practical characteristics is discernible. This paper presents a novel approach, based on the Markov chain theory to analyze various scenarios of the FIT policies by modeling the cost and benefit of the RE developer during the project period. Furthermore, a sensitivity analysis is performed to investigate the impacts of variation in the parameters in the FIT model.

2. Price and FIT models

Markov chain is a mathematical model that undergoes transitions from one state to another (from a finite or countable number of possible states in a system) in a chainlike manner [20]. It is a random process characterized as memory less (i.e. exhibiting the Markov property), which means that the next state depends only on the current state and not on the entire past. Markov chains have many applications as statistical models of the real-world processes, and can be used for modeling the systems with random behavior. Under this model, the system behavior is described by different states .

There are two main Markov models: the discrete model and continuous model [21]. The continuous one is utilized in this paper to model the electricity price, generation, load demand, and cost-benefit of RE developer. In all steps, the Markov chain theory will be applied to calculate the main parameters such as the state probabilities and the transition rates. The explanation of this theory is beyond the scope of this paper and is presented in detail in [21]-[24].

2.1. Price Model

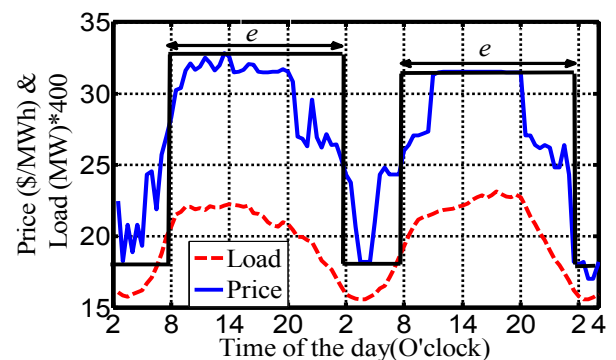


Figure 2. Daily electricity price and load variation in NSW region in Australia. (Source: AEMO [25])

Since the electricity price is a reflection of the electricity load variation, the price can be determined as a stochastic

system in time, which can be modeled with Markov chains [23]. Fig. 2 shows the electricity price and the load demand variation in a typical day in the NSW region in Australia [25]. J.D. Hall et al [23] have described how the load demand can be represented by a simple Markov chain model regarding to peak levels. Since the electricity price almost always follows the load demand in competitive markets, it can be modeled similarly. Consequently, the price variation can be approximated by two step function as a daily price model. This model consists of a peak price level with duration e (exposure factor), and a low price with duration of $1 - e$ for the remaining time. This two-level daily model for the electricity price can be used in all days of period D (days). Fig. 3 represents an approximation model for the price cycle for period $D = 7$ days. To obtain the Markov model of electricity price, it is assumed that the price data for the past years (e.g., the past 10 years) are available. First, the price data of each of the previous years are discounted back to its value in the first year using the average inflation rate. Second, the calculated values are considered to determine a two-level model for the electricity price in upcoming years.

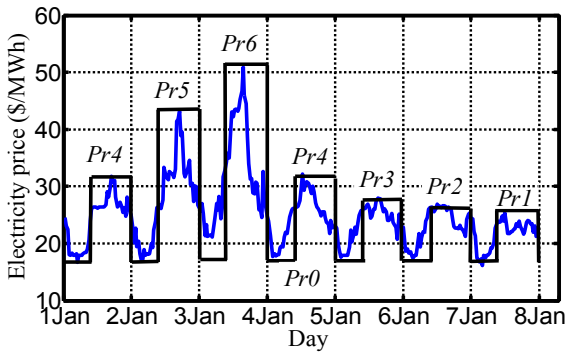


Figure 3. Price cycle approximation with peak levels and fixed low level. (Source: AEMO [25])

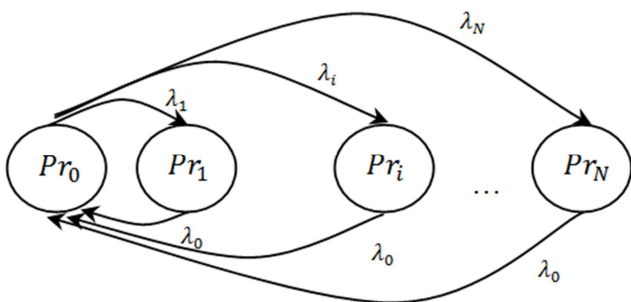


Figure 4. Markov model for the electricity price.

The Markov chain for this price model is depicted in Fig. 4. This model contains $N + 1$ states Pr_0, Pr_1, \dots, Pr_N and each state occurs on average n_k times during the past years [23]. The peak price returns to the low level (usually during nights) every day [23]. Additionally, the exposure factors for all days can be assumed to be equal to the average of exposure

factors for all days [25]. These assumptions are acceptable for modeling the market price in a period of a month or a year. To study longer cycles, the price levels for the initial year should be updated by taking into account the inflation rate. Therefore, the proposed model can be applied with new parameters [23], [24].

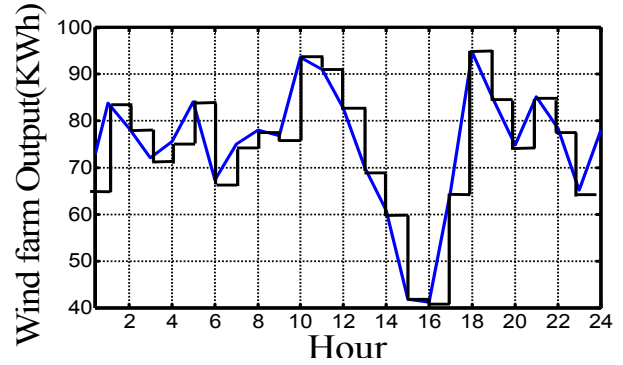


Figure 5. Two states Markov model for Generation and load for certain day. (Source: AEMO [25])

2.2. Generation-Load State Model

On a given day, output generation of a RE plant varies hourly and may be different from its local load demand. As an example, Fig. 5 shows the output power for a certain wind turbine in Tasmania [26]. Using the Markov chain theory [20], generation of the RE plant, as shown in Fig. 5, can be approximately modeled by a number of average states denoted by G_1, G_2, \dots, G_m in descending order of generation level. In this paper, for the sake of simplicity, it is assumed that the load is constant. The method can be also applied for variable load demand which can be modeled with different states (see the general case in [21] and [22]). By combining the generation and load Markov models, margin states are defined as the difference between the available capacity and the load demand [21]. They are represented by n states M_1, M_2, \dots, M_m as follows:

$$M_i = \begin{cases} G_i - L > 0, & i \leq k \\ G_i - L \leq 0, & i > k \end{cases} \quad (1)$$

$$M_j = G_i - L_k \quad (2)$$

Index k denotes the last state in which generation is more than load. Note that with generation states ordered descending, M_i values are also in descending order. The state probabilities and transition rates of the margin states can be calculated using the Markov chain theories which are explained in detail in [21]. For simplicity and without loss of generality, it is considered that there are m distinct generation states all equally likely. Thus, the transition rate and probability of each state are

$$\lambda_{ij} = 1 \quad (3)$$

$$p_i = 1/m \tag{4}$$

An advantage of modeling the generation and load using the Markov theory is the ability of modeling variation in the renewable energy sources such as wind turbines and PV cells [22]. Moreover, by considering more levels in shorter time intervals and acquiring more data on the past behavior of the generated power, more accurate margin states model can be obtained [23].

2.3. Cost-Benefit State Model

To analyze FIT policies using Markov model, it is required to develop a cost-benefit Markov model that shows the costs and benefits of trading electricity between the market and the RE developer. In steps *a* and *b*, two Markov chain models are obtained, one for the market price levels and the other one for the margin levels. It can be considered that for the small scale of renewable generations in the electricity markets, these two models are mutually exclusive. The combination of these two state models will be a Markov model with $m(N + 1)$ states. In this mixed Markov model, state S_{ij} ($i = 1, 2, \dots, m, j = 0, 1, \dots, N$) denotes the state, in which the margin level is in state i , (M_i) and the market price is in state j , (Pr_j). Method of combination the two Markov models is similar to the method used in developing margin states model from the load and capacity, as discussed in [21].

To obtain a Markov model for the cost and benefit of developer in the premium price FIT scheme, it is essential to distinguish all situations in which the RE developer would make benefit or pay cost. In this paper, it is assumed that the

$$CB_{ij} = \begin{cases} M_i \cdot Pr_j \cdot (a + 1) & 1 \leq i \leq k, j = 0, 1, \dots, l \\ M_i \cdot Pr_j \cdot (b + 1) & 1 \leq i \leq k, j = l + 1, \dots, n \\ M_i \cdot Pr_j > k, j = 0, 1, \dots, n \end{cases} \tag{5}$$

where CB_{ij} (\$/year) denotes the state ij of the cost-benefit model. This approach can also be applied for modeling other types of FIT policies. Additionally, the above model contains only the cost and benefit of buying and selling electricity; however, other costs such as the investment, operation and maintenance costs can be added to the model to determine the total RE developer's profit.

3. A Premium Price Fit

In this section, the proposed model is used for a specific wind turbine project, to investigate the characteristics of a given FIT policy. The results are used to present design issues for an appropriate premium price FIT. The price levels and transition rates are given in Table I. The operational data of the wind turbine is given in Table II. To obtain the Markov model for the electricity market, it is assumed that the

FIT payment is "Net", which means that the RE units sell their extra generation over the local load to the grid and receive FIT support [13]. This approach is different from "Gross" payment, in which the RE units receive government's support for all their generated electricity [13]. Accordingly, positive margin state M_i , corresponds to the states S_{ij} ($0 \leq j < n, i \leq k$), in which the developer would sell its extra generated electricity (with the amount of M_i) to the grid based on FIT price and makes benefit. On the contrary, if the load demand exceeds the generation of RE plant then the developer will buy electricity from the grid but based on the market price. In this case, we are in the margin state $M_i \leq 0$ corresponds to the states S_{ij} ($0 \leq j < n, i > k$). It is important to note that the Gross FIT policies can also be examined with a little change in modeling of the cost and benefit. In addition to the above issues, there are other costs such as investment, operation and maintenance costs that will be considered in the model in the simulation. Consistent with the market dependent FIT policies, the premium amount declines as the electricity prices increase [13]. In its simplest form, when the current electricity price is in the lower levels (first l levels), the developer sells its extra generation at a percent higher than the market electricity price. If the current market price beat the higher levels, the developer will sell its extra generation at " b " percent higher than the market price, and $b < a$. Parameters a and b are premiums of the market dependent FIT. This kind of FIT modeling mainly prevents windfalls phenomena that cause unreasonable profits for the RE developers [13]. Accordingly, the cost and benefit for premium price FIT are as follows:

simulation is performed for the NSW market from 2006 to 2014 [25]. The Markov model is obtained for the next 30 years of the project period. The parameters of this model are $D=365$ (days), $N = 9$, $e = 0.5$. Hence, nine peak levels and one low level for the price in each year is considered. According to Table I, the data for this price model can be calculated as shown in Table III. The generated electricity is also modeled with $m = 10$ distinct equally likely levels with transition rates of $\lambda_k = 1$ ($trans/hour$) = $24(trans/day)$. Local load level is assumed to be constant at $L = 10$ KW. Accordingly, the margin states model data for this proposed turbine are calculated as shown in Table IV. Using the data given in Table IV for the wind turbine, the present worth of total cost for studied turbine can be calculated as:

$$C_t = G \cdot (C_{inv} + C_{O\&M} \cdot \sum_{j=1}^{29} (1 + INF)^{-j}) = 233,600(\$) \tag{6}$$

where G is the generation capacity of the wind turbine. C_{inv} is the investment cost. $C_{O\&M}$ is the operation and maintenance cost. INF is the Inflation rate. Renewable sources have high capital cost. Hence, it is imperative for the RE developer to setup a project with an acceptable payback period. In the following subsection, the effects of FIT parameters will be examined to design the best policy.

Table I. Transition rates and state probability for price Markov model

State number	Price States Data	
	Transition rate to the state	State probability
Low level Pr_0	$1/e$	$1 - e$
Peak level Pr_k	$n_k/D(1 - e)$	$n_k e/D$

Table II. Operational data for the proposed wind turbine

Generation capacity, G	100 KW
Generation cost, C_{gen}	2000\$/ KW
Maintenance cost, $C_{O\&M}$	15 \$/KW.Year
Capacity factor, C_{fac}	0.36
Inflation rate, INF	2% per Year
Plant life	30 Years

Table III. Price levels, transition rates and probability of each price level

Price level state	Price level data			
	Price level Pr_i (\$/MW)	n_k	λ_k	p_k
1	37	73	0.4	0.100
2	39	63	0.34	0.085
3	41	51	0.28	0.070
4	43	44	0.24	0.060
5	45	37	0.20	0.050
6	47	32	0.18	0.045
7	49	32	0.18	0.045
8	51	25	0.14	0.035
9	53	8	0.04	0.010
0	35	365	2.0	0.500

Table IV. Generation and margin levels for a sample wind turbine

State number	Generation levels data			
	Generation level G_i (KW)	Margin level $M_i = G_i - L$	λ_k	p_k
1	72	62	24	0.166
2	64	54	24	0.166
3	56	46	24	0.166
4	48	38	24	0.166
5	40	30	24	0.166
6	32	22	24	0.166
7	24	14	24	0.166
8	16	6	24	0.166
9	8	-3	24	0.166
10	0	-10	24	0.166

3.1. Premium FIT calculation

Fig. 6 shows the payback period of implementing the proposed wind turbine in terms of FIT payment parameter a . It is assumed that $b = 10\%$ is applied to the three highest

price levels. By increasing the payment, the payback period will decrease, but choosing a proper payment depends on various factors from both RE developers' and the government's points of view. For instance, choosing $a = 53\%$, results in about 20 years payback period. Besides, Fig. 7 illustrates that by choosing $a = 53\%$ as an incentive, the RE developer's present value of gross benefit in 30 years will be 8.5×10^4 (\$), which is enough for such a small-scaled project. The results presented indicate that the proposed method can easily model the cost, benefit and payback period of the RE developer to design a proper FIT policy.

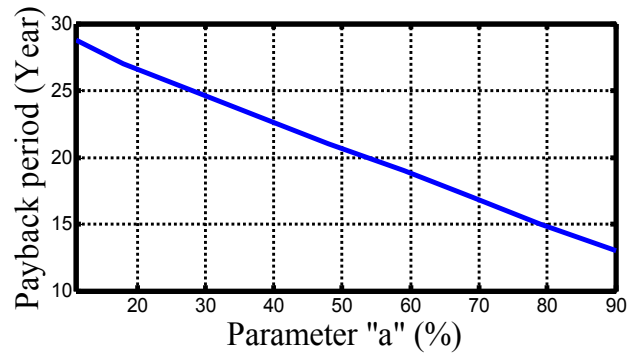


Figure 6. Payback period in terms of incentive payment.

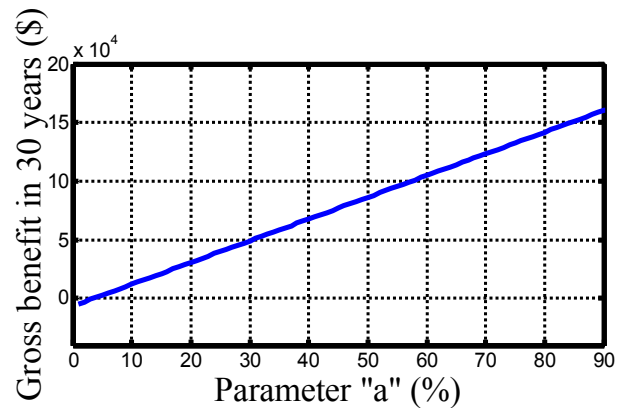


Figure 7. Total gross benefit in terms of parameter "a".

3.2. Windfall Profit

Unreasonable values for FIT parameters could result in more than necessary profit or windfall profit for the RE developer [13]. A windfall profit refers to an unreasonable high profit caused by rising market price unexpectedly. In case of premium price FIT policy, the improper value of parameter b may result in windfall profit for the RE developers [13]. Fig. 8 depicts the impact of increasing premiums in lower and higher price levels. It can be seen that for a given year, an increase in parameter b from 10% to 100% results in less increase in the benefit than that of increasing parameter a from 30% to 60%. This indicates that increasing premiums for lower levels result in much more benefit for the RE

developers. This fact implies that high premiums in higher price levels result in not only inflation and windfall profit which are not acceptable in the market, but also a slight increase in the developer's benefit in long-term. Accordingly, to avoid these consequences, policy makers must always choose low payment in higher market price [13].

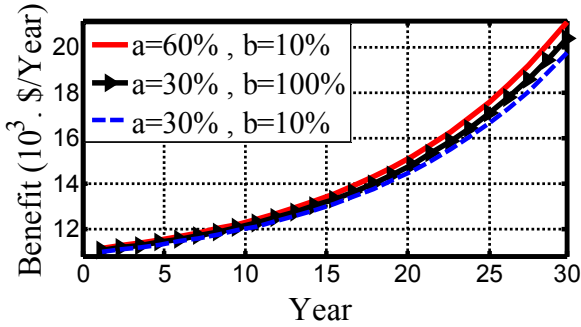


Figure 8. Impact of increasing parameter "b" and parameter "a" on benefit.

3.3. Gradual Degression of RE Premium

FITs often include technology improvement factors designed to reduce payments over time. Gradual degression of premium is utilized to encourage the developer to update the RE plant technologically [11]. The degression would be influential for the developer if it gradually increases. Then, the RE developer will be forced to expand its technologies to compensate lower benefits in the last years of the project. Here, a second order function is used to model degression in the premium of lower price levels (parameter *a*). Parameter *b* is assumed to be fixed at a value of 10%. Fig. 9 depicts the degression of parameter *a* from 53% to 33% during the first 15 years of the project period. As Fig. 10 shows, yearly benefit of the RE developer decreases gradually because of the FIT degression. Hence, the developer is forced to increase the generation to gain benefit by selling more electricity to the grid. The proposed method signifies that in case of degression, the developer should increase its generation at a rate of 9.5% yearly to gain the previous gross benefit without degression (8.5×10^4 (\$)). The yearly benefit of developer with degression and generation growth is shown in Fig. 10 with dashed line.

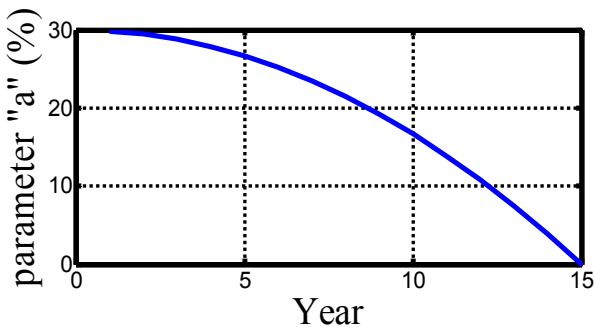


Figure 9. Degression in premiums for premium price FIT.

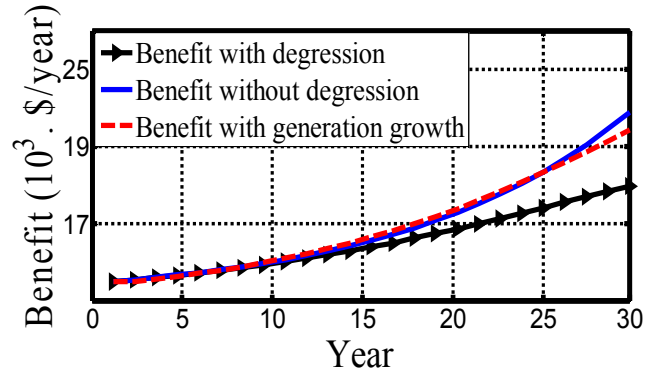


Figure 10. Generation growth (about 9.5% per year) can neutralize degression effect and increase the gross benefit.

3.4. Risk Assessment Analysis

Another fact associated with the financial decisions in FIT policies is the probability of insufficient income for RE developer. Insufficient income can be seen from different points of view, one of them is being potential failure to pay the monthly payment of the loan which is received for starting up the renewable project.

Since the capital cost of renewable technologies is very high, it is common practice for the governments to lend a loan to RE developers for purchasing the technologies. This policy not only encourages people to use renewable, but also compels them to expand their technology in an effective way to reduce the risk of failure to pay the monthly payment of the loan. This risk is defined as the RE developer risk or RER index. The RER index is dependent on the amount of FIT payment, market price, and generation conditions. Raising the FIT payment or the electricity price as well as improving the generation will result in decreasing the risk of failure to pay back the loan. Thus, it is imperative to decide on a proper amount of FIT payment, parameter *a*, to have an acceptable payback period and small enough RER index.

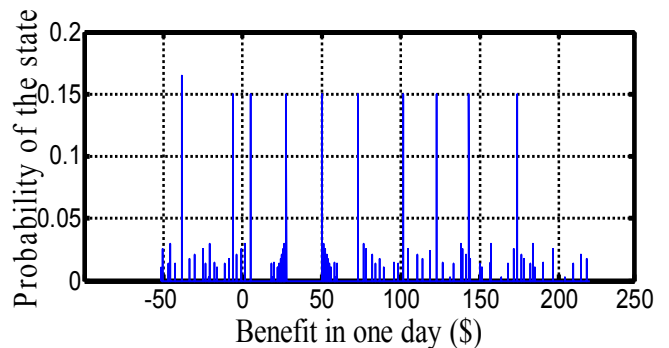


Figure 11. Probability density function of daily benefit.

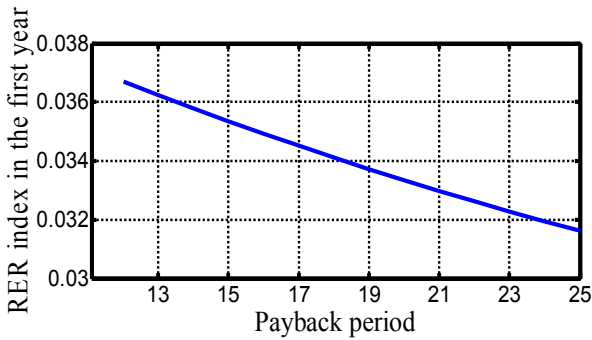


Figure 12. RER index in the first year of the project in terms of payback period.

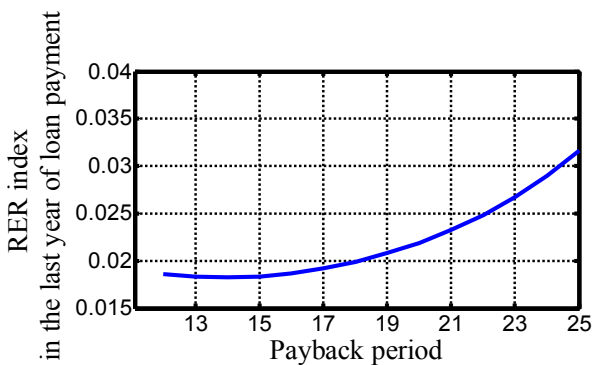


Figure 13. RER index in the last year of the loan payment in terms of payback period.

In the following analysis, the duration of the loan is assumed to be equal (or proportional) to the payback period of the project. It means that if the government chooses an incentive FIT policy to lower the payback period, then the duration of paying the loan also gets lower. Assume that the amount of loan for the yearly interest rate of 2% equals to the renewable technology capital cost of 233600\$, the monthly interest rate is approximately

$$INT = 0.02/12 = 0.00166 \tag{7}$$

Thus, the monthly payment, P of the loan can be written in terms of the loan duration as shown below.

$$P = \frac{INT \times A}{1 - (1 + INT)^{-N_{loan}}} \tag{8}$$

Accordingly, different values of payback periods result in various range of loan duration, N_{loan} and consequently different amount of monthly payments. The daily Markov model for the project gives us the probability of a valid amount of benefit or cost of RE developer in each day. These states and their respective probabilities can be seen as the daily probability distribution function (PDF) of the benefit and cost of the developer, which is shown in Fig. 11. By considering the fact that monthly cost and benefit of the RE developer is sum of the 30 daily costs and benefits, and the obtained daily PDF function for all days are the same, then the monthly PDF function in terms of the daily

PDFs functions is [13]:

$$f_{30}(x) = f_1(x) * (f_1(x) * (\dots * f_1(x) \dots)) \text{ (30 times)} \tag{9}$$

where "*" denotes the convolution integral of the two functions. After obtaining the probability distribution function of monthly cost and benefit of the RE developer, the RER index is determined as follows:

$$RER = \int_{-\infty}^P f_{30}(x) dx \tag{10}$$

The parameter P in (8) is equal to monthly payment of the loan defined in (8). Fig. 12 and Fig. 13 illustrate the RER index for the first and last years of the loan period in terms of the payback period. According to these figures, in the first year RER decreases when the payback period increases; however, in the last year of loan payment (which is equal to the payback period in this study) the RER is a convex function of the payback period. Consequently, it is necessary to decide on a policy with appropriate enumeration payment that results in proper payback period and RER index for the total loan payment period. In this case, as Fig. 11 and Fig. 12 represent, a suitable value for the parameter a can be chosen within 50% to 60% which yields payback period from 17 to 21 years, and the RER index within 3.3% to 3.43% in the first year and 1.8% to 2.3% in the last year of the loan payment, respectively. This analysis can help the policy makers to evaluate various premiums and select the best one according to both the government and the RE developer's viewpoints. By choosing this value as the FIT payment, the payback period becomes sufficiently small, while the RER index will be small in the first and last years of the loan.

4. Conclusion

FIT policies promise great encouragement for RE developers in order to increase their generation as well as to make renewable sources a major supply of energy. This paper introduces a noble technique based on Markov state theory to predict load, generation and electricity price behavior. Simulation results approve high potential of the technique in order to design and analyze different types of FIT policies. In summary, the proposed method can be used to design a model for electricity price and prediction of future behavior of the market. This model can be in terms of hour, day, week, month and year depending on the goals and required accuracy of the analysis. It can be used to design a model of cost and benefit of RE plants in both net and gross FIT policies, and to examine the RE developer risk in various circumstances for example in project loan payments. This method can also be utilized to compare various FIT policies in order to determine the best choice for a certain country. Furthermore, the influence of unexpected variations in

market price, inflation rate, etc. can be added in the models. The method can be applied for the scenarios with more than one RE developers with different types of RE technologies.

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