CHAPTER 4
Technology Diffusion Models

4.1 Introduction

The technology diffusion models are particularly useful for new or emergent technologies where no sales history is available and the nature of the offering to the market has a new or novelty dimension. The purpose of this thesis is to apply the theory of diffusion of innovation (DOI) and other models for the power sector which is undergoing crisis under peak hours and to make a decision as per the assessment of investments in new or emerging technologies in the next decade up to 2020A.D. The speed with which a new technology can be introduced and accepted by the power sector can also be obtained from the technology diffusion models (TDM). The risk in adopting a new technology cannot be ignored in the long run. Thus we need to access from the models as to which technology is most suitable in the present energy scenario of the country. All the diffusion models are well established mathematical models which are used in decision making process. We need to understand both the capital and organizational capabilities required to successfully exploit the technological opportunity. There are multiple diffusion models and the understanding of the dynamics and applicability of various models is also crucial to the investment analysis.

The economical growth of a country depends on the diffusion of new or novel technology which is cost effective and feasible. In the present work an attempt has therefore been made to find the suitability of the novel renewable based energy generation technologies using well established technology diffusion models in the developing countries like India, China, Brazil, South
Africa etc. in the present scenario. When assessing the attractiveness of an investment as an external investor or when building a business case for internal funding, the key element of the analysis is the rate at which customers will take up or adopt the technology. Often, the entire business case is premised on a gross level assumption that new technology will be used by 5% of the population of final users in less than four years time. This approach is based on the “large market fallacy” that argues, the market is big, we therefore only need a fraction of that market to adopt the technology in order to reach break even or return the investment, and therefore the potential upside is massive. This is hardly a realistic or satisfactory approach and the underlying market assumptions typically have no validity if this approach or some variant on it is used.

4.2 Diffusion of Innovation (DOI)

The major development of the DOI theory and practice is attributed to Rogers (Rogers, 1962) who framed innovation adoption as a life cycle involving; innovators; early adopters; early majority; late majority and laggards. Roger’s research has indicated that the spread of a new technology depends mainly on two factors; innovation and imitation. Innovators are driven by their desire to try new technologies or methods and the likelihood of an innovator using a new technology does not depend on the number of other users. On the other hand, imitators are primarily influenced by the behavior of their peers. The likelihood of an imitator embracing a new technology or new way of doing work is dependent on the number of people who are already using it. Normally imitators are the main contributors to the diffusion or spread of innovation (i.e. early and late majority).
The innovation and imitation factors shape the speed at which the technology is accepted into everyday use. For example, the color-TV adopters were mainly imitators (and almost no innovators). On the contrary, for the new item in the market such as battery operated vehicle (BOV); innovators are more relevant to the uptake of the technology than imitators.

4.3 Theory of Adoption and Diffusion

The theory of adoption and diffusion of new products by a social system has been discussed at length by Rogers (Rogers, 1962). This discussion is largely literary. It is, therefore, not always easy to separate the premises of the theory from the conclusions. In the discussion the timing of adoption is also evaluated.

4.3.1 Bass Model

Bass model of technology diffusion is used in a number of applications such as estimation of the growth rate of product being consumed by the people, it could be a simple item purchased from a small shop or it could be from large utilities such as power companies. In this thesis, the power is considered as a consumable item by analogy. If we consider the human system then we see that most human being are attracted by the new things they adopt without analyzing the impacts on the environment in which they are living.

Some individuals decide to adopt an innovation independently of the decisions of other individuals in the social system. The first adopters of technology are considered as innovators, the next come the early adopters then early majority thereafter late majority and lastly laggards. These
classifications are based upon the time of adoption respectively. Apart from innovators, adopters are influenced in the timing of adoption by the pressures of the social system, the pressure increases for later adopters with the number of previous adopters (Bass, 1969).

In the mathematical formulation of the theory presented, the various classes of people who are adopting new technologies can be classified as innovators and imitators respectively. The imitators are influenced by the people who adopted earlier. The innovators influence the people who adopt the technology later without getting influenced by their decisions. Rogers (Rogers, 1962) defines innovators rather arbitrarily, as the first two and one-half percent of the adopters. Innovators are described as being venturesome and daring. They do not interact with other innovators. When we say that they are not influenced in the timing of purchase by other members of the social system, we mean that the pressure of adoption, for this group, does not increase with the growth of the adoption process. In fact, the opposite may be true. In applying the theory to the timing of initial purchase of new consumer product, the following assumptions are made. That the initial purchase be made at time ‘T’ given that no purchase has been made earlier and purchasing is a linear function of the number of previous buyers. Thus;

\[ P (T) = p + (q/m) Y (T), \]

Where ‘p’ and ‘q/m’ are constants and ‘Y (T)’ is the number of previous buyers.

Since \( Y (0) = 0 \), the constant ‘p’ is the probability of the initial purchase at \( T=0 \) and its magnitude reflects the importance of innovators in the social
system. Since the parameters of the model depend upon the scale used to measure time, it is possible to select a unit of measure for time such that ‘p’ reflects the fraction of all adopters who are innovators in the sense in which Rogers defines them. The product ‘q/m’ times ‘Y (T)’ reflects the pressures operating on imitators as the number of previous buyers increases.

The following assumptions characterize the model:

(a) Over the period of interest (life of product) there will be ‘m’ initial purchases of the product. Since we are dealing with infrequently purchased products, the unit sales of the product will coincide with the number of initial purchases during that part of the time interval for which replacement sales are excluded. After replacement purchasing begins, sales will be composed of both initial purchases and replacement purchases. Here the interest in sales to time interval for which replacement sales are excluded, although our Where ‘f (T)’ is interest in initial purchase will extend beyond this interval.

(b) The likelihood of purchase at time ‘T’ given that no purchase has yet been made is \[ \frac{f(T)}{1 - F(T)} \] which is equal to

\[
P(T) = p + q/m \ Y(T) = p + q \ F(T),
\]

Where ‘f (T)’ is the likelihood of purchase at time ‘T’ and

\[
F(T) = \int_0^T f(t) \, dt,
\]

At ‘T’ equal to zero, \( F(0) = 0 \).

Since ‘f (T)’ is the likelihood of purchase at ‘T’ and ‘m’ is the total number purchasing during the period for which the density function was constructed,
Y (T) = \int_0^T S(t) \, dt = m \int_0^T f(t) \, dt = m \, F(T) \text{ is the total number purchasing during in the (0, T) interval. Therefore, sales at ‘T’ is equal to}

S(T) = m \, f(T) = P(T) \, [m - Y(T)] = [p + q \, \int_0^T S(t) \, dt / m] [m - \int_0^T S(t) \, dt]

Expanding this equation, we have

S(T) = p \, m + (q - p) \, Y(T) - q / m [Y(T)]^2

The behavior rationales for these assumptions are summarized:

(a) Initial purchases of the product are made by both “innovators” and “imitators”, the important distinction between an innovator and an imitator being the buying influence. Innovators are not influenced in the timing of their initial purchases by the number of people who have already bought the product, while imitators are influenced by the number of previous buyers. Imitators “learn”, in some sense, from those who have already bought.

(b) The importance of innovators will be greater at first but will diminish monotonically with time.

(c) We shall refer to ‘p’ as the coefficient of innovation and ‘q’ as the coefficient of imitation.

Since \( f(T) = [p + q \, F(T)][1 - F(T)] = p + (q - p)F(T) - q[F(T)]^2 \)

In order to find ‘F (T)’ we must solve this non-linear differential equation:

\[ dT = dF / (p + (q - p)F - qF^2) \]

The solution is:

\[ F = (q - p) \, e^{-(p+q) / q} \, / (1 + e^{-(p+q)}) \]
Since $F(0) = 0$, the integration constant may be evaluated:

$$-C = \frac{1}{(p + q)} \ln \left( \frac{q}{p} \right) \text{ and } F(T) = \frac{(1 - e^{-(p+q)T})}{(q/p \cdot e^{-(p+q)T} + 1)}$$

Then,

$$f(T) = \frac{((p + q) \cdot e^{-(p+q)T}}{(q/p) \cdot e^{-(p+q)T} + 1)} \cdot \frac{1}{(p+q)}$$

and

$$S(T) = \frac{m/p \cdot (p + q)^2}{p \cdot [e^{-(p+q)T}/(q/p \cdot e^{-(p+q)T} + 1)^2]},$$

To find the time at which the sales rate reaches its peak, we differentiate 'S', we get,

$$S'(T) = \frac{m/p \cdot (p + q) \cdot e^{-(p+q)T}}{(q/p \cdot e^{-(p+q)T} + 1)} \cdot \frac{1}{(p+q)}$$

Thus, $T^* = -\frac{1}{(p+q) \ln (p/q)} \approx \frac{1}{(p+q) \ln (q/p)}$ and if an interior maximum exists, $q > p$.

We note that $S(T^*) = \frac{m(p + q)^2}{4q}$ and $Y(T^*) = \int_0^T S(t) dt = m(q - p)/2q$. Since for successful new products diffusion in the market the coefficient of imitation will ordinarily be much larger than the coefficient of innovation, sales will attain its maximum value at about the time that cumulative sales is approximately one half ‘m’. The expected time to purchase, ‘E(T)’, is given by $1/q \ln((p + q)/p]$. well as the product’s appeal. The model attempts to predict how many customers will eventually adopt the new product and when they will adopt. Bass suggested that the likelihood ‘L(t)’ that a customer will adopt an innovation at time $t$ (given that the customer had not adopted before) could be characterized as given in eq. (1),
\[ L(t) = p + (q/N) \cdot N(t) \]  \hspace{1cm} (1)

Where,

\[ N(t) = \text{the number of customers who have already adopted the innovation by time} \ 't'. \]

\[ N = \text{parameter representing the total number of customers in the adopting target all of whom will eventually adopt the target.} \]

\[ p = \text{the coefficient of innovation (or coefficient of external influence).} \]

\[ q = \text{the coefficient of imitation (or coefficient of internal influence).} \]

The equation (1) above suggests that the likelihood that a customer will adopt at time ‘t’ is the sum of two components. The first component ‘p’ refers to a constant prosperity to adopt that is independent of how many other customers have adopted the innovation before time ‘t’. The second component ‘(q/N).N(t)’ is proportional to the number of customers who have already adopted the innovation by time ‘t’ and represents the extent of favorable interactions between the innovators and the other adopters of the product (imitators). After transforming the above equation into one that looks at the number of adopters at time ‘t’, which is ‘n(t)’ presented in eq. (2),

\[ n(t) = p \cdot N + (q - p) \cdot N(t) - (q/N) \cdot [N(t)] \]  \hspace{1cm} (2)

If \( q > p \), then imitation effects dominate the innovation effects and the plot of \( n(t) \) against time ‘t’ will have a S shaped curve as it is obtained for the color televisions. On the other hand,

If \( p > q \), then the innovation dominates the imitation of that particular technology which implies that in the beginning the adoption rate is high but
there will be decline of the technology adoption with time. If the value of the ‘p’ is low then longer time will be taken for the realization of technology. When both ‘p’ and ‘q’ are high, then it implies that there will fast growth and fall of the technology with time.

4.3.1.1 Basic Model

The basic model is given by

\[ S(T) = pm + (q - p) Y(T) - \frac{q}{m} Y^2(T). \]

In estimating the parameters, ‘p’, ‘q’ and ‘m’ from discrete time series data we use the following analogue: \( S_T = a + bY_{T-1} + c(Y_{T-2})^2 \), where, \( T=2, 3... \)

\( S_T \) = Sales at ‘T’ period, \( Y_{T-1}=\sum_{i=1}^{T-1} S_i \) = cumulative sales through period ‘T-1’.

Since ‘a’ estimates ‘p.m’, ‘b’ estimates ‘q – p’, and ‘c’ estimates \(-\frac{q}{m}; -mc=q\) and \(a/m=p\) respectively.

Then \( q - p = -m.c-a/m = b \) and \( cm^2+bm+a=0 \), or \( m = \frac{-b \pm \sqrt{b^2 - 4ac}}{2c} \), and the parameters \( p, q, \) and \( m \) are identified. Therefore, the maximum value of ‘S’ as a function of time coincides with the maximum value of ‘S’ as a function of cumulative sales.

4.3.1.2 Regression Analysis

In order to test the model, regression estimates of the parameters were determined using annual time series data for different consumer durables. The period of analysis was restricted in every case to include only those intervals in which repeat purchasing were not a factor of importance. These intervals were determined on the basis of a subjective appraisal of the durability of the product as well as from limited published data concerning “scrap age rates” and repurchase cycle. The \( r^2 \) values indicate that the model describe the
growth behavior rather well. Furthermore, the parameter estimates seem reasonable for the model. The regression estimates for the parameter ‘c’ are negative in every case, in order for the model to make sense, and the estimates of ‘m’ are quite plausible. One of the more important contributions derived from the regression analysis is the implied estimate of the total number of initial purchases to be made over the life of the product. In addition, the regression equation describes provides a very good fit with respect to both the magnitude and the timing of the peaks for all of the products. Deviation from the trend is largely explainable in terms of short term income variations.

4.3.1.3 Model Performance

The performance of the regression equation relative to actual sales is a relatively weak test of the model’s performance since it amounts to an ex post comparison of the regression equation estimates with the data. A much stronger test is the performance of the basic model with time as the variable and controlling parameter values as determined from the regression estimates. Table 4.2 predicts the peak sales time of the consumer products.

4.3.1.4 Long Term Forecasting

There are two cases worth considering in long term forecasting firstly for no data case secondly limited data case. In order to analyze the potential market and buying motives should make it possible to guess at ‘m’, the size of the market, and the relative values of ‘p’ and ‘q’, the latter guess being determined by a consideration of the buying motives.
In order to illustrate the forecasting possibilities in the limited data case, we had developed a forecast for battery operated vehicle sales. In principle, since there are three parameters to be estimated, some kind of estimate is possible with only three observations of the first of these observations occur at ‘T’ equal to zero. Any such estimate should be viewed with some skepticism; however, since the parameter estimates are very sensitive to small variations in the three observations. Before applying estimates obtained from a limited number of observations, the plausibility of these estimates should be closely scrutinized (Bass, 1969).

In substituting $\int_{i=0}^{r-1} S_i$ in the discrete analogue for $\int_{0}^{r} S(t)dt$ in the continuous model, a certain bias was introduced. This bias is mitigated when there are several observations, but can be crucial when there is only few. Thus, the proper formulation of the discrete model, if $S_r = S(T)$ is expressed as follows:

$$S_r = a + b \cdot k(T) \cdot Y_{r-1} + c \cdot k^2(T) \cdot Y^2_{r-1}$$

Where ‘$k(T)$’ is equal to

$$k(T) = \frac{Y(T)}{Y_{r-1}}$$

We note that for any probability distribution for which ‘$f(x)$’ is equal to ‘$1/k \ [F(x+1)-F(x)]$’ and ‘$F(0)$’ is equal to zero, $\sum_{i=0}^{r-1} f(t) = 1/k \ F(x)$ respectively. In particular, these two properties hold for the exponential distribution. Therefore, for this distribution $\sum_{i=0}^{r-1} F(x)/f(t) = k$.

The density function ‘$f(T)$’ in the growth model is approximately exponential in character when ‘$p$’ and ‘$T$’ are small. Thus, ‘$f_{\text{expa}}(T)$’ is equal
to ‘$1/k \left[ F_{expa}(x+1)-F_{expa}(x) \right]$’ and ‘$1/k$’ is equal to ‘$(p+q)/\left[ e^{(p+q)} - 1 \right]$’. For small values of ‘$T$’ we therefore write ‘$S_r$’ as follows

$$S_r = a + b' Y_{r-1} + c' Y^2_{r-1}$$ (3)

Where, $b' = k.b; \; c' = k^2 \; c; \; m = k. \; m'; \; q = 1/k \; q'$ and $p = 1/k \; p'$.

On the basis of the relationship between ‘$k$’ and ‘$(p+q)$’ Bass devised a model for forecasting the consumption of durables.

The innovation and imitation parameter namely ‘$p$’ and ‘$q$’ are expressed as follows

$$p = 0.97 \frac{p'}{(1 + 0.4(1 + \theta) p')}$$ (4)

$$q = 0.97 \frac{q'}{(1 + 0.4(1 + 4\theta) q')}$$ (5)

### 4.3.2 Pearl Model

As per this model, the following expression can be used for cumulative number ‘$N(t)$’, of the renewable energy based technology disseminated up to the $t^{th}$ year, with the coefficients ‘$b$’ and ‘$k$’ determined from the earlier data on the diffusion of technology (Pearl, 1924).

The logistic reliability growth curve has an S-shaped curve and is given by equation given below

$$N(t) = \frac{1}{1 + b.e^{-kt}}, \; b > 0, \; k > 0, \; T_a \geq 0$$

The least squares estimators of the logistic growth curve parameters are:

$$b = e^{b_0}$$

$$k = -b_1$$
\[ b_1 = \sum_{i=0}^{N-1} (T_i - N \cdot T \cdot Y) / \Sigma (T_i^2 - N \cdot T^2) \]

\[ b_0 = Y - b_1 T \]

\[ Y_i = \ln \left( \frac{1}{R_i} - 1 \right) \]

\[ Y = \frac{1}{N} \sum_{i=0}^{N-1} Y_i \]

In our case, the least square estimator of the logistic growth curve parameters are calculated using the past data obtained from the annual report obtained from the ministry of new and renewable energy (MNRE report, 2007-08) as depicted in the Table 4.1 below.

**Table 4.1 MNRE Annual Report, GoI.**

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<td>Biomass</td>
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<td>510</td>
<td>606</td>
<td>703</td>
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</tbody>
</table>

Source: MNRE Report

**4.3.3 Logistic Model**

The diffusion of a technology measured in terms of the cumulative number of adopters usually conforms to an exponential curve as long as the new technologies manage to become competitive with incumbent technologies. Otherwise, the steep section of the curve would never be reached because technology use falls back to zero at the removal of subsidies. The exponential pattern growth may be of three namely, (i) simple exponential, (ii) modified exponential, and (iii) S-curve. Out of these three growth patterns, the simple exponential pattern is not applicable for the dissemination of renewable energy technologies, as it would imply infinite
growth. The modified exponential pattern (with a finite upper limit) is more reasonable but such a curve may not match the growth pattern in the initial stage of diffusion (Geroski, 1998). Empirical studies have shown that in a variety of situations the growth of a technology over time may conform to an S-shaped curve, which is a combination of simple and modified exponential curves. The S-shaped curves are characterized by a slow initial growth, followed by rapid growth after a certain take off point and then again a slow growth towards a finite upper limit to the dissemination (Solar photovoltaic, CII, 2004). However, a logistic model is used to estimate the theoretical cumulative potential of renewable energy source (RES) based power that can be generated over any period of time.

As per the logistic model, the cumulative number, \( N(t) \), of the renewable energy technology disseminated up to a particular period \( (t^{th} \text{ year}) \) can be expressed as (Purohit, 2004).

\[
N(t) = M \left[ e^{(a+bt)}/1 + e^{(a+bt)} \right]
\]

Where, ‘M’ represents the estimated maximum utilization potential of the renewable energy technology in the country. The regression coefficients ‘a’ and ‘b’ are estimated by a linear regression of the log-log form of Eq. (I) as given below

\[
\ln \left[ (N(t)/M)/1 - (N(t)/M) \right] = a + bt \quad (I)
\]

The values of the regression coefficients using a logistic model have been estimated by regression of the time series data for the implementation of renewable energy based power generation in India. The fundamental assumption of the logistic growth curve is that there is an upper limit or
asymptotic value to the growth curve. Such a growth follows a general pattern of a right skewed S-curve. There has been wide application of logistic curves in the fields of science, technology and economics. Of relevance to the electricity consumption modeling’s the models presented by Pearl and Fisher (Pearl, 1924; Fisher, 1971). These models all feature the logistic growth curve in spite of their different starting points and assumptions. This confirms the argument that such a model has a strong physical background and has received application in various fields. The annual electricity consumption can be obtained by using the logistic growth curve as expressed by the function ‘f’ which is given below:

\[ f = \frac{F}{[1+\exp(C_a + C_i t)]}, \]

Where

‘F’ is the asymptotic value;

‘f’ is the annual consumption data;

‘t’ is the time in years.

To fit the curve to historical data using regression analysis, the linear form of this equation was used:

\[ \ln \left[ \frac{f}{F - f} \right] = C_0 + C_1 t \]

The future values of electricity consumption and correspondingly green house gases emission can be calculated from eq. (2) using regression analysis.
4.4 Historical data

The historical data of the conventional fuel consumption is taken from 1981 up to 2005. It is found that the consumption of the fuel is increasing linearly in this period of 25 years (IEA, 2006). So to forecast the consumption up to 2020 A.D. it is expected that it will increase accordingly using the logistic model, it is possible to determine the consumption pattern of conventional fuel for the next decade and later.

4.4.1 Estimation of Upper Limit

In the logistic equation, the value of the asymptote, ‘F’ should not be determined by regression analysis if the growth or development is still at the early stages (Albright, 2002). This is because the early development, well below the ultimate limit, is not at all strongly influenced by the limit. The value of ‘F’ should be calculated a priori, based on fundamental physical constraints or limits. The argument can turned around to imply that, if the growth pattern has gone beyond the “early” stages of development, the goodness of fit of the curve to the historical data can be used to estimate an optimal asymptote. Hence, a Fibonacci search technique was used to obtain the optimal asymptotes for the logistic curves fitted to the consumption data in the various sectors. The logistic curve fitting with the Fibonacci search technique was applied to the different renewables in this thesis.

4.4.2 Determination of correlation between observed and predicted values

The correlation between observed and predicted values is determined by the estimation of correlation coefficient ‘r’ which is a measure of how well
trends in the predicted values follow trends in past actual values. It is a measure of how well the predicted values from a forecast model ‘fit’ with the real life data. The correlation coefficient is a number between ‘0’ and ‘1’. If there is no relationship between the predicted values and the actual values the correlation coefficient is ‘zero’ or very low (the predicted values are no better than random numbers). As the strength of the relationship between the predicted values and actual values increases so does the correlation coefficient. A perfect fit gives a correlation coefficient of ‘1’. Thus the higher the correlation coefficient the better is the predicted values.

A statistic representing how closely two variables co-vary; it can vary from -1(perfect negative correlation) through 0(no correlation) to +1(perfect positive correlation). Correlation coefficient is a measure of the independence of two random variables that ranges in value from ‘-1’ to ‘+1’. The correlation coefficient, denoted by ‘r’, is a measure of the strength of the straight line or linear relationship between two variables. The correlation coefficient takes on values ranging between +1 and -1. The following are the accepted guidelines for interpreting the correlation coefficient:

‘0’ indicates no linear relationship.
‘+1’ indicates a perfect positive linear relationship i.e., as one variable increases in its values; the other variable also increases in its values via an exact linear rule.
‘-1’ indicates a perfect negative linear relationship i.e., as one variable increases in its values, the other variable decreases in its values via an exact linear rule.
Values between ‘0’ and ‘+0.3’ (0 and -0.3) indicate a weak positive (negative) linear relationship via a shaky linear rule.
Values between ‘+0.3’ and ‘+0.7’ (-0.3 and -0.7) indicate a moderate positive (negative) linear relationship via a fuzzy-firm linear rule. Values between ‘+0.7’ and ‘+1’ (-0.7 and -1) indicate a strong positive (negative) linear relationship via a firm linear rule. The value of ‘r’ squared is taken as “the percent of variation in one variable explained by the other variable”, or “the percent of variation shared between the two variables” (Bruce thesis).

Mathematically, the correlation coefficient ‘r’ is expressed as follows

\[ r = \frac{\sum XY - (\sum X \sum Y)/N}{\sqrt{\left( \sum X^2 - (\sum X)^2/N \right) \left( \sum Y^2 - (\sum Y)^2/N \right)}} \]

Where ‘X’ is the actual value of the renewable power and ‘Y’ is the predicted value of the renewable power taken into consideration. The ‘N’ represent the period between which the power is considered. In this thesis, the period is taken from 2001 up to 2009.

4.5 Forecasting Accuracy

Long range forecasting of new product sales is a guessing game, at best. Some things, however, may be easier to guess than others. The theoretical framework presented here provides a rationale for long-range forecasting. The theory stems mathematically from the contagion models which have found such widespread application in epidemiology (Barlett, 1960). Behaviorally, the assumptions are similar in certain respects to the theoretical concepts emerging in the literature on new product adoption and diffusion (Verne, 2001; MNRE report, 2008) as well as to some learning models (Bass, 1969). The model differs from models based on log-normal
distribution (Bain, 1964) and the other growth models in that the behavioral assumptions are explicit.

In order to determine the accuracy with which it would have been possible to “forecast” the period of sales over a long period with prior knowledge of the parameter values, the regression estimates of the parameters were substituted in the basic model,

\[ S(T) = \frac{m(p+q)^2}{p} \left[ e^{-(p+q)T}/ \left( \frac{q}{p} e^{-(p+q)T} + 1 \right) \right]^2, \]

The model provides a good fit to the data. Even in the cases where the value of the regression coefficient is low the model provides a good description of the general trend of the sales curve. So the model has, then, in some sense, been tested and verified. The model implies exponential growth of initial purchases to the peak and then exponential decay. In this thesis the model is used to predict the time when maximum potential of the renewable energy based power can be achieved. Moreover the theoretical green house gases (GHG) mitigation potential is also determined up to 2020 A.D. The long term forecasting can also be predicted using the bass model with considerable accuracy.