Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Lecture with Computer Exercises:
Modelling and Simulating Social Systems with MATLAB

Project Report

Bass innovation diffusion model and its application in policy analysis for adoption of renewable energy technologies

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Contents

1. Individual contributions

This project was carried by me, Ivan Ostojic and all code was written by me as well. This paper was motivated by three papers: Parker 1994; Bass 1980; Bass 1969 and one book: Sterman & Sterman 2000. Some graphs from the book were used in the introduction and they have been properly referenced.

2. Introduction and Motivations

One of the key aims of companies is to successfully launch and market and their products or technological innovation. Just before the product launch or in the early stages of the product lifecycle market reliable forecasts are critical for managing resources and planning product lifecycle. Since 1960 there was a strong wave in development of models which would forecast adoption of new products over time. Most of these models analogize the process of new product or technology adoption with the epidemic processes. Information spreading (rumors and new ideas), the adoption process (new technologies), product growth can all be regarded as epidemics spreading by positive feedback and the adopters of the innovation "infect" potential adopters. The concept of positive feedback as a driver of adoption and diffusion is very general and can be applied to many domains of social contagion (Sterman & Sterman 2000).

Positive feedbacks have another attribute namely that they create exponential growth. However there are limits to this growth since real quantities can't grow forever. In nature so called "carrying capacity" of the environment exists which sets limits to this growth. Every system with exponential growth will eventually reach this point and its growth will diminish. As the growth is approaching its limits there is a subtle transition from positive to negative feedback dominance. These kinds of processes often produce S-shaped growth curves, where after some threshold level population grow exponentially and eventually it reaches equilibrium. In this project I will focus on the modeling of particular S-curve based on Bass innovation diffusion model (Bass 1969) which can be applied to describe the diffusion of innovations, the growth of sales, the growth of market for new products, and the role of marketing and viral marketing in these processes. I will than extend the scope of these models by introducing additional parameters which will help to apply these models in the analysis of polices (i.e subsidies) needed for adoption of new technologies especially in the field of renewable energies.

In order to introduce the Bass innovation model it is important to note that the spread of information like rumors or new ideas, the adoption of new technologies, and the growth of new products can be regarded as viral processes. The underlying mechanism of these processes is epidemics spreading of information from the people who adopted the information, idea or the innovation to the people who did not. We say that the adopters "infect" non-adopters. This concept of adoption driven by feedbacks can be generalized on many domains in social sciences for example explosion of violence, cocaine epidemics etc.

The processes of social contagion can be regarded as "viral" or "mouth to mouth" processes. For example the rumors spread from the people who heard it to the others, and from the "others" to more people thus creating a positive feedback and exponential growth. Similar process is seen when it comes to new ideas. The people who are convinced about some idea come in contact with the ones who have not heard about it and transmit them their beliefs. The newly created believers in turn convince others to adopt new ideas and so on. Similar process is seen when it comes to new technologies. In all these cases the people who have accepted the novelty (information, product or technology) come in contact to the people have not and “infect” them with the idea, or desire to by new product or technology thus increasing population of potential adopters. As the population of potential adopters is being depleted, adoption rate fails to zero. More generally any situation in which people act as the imitators of behavior, beliefs, ideas or purchases or any situation in which people join the emerging mainstream behavior can be regarded as positive feedback by social contagion. There are several examples in practice where these kinds of processes could be observed. Two of those examples are shown on the Figure 1.

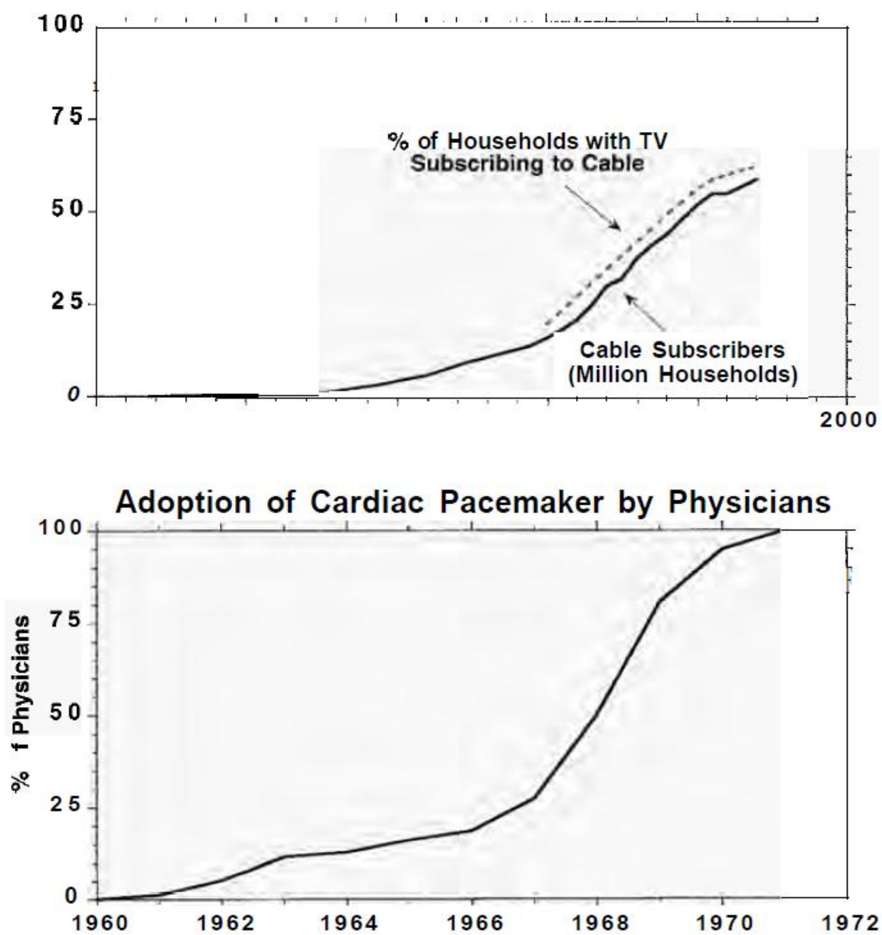

Figure 1. Adoption rates of the real products follow S-shaped curve which can be described by logistic growth (Sterman & Sterman 2000)

In the case of the cable television adoption household’s decision to subscribe given the availability of the cable in the community, is influenced by favorable word of mouth from subscribers and positive personal and social experiences from possessing cable TV at the home. Further benefits include utility from watching channels available only on the cable, than being hip by following the new technology trend, or maintaining or enchasing their social status among peer group. Together these factors and sources of awareness create positive feedback loop which can be regarded as contagion loop in the epidemic models.

Figure 2 depicts the basic logic which is based on **SI** epidemic model, adapted to innovation diffusion process. Instead of infectious population there is the population of adopters (A) which represent the people who adopted the new technology or product. Susceptible population is replaced by pool of potential adopters P. Adopters and potential adopters encounter each other in the word of the mouth process with a frequency determined by the contact rate, c. However in contrast to infectious diseases word of the mouth encounters that ultimately lead to adoption are performed trough direct contact, telephone, mail, e-mail or other means of communication. Similar to the infectious models not every contact results in the successful "infection". The proportion of contacts that are enough convincing to induce adoption of the innovation is named adoption fraction and denoted with i(due analogy with infectivity in the SI model).

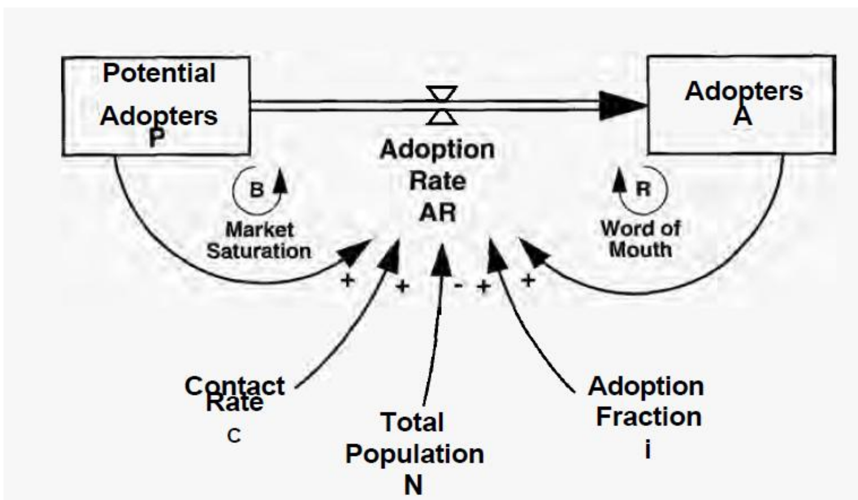

Figure 2. Feedback structure of logistic growth model. Potential adopters are converted to adopters in the process that resembles infective processes. Contact rate, adoption fraction of total population, size of potential adopters population and size of adopter population positively influence adoption rate. (Sterman & Sterman 2000)

The logistic growth curves can be observed in the diffusion of many new products or technologies. For instance, Figure 3 represents sales of the Digital Equipment Corporation VAX 11/750 minicomputer in Europe (Modis 1992). The VAX series of minicomputers was priced about $100,000 to $150,000 a unit, depending included peripherals. Customers for these minicomputers were large companies, research institutes and academic institutions, who used them for processing data and support complicated scientific and engineering calculations and simulation. The 11/750 model was introduced in 1981. If we look at historic data we can see that sales follow bell-shape curve which is peaking in 1984. Also it is noticeable that accumulated sales clearly follow S-shaped curve indicative of positive feedback and logistic growth. Since the

VAX lifetime is much monger compared to horizon of its sales it is reasonable to assume that this S-shaped curve can also represent installed base of this product.

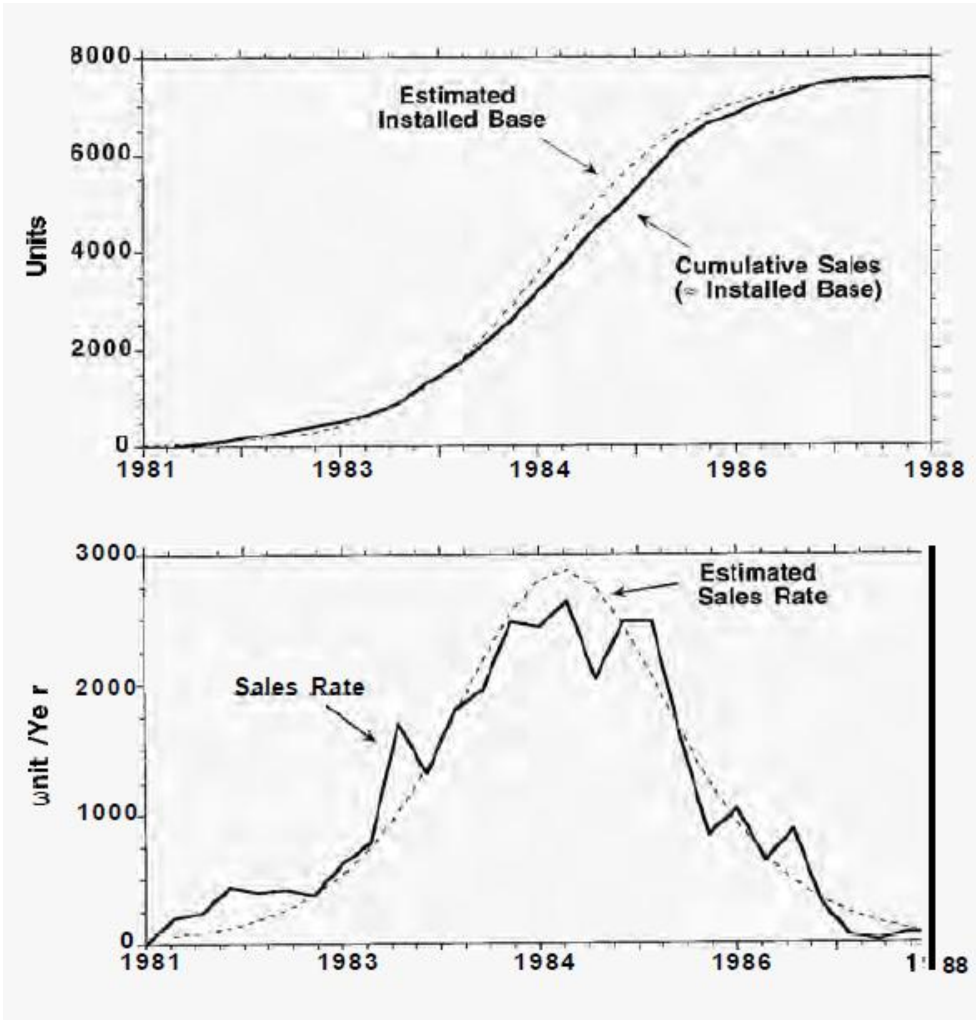

Figure 3. Adoption and sales of the Digital Equipment Corporation VAX 11/750 minicomputer in Europe. Full line represents real data and dashed line represents predictions based on logistic growth model. (Sterman & Sterman 2000)

Although the logistic growth models are able to reproduce the shape of the S curve they have one big flaw and that is the startup problem. Logistic and other simple models (ie Richards and Weibull families), cannot explain the genesis of the first set of adopters or the opinion leaders. For example prior to the acceptance of cable television, the number of people using it was zero; prior the first VAX minicomputer was sold there was no users of it. So it is hard to implement initial positive feedbacks in these models since they are absent because there are no or only few adopters. This leads to conclusion that initial feedbacks are exogenous to these models i.e driven by a parameter outside of their boundaries. This problem can be solved by adding external source which does not depend on the initial population of adopters. For example there are several sources of awareness that can induce early diffusion and adoption of new products, ideas and innovations besides the processes dependant on the initial population. Such examples include media advertisement, PR or direct sales.

The problem of cold start was solved by Frank Bass (1969) who developed so called "Bass diffusion model". This model became one of the most popular and widely used models in different fields like marketing, strategy, technology management and other fields. Simple idea which led to solution of the cold start problem was that potential adopters become aware of the innovation trough external information emitting source whose size and persuasiveness do not change over time in the original model. The Bass model was initially widely used for new products sales forecasts. The positive feedback loops consist of a word of mouth processes (social interaction and imitation) and emission and reception of information from external sources, most commonly effects of advertising.

Figure 4 shows the element interdependence in the Bass innovation model. The adoption rate is the sum of adoption originating from word of mouth like processes and adoption resulting from advertising processes. Adoption from word of mouth are formulated exactly as in logistic models or infective models on which they are based on. On the other hand this model also assumes that the probability of the adoption after exposure to advertisement is constant. At each period of time certain fraction of potential adopter is converted in to adopters due to these influences.

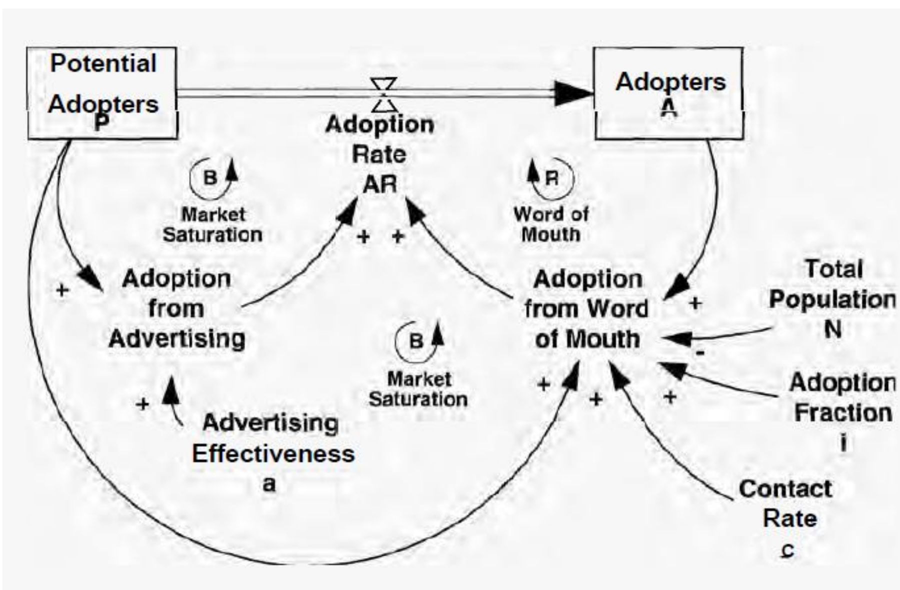

Figure 4. Feedback structure in the Bass diffusion model. Note that there are two factor influencing adoption, word of mouth processes and adoption from advertising. (Sterman & Sterman 2000)

This model manages to address startup problem present in the logistic models because adoption rate from advertising doesn't depend on the adopter population. At the beginning the adoption consists only from people who heard about the product or technology from external sources via advertising and after the population of adopters increases the social contagion process start to dominate the adoption rate.

To illustrate the process we can again look at the sales of VAX 11/750 (Modis 1992). The only way to model VAX product life cycle with the logistic diffusion is to start from non-zero installed base after the product has been already introduced. However careful analysis of the Figure 3 shows that this model underestimates the sales in the first year, and overestimates sales at the peak, due to omission of external sources like marketing. Figure 5 shows the comparison of the Bass model, logistic models and the VAX sales. Small change in the feedback structure of the diffusion leads to better fitting of the model to the empirical data in the first two years of the sales and predicts the peak more accurately. More importantly introduction of the advertisement influence solves the cold start problem. In the particular example the effects of advertisement to sales are small and can be observed only in the initial period, as it can be seen in the lowest panel of the Figure 5. However the can be also larger and they can have their own dynamics with time as we will see later.

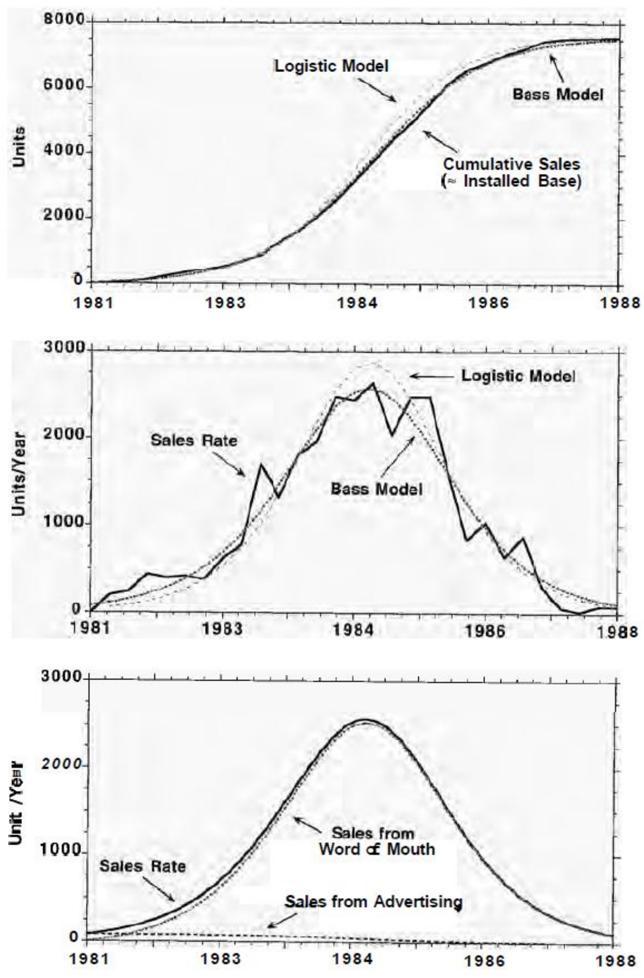

Figure 5. Adoption and sales of the Digital Equipment Corporation VAX 11/750 minicomputer in Europe. Full line shows real data, and dashed lines shows the data obtained from the Bass model and logistic model. Lowest panel shows which fraction of sales originates from advertisement and which originate from word of mouth processes, according to the Bass model . (Sterman & Sterman 2000)

The Bass model is important extension of the basic logistic models of innovation diffusion. Until now this model has been widely used for different application in the area of innovation diffusion and growth. There is a wide range of literature which applies these models to innovation diffusion or sales of new products (Mahajan et al. 1990; Parker 1994).

In the light of the current debate on the sustainable development and climate change it is necessary to address the question of the adoption of new technologies in energy production. Despite the awareness of these fundamental problems and of these technologies as the mean for their solution its adoption rate still remains low. For that reason it is interesting to think within the framework of the technology diffusion and adoption what can policy makers can do in order to optimize adoption process. The attempts to answer these question using basic linear econometrics models have not given satisfactory answers since they do not integrate sufficient parameters and do not capture the mechanics of underlying diffusion process. Widely verified model like Bass innovation diffusion model might be more suitable for that purpose. Due to those reasons in the reminder of this report I will focus on the implementation of the basic Bass model in the MATLAB with particular aim to use it as a tool for analysis of different policy designs in order to optimize adoption process. First I will reproduce the basic Bass model and then try to extend it and apply extended Bass innovation model for the analysis of incentives for adoption of new technologies.

3. Description of the Model

In this chapter I will present mathematical formalization of the basic Bass innovation model(Bass 1969) and then extend it by adding additional parameters or making some of them dynamics. First step is to formalize the diffusion of the innovation as the result of the word of the mouth processes. When the diffusion process starts there is a population P consisting of potential adopters. As the sales are increasing the number of potential adopters is decreasing. This means that each consumer can adopt technology or the product only once. In order to represents this effect we can define the sales as S and indicate that they change as a function of time, *t*. We can also define cumulative sales and cumulative sales are equivalent to the population of adopters, A. Cumulative sales are also function of time. Mathematically this can be represented with following equations:

P = total number of households who could ever adopt the new product

$S(t)$ = the number of households who adopt the new product in the t-th month

$A(t)$ = the total number of households who have adopted the new product up to and including the t-th month

In this model we will assume simple structural definition and that is that the total number of sales, thus total number of unique adopters A(t) is equal to the sum of all sales over all time periods.

$A(t)=\sum S(t)$

Number of potential adopters at particular time period t can be calculated by simply subtracting the total number of adopters from the total number of potential adopters:

(1) $P - A(t)$ = potential adopters at month t

As I already mentioned the consumers adopt the products due to influence of two forces. First are the marketing actions, due to which some consumers will adopt product on their own without being influenced by others. These consumers are called innovators or lead users. In mathematical term we say that there is some innovation rate, p. This innovation rate can be altered by different marketing strategies or different marketing mix. For example stronger advertisement can make more lead users informed of the product and its benefits. Better distribution or lower price can both affect the product adoption. Thus we have:

p = the rate of innovative adoption as a percent of those that have not yet adopted

As described above second source of the adoption is the contact between the users (consumers) themselves. The talk to each other, they hear about product from different personalized communication channels like internet, blogs etc. This process represents word of mouth forces or viral marketing. The more products in circulation there are meaning the bigger the population of adopters the stronger is this force. Due to resemblance to epidemic models we call this process social contagion. In order to model effect of contagion we can introduce the parameter q. Similarly like in epidemic models q sums up the effect of the contacts between the users and probability that the contact will induce the adoption. However since we said that the strength of this process depends on the number of people who already adopted the particular product or technology we have to multiply this parameter with number of adopters A(t) as a fraction of total number of potential adopters P. Like this we can get contagion effect:

$qA(t)/\mathrm{P}$ = the rate of adoption as a percent of those that have not yet adopted (contagion effect)

Total adoption rate can be obtained by adding adoption rate originating from the advertisement efforts and adoption rate originating from social contagion

(2) $p + qA(t)/\mathrm{P}$ = total rate of adoption.

Finally this leads to the basic Bass model which has simple formulation. We can find the number of sales (adopters) in the given period of time by multiplying just the rate of adoption with the size of the population of potential adopters at a given time. By combining the equations (1) and (2) we obtain

(3) S(t)= [p+qA(t)/P]*(P-A(t))

As previously mentioned cumulative adoption is sum of S(t) or otherwise written

A(t)/dt=S(t) that is A(t)=S(t)*dt;

We can generate simple MATLAB code that would simulate this model. We can use the empirical example of the adoption of cellular phones. It was estimated that for the cellular phone adoption parameter p=0.008 while parameter q=0.432;

We can perform this simple simulation on the hypothetical population of one million people within 30 years.

MATLAB code to generate basic Bass innovation model is as follows:

```
Clear
iter=2000;
time_step=0.01;
q=0.432;
P=1000000;
A(1)=0;
p=0.008;
t(1)=0;


for i=2:iter

   s(i)=(p +q*A(i-1)/P)*(P-A(i-1))*time_step;
   A(i)=s(i)+A(i-1);
   t(i)=t(i-1)+time_step;

end

plot(t,P-A,'r')
hold on

plot(t,A,'b')
hold on
```

And to plot the sales in particular time period on separate graph we can use command:

```
plot(t,s)
```

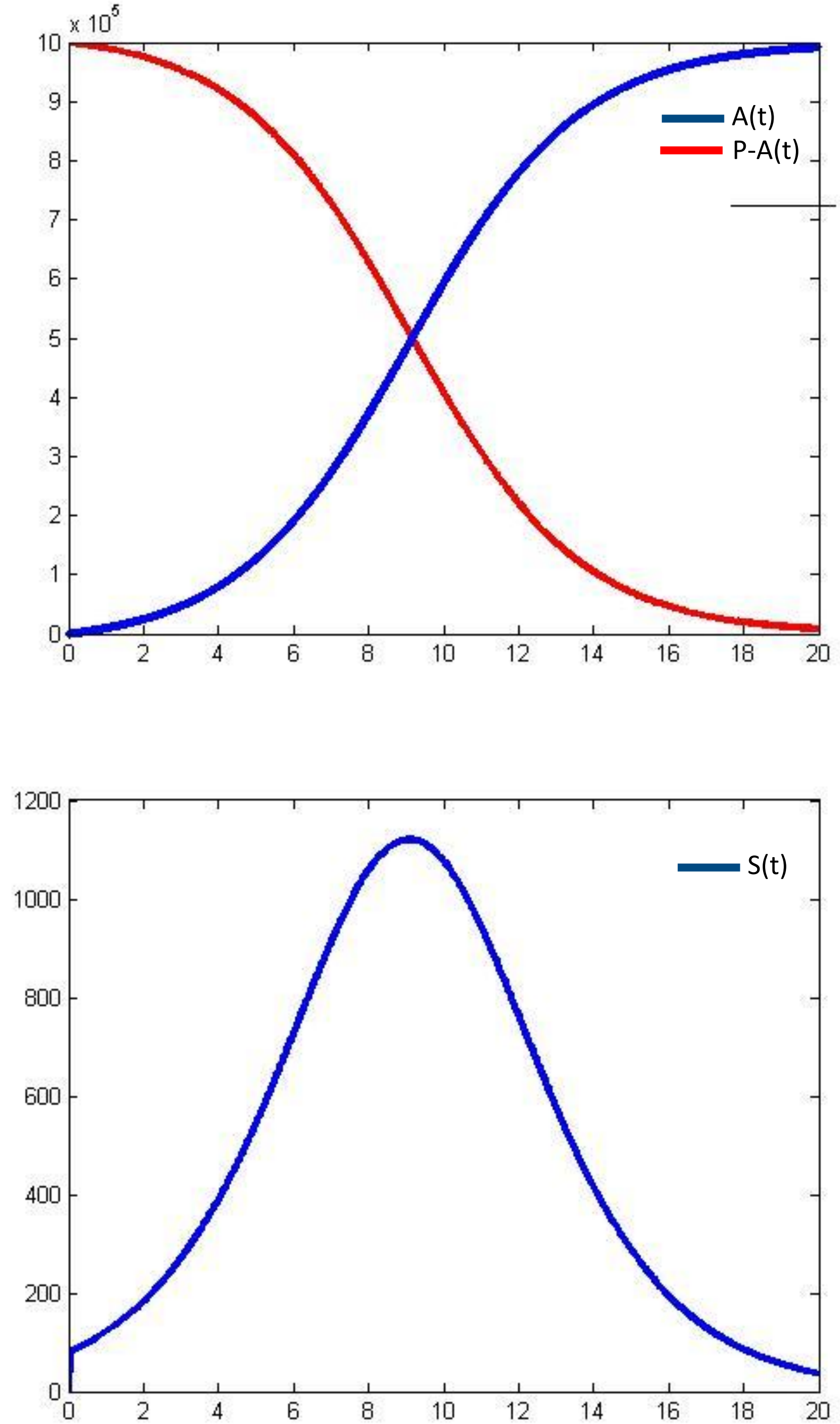

Figure 6. Bass diffusion model generated using MATLAB. At the beginning number of adopters is small (blue curve upper panel, A(t)) relative to the number of potential adopters (red curve, P-A(t)). The lower panel shows sales at each time period. Peak of the sales is good proxy for the speed of the adoption.

Based on these results we can see that in the beginning when the number of adopters is small relative to the number of potential adopters there is acceleration in sales. More adopters with time mean more contagion and more sales. As the number of adopters A(t) approaches the value of P, market saturate and sales decline.

Bass model manages successfully to model wide range of empirical data(Parker 1994). However some products show deviation from theoretical predictions. They can be skewed left, skewed right, or have multiple peaks. Additionally, since the parameters in the model p and q lack external constraints, the Bass model inadequately model early variations in adoption (e.g. due to seasonality, business cycles, data reporting errors, etc.) peaks, which can lead to unreasonable parameter estimates and forecasts in the long run. In seventies and eighties various extensions to the basic Bass model were introduced in the attempt to overcome some of its shortcomings. Important extensions included adding different marketing mix elements. Furthermore modeling was expanded by dynamic market potential (Mahajan et al. 1990; Mahajan & Peterson 1978), non-uniform interpersonal influences (Easingwood et al. 1983), and heterogeneous adopter populations (Jeuland 1981). The following model depicts, introduced changes:

$$S(t)= [p+(qA(t)/P(t))^{(1+d)}]*(P(t)-A(t))^{(1+e)}$$

Since the influences might change with time, either by intensifying or diminishing, Easingwood et al. (1981) have introduced the constant d ($-1<d$), which describes nonuniform interpersonal influence (NUI). Low values of this constant result in shorter take-off periods and faster adoption, while higher values indicate higher resistance. NUI can be seen as the change of immunity of population to social contagion. This parameter can make sales curve skewed or non-symmetric. Additionally Jeuland (Jeuland 1981) added parameter e ($0<e$) which is accounting for heterogeneous adopter population. Since the members of the population differ in different ethnographic and socio-graphic parameters this might also affect probability that they will adopt particular innovation.

Since the aim of this report is to develop the model which can serve as a tool for policy analysis for adoption of novel technologies it is important to extend the model by adding other parameters in order to integrate some other important considerations for policy design. For example it is reasonable to assume that the adoption rate is inversely proportional to the price and that the price decline with time due to increase in supply, and economies of scale. Mathematically this can be represented in the following manner (Ruiz-Conde et al. 2006):

$S(t)= [p+(qA(t)/P)^{(1+d)}]*(P-A(t))^{(1+e)} *price(t)^{-\delta}$

Where $price^{\delta}$ represents drop of price due to production experience effects. Delta, δ is the price parameter and it represents price elasticity. Starting from two basic assumptions (Bass 1980):

Marginal costs = $C_0*[E(t)]^{-\lambda}$

where E(t) is cumulative output at the time t, and C_0 is a scaling parameter (sometimes referred as the price of production of the first unit) it can be shown that

Demand= $f(t)*C_0*price(t)^{-\delta}$,

Where f(t) is the basic Bass innovation diffusion model. More details are given in Bass (1980).

Finally it can be shown that the effect of price can be model as:

$S(t)= [p+(qA(t)/P)^{(1+d)}]*(P-A(t))^{(1+e)} *price(t)^{-\delta}$

In order to simplify the model we can drop the 1+e part since if we talk about adoption of renewable energies the potential adopters are either energy supplier companies which can be regarded as quite homogenous or households which also can be regarded as homogenous if the proper tax instruments are in place which takes into account the income inequalities. However parameter d is still very important since the policy maker can influence the speed of adoption by promoting networking of the energy suppliers in order to exchange the experiences related to use on new technologies.

In summary the model can be written as:

$S(t)= [p+(qA(t)/P)^{(1+d)}]*(P-A(t))*price(t)^{-\delta}$

where δ ranges between 1 and 6 for consumer goods based on the empirical estimates, and for energy it is probably lower (Bass 1980).

4. Implementation

In order to test influence of different parameters on the adoption rate I developed extended MATLAB code that take into consideration these additional assumptions described in the model above. In this chapter I will present short implementation of this model and in the subsequent chapter I will change the values of different parameters in order to see how different policy designs that influence values of these parameters can influence adoption rates.

```
clear

iter=2000;
time_step=0.1;
q=0.4;
P=1000000;
d= - 0.25;
p=0.0001;
t(1)=0;
price=0.24;
A(1)=0;
delta=3;


for i=2:iter

   s(i)=(p +q*(A(i-1)/P)^(1+d))*(P-A(i-1))/price^delta*time_step;

   A(i)=s(i)+A(i-1);

   t(i)=t(i-1)+time_step;

end


plot(t,s,'g')
hold  on
```

5. Simulation Results and Discussion

In order to analyze the influence of different policies on adoption of new technologies, I simulated several scenarios where different parameters in the model were changed. I used total sales as the proxy of the effects of particular policies. Sales were chosen because they are good indicator how fast is particular technology adopted. Peak of sales tells about the magnitude of adoption and particular time point. Both very rapid diffusion and very slow diffusion can have severe consequences on the revenues, capacity planning, and new product development. One good illustration how important it is to set proper policy tools in place are the incentives in the development of technologies for renewable energies and particular solar energy. On one hand rapid diffusion would create tremendous pressure on the capacities and natural resources needed for solar modules production (i.e. tellurium) but on the other hand too slow diffusion would endanger hopes to develop solution for global climate challenges.

5.1 Changing strength of the advertisement.

Policy makers might attempt to stimulate the adoption of particular technologies (i.e. renewable) trough usage of active campaigns and advertising. Different efforts can be modeled trough changes in the parameter p. Increasing value of p is equivalent to increases in the strength of the advertisement efforts. Results of MATLAB simulation for three different values are presented on the graph below.

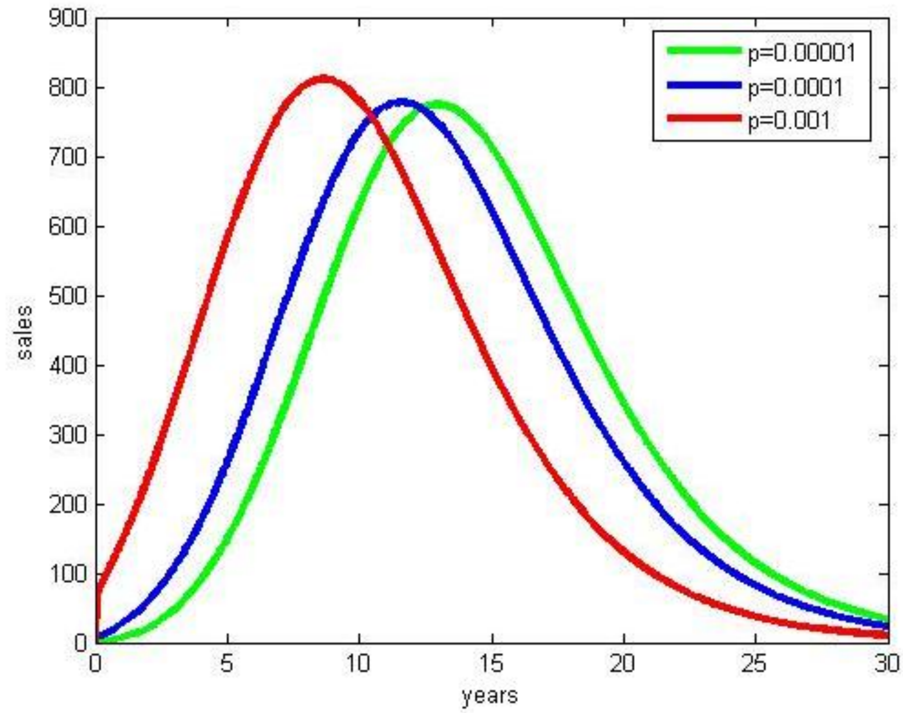

Figure 7. Changing the strength of external advertisement can speed diffusion process but does not change the magnitude.

As we can see advertisement efforts does not have effect on the overall shape of the adoption curve but just affect years needed to reach the peak. Stronger efforts will lead to earlier adoption and weaker efforts would extend the time needed to fully adopt new technology.

5.2 Changing strength of word of mouth processes

Successful viral marketing might be a key of the success in the modern world. Policy makers might stimulate adoption of particular technology on the level word of mouth processes by increasing probability that particular technology will be adopted or by increasing the contact rate between adopters and potential adopters. Probability of technology adoption can be achieved through particular tax incentives or policy schemes like for example Renewable portfolio standards or Fed-in tariffs in the field of renewable energy. Increasing the contact rate can be achieved through different conferences, workshops or trough creation of environment where adopters and potential adopters would come in contact and exchange their opinions. Using our model we can analyze what kind of effect does change in the rate of diffusion due to word of the mouth processes has on the adoption by changing the value of the parameter q.

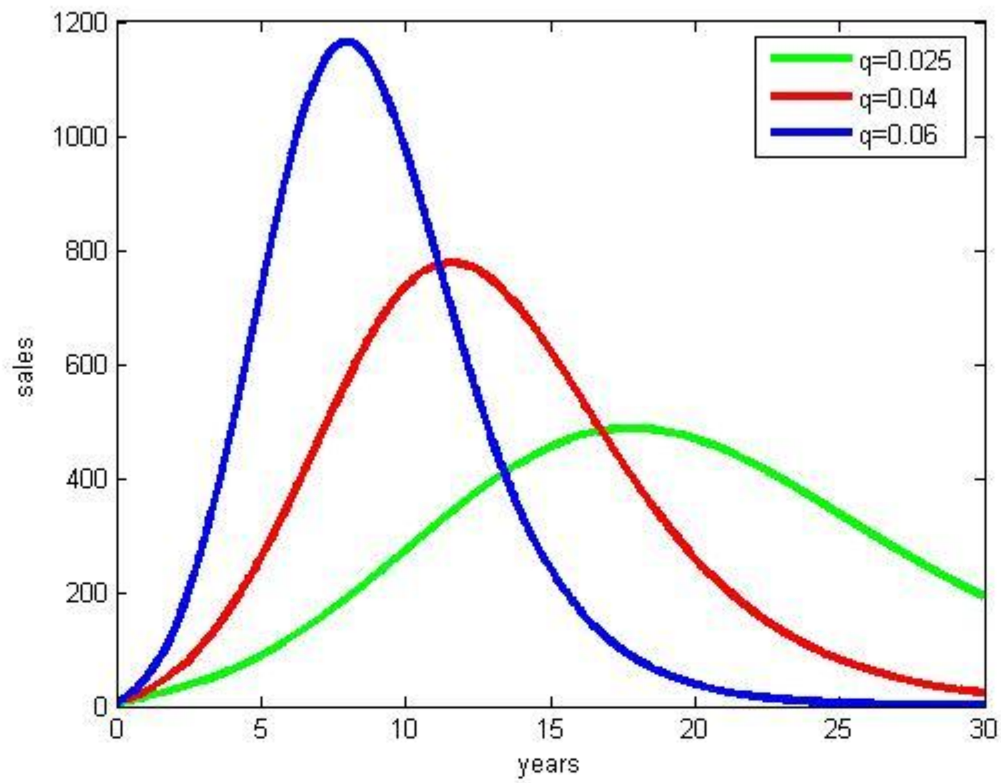

Figure 8. Influencing the word of mouth processes trough increase of contact rate of probability of adoption can increase both the magnitude and the speed of adoption

As we can see parameter q has influence on both size and the shape of the diffusion curve meaning that it influences both, size of the peak and timing of the peak.

5.3 Influencing the interpersonal influence – changing the structure of diffusion network

Changing the value of d which represents the nonuniform interpersonal influence (NUI) in the diffusion process we can change the timing of the peak and its amplitude to lower extent. This means that timing of policy maker's action to improve interpersonal exchange of information or support networking between interested parties can have influence on the adoption rate

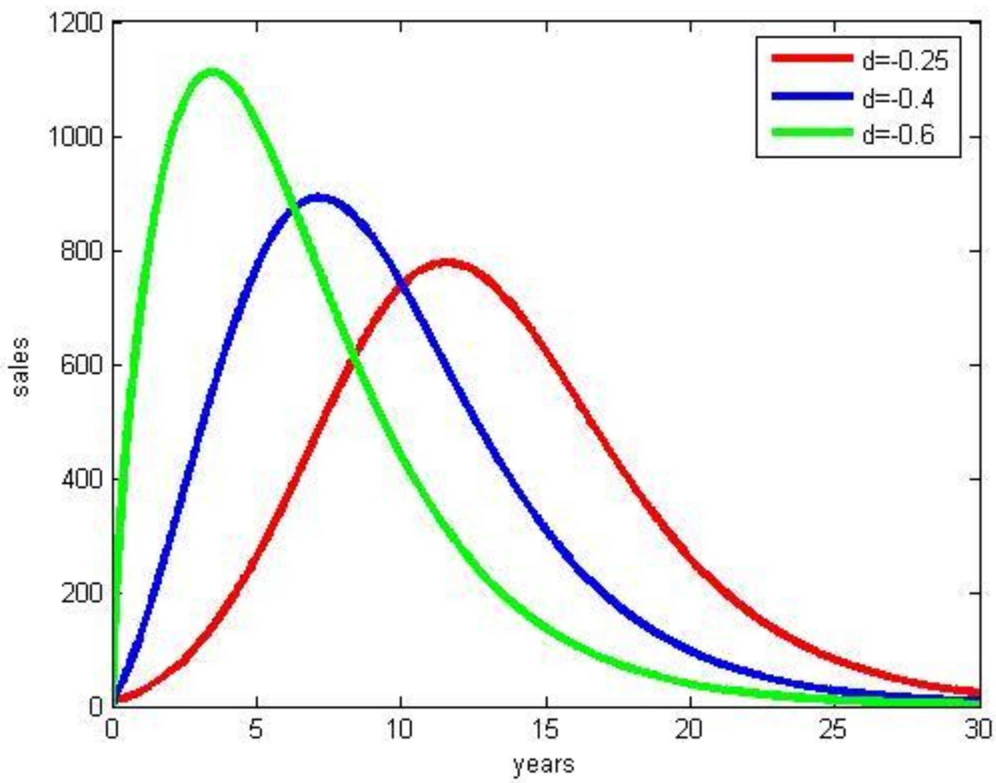

Figure 9. The NUI parameter affects the timing and the partly the magnitude of the adoption rate

5.4 Effects of price subsidies

Finally one of the widely used policy measures to stimulate adoption of particular technology is the subsidies. For demonstrative purposes we can assume that policy maker sets price to be constant, and that they are just changing amount of subsidies provided in each time step. Since the price is dropping with time, amount of subsidies will also drop until eventually it reaches zero. This scenario is observable for many renewable energy technologies.

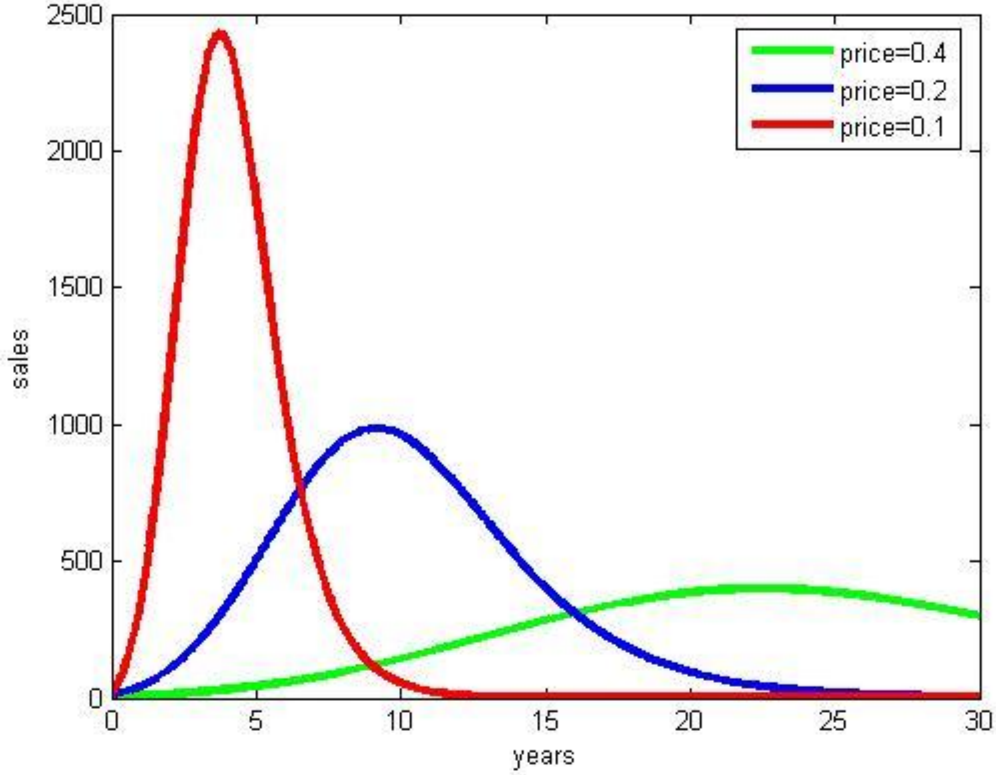

Figure 10. Price subsidy increase speed and the magnitude of the adoption rate. Price is fixed to a constant level and subsidy is adjusted over time to maintain that level.

We can from this simulation that subsidizing price speeds up adoption process and alters the timing and the amplitude of the peak of sales. As already mentioned this can have huge consequences in terms of capacity needed, and hidden environmental and economic trade-offs.

Finally we can let the price change by not fixing the lower boundary of the price but letting it drop with the adoption rate.

$$\frac{d(price\ (t))}{dt} = -\,price(t) * \frac{df\,(t)}{d(t)}$$

The MATLAB code for implementing this equation should be placed within the “for loop”:

```
price(i)=price(i-1)-price(i-1)*(p +q*(A(i-1)/P)^(1+d))*(1-A(i-1)/P)*price(i-1)^-delta*time_step;
```

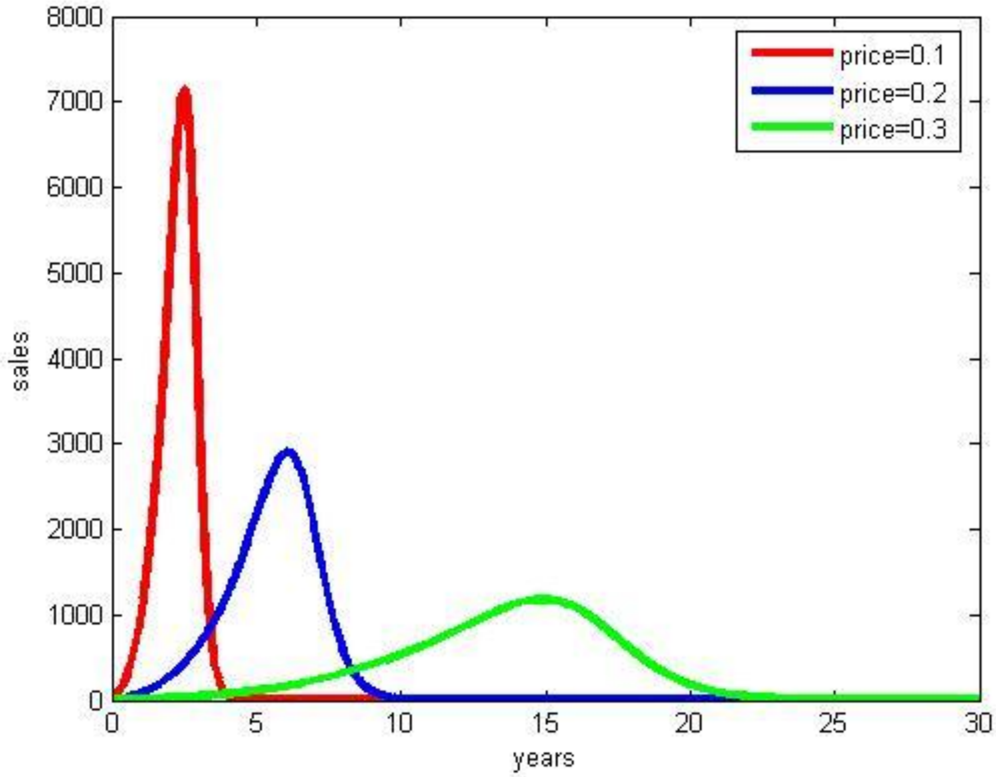

Figure 11. Subsidy affects the speed and the magnitude of adoption even when the price is free forming.

By simulating the model like this we can see that this makes the curve slightly skewed but however it does not change the overall conclusions. Subsidies still increase both peak and the speed of adoption.

6. Summary and Outlook

In this paper I described Bass innovation model. This model is able to reproduce the S-curve typical for new technology diffusion. Furthermore this model copes well with empirical data when it comes to lunch of new products of adoption of new technologies. I introduced mathematical treatment of the model and expanded it with various parameters to made model more realistic. This also provided me with the opportunity to apply this model as tool for analysis of policies that would enhance the diffusion of renewable energy technologies. I identified several important factors that could be target of the energy policies. First of all I was able to show that the advertisement increases the speed of adoption without changing the shape of the adoption curve. This suggests that the policy makers can increase their external advertisement efforts trough electronic and print media or other channels. Further I identified that the enhancement of the word of the mouth processes can increase the peak of adoption as well as the speed of the adoption. Thus by targeting particular communities of producers or households (for example in the case of the solar PV panels) trough various networking events, viral marketing strategies, renewable portfolio standards and tax benefits policy maker would increase either the contact rate or the probability of adoption and consequently the speed and the peak of adoption. However as seen with the figure 9 it is not only the word of the mouth processes that are important for the diffusion but the adopters resistance and underlying network. Appropriate stakeholders management as well as the activities that would promote networking of the users to promote the adoption of the renewable might be important step in this direction. Finally I showed that monetary incentives in form of the price subsidies have similar effects on the adoption rate. Increasing the price subsides can lead to faster adoption and higher peak of sales. Having in mind this data I believe that extended Bass innovation model is better tool for policy analysis than conventional linear econometrics models. It combines simplicity with lot of power to reproduce the real data and to give indications what are important parameters to control technology diffusion. Proper control of diffusion process is really important because the speed shouldn't be too slow but it also should not be too fast. Too slow speed would hamper the efforts to solve energy and sustainability problems, while too high speed would lead to other problems like hidden environmental tradeoffs or perturbation on the markets for raw materials used for production of technological products.

In perspective this model could be used for policy design but it is necessary to accurately determine parameters of the model in the field work. Only than this model will become valuable tool for diffusion and policy analysis.

One of the shortcomings of this model is that it doesn't integrate competing technologies. This would help to get even more realistic picture and also to analyze potential secondary effect that the adoption of particular technology can induce. However despite that I feel that this analysis is valuable contribution in the field of energy policy analysis.

7. References

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