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Development of An Innovation Diffusion Model for Renewable Energy Deployment

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Abstract

Investment in renewable energy, such as building photovoltaic (PV), has higher volatility than normal products due to uncertain product performance and such high uncertainties become the roadblock to the growth of renewable energy market. Previous studies focus on diffusion of innovation from macro aspect but ignore the managerial flexibility of individual's investment. This paper established a novel diffusion model that integrates agent-based modelling (ABM), real option and social networks to assess the propagation of renewable energy adoption. The proposed model incorporates the heterogeneity of individuals' risk preferences into real option decision to determine one's willingness to invest renewable energy. The perceptual risks vary through one's interaction with network peers after knowing the past experiences from those peers. The model is then applied to the residential PV diffusion in Singapore, with results that validate the effectiveness of the model and also imply policy recommendations to stimulate the development of PV market.

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Keywords: Diffusion of Innovation; Agent based model; Perceptual uncertainty; Real option analysis; Photovataic

1. Introduction

Renewable energy innovations, like Photovoltaic (PV) product, play an important role in reducing carbon emissions since they replace the fossil fuels by clean and renewable energy. In order to build the sustainable society, the key is to make good use of renewable energy innovations, which should be largely invested and adopted in our society. However, due to attributes of renewable energy innovations, diffusion of the product in the market is often slow. For example, residential photovoltaic (PV) adoption in Singapore started bedding test since 2008. Up to 2017, the

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accumulative residential PV adoption capacity is only 747.22kWp, which is only 4% of the total PV installed capacity in Singapore [1]. In order to boost market of innovations, analysts need to assess diffusion of innovation before launching new innovative products into the market. Based on the market evaluation results, they can propose efficient product lifecycle strategies that can directly influence the innovations' market success. Therefore, an informative and accurate diffusion of innovation model is expected by analysts in order to provide correct and valuable evaluations.

In the literature, there are two main classifications of models with regard to diffusion of innovation. The first category is called macroeconomic models, in which potential market is presumed to be perfectly mixing or can be divided into serval perfectly mixing segments [2]. Based on this assumption, differential equations are derived to plot the aggregative diffusion curve. An apparent flaw of this category is its incompetency of considering the impact of network structure or individual heterogeneity [2]. Individual customers differ in their adoption behaviors since they have different preferences, ways to communicate or to obtain information. Additionally, the diversity of social network structures is also proofed to have a significant impact on the diffusion process both theoretically[3], [4] and empirically [5].

The second category is called micro-level based models, and they are majorly developed based on Agent-based model (ABM). ABM overcomes obstacles of macroeconomic models by modeling the diffusion process at the individual level. In ABM, individuals make adoption decisions based on the proposed decision rule, which considers agents' heterogeneity and their interpersonal communications. The overall diffusion of innovation is aggregated across the network. Therefore, individual adoption rule is vital in ABM since it connects all the elements and it differs in different models. For example, in the existing ABM diffusion models[6]–[8], adoption decision rule is constructed based on individual's utility function. Only when the individual's utility exceeds his/her corresponding status quo, he/she adopts the innovation. Otherwise, the agent abandons the investment. For a comprehensive summary of agent-based diffusion models and their advantages, see [9].

However, in innovative products investment, such either adopt or abandon decision rule doesn't fit the real investment decision because the innovative products, like Photovoltaic (PV) products have higher intrinsic performance volatility than regular products. The high intrinsic products' volatility will cause managerial flexibility in innovation investment while existing ABM diffusion models ignore such additional managerial options. For example, a potential adopter could choose to invest the PV later when electricity price reaches high, or PV cost reduces. These managerial options in finance are named real options and researchers usually employs Real Option Analysis (ROA) approach to calculate real option value and provide guidance in innovation investments. Herein, ROA as defined by [10], offers a right not an obligation to take flexible strategies depending on how uncertain of innovation performance evolve. In addition, [10] also indicated that ROA is particularly appealing to innovative products investment, such as PV technologies, where decisions with substantial capital cost must be made under great product uncertainty.

This paper aims to understand the consumers' reaction/behavior towards innovative products and the dynamic process of innovation diffusion. We extend the existing ABM diffusion models in terms of (1) proposing Real Option analysis (allows defer option) in decision making model to deal with innovations with high performance volatility; (2) Considering relationship diversity among potential adopters in social network structure; (3) Examining the impact of external influences (government subsidy and market performance) on diffusion process.

The structure of rest paper is organized as follows: Section 2 constructs the proposed model in detail. Firstly, Section 2.1 derives the decision-making rule under perceptual uncertainty based on the utility function. Afterward, we integrate the ROA into the decision-making rule, which considers both project value as well as waiting options value. Section 2.2 explores the evolution processes of adopters' perceptual uncertainty. Section 2.3 incorporates the proposed decision rule and evolution processes into the ABM. Section 2.4 briefly shows the results of applying proposed model on residential PV diffusion in Singapore. Section 3 makes a summary.

2. Modelling

ABM is more a conceptual model than a real model that analysts can integrate anything of interests into their models to make their models close to the real case. In ABM diffusion model, there are four basic components that nearly every ABM diffusion models share:(1) heterogeneous agents; (2) network structure; (3) interpersonal communications and (4) adoption decision rule. In this paper, we utilize ABM to simulate the diffusion of innovation from individual level based on the four components. In the meantime, we innovatively add ROA approach in individual's investment decision. Figure 1 shows the overall framework of our model, which clearly explained the relationship of four basic components in our model. In figure 1, we can find that individuals in the social network make adoption decision based on ROA integrated decision rule, where potential adopters are offered defer option in their investment decisions. What's more, our model not only simulates the interpersonal communication among individuals in the network, we also explore relationships between network and external factors, which are commonly existing in empirical cases. For example, government subsidy depends on overall diffusion rate in the network; PV panel cost will be reduced over time due to the effect of learning by doing [11].

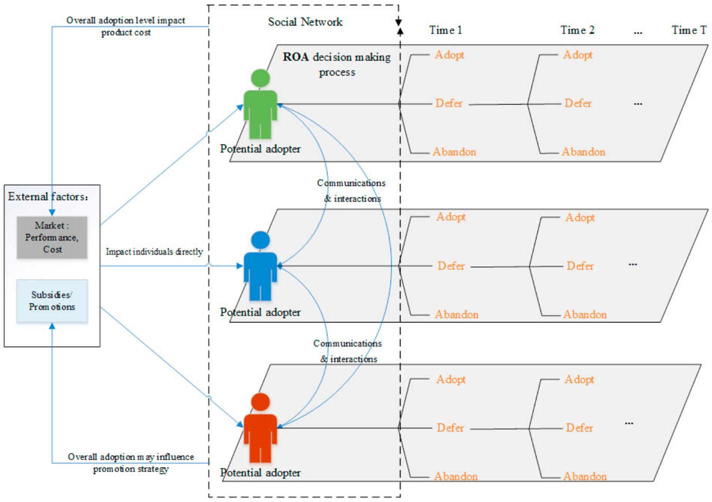

Figure 1. Overall structural of the proposed model

2.1 Individual's Decision making rule

Conventionally, potential adopters evaluate the innovations in light of two aspects, project value ($V_{t,j}$) and capital cost ($C_{t,j}$). The rational decision-making rule indicates that when the project value is higher than the capital cost ($V_{t,j} > C_{t,j}$), the investment is profitable for adopter j. However, when an innovation initially launches to the market, adopters know the price but are uncertain about the performance (product value v_t). This perceptual uncertainty could prevent adopters from investing the innovative product. Different adopters differ in their initial perceptual uncertainties and we assume adopters' perceptual uncertainty evolves due to interactions and communications in the social network. Here, the project value ($V_{t,j}$) and capital cost ($C_{t,j}$) are different from different adopter j since they demand different product quantity (Q_j). Therefore, they can be calculated as $V_{t,j} = v_t \cdot Q_j$ and $C_{t,j} = c_{t,j} \cdot Q_j$, where v_t represents the unit value of the innovative product, and $c_{t,j}$ is the unit cost of the product for adopter j (unit product price minus personal incentives). Here, the product performance v_t does not change across potential adopters, but unit cost $c_{t,j}$ is different among agents since different product quantity demands will result in different incentive levels.

In order to measure this perceptual uncertainty about the project's performance, the subjective performance ($V_{t,j}$) of the consumer j at time t is assumed to follow a normal distribution with mean $v_t \cdot Q_j$ and variance $S_{t,j}^2$ [12]. $v_t \cdot Q_j$ is the real project value of adopter j at invest time t. $S_{t,j}^2$ measures the adopter's perceptual uncertainty about the project.

Besides the perceptual uncertainty of an adopter, we also consider the risk attitude of the adopter, which is an important factor in the decision-making process. Here, the personal risk attitude of adopter j is denoted by m_j. Adopters are risk-averse in adopting the innovative products by assumption and hence $m_j > 0$ for all j. Given, subjective project value ($V_{t,j}$) and risk attitude (m_j), we utilize the uni-attribute utility function to denote the project value:

$$U(\tilde{V}_{t,j}) = 1 - \exp(-m_j \tilde{V}_{t,j}) \tag{1}$$

Given the cost at time t ($C_{t,j}$) can also be measured by the same utility function shown as above, adopters decide to invest the innovative production only when the expected project value is greater than its cost $\mathrm{E}[\mathrm{U}(\tilde{V}_{t,j})] > \mathrm{U}(C_{t,j})$. Note the performance $\tilde{V}_{t,j}$ follows the normal distribution. Here, we use the expected value of the utility function. Thus, the above inequality rule can be simplified as follows:

$$1-\exp(-m_j v_t \cdot Q_j + m_j^{\,2}\, {S_{t,j}^2}/{2}) > 1-\exp(-m_j c_{t,j} \cdot Q_j) \qquad (2)$$

$$v_t - c_{t,j} > \frac{m_j}{2} E_{t,j} \quad E_{t,j} = \frac{S_{t,j}^2}{Q_j}$$

where, $E_{t,j}$ is used to denote the unit perceptual uncertainties of adopter j. The rule indicates that the investment decision is made only when the project profit $(v_t - c_{t,j})$ is greater than an individual's risk adjusted perceptual uncertainty $(0.5 \cdot (m_j E_{t,j}))$.

Noted that there exists managerial flexibility in innovation investment since innovative products have high intrinsic performance volatility. ROA method herein is proposed to capture the performance uncertainty in innovation investment. Herein, we calculate the value of waiting option (w_t) at different time step *t*. Waiting option serves as a right not the obligation to the agents in the model allows them to invest later when conditions are satisfied. A positive waiting option value in ROA model indicates that the project has positive potential to make a profit if invested in the future. When the project value at time *t* is not enough to overcome an adopter's perception uncertainty, but the corresponding waiting option value is greater than zero, the adopter could choose to defer the project rather than abandon the project. Therefore, the proposed decision rule considering both perceptual uncertainty and real option value is shown as follows:

$$\textit{Decision rule}: \begin{cases} I_{t,j} = 2 \quad \textit{Invest} & v_t - c_{t,j} > \frac{m_j}{2} E_{t,j} \\ I_{t,j} = 1 \quad \textit{Defer} & 0 < v_t - c_{t,j} \le \frac{m_j}{2} E_{t,j},\, w_t > 0 \\ I_{t,j} = 0 \quad \textit{Adandon} & v_t - c_{t,j} \le 0 \end{cases} \qquad (3)$$

where, $I_{t,j}$represents the investment status of the agent j at time *t*. The adopter once decide to invest or to abandon, his/her investment status remain unchangeable in the following years. Here, the project value and waiting option value are calculated based on real option theory [13].

2.2 Personal Perceptual Uncertainty

Over time, potential adopters' uncertain perception about the performance $(E_{t,j})$ will be updated if the new information received, for example through communicating with the others who adopted the product or observing the adopted products in their peer network. If an adopter whose neighbors have adopted the product, he or she is more likely to reduce his/her uncertainty perception and therefore adopt the innovative product too. Hence, the perceptual uncertainty $(E_{t,j})$ of adopter j is effected by the number of neighbors of agent j (Nei_j), the set of neighbors who have adopted the product (Nad_j) and their tie strength. In addition, the agent and neighbors' perceptual uncertainties also play a crucial role in perceptual updating. Herein, tie strength $(Cl_{i,j})$ measures the degree relative closeness between agent j and her neighbors *i*.

For each agent at time *t*, we collect the set of adopters Nad_j from his/her overall neighbors Nei_j. If Nad_j is not empty, this indicates agent j has neighbors who has adopted the innovative product. The agent j is likely to be influenced and change his/her perceptual uncertainty according to the project performance. If at time *t*, the project unit cost is greater than the unit cost, agent j's perceptual uncertainty is probability to decrease. Otherwise, it may increase since the neighbors will provide negative information about the product. The impact factor $(R_{j,nad})$ of agent j is the sum of tie strength assigned in Nad_j.The greater the value of $R_{j,nad}$), the more likely that the new information can influence the agent j's perceptual uncertainty. Note the relative influential effect of agent j has the range between 0 and 1. We utilize the uniform distribution to generate random number between 0 and 1. If the random number is smaller than $R_{j,nad}$), agent j is supposed to be influenced by the new information and his or her perceptual uncertainty should be updated accordingly. Otherwise, his or her perceptual uncertainty remains unchanged.

Suppose the received information from neighbors are positive, so agent j reduces his/her perceptual uncertainty by applying Bayes' rule shown as following [12].

$$E_{t,j} = \frac{1}{1/E_{t-1,j} + 1/\sigma^2} \tag{4}$$

where σ^2 is the variance of the new information and it equals to the average of the perceptual uncertainties of agent j's neighbors who has adopted the product. However, if Nad_j is empty, which means there is no adopters in agent j's neighbors, we do not update agent j's perceptual uncertainty.

2.3 Agent Based Model

The previous sections give descriptions of individual decision rule and algorithm of interpersonal communication. In this section, we introduce how to start the simulation, where *N* agents rather than one agent interact and make decisions in the network. The initial step is to set model parameters, which are concluded in Figure 2.There are four different groups of parameters in our models (agent, network, input, and output). Parameters of agents and network here is used to ensure heterogeneity of agent and structure of network. Analysts can test different external factors through adjusting inputs and analyze results of interest by choosing different outputs.

After parameters setting, our simulation model starts from *t*=1. At time step t, our model firstly calculates the unit product value and corresponding waiting option value based on ROA theory. Afterward, it checks the adoption statue in the network one by one. For agent j who has not adopted with $I_{t,j} = 1$, the proposed model simulates the interpersonal communications and updates their perceptual uncertainty (as described in section 2.2). Agent j then makes adoption decision under ROA integrated decision rule. Next, the proposed model makes a record of adopters in the network at time t and increases the time step by one. One replication run is finished when time step t exceeds the project expire time T. Due to random errors in unit product values, we run the simulation *n* independent replications and final results obtained through averaging all replications.

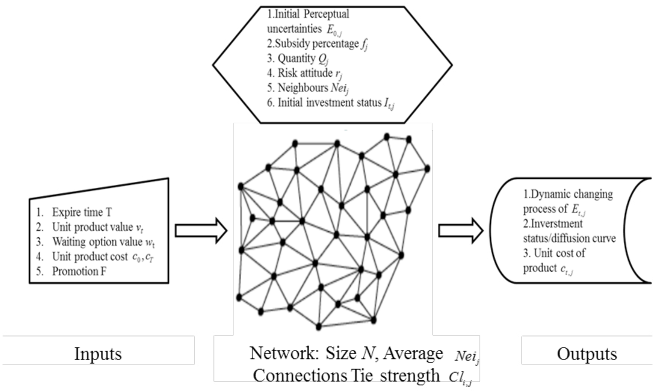

Figure 2. Inputs and Outputs of the proposed model

2.4 Model Application

The proposed model has applied in the PV market of Singapore. In Singapore, PV products are getting popular and installed a lot in commercial and industrial buildings since 2008, but it remains a meager adoption rate in residential buildings. Therefore, our model is utilized in the PV case to examine the impact of different factors on the diffusion of PV products, for example, network structure, government subsidy strategies and uncertainty of PV performance.

In this case study, we found that individualistic social network is more suitable for innovative products diffusion than a collectivistic social network. Because comparing to collectivistic social network, the social network with individualism culture is tighter and smaller than, which is better for information transmission and innovative products' adoption. Additionally, when testing the optimal subsidy strategy given the fixed government incentive budget, we found that the higher level of subsidy, the more numbers of the initial adopter, the faster and higher of the diffusion curve. As indicated by the results, every 10% increment in subsidy level causes around 30% increment in overall adoption level. Based on these findings, marketing managers could make better and wiser strategies to promote PV in the Singapore market. For example, increase the subsidy levels, hold the promotion campaign in communities where customers' relationship is close.

3. Conclusion

In conclusion, this paper established an agent-based model for evaluating diffusion of innovative products in the social network. Different from typical macroeconomic diffusion models like Bass model [14], the proposed model starts from individual adoption decisions and aggregates diffusion curve across agents in the network. In this model, we defined a specific social network with heterogeneous agents and dynamic interpersonal communications. Such Agent-based models, as stated by Kiesling [9], are superior to macroeconomic ones since they can capture more detail population heterogeneity and social processes. Moreover, we innovatively utilized real option analysis approach in our individuals' adoption rule to deal with high products' intrinsic uncertainties and value of managerial flexibility in innovation investment, which are often ignored in existing models. Last but not least, we integrated external factors, such as PV cost and government subsidy into the model and defined their evolving processes. Analysts then can test different cases and settings concerning external factors when applying our model.

Even though the proposed model covers more details than existing ABM model, it remains several limitations need to be solved in the future. For example, in this model, we focus on the effect of project uncertainty and interpersonal communications on the individuals' adoption. Even though these two are major factors that give impetus to diffusion of innovation, many other factors can effect adoption decisions and need to be studied in the future. In addition, model validation is a challenging work since ABM are constructed based on individual agent behaviors, which consists plenty of parameters and interactions. Future works should pay more attention to this area to make the proposed model valid.

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