OPTIMAL SPATIAL ALLOCATION OF BUDGET TO PROMOTE UPTAKE OF NEW VEHICLE TECHNOLOGY

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ABSTRACT

Social exposure is one of the factors affecting the diffusion dynamics for Electric Vehicles (EV) uptake. It could be increased by advertising, but the effects of it change among different groups of people and residential zones. This study develops an optimization model that determines efficient allocation of advertising budget to zones. This model includes a dynamic market diffusion model (Struben-Sterman model, 2008) that incorporates the advertising effects. The dynamic interaction of Origin-Destination (OD) travel demand influences the dynamics of the advertising effects that increases the complexity of the model. Equity is also considered when allocating the budget to each zone. The output provides the most effective budget allocation scheme for each zone to decision makers to maximize EV uptake. We implement the model to 11 zones in Sydney network and the results prove the effectiveness and feasibility of the proposed model.

Keywords: EV uptake, advertising, discrete choice model, OD travel.

1. INTRODUCTION

Due to growing environmental concerns of the greenhouse gas emissions from conventional Internal Combustion Engine (ICE) vehicles, which account for over 10% of total greenhouse emissions in Australia (DCCEE, 2012), there is an increasing governmental interest to improve uptake of Electric Vehicles (EV). EV have significant lower CO_2 emissions compared to ICE: Steenhof and Mclnnis, (2008) argued that each driver can reduce CO_2 emissions by 3 tons per year if he/she replaces his/her ICE vehicle with an EV. However, there is a substantial challenge associated to the market diffusion of EV. Since a broad range of factors affects the diffusion of EV, a number of policies could be used to promote its uptake and policy-makers are seeking the best approach.

Many diffusion models have been proposed to represent the diffusion process of EV, and these models can be grouped in three categories (Edwards *et al*., 2013): product diffusion models, discrete choice models and system dynamics approaches. The basic theoretical foundations of product diffusion models was first described by Bass (1969), and refined by other studies (Dodson and Muller, 1978; Schmidt and Druehl, 2005). It identifies two types of consumers: innovators and imitators based on theories of adoption and diffusion within social systems, and estimate the diffusion of new products. These models can provide the final results but factors affecting the diffusion process are usually not examined. Discrete choice models seek to predict the demand of new products according to their performance; namely, data gathered through stated or revealed preference surveys is used to evaluate consumer behaviour. Discrete choice models are widely used to analyse vehicle choices (Brownstone et al, 2000; Hensher and Greene, 2004). While these models capture vehicle characteristics, they are still unable to incorporate the temporal and social dynamics of vehicle choices. System dynamic approaches seek to represent nonlinear dynamic processes and choices, diffusion models and feedback effects, which make these approaches complex but able to provide more reliable predictions of EV uptake in city markets. Most system dynamic models were developed in the last 20 years (Michalek et al., 2004; Struben and Sterman, 2008; Zhang et al., 2011). Studies based on system dynamic models accessed factors affecting the uptake of Alternative Fuel Vehicles (AFV) including vehicle performance (Powell et al., 1998); fuelling infrastructure (Jassen et al., 2006); coordinated policies (Supple, 2007; Edwards *et al*., 2013) and subsidies (Shephered et al., 2012). However, though a large number of factors related to EV uptake have been analysed, most studies consider the whole study region as one zone and average out the difference of social dynamics and characteristics between zones.

In this paper, we refine the dynamic model proposed by Struben and Sterman (2008) that seek to maximize the number of EV within a region of interest, through the optimization of EV advertising effects, which can be considered as the proxy of social exposure. The incorporation of the variation of characteristics between zones and the interactions between them drives complex model and causes the concerns of equity, since the budget allocation according to traffic demand or population of each zone is usually be considered as equity allocation, but the optimum model may produce different distribution plan. The refined model not only improves the accuracy and reliability of the diffusion model, but also enables government allocate the budget optimally to each zone towards a maximum uptake of EV.

This paper is structured as follows. Section 2 describes the EV social exposure optimization model including the concern of equity and the EV diffusion model based on the optimized social exposure. The results are presented and analysed in section 3. Section 4 closes the discussion.

2. SOCIAL EXPOSURE AND DIFFUSION MODELS

Struben and Sterman (2008) proposed a dynamic diffusion model for Alternative Fuel Vehicles (AFV) – hereby referred to as the Struben-Sterman model – which incorporates and integrates various factors affecting the AFV adoption process such as vehicle characteristics, driver's experience and social exposure. Figure 1 depicts the dynamics of the Struben-Sterman model and its feedback mechanisms.

The number of EV increases with new vehicle sales and reduces with vehicles discards, while the sales of EV depend on its market share. A standard multinomial logit choice model is used to estimate the EV market share, but instead of utility, perceived affinity is used in this model. The perceived affinity is the product of the Willingness to Consider (WtC) for EV, which measures the driver's familiarity with EV and the utility of EV. The WtC can be scaled to the interval [0,1]; it increases with social exposure and decays over time. Struben and Sterman (2008) argued that the lack of sufficient familiarity with EV obstructs drivers to consider EV when they make decisions – without policy support and this argument is supported by Shepherd *et al* (2012). In turn, the WtC for ICE is considered to be 1 for everyone since ICEs are highly prevalent in our society, and the WtC for EV is assumed to be initially close to 0, the same assumption as Shephered *et al* (2012). The large difference of WtC between EV and ICE means that WtC has a significant effect on EV market share. Specifically, even if EV has a higher utility than ICE vehicles, a low WtC would ensure that people would not choose an EV. Hence, it is imperative to make people familiar to EVs in the most cost effect way.

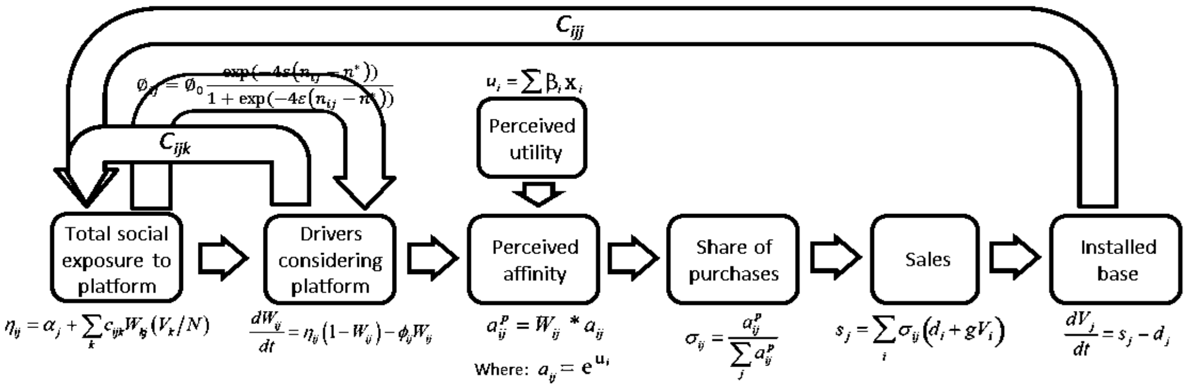


Figure 1: Schematics and Equations for Struben-Sterman Model

The WtC for EV increases with social exposure and decays with time, and as shown in 1. The decay of the WtC is also dependent on social exposure: when EV exposure is low, WtC decays rapidly and vice versa. It implies that the social exposure for EV is a controllable factor that influences the WtC for EV. According to Struben and Sterman (2008), EV exposure arises from three components: marketing effects, word of mouth contacts with EV drivers, and word of mouth of EV among ICE drivers. Word of mouth effects captures the feedbacks about EV of drivers, and marketing effects show the effort by manufacturer and government to boost consideration and adoption of EV among drivers. Thus, the optimization of advertising budget allocation is an important process of promotion the uptake of EV.

2.1 Advertising effects optimization model

The following proposed model is applied when the number of EV, the number of ICE and the willingness to consider EV at the beginning of this time period are known.

Sets:

- I: set of zones, indexed by i.

Decision variables:

- $f_i \in R$: advertising effects on social exposure in zone i $\forall$ i $\in$ I;
- $b_i \in R$: advertising budget in zone i $\forall i \in I$;

Parameters:

- ε: the maximum allowable budget difference between any pair of zones;
- β_{ij}: number of trips from zone i to zone j, $\forall i, j \in I$;
- φ: strength of advertising investment per person for social exposure of EV;

- B_I: total budget available;
- n_i: total number of trips of zone i, defined as: $\forall i \in I$

$$n_i = \sum_{,j \in I} \beta_{ij} + \sum_{j \neq i, j \in I} \beta_{ji} \tag{1}$$

Objective function:

$$\max \sum_{i \in I} f_i \tag{2}$$

Subject to:

$$f_i = 0.5\left(\sum_{j \in I} \frac{\varphi b_i \beta_{ij}}{\sum_{,j \in I} \beta_{ij}} + \sum_{j \in I} \frac{\varphi b_j \beta_{ji}}{\sum_{j \neq i, j \in I} \beta_{ji}}\right) \qquad \forall\, i \in I \tag{3}$$

$$\frac{(b_i n_i - b_j n_j)}{((n_i + n_j) B_I)} \leq \varepsilon \qquad \forall\, i, j \in I \tag{4}$$

$$\sum_{i \in I} b_i \leq B_I \tag{5}$$

$$b_i \geq 0 \qquad \forall\, i \in I \tag{6}$$

The objective function (2) maximizes the effects on EV social exposure from advertising, which is defined in Equation (3). We take into consideration the influence from the dynamic interaction of Origin-Destination (OD) travel demand between different zones on the dynamics of the advertising effects. The effect of advertising in a zone is assumed to be linearly related to the budget allocated to this zone and we also assume that the effects between any two zones is linearly related to the number of trips between them. The total number of trips generated from this zone, i.e. production, and the total number of trips to this zone, i.e. attraction, as well as the 0.5 coefficient are used to ensure the effects of advertising have the same scaling with other effects in Struben-Sterman model (2008).

Equation (4) is the budget dispersion constraint which seeks to control the allocation of the budget among zones using the parameter ε to measure the level of equity. A larger value of ε means less consideration about equity and the larger difference between the allocated budgets of each zone, but the increase of ε provide a more relaxed constraints equity and we have more feasible space to adjust the local budget towards a more optimal result. When $\varepsilon = 0$, all the budget must be allocated according to the number of tips of each zone, and this scenario is considered as an equitable scenario. Constraint (5) defines the total budget of the whole city and constraint (6) ensures that all variables are positive.

2.2 EV uptake model

The advertising effects optimization model provides the optimal effects of advertising. Based on the results, the following algorithm is based on the Struben-Sterman model (2008) and can be used to estimate the number of EV and the WtC for EV over a specified time period.

Table 1. Parameters and initial conditions of EV uptake model

	Notation:	**value**	**source**
$\mathbf{x_{i,0}}$	Initial number of EV in zone i	0	assumption
$\sum_{i \in I} \mathbf{y}_{i,0}$	Initial total number of ICE	2 786 892	ABS, 2011
$\mathbf{w_{i,0}}$	Initial value of WtC for EV	0	assumption
$\boldsymbol{u_e}$	utility of EV	4.6363	Brownstone et al, 2000;
$\boldsymbol{u_i}$	utility of ICE	1.3406	Hensher and Greene, 2004
$\boldsymbol{\theta}$	marketing effects by EV manufacturers	0.01	Struben and Sterman, 2008
$\boldsymbol{\lambda}$	average vehicle service life	10 yr	Struben and Sterman, 2008
$\mathbf{g}$	growth factor of number of vehicles	0.02	ABS, 2013

Algorithm:

Let T be the set of years, index by t.

for t=0…|T|

for i=1…|I|

$$\eta_{i,t} \leftarrow \theta_i + 0.25\frac{x_{i,t-1}}{x_{i,t-1}+y_{i,t-1}} + 0.15 w_{i,t}\frac{y_{i,t-1}}{x_{i,t-1}+y_{i,t-1}} + f_i \tag{7}$$

$$w_{i,t} \leftarrow w_{i,t-1} + \eta_{i,t}\left(1-w_{i,t-1}\right) - \frac{\exp\left(-40\left(\eta_{i,t}-0.05\right)\right)w_{i,t-1}}{1+\exp\left(-40\left(\eta_{i,t}-0.05\right)\right)} \tag{8}$$

$$x_{i,t} \leftarrow x_{i,t-1} + \frac{w_{i,t-1}u_e}{w_{i,t-1}u_e+u_i}\left(\frac{y_{i,t-1}}{\lambda}+gy_{i,t}\right) + \frac{u_e}{u_e+u_i}\left(\frac{x_{i,t-1}}{\lambda}+gx_{i,t-1}\right) - \frac{x_{i,t-1}}{\lambda} \tag{9}$$

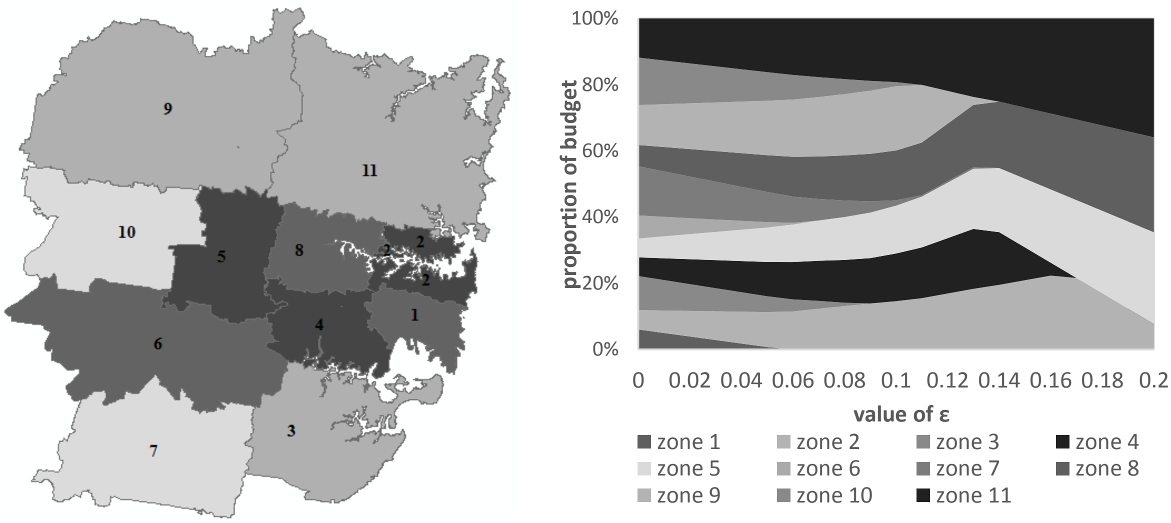
$$y_{i,t} \leftarrow y_{i,t-1} + \frac{u_i}{u_e+u_i}\left(\frac{y_{i,t-1}}{\lambda}+gy_{i,t-1}\right) + \frac{u_i}{u_e+u_i}\left(\frac{x_{i,t-1}}{\lambda}+gx_{i,t-1}\right) - \frac{y_{i,t-1}}{\lambda} \tag{10}$$

Determine $\sum_{i\in I} x_{i,t}$; $\sum_{i\in I}\frac{w_{i,t}n_i}{\sum_{i\in I} n_i}$

Equations (7) and (8) give the social exposure and WtC for EV for each zone i and for each year t, which are used to update the number of EV, $x_{i,t}$ and ICE, $y_{i,t}$ through Equations (9) and (10). Initial conditions and parameters are selected based on the case of Sydney, as listed in Table 1. Initially, we assume that there is no EV in the study area and that the WtC for EV is 0, and the ICEs are distributed uniformly in each zone according to the population of this zone. The parameters in Table 1 are assumed to be constant with time, and we assume that the WtC for EV for EV drivers is 1, since they must be familiar with their car. Some other parameters and coefficients which are independent of the location of the study city are sourced from Struben and Sterman (2008) and have been incorporated into the equations.

3. RESULTS AND DISCUSSION

We optimize the budget allocation using different values of ε, and estimate the number of EV after 20 years. The advertising budget is set to be $ 1.2 million every year and φ is set to be $2.5*10^{-6}$. Figure 2 (a) shows the geographical map of 11 zones in Sydney that we select to study. The 11 zones are in the east and centre of Sydney where the most majority of residents live there. The zones in darker grey generate larger number of trips per day, while those zones in lighter grey yield fewer trips per day.



(a) (b)

Figure 2 (a). Geographical map of Sydney 11 zones; (b). Optimized budget allocation of each zone

We first evaluate the allocation of budget among zones, this allocation is constrained by the acceptable regional budget difference values, ε. Figure 2 (b) shows the variation of the proportion of budget allocated to each zone according to ε. As discussed in Section 2, a high value of ε means that the higher level of optimization we can achieve. It shows that with the increase of the value of ε, the budget is allocated to less number of zones, and thus, the amount of the advertising budget of these zones become large, which implies that advertising frequently in fewer zones could provide more considerable effects than advertising in more zones less frequently.

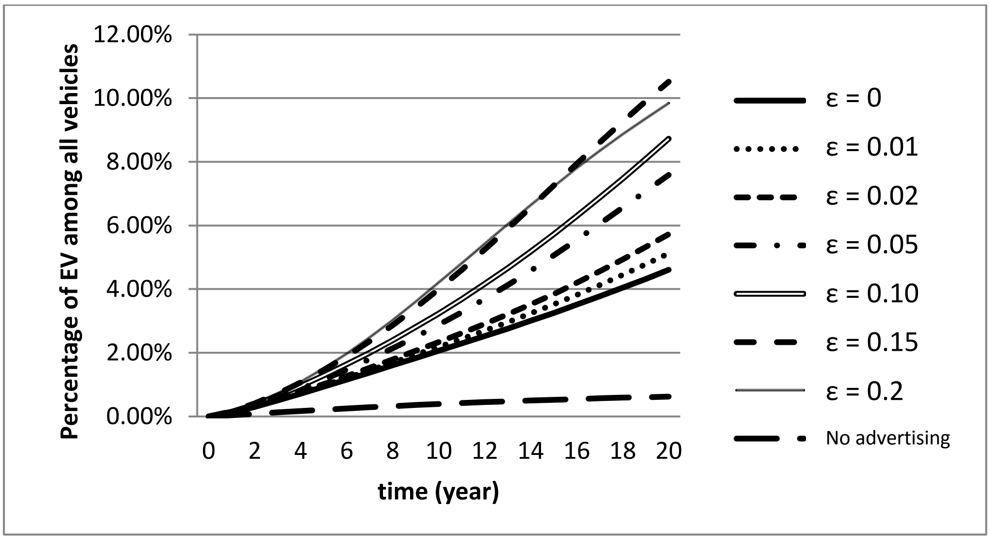


Figure 3. Variation of the total number of EV with time for different values of ε

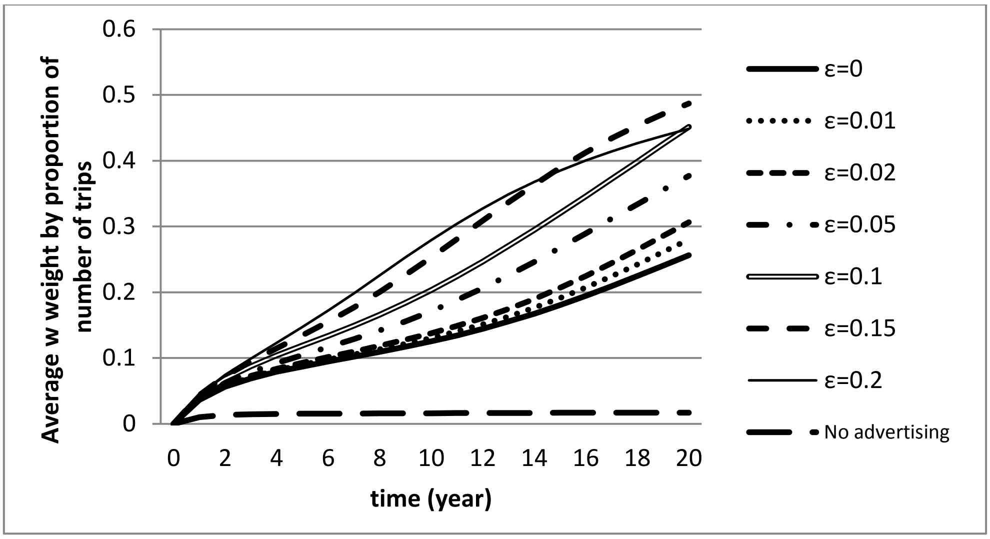


Figure 4. Variation of WtC with time for different values of ε

The variance of the percentage of EV among all vehicles with time is shown in Figure 3: 7 values of ε are used and a no advertising scenario is included, i.e. the budget equals to 0. The comparison between no advertising scenario and the scenario of ε = 0 illustrates the influence of advertising on EV diffusion: it makes the percentage of EV among all vehicles increase from 0.6% to 4.6% at the end of 20 years. The other curves depict the improvement of the objective function. In the best scenario, when ε = 0.15, EV account for 10.5% of all vehicles, and the increasing pattern of the percentage of EV tends to be logarithmically changing with time. In general, the percentage of EV at the end of the 20th year is higher for larger ε, except for ε = 0.2, in this case, even though the percentage of EV grows most rapidly during the first 10 years, its growth rate slows down after the 15th year, and the percentage of EV for ε = 0.2 falls below than that of ε = 0.15 at the end of the time period of interest.

To have a better understanding of the diffusion process, we evaluate the variance of the WtC with time. For each value of ε, the average WtC of all zones weighted by proportion of trip numbers are plotted with time in Figure 4. The behaviour of the WtC can be classified in three groups: the first group only contains the no advertising scenario, in which the WtC is small and almost constant. The second group comprise five scenarios with ε between 0 and 0.1, we observe nearly logarithmic growths of WtC with time expect for the first 2 years, and at the end of advertising time period, higher ε produces higher WtC. The results of this group of scenarios verify that the increase of the level of inequity, i.e. budget dispersion, can enable us to achieve a more efficient budget allocation. The last group contains the scenarios when ε = 0.15 and 0.2 and the behaviour of the WtC is complex in this case. It begins with a logarithmic growth at first few years but the rate of increase drops after about 10 years. This is caused by the difference amount budget allocated to each zone, as shown in Figure 2, all budget is distributed to 5 and 4 zones when ε = 0.15 and 0.2, respectively, and there is no budget for the remaining zones. The benefit of this allocation is that we have sufficient budget to obtain a high level of advertising effects in these selected zones and to increase the WtC of these zones rapidly. However, since the WtC is defined to be lower than1, once the WtC of these zones near 1, the effects of advertising is unable to transfer to WtC, as a result, the growth rate of overall WtC drops.

The total number of EV at the end 20 years vs. ε is plotted in Figure 5 to determine their relationship. It is obvious that there is a threshold value of ε, if ε is less than the threshold value, the total number of EV increase linearly with ε, but when ε is larger than this value, the total number of EV decreases with ε. Another results can be seen from Figure 5 is that there is a drop of the number of EV after 20 years when the value of ε is about 0.07. This is because of the number of zones that receives budget reduced in this region, as shown in Figure 2 (b). The cause of this threshold is discussed, which is because of the reduction of number of zones receive budget, and the drop around ε = 0.07 is also caused by the same reason. To deal with this reduction after threshold, a feasible approach is to include a feedback mechanism based on the WtC in order to refine the budget allocation model. This mechanism should update the parameters of the optimization model to avoid distributing the budget to zones with a high WtC. However, practically, an obvious inequity policy, for example, the difference between the budgets allocated to each zone is higher than 10% of the total budget, i.e. ε > 0.1, is almost unacceptable for public. Thus, the value of ε should be less than 0.1, and in this range, the optimization model is proved able to provide a considerable improvement of EV uptake.

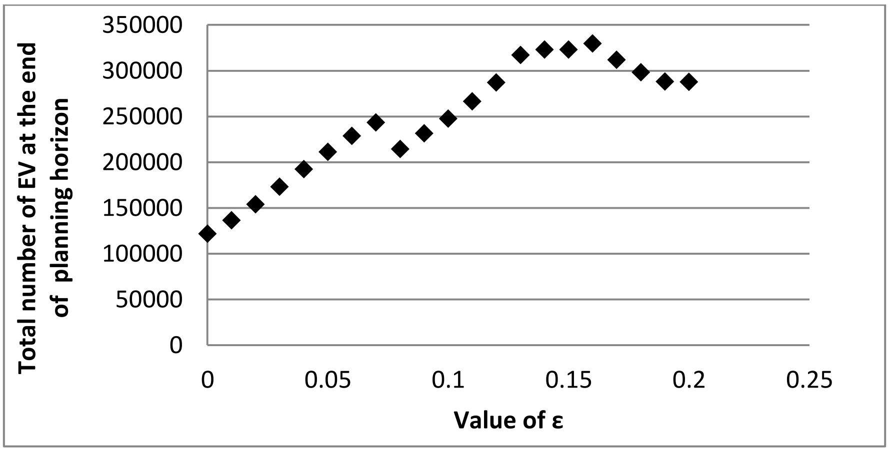


Figure 5. Total number of EV after time period T with different ε

4. CONCLUSION

In this paper, we have proposed an optimization model to allocate advertising budget in order to promote the uptake of EV. The dynamic interaction of Origin-Destination (OD) travel demand and the constraint of equity have been taken into consideration. The system dynamic model for the diffusion of AFV proposed by Struben and Sterman (2008) is used to estimate the number of EV, and a case study in the region of Sydney, Australia is used to test the proposed model. The effects of advertising on the social exposure of EV are optimized, and the number of EV and the WtC for EV are used as indicators to examine the performance of this model. The results show that the optimization model can provide equitable budget allocation among the zones of the region of interest, and in general, less consideration about equity provide more uptake of EV, expect for the extremely unequal conditions and an extremely long advertising time period. Future studies should focus on the feedback mechanism of the optimization model and the incorporation of other policies to the optimization model, these studies will increase the efficiency of policies, especially for long-term policies.

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