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Influence of advertisement control to residential energy savings in large networks

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HIGHLIGHTS

- Investigate network influence to energy savings with a novel systematic approach.
- Develop a network model to quantify advertisement impact to adoption of energy products.
- Develop advertisement control via optimisation design for energy saving targets.

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ABSTRACT

User awareness and behaviour have a strong impact on energy savings especially through large-scale mass rollout programmes for new energy products. Such energy programmes are mostly funded by government with specific energy saving targets. In this work, we aim to investigate the influence of advertisement control to residential energy savings in large population networks. A mathematical model is established to predict the expected energy savings (EES) in a network where advertisement is used to influence user adoption rate of energy efficient product. The proposed dynamic network model consists of information diffusion, EES calculation, and advertisement control. It can be applied to mass rollout programmes to forecast the EES and the adoption rate of new energy products, based on which the advertising investment required to accelerate energy savings can be determined by optimisation design. The proposed approach is tested first with a small population network involving 40 participants, then applied to a large population network with one million internet users. Case studies for different scenarios consider various optimisation targets including adoption rate, time cost, advertisement cost, and total energy savings subject to programme budget and time constraints. The optimisation results show that 32.21 % and 18.15 % of EES are achieved for the small- and large-scale networks, respectively, suggesting the potential benefits of taking advertisement as a means to promote energy efficient product through social networks.

1. Introduction

1.1. Background and state of the art

Affected by the recent global COVID-19 pandemic, some industry supply chains have become shortened or even moved from overseas to local areas, such as food, medicine and personal protective equipment [1]. These supply chain reforms will increase the total energy consumption of OECD (Organisation for Economic Co-operation and Development) countries including UK in the long term. As reported in [2] the energy intensity increases in USA, China, EU, Japan, leading to the increases of the cost of energy converted into GDP. Residential energy consumption and cost have shown an increase due to the lockdown restrictions applied in the past few years [3]. Results in [4] indicate that when employees overcome the initial personal stress, they are more willing to work from home for consecutive days. Some occupations are likely to remain working at home even when the pandemic restrictions are lifted [5], which makes residential sector continue to account for a large portion of the total energy consumption [6]. Thus, energy usage reduction on residential consumption side will become an important breakthrough for Paris Agreement target [7]. There are many government and utility funded mass rollout projects targeting for residential users, such as use of compact fluorescent lighting (CFL), LED lighting,

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Nomenclature

Symbols	[units] [values and range]
B	programme total budget [£]
C_T	total cost of advertisement from time 1 to T [£]
E	effect of impressions [0,1]
EES_T	expected energy savings achieved from time 1 to T [kWh]
H	the amount of energy saved by one piece of energy efficiency product [kWh]
J	optimisation performance function
N	network population size [positive integers]
N_g	programme target number of product adoption [positive integers]
P_0	the cost of one piece of free trial product [£]
{S, I, R}	states – aware, unaware and adopted the energy efficiency product [0,1]
$\{S_0, I_0, R_0\}$	initial values for S, I and R
X	impressions (number of views) [non-negative integers]
y_R	adoption rate data from survey
$\alpha,\ \alpha_\omega$	lower threshold of the adoption rate [0,1]
$\beta,\ \beta_\omega$	upper threshold of the adoption rate [0,1]
$\rho,\ \rho_\omega$	decaying rate of the adoption rate [0,1]
$\gamma,\ \gamma_\omega$	diminishing return parameter of adoption rate [0,+∞)
δ	probability to transit from state I to state R [0,1]
ε	average network degree [positive integers]
θ	vector of model parameters
ν	probability to transit from state S to state I [0,1]
π	electricity tariff [£/kWh]
τ	cost of one million impressions [£]
φ	probability to transit from state I to state R in information diffusion [0,1]
ψ	probability to transit from state S to state I in information diffusion [0,1]
μ and ω	advertisement adoption rate and positive response rate to advertisement [0,1]

solar water heater, heat pump programmes. It has been recognised that media publicity has a positive effect on energy-saving appliance adoption [8]. Thus, in order to achieve energy saving targets, the decision-makers can take advertisement as a tool to engage more residential homes for their rollout programmes. This is a challenging task since network impacts are rarely investigated in any energy saving programmes. There's a lack of mathematical models or quantitative tools to predict the project progress for large networks, and provide guidance on advertising investment to engage customers, influence their adoption choice, and eventually achieve energy saving.

Curtailment and efficiency are two categories of household behaviours found to be related to residential home energy consumption [9]. Curtailment behaviours involve repeated efforts to reduce energy use, for example, adjusting thermostat settings, turning on and off lights based on household need. It is suggested that long term energy consumption reduction can be achieved by adopting pro-environmental behaviour patterns [10]. Simulation results in [9] indicate that designed behaviour measures can achieve more than 20 % of energy savings. In [11] it is shown that operational behaviour can influence the energy usage of domestic hot water supply system. Curtailment behaviours are strongly related to households' income, age and education level [12], and these factors are found to play an important role in household energy savings [13]. Residents with more environmental awareness have greater possibility to establish energy saving behaviours [14]. On the other hand, efficiency behaviour involves purchase of energy efficiency equipment, such as improving lighting system, roof and wall insulation. This one-off behaviour has a long-term effect on routine energy consumption. It is discovered that lighting and heating occupy a large portion of domestic energy consumptions [15]. Optimised heating and lighting behaviour can reduce energy consumption while improving comfort [16]. Even small efficiency behaviour changes such as replacing a normal kettle by a smart one can save 40kWh per year for a household [17].

Energy consumption patterns in a building, including curtailment and efficiency behaviours, are affected not only by the occupants but also by neighbouring buildings [18]. Collective behaviour change has a strong influence on energy consumption reduction [19]. It is revealed that collective behaviour change will provide a large amount of energy savings even in a small network [20]. The households' sustainable lifestyle can be influenced by their neighbours [21]. Sharing energy efficiency information between families can lead to reduction of energy consumption [22]. Diffusion of innovation is found to depend strongly on the interaction between individuals within the social network [23]. There are also application software tools developed to promote energy savings by sharing energy efficiency information via social media platform [24]. Research in [25] indicates that social influence especially through web media communication is important for energy-efficiency heating application adoption. These recent developments suggest great potential in energy savings from the perspective of user behaviour influenced by networks.

In a social network, individual users can be considered as nodes, and those nodes that carry energy savings information are defined as hosts. Similar to the epidemics theory, when hosts interact with other nodes in the network, information starts to diffuse. In a mass rollout programme of energy efficiency products, the initial households with products installed can be seen as hosts. These hosts that benefit from the energy efficiency product may spread the information among their neighbouring nodes. The latter that followingly install the product then become sub-hosts. It is noted that even if some neighbour nodes do not install the energy efficiency product, they still carry energy saving product information that can be further spread to wider neighbours. In this way, more adoption of energy saving products are expected to be achieved through the interactions between individuals within the network.

For a mass rollout programme, there is always an installation or savings target to be achieved within a given time. During the implementation process of the programme, the actual product rollout may be slower than expected. In this situation, household engagement measures such as advertisement can be taken to increase the adoption of energy efficiency products. This process of increasing energy savings depends not only on user behaviour but also on the energy efficiency products. For an effective long-term goal, the energy efficiency product needs to be profitable. Traditionally, energy supply companies increase product profit either by expanding market or by decreasing product cost [26]. The cost setting is constrained by technical limitations and requirements on product quality. Therefore, expanding market is regarded as a favoured option in many energy saving schemes.

It is proved that increased advertisement has a positive association to improved market share [27]. The rapid development of modern technologies leads to various means of advertising, such as TV advertisement, newsletters, emails, social media, internet website and online video streaming. Hence, it is crucial to understand the effectiveness of advertisements to promoting energy efficiency products, and particularly those popular online advertisements through internet. In online advertisement business, standardised units of advertisement are called impressions. Impressions refer to the exact times that the advertisement has been viewed. The increasing number of purchasing energy efficiency products is expected to be affected by advertising. A crucial and challenging task is to quantify the relationship between the impressions and the products adoption rate, which hasn't been reported in any literature as far as we know. This motivates the development in this work.

1.2. Proposed work and novelty

The influence of user behaviour to energy savings in social networks are studied in [28], where concepts of direct and indirect energy savings are introduced and used in calculation of the total expected energy savings (EES) of a small network. The model developed in our earlier work [29] can simulate the diffusion of energy savings information within a small population network (40 individuals included) using survey data on how individuals are connected with each other. These studies rely on detailed network connection information, suitable for small scale networks only. To the best of our knowledge, none of the existing models considers the advertisement factor which has a clear influence on user behaviour and will eventually affect the adoption speed of energy savings technologies.

In this work, the influence of online advertisement to energy saving programme is studied through modelling of EES and advertisement control based on the Bayesian forecasting theory [30]. The model includes the information diffusion model, the advertisement model and the electricity cost savings calculation, where the key input is the daily advertisement rate and the output is the increased adoption rate due to advertisement. In order to describe the information diffusion dynamics within the network, two methods from complex network theory, the epidemics theory [31] and the small-world network theory [32], are employed to establish the model. With this model, the energy savings due to the advertisement influence in the network can be quantitatively determined.

The remainder of the paper is structured as follows. A novel model of EES that includes information diffusion and advertisement input is established in Section 2 to quantify the energy savings influenced by advertisement control in large social networks. An advertisement control optimisation method is proposed in Section 3 considering several design objectives. The case studies are conducted for small and large networks, with results and discussions presented in Section 4. Conclusions are given in Section 5. The campaign data for large population network case studies are given in the appendix.

2. Expected energy saving model with advertisement input

In this section, a mathematical model is developed to calculate the EES dependence on advertisement and network interactions. Different from the model in [29] that uses network connection details between individuals, the information diffusion model in this work is established based on the epidemics theory, which does not rely on individual connection information, thus can be applied to large population networks.

2.1. Initial information diffusion model

Consider a network with N nodes, and each node in the network can only have one state at any given time instant. In a typical epidemics model, nodes are classified according to whether it carries virus or not including three states: susceptible, infected, and recovered [31]. The combinations of the three states lead to an SIR (Susceptible, Infectious and Recovered) model. Similar to an SIR model, the states of nodes in energy networks can be defined as follows: unaware of the energy efficiency information, represented by state S; aware of the energy efficiency information, represented by state I; purchased the product, represented as the adopted state R. In a size-N network at time t, the three states are represented by $S(t)$, $I(t)$ and $R(t)$, respectively. The sum of $S(t)$, $I(t)$ and $R(t)$ is equal to one at all times [31], that is,

$$S(t)+I(t)+R(t)=1 \tag{1}$$

Define the probability to transit from the unaware state, S, to the aware state, I, to be ν, and the probability from the aware state, I, to the adopted state, R, to be δ. It is assumed that ν and δ are constant parameters taking values between 0 and 1. In the SIR model in [31], a node in state R will not interact with other nodes in the network. Thus, the changing rate of $S(t)$ only depends on the interactions between nodes in state S and state I. However, in this study, individual users that have already adopted the energy efficiency product may interact with unaware users and pass energy saving information. Therefore, the changing rate of $S(t)$ in the energy network should consider interactions from nodes under both state I and state R. Then, the dynamics of the three states can be represented by the following set of ordinary differential equations.

$$\begin{aligned}\frac{\mathrm{d}S(t)}{\mathrm{d}t}&=-\nu S(t)(I(t)+R(t))\\ \frac{\mathrm{d}I(t)}{\mathrm{d}t}&=\nu S(t)(I(t)+R(t))-\delta I(t)\\ \frac{\mathrm{d}R(t)}{\mathrm{d}t}&=\delta I(t)\end{aligned} \tag{2}$$

Following the small-world network theory, denote ε as the average network degree of the considered network, then the probabilities ν and δ in (2) can be represented as $\nu=\varepsilon\psi$ and $\delta=\varepsilon\varphi$, where ψ is the probability of state transition from S to I, and φ is the probability of state transition from I to R. The three parameters, ε, ψ and φ are considered as constant. For a network with a large population, the initial value of the adopted state R can be assumed to be zero because the information sources only occupy a negligible bit of the whole population. Therefore, $S(0)=S_0$, $I(0)=I_0$ and $R(0)=0$, where S_0 and I_0 are the initial states for S and I. With the use of the average network degree term, the model in (2) can be written as.

$$\begin{aligned}\frac{\mathrm{d}S(t)}{\mathrm{d}t}&=-\varepsilon\psi S(t)(I(t)+R(t))\\ \frac{\mathrm{d}I(t)}{\mathrm{d}t}&=\varepsilon\psi S(t)(I(t)+R(t))-\varepsilon\varphi I(t)\\ \frac{\mathrm{d}R(t)}{\mathrm{d}t}&=\varepsilon\varphi I(t)\end{aligned} \tag{3}$$

This is the information diffusion model without including the advertisement impact.

2.2. Information diffusion model with advertisement input

When consider advertisement influence alone, similar to the information diffusion mechanism in Section 2.1, the changing rates of $S(t)$, $I(t)$, and $R(t)$ can be described as follows,

$$\begin{aligned}\frac{\mathrm{d}S(t)}{\mathrm{d}t}&=-\omega(t)S(t)-\mu(t)S(t)\\ \frac{\mathrm{d}I(t)}{\mathrm{d}t}&=\omega(t)S(t)-\mu(t)I(t)\\ \frac{\mathrm{d}R(t)}{\mathrm{d}t}&=\mu(t)(S(t)+I(t))\end{aligned} \tag{4}$$

where $\mu(t)$ is the advertisement adoption rate, $\omega(t)$ is the advertisement positive response rate. Integrating the advertisement model in (4) with the original information diffusion model in (3), the network adoption dynamics is written as the following differential equation model.

$$\begin{aligned}\frac{\mathrm{d}S(t)}{\mathrm{d}t}&=-\varepsilon\psi S(t)(I(t)+R(t))-\omega(t)S(t)-\mu(t)S(t)\\ \frac{\mathrm{d}I(t)}{\mathrm{d}t}&=\varepsilon\psi S(t)(I(t)+R(t))-\varepsilon\varphi I(t)+\omega(t)S(t)-\mu(t)I(t)\\ \frac{\mathrm{d}R(t)}{\mathrm{d}t}&=\varepsilon\varphi I(t)+\mu(t)(S(t)+I(t))\end{aligned} \tag{5}$$

with $S(0)=S_0$, $I(0)=I_0$ and $R(0)=R_0$. In this way, the advertisement control is integrated in the network model, and its time-dependent influence to the adoption rate can be described.

Since the advertisement operation is run in discrete time, the continuous model in (5) is discretised into the following model,

$$\begin{aligned} S(k+1) &= S(k) - (\varepsilon\psi S(k)(I(k)+R(k)) + S(k)(\omega(k)+\mu(k)))\cdot\Delta T \\ I(k+1) &= I(k) + (\varepsilon\psi S(k)(I(k)+R(k)) - \varepsilon\varphi I(k) + \omega(k)S(k) - \mu(k)I(k))\cdot\Delta T \\ R(k+1) &= R(k) + (\varepsilon\varphi I(k) + \mu(k)(S(k)+I(k)))\cdot\Delta T \end{aligned} \tag{6}$$

where k is discrete time index, ΔT is the sampling period which is taken as one day in this study. Note that the two parameters in the advertisement model, $\omega(k)$ and $\mu(k)$, are time varying and need to be updated at each time instance. The calculation of these two parameters is discussed in the next section.

2.3. Calculation of two parameters in the advertisement model

At time k, the parameter $\mu(k)$ is the adoption rate affected by the advertisement impressions, denoted by $X(k)$. Similarly, the advertisement positive response rate, $\omega(k)$, is the ratio of the number of users who have positive response to the advertisement over the impressions. To be more specific, following an online advertisement, the purchasing behaviour is taken as an action of adoption, the action of clicking the advertisement is taken as a positive response. A positive response doesn't necessarily lead to adoption directly, however, it provides a chance of information diffusion through the network. In this work, the number of users giving positive response does not include those who have already adopted the product before viewing the advertisement. In the following, the Bayesian forecasting approach in [30] is employed to calculate the advertisement adoption rate and the positive response rate.

Define $E(k)$ to be the effect of impressions $X(k)$ imposed on the adoption rate. Impressions $X(k)$ is the number of views of advertisements in various forms. In order to calculate the relationship between $X(k)$ and the advertisement adoption rate, $\mu(k)$, the following settings are required.

- Lower threshold

The minimum level of the advertisement adoption rate is denoted by the lower threshold parameter α, i.e., $0 \le \alpha \le \mu(k) \le 1$. In this work, α is taken as zero for a large population network.

- Upper threshold

The maximum level of the advertisement adoption rate is denoted by the upper threshold parameter β, thus $0 \le \mu(k) \le \beta \le 1$. In this work, β is set to be 0.85 following the suggestion in [30].

- Decaying factor

Due to the memory decaying nature of innovation information, the adoption rate is assumed to decay between times $(k-1)$ to k by a factor of $100 \bullet (1-\rho)\%$, where $\rho (0 \le \rho \le 1)$ is the decaying factor for $\mu(k)$; its value is set to be 0.90 as in [30].

- Diminishing returns

According to the principle of diminishing returns in economics, when any factor of a production is increased while other factors are kept constant, the benefits gained will proportionally get smaller. At time k, the influence of $X(k)$ will change by $\exp(-\gamma X(k))$, which decays exponentially as $X(k)$ increases for some constant $\gamma > 0$. Here γ is called the diminishing return factor, the initial value of which is set to be 0.02 in this study, following reference [30].

With the above four parameters given, the effect of impressions at time k can be calculated by the Bayesian forecasting approach [30], i.e.,

$$E(k) = (\beta-\alpha) - (\beta-\alpha-\rho E(k-1))\cdot\exp(-\gamma X(k)) \tag{7}$$

The adoption rate is then written as,

$$\mu(k) = \alpha + E(k) = \beta - (\beta-\alpha-\rho E(k-1))\cdot\exp(-\gamma X(k)) \tag{8}$$

Similarly, the advertisement positive response rate, $\omega(k)$, can be determined by.

$$\omega(k) = \beta_\omega - (\beta_\omega - \alpha_\omega - \rho_\omega E_\omega(k-1))\exp(-\gamma_\omega X(k)) \tag{9}$$

The subscript 'ω' is introduced in (9) to distinguish the parameters for the positive response rate from those for the adoption rate.

2.4. Estimation of model parameters

The model parameters for energy product information diffusion and advertisement impact are unknown. In this work, we use survey data and least-square data fitting method to estimate the parameter values. Denote.

$$\boldsymbol{\theta} = [\psi \quad \varphi \quad \alpha \quad \beta \quad \rho \quad \gamma \quad \alpha_\omega \quad \beta_\omega \quad \rho_\omega \quad \gamma_\omega] \tag{10}$$

The initial values are set up as follows. In the information diffusion model, $\psi_0 = 0.1$ and $\varphi_0 = 1e-4$ for small network, $\psi_0 = 0.01$ and $\varphi_0 = 1e-5$ for large network. In the advertisement model, $\alpha_0 = a_{\omega 0} = 0, \beta_0 = \beta_{\omega 0} = 0.85, \rho_0 = \rho_{\omega 0} = 0.9, \gamma_0 = \gamma_{\omega 0} = 0.02$. The values of θ can be calculated by.

$$\theta^* = \mathrm{argmin}_{\theta\in\Theta} J_\theta(\theta) \tag{11}$$

where.

$$J_\theta = \sum_{k=1}^{M} (R(k,\theta) - y_R(k))^2 \tag{12}$$

is the residual function to be minimised for parameter estimation, M is the length of data used for modelling, Θ is the searching domain for θ, which is a set of positive real numbers in the range of $[0,1]$, $y_R(k)$ is the adoption rate data obtained from survey, $R(k,\theta)$ is the adoption rate data calculated by the model.

The data fitting algorithm is implemented in MATLAB. Two global searching functions, 'ga' and 'fmincon', are used to find the optimal solution, where 'ga' uses the popular genetic algorithm and 'fmincon' uses a gradient-based searching algorithm.

2.5. Electricity cost saving calculation

In this subsection, a cost saving calculation model is written for decision makers managing a mass rollout programme. For a network of size N operating from time $k=1$ to $k=T$, the EES is used to quantify the influence of advertisement, which can be calculated for the whole network as follows,

$$EES_T = N\cdot\sum_{k=1}^{T} R(k)\cdot H(k) \tag{13}$$

where $H(k)$ is the amount of energy saved by one piece of energy efficiency product on Day k (compared to the case when the energy product is not adopted), and $R(k)$ is calculated by the information diffusion model in (6).

Assume that the target number of products installed (purchased) is N_g in a given period of time up to T, the total budget is £B, the electricity tariff is £$\pi(k)$ per kWh on Day k, the price of 1 million impressions is τ, and the cost of one free-trial product offered by the programme is P_0.

When z free trial products are given to the network, the initial conditions are $S(0) = 1-(z/N)$, $I(0) = 0$ and $R(0) = z/N$. With the same price assumed for each product, the initial cost can be calculated as zP_0. The cost of advertisement on day k is $C(k) = \tau X(k)$.

The total cost of advertisement from Day 1 to Day T is calculated by.

$$C_T = \sum_{k=1}^{T} C(k) = \tau \sum_{k=1}^{T} X(k) \tag{14}$$

3. Advertisement control design

In real world applications, the objective of an energy saving product rollout programme should focus on the balance between multiple measures such as the adoption rate, the time period applied, and the total cost savings, etc. The following optimisation objectives are proposed in this work: (i) minimise the total cost of advertisement, (ii) minimise the time (cost), (iii) maximise the total energy savings, and (iv) maximise the adoption rate.

The advertisement strategy is designed using an optimisation algorithm. The control variable is the advertisement daily impressions. Denote.

$$\mathbf{X} = [X(M+1), X(M+2), \cdots, X(M+K)]^T \tag{15}$$

as the time sequence vector of impressions over K days, M is the number of days used for modelling, therefore $(M+1)$ is the starting day of the optimisation design. The design of the daily impressions can be formulated as a general optimisation problem, i.e.,

$$\mathrm{X}^* = \mathrm{argmin}_{\mathbf{X} \in zx} \mathrm{J}(\mathbf{X}) \tag{16}$$

where J is the objective function to be minimised for each scenario, the set Z_X is the searching domain for $\mathbf{X}$.

In the following, four methods are proposed considering different objectives in the energy saving scheme.

- Method 1: targeting the lowest advertisement cost

The objective of this method is to reach the target adoption rate at the end of the programme with the lowest advertisement cost. Two constraints need to be applied, one is to keep the total cost under the given budget, i.e.,

$$C_T(\boldsymbol{X}) + P_0 \leqslant B \tag{17}$$

where $C_T(\boldsymbol{X})$ is calculated by (14), P_0 is the price of free trial product, B is budget limit. The other constraint is that the adoption rate at the end of the programme must reach the target rate, i.e.,

$$R(M+K, \boldsymbol{X}) \geqslant \frac{N_g}{N} \tag{18}$$

where $R(M+K)$ is the adoption rate at the end of the programme, N_g/N is the target adoption rate to be reached for the network. The optimisation problem is written as.

$$\boldsymbol{X}^* = \underset{\boldsymbol{X} \in Z_X}{\mathrm{argmin}} C_T(\boldsymbol{X}) \tag{19}$$

subject to: (17) and (18).

- Method 2: targeting the shortest time to achieve required adoption rate

The objective is to be reach the target adoption rate within the shortest time under the given budget. This is achieved through the following optimisation route.

$$\boldsymbol{X}^* = \underset{\boldsymbol{X} \in Z_X}{\mathrm{argmin}} T_s(\boldsymbol{X}) \tag{20}$$

subject to: (17) and (18).

where T_s is the time to achieve the required adoption rate, it is calculated from the numerical procedure by recording the time once the required rate is reached.

- Method 3: targeting the largest energy savings

The objective is to achieve the largest electricity cost savings while reaching the target adoption rate within the budget and given time. To achieve the maximum EES_T, calculated by , the optimisation problem is written as follows.

$$\boldsymbol{X}^* = \underset{\boldsymbol{X} \in Z_X}{\mathrm{argmin}} - EES_T(\boldsymbol{X}) \tag{21}$$

subject to: (17) and (18).

- Method 4: targeting the largest adoption rate

This design aims to achieve the largest adoption rate within the given budget and time. The adoption rate is calculated from the information diffusion model in (6). The objective function is formulated as follows.

$$\boldsymbol{X}^* = \underset{\boldsymbol{X} \in Z_X}{\mathrm{argmin}} - R(M+K, \boldsymbol{X}) \tag{22}$$

subject to: (17) and (18).

The above advertisement control design procedure can be summarised into four main steps as follows.

(i) Initialise model parameters and the initial states of S, I and R.
(ii) Determine the ten parameters in (10) using survey data and the fitting algorithm in (11).
(iii) Calculate the two time-varying parameters in the advertisement model (6), $\omega(k)$ and $\mu(k)$, using the Bayesian forecasting method in (7) - (9). Here the parameters calculated from Step (ii) are used and the calculation applies to a time sequence.
(iv) Calculate the energy savings EES_T in (13), the advertisement cost C_T in (14), the adoption rate by model (6), apply the optimisation design for different scenarios in (19), (20), (21) and (22) subject to budget and time constraints in (17) and (18).

4. Case studies

Two case studies are investigated for a small population network and a large network. The small-size network is based on a survey carried out including a group of 40 people within one apartment building of a company. The survey was proceeded in three stages. In the first stage, all participants were asked about their connections with other people in the group. In the second stage, they were asked to answer their responses to recommendations of a new energy efficiency product given by people who have connections with them. In the third stage, responses to advertisement in different exposure frequencies were asked. The survey data were collected, and the connections among participants were calculated and illustrated in Fig. 1, reproduced from modelling in [29], where the 40 nodes are denoted by $P_i (i = 1, \cdots, 40)$, representing 40 individuals in this social network. The system shows a high network degree since participants are mostly colleagues from the same company and tend to have strong connections between each other.

The second case study is based on online advertisement data collected from an advertisement company with one million internet users. The collected data contains the amount of daily advertisement investment and the actual sale information about a new energy saving air conditioner within four weeks.

4.1. Experimental settings and parameter estimation

(1) Assumptions for the small population network
- At the beginning of the programme, one individual is given one free trial product.
- The weekly advertisement is applied in the middle of each week.
- Assume that there are 12 incandescent light bulbs having three hours' daily usage in each user's flat, and all the flats are under the same electricity tariff, which is fixed at £0.20/kWh as in [33].

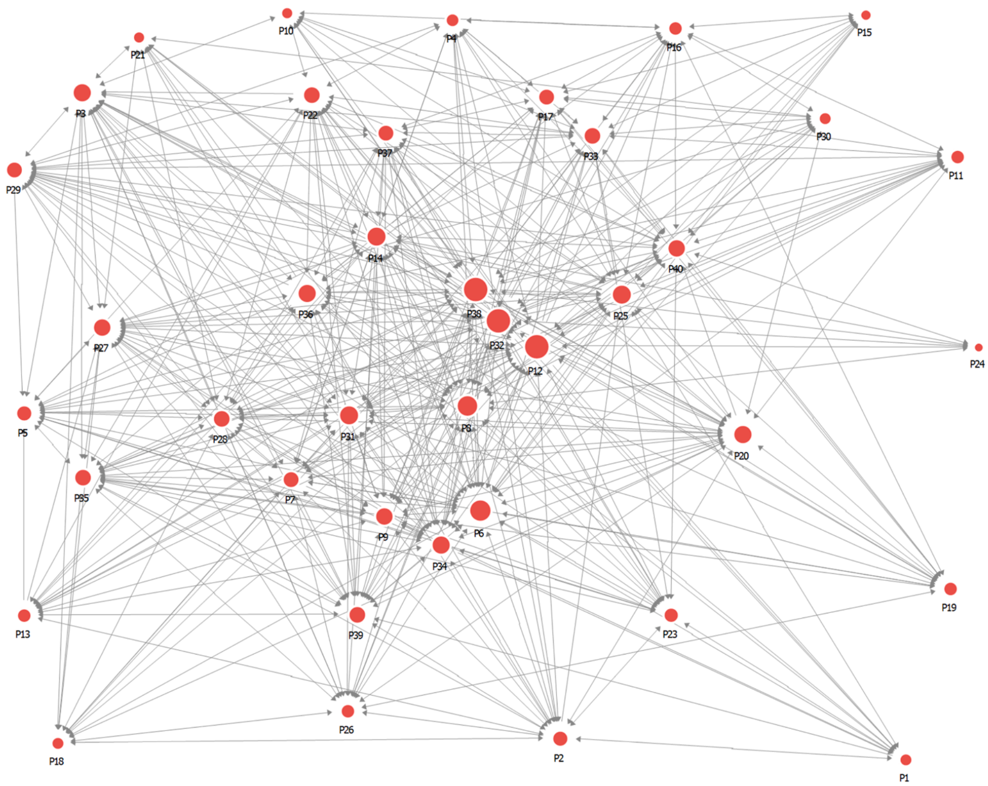

Fig. 1. Graph of small population network with nodes and connections, reproduced from model in [29].

The electricity consumption of the incandescent and LED light bulbs are 40 W and 4.6 W, respectively [29].

- Assume that the price of the advertisement is £0.5 per item view for the small population network, coming from flyer and souvenir. The total budget is £110, among which £30 is used for the first two weeks including £10 for the free trial product and the £20 for advertisement investment.
- The target of the product promotion programme is to reach 70 % adoption rate within 28 days.

(2) Assumptions for the large population network

- Assume that there are no free trial products in this rollout programme.
- Assume that the electricity price is £0.20/kWh as in [33], the energy efficiency product will have 1 kW power savings for two hours daily usage.
- Assume that the cost of advertisement is £0.1 per thousand impressions. This unit price is much smaller compared to that of the small network because for large population networks, the advertisement costs come from online advertising in a large volume. The total budget of advertisement is £40,000, in which £20,080 is allocated for advertisement in the first two weeks.
- Assume that the target adoption rate on the 28th day is 0.13 %. This target value is assumed to be higher than the original adoption rate 0.1264 % from the advertisement company data, which is calculated from Column Deal amount/ Population in the appendix.

(3) Estimation of Model Parameters

For both the small and the large networks, collected data on adoption rate over the first 14 days are used to determine the parameters in (10) using the data fitting method in (11) and (12). The data in the next 14 days are used to design the advertisement strategy. We first use 'ga' to obtain the preliminary estimation, then take the results from 'ga' as the initial values for 'fmincon' to obtain the final results for model parameters. The results are given in Table 1.

Table 1
Estimated model parameters for the small and large networks.

	ψ	α	β	ρ	γ
Small network	0.1078	1.6971e-2	0.3035	0.2754	0.1218
Large network	1.0999e-2	3.8147e-6	0.2902	0.0141	4.7090e-6
	φ	α_ω	β_ω	ρ_ω	γ_ω
Small network	1.4007e-4	1.6662e-2	0.4802	0.5440	0.2000
Large network	8.1877e-6	0.0541	0.9396	3.7540e-4	5.3738e-4

4.2. Sensitivity analysis with Monte Carlo calculation

The parameter values in Table 1 are taken as nominal values for the model. The uncertainty of this model will inevitably affect the design outcome. To understand the impact from model uncertainties, sensitivity analysis and Monte Carlo calculation are performed for the large network. All parameters are assumed to follow Gaussian distribution, the mean value is the nominal value, the standard deviation is taken at four levels, i.e., $[0.1, 0.2, 0.5, 1]$ of the mean value. The uncertainty range for each parameter is between zero and twice of the nominal value. In each calculation, one parameter is varied within the uncertainty range and the other parameters are kept at their nominal values.

For each parameter, nine points are uniformly sampled between the uncertainty range. Taking the i-th parameter in θ as an example, the sampled parameters are written as $[\theta_i(1) \quad \cdots \quad \theta_i(9)]^T, (i = 1, \cdots, 10)$. The values of the probability density function (pdf) corresponding to the nine sampled parameters are written in vector $\mathbf{p}_i$. Then for the j-th sampling point in the i-th parameter, the k-th day adoption rate can be calculated as $R(k, \theta_i(j)) \bullet \mathbf{p}_i(j)$. To assess the relative impacts from the 10 parameters, the following residual function between the calculated adoption rates and the surveyed adoption rates, weighted by pdfs, is used as the output for the i-th parameter.

$$J_i = \sum_{k=1}^{M+K} \sum_{j=1}^{9} \left(R(k, \Lambda_i(j)) - y_R(k))\right)^2 \cdot \boldsymbol{p}_i(j) \tag{23}$$

The results of J_i for $i = 1, \cdots, 10$ are used for sensitivity analysis. Taking the standard deviation at four levels, i.e., 10 %, 20 %, 50 % and 100 % of the nominal value, the sensitivity graph is shown in Fig. 2, where the output J_i is normalised by the value calculated at the nominal parameters for θ.

From the sensitivity analysis, it can be observed that among the 10 parameters, φ, β, γ, and α_ω have stronger influence on the formed output function in (23), φ is the most sensitive parameter. Next, this parameter is chosen for further calculations under four different standard deviations. Again, the same sampling of nine points is applied to φ, and the calculated adoption rates are weighted by pdf values. The daily adoption rates calculated by this Monte-Carle study is compared against the surveyed adoption rates, the difference between these two are shown in Fig. 3, from which it can be seen that when the parameter uncertainty is larger (larger standard deviation), the difference between the model result and the surveyed data is larger as expected. However, the difference caused by model uncertainty seems to be very small, at a level of 1e-7, over the 28 days. This indicates the robustness of the proposed model against parameter variations to some extent.

4.3. Advertisement control design for small population network

4.3.1. Baseline strategy

At the beginning of the programme, the initial values for the three states in model (6) are set to be $S(0) = 0.925$, $I(0) = 0$, and $R(0) = 0.025$. It should be mentioned that two individuals are excluded in this social network as they show no interest on the energy saving product during the survey. The impressions are exerted on 4 days only, i.e., Day 4, Day 11, Day 18 and Day 25, with 20 impressions for each day. For the other 24 days, the impressions are zero under the baseline strategy.

The adoption rate is calculated from the initial information diffusion model in (3) using its discrete-time format. The results are shown in Fig. 4, in which the adoption rate values over the first two weeks are represented with solid square marker in black, and the next two weeks with red square hollow markers. It can be seen that the adoption rate is 35.88 % at the end of Week 2, and is 57.24 % at the end of Week 4. The Day-28 adoption rate is lower than the targeted value of 70 %. Therefore, more advertisement is required in order to accomplish the target over the period of Day 15 to Day 28. The costs of advertisement for the first 14 days and last 14 days are calculated by (14) to be the same as £20. In the next section, the four proposed optimisation design methods are applied to achieve the target adoption rate.

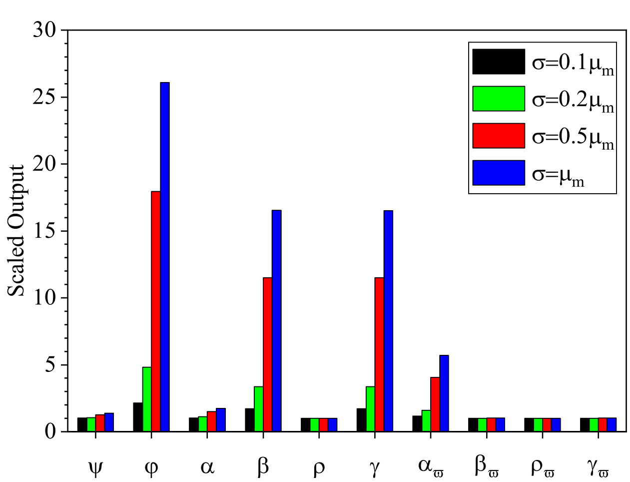

Fig. 2. Sensitivity analysis of model parameters under four standard deviation levels.

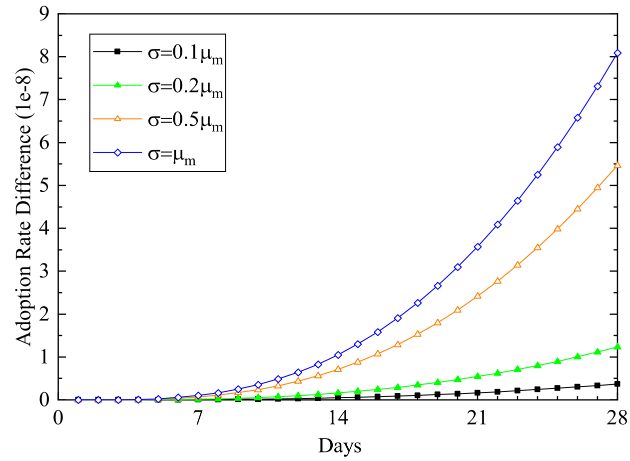

Fig. 3. Difference between the survey data and the adoption rates from Monte-Carlo calculation under parameter variation (parameter φ, standard deviations: 10 %, 20 %, 50 % and 100 % of mean value).

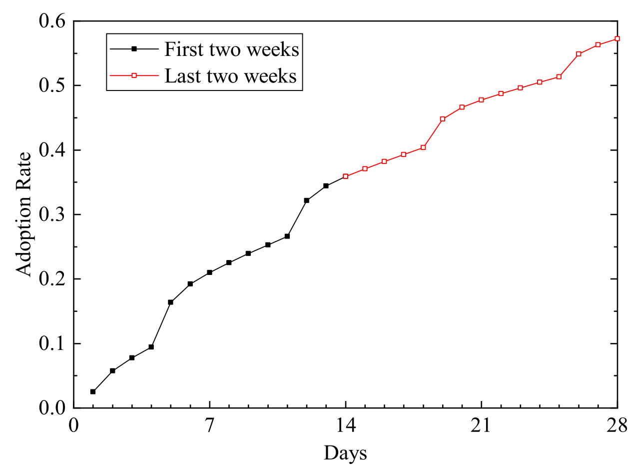

Fig. 4. Baseline daily adoption rates for small network (the first 14 days data from survey, the last 14 days data from model calculation under baseline advertisement impressions).

4.3.2. Method 1: Achieve the lowest advertisement cost

The design results for optimisation in (19) are listed in Table 2 covering the daily impressions from Day 15 to Day 28. The results of daily impressions from other design methods are also listed in this table for comparison purpose.

The total cost on advertisement from Day 15 to Day 28 can be calculated by (14) to be £66.5. Considering the cost in the first 14 days using the baseline strategy, the total advertisement cost over the four

Table 2
Optimal advertisement investment of different methods in small population network.

Impressions\Days	15	16	17	18	19	20	21	
Baseline	0	0	0	20	0	0	0	
Method 1	17	18	17	4	11	12	15	
Method 2	25	22	20	16	21	16	10	
Method 3	61	37	29	21	12	0	0	
Method 4	17	14	13	13	13	13	14	
Impressions\Days	22	23	24	25	26	27	28	**Total**
Baseline	0	0	0	20	0	0	0	**40**
Method 1	8	6	11	9	3	2	0	**133**
Method 2	24	6	0	0	0	0	0	**160**
Method 3	0	0	0	0	0	0	0	**160**
Method 4	15	13	13	13	9	0	0	**160**

weeks is £96.5, which is within the budget limit of £110. It can be seen that the number of daily impressions is between 2 and 18 in the last two weeks, which are displayed as green colour curves in Fig. 5.

Next the daily adoption rate under different methods of advertisement control is examined. Results under the four designs are compared with the baseline strategy, as illustrated in Fig. 6. It can be seen that the adoption rate under Method 1 reaches the target rate of 70 % at the end of Week 4 (Day 28), and all the design methods achieve the target adoption rate during the control period.

4.3.3. Method 2: Targeting the shortest time

The results of daily impressions from Day 15 to Day 28 are listed in Table 2. It can be seen that from Day 15 to Day 22, the daily impression investment is between 16 and 24. The higher investment on advertisement in the early period leads to a fast-growing curve of the adoption rate (see Fig. 6, line with orange colour hollow triangles) and reaches the target of 70 % on Day 24, 4 days ahead of the end of the programme. With this method, the total cost on advertisement (£110) is all used, which is a price paid to achieve the target rate within a shorter time. In this case, the overall cost benefit can be expected from the saved energy cost. It should be noted that the adoption rate after Day 24 continues to have small increase although there're no more advertisement exerted in the last four days. This minor increase is due to the information diffusion mechanism.

4.3.4. Method 3: Targeting the largest energy savings

The daily impressions under Method 3 are listed in Table 2, which shows that large amount of advertisement investment is made at the beginning of Week 3. This suggests that the total energy savings are highly related to early-stage adoption rate. The daily impressions in Method 3 are shown in Fig. 5, in which there is a spike on the first day (Day 15) followed by gradually decreased daily impressions in the next four days, and then becomes zeros. This decrease of daily impressions is due to the diminishing return effect, as shown from the Bayesian update of the adoption rate and the positive response rate in (8) and (9). The daily adoption rate values under Method 3 are shown in Fig. 6 with blue solid diamond markers. By applying this method, again all the budget is required to achieve the largest energy savings.

The electricity savings of all methods for the last 14 days are shown in Fig. 7 with a comparison made with the baseline strategy. It shows that among all methods, Method 3 has the largest energy savings. The total energy savings over the last 14-day period is 446.6 kWh with Method 3 and 337.8 kWh with the baseline plan, respectively. There's an increase of 32.21 % on energy savings with Method 3. This method shows the significance of early adoption of energy efficiency product in

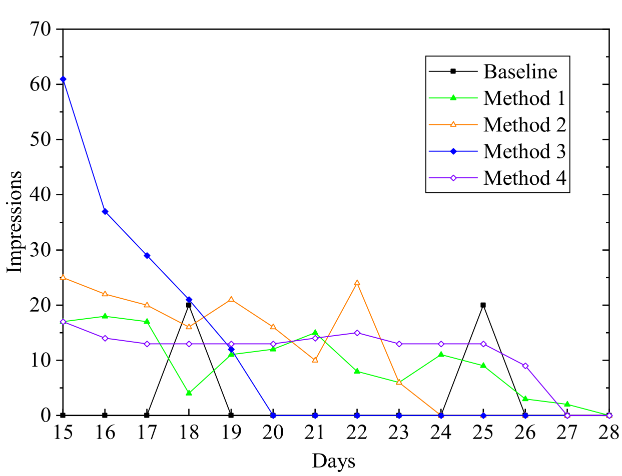

Fig. 5. Daily impressions under different strategies in small population network.

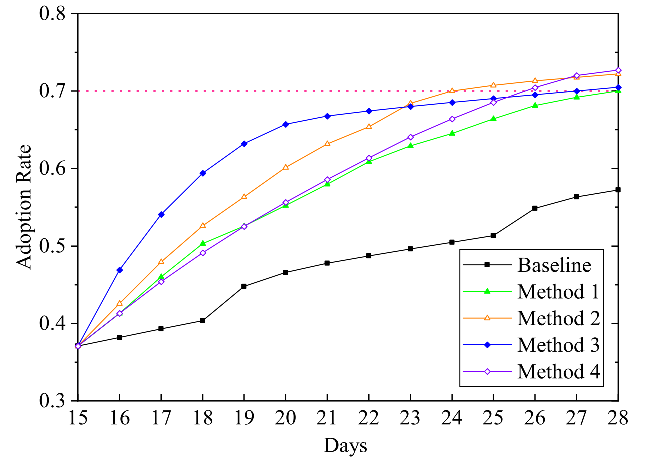

Fig. 6. Adoption rates under different programmes (one baseline strategy and four design methods, target level at 0.7).

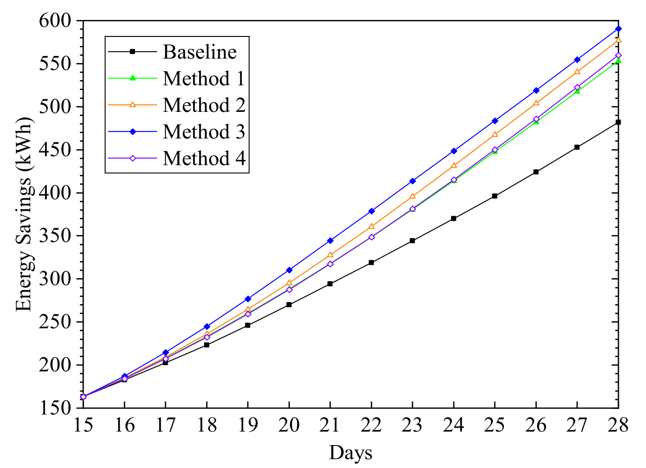

Fig. 7. Daily energy savings of small network (baseline strategy and four design methods).

total energy savings. Using the assumed electricity tariff in Section 4.1, the electricity bill reduced for the network over the whole 28-day period with Method 3 is £118.17 which is larger than the total budget (£110) that is spent using advertisement for product promotion.

4.3.5. Method 4: Targeting the largest number of installations

The results of daily impressions under Method 4 are listed in Table 2, showing that the advertisement investment from Day 15 to Day 25 follows a relatively smooth pattern. The daily adoption rate profile of Method 4 is shown in Fig. 6 by the violet hollow diamond markers, from which it can be seen that the adoption rate reaches 72.72 % on Day 28. Comparing to the baseline strategy, the strategy in Method 4 has an increase of 15.48 % in adoption rate.

4.3.6. Summary for small network simulation

For a small population network, the information diffusion within the network contributes a lot to the adoption rate achieved. This can be seen from Fig. 6 that even under zero impressions for some days, e.g., the last few days under Method 2 and Method 3, the adoption rate continues to grow although gradually. Meanwhile, advertisement also has a strong impact on the adoption rate, all advertisement control methods achieve a clear increase in the final adoption rates compared to the baseline strategy. For Method 3, the adoption rate has an increase from 37.08 % to 65.72 % within only five days (Day 15 to Day 20) of advertisement investing, and the EES for the last 14 days increases 32.21 % compared to the baseline strategy. It can also be seen from Fig. 7 that Method 3 achieves the largest energy savings among the four methods as it has the objective to maximise the total energy savings.

4.4. Advertisement control of large population network

4.4.1. Baseline strategy

The collected data from an advertisement company for a large population network with 1 million users is attached in the appendix.

From the survey data shown in Table 3, it can be seen that a total amount of £20,080 is used for advertisement in the first two weeks, and £14,460 for the next two weeks. The adoption rate is calculated to be 0.0486 % at the end of Week 2.

Based on the developed model, the adoption rates are calculated for the next 14 days using the baseline strategy, which gives the adoption rate of 0.1254 % on Day 28. This figure is lower than the expected rate of 0.13 % set up for optimisation design. The adoption rates in the first 14 days (surveyed) and the last 14 days (modelled) are represented by black solid diamonds and red hollow diamonds in Fig. 8. Similar to the small population network case study, four advertisement control methods are implemented to achieve the target adoption rate under the given budget of £40 k and the given time of 28 days.

4.4.2. Method 1: Targeting the lowest advertisement cost

With the optimisation design in (19) to minimize the advertisement cost, the daily impressions are given in Table 4. The results of daily impressions from other design methods are also listed in the same table for comparison. It can be seen that the total number of impressions for Method 1 is the lowest among the four design methods, which means the advertisement cost is the smallest with Method 1.

Fig. 9 shows a comparison of the daily impressions between the four control methods and the baseline strategy, from which it can be seen that the advertisement investment is mostly spent in Week 3 for Method 1, to be more specific, on the first day (Day 15) of that week.

The investment in this solution is calculated to be £36,546.4 which is within the budget. The adoption rates from the optimal solution and the baseline result are shown in Fig. 10. The baseline forecasted results are represented in black curves. The optimal solution results under the four methods are shown in green, orange, blue and violet curves, respectively. As shown in Fig. 10, the optimal solution in Method 1 reaches the target adoption rate of 0.13 % on Day 28.

4.4.3. Method 2: Targeting the shortest time

The optimal control solution on daily impressions can be seen in Table 4. The investment in this solution is £39,965, which is also within the budget limit, and the adoption rate is shown in Fig. 10 by the orange curve. The adoption rate reaches 0.13 % on Day 27, which is one day ahead of the end of the programme.

4.4.4. Method 3: Maximise the total energy savings

The calculated daily impressions are listed in Table 4. The adoption rate is shown by the blue curve in Fig. 10. There is a clear increase of impressions on the first day of week 3 (Day 15). This method uses all £40 k budget to achieve the designed target with an adoption rate of 0.1349 % achieved on Day 28.

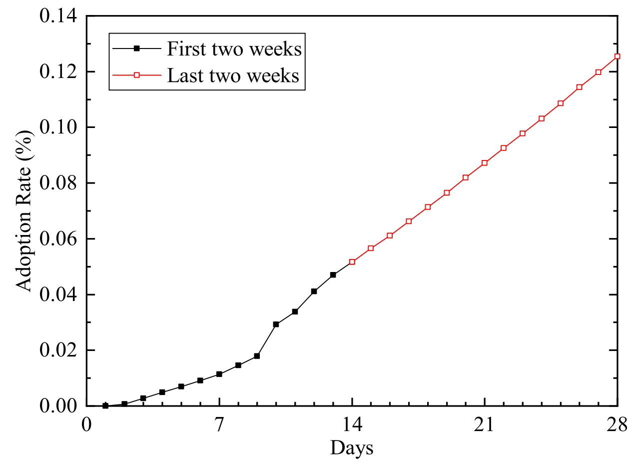

Fig. 8. Baseline daily adoption rates for large network (the first 14 days data from survey, the last 14 days data from model calculation under baseline advertisement impressions).

The energy savings profiles of all methods are shown in Fig. 11, where the baseline strategy data and the optimal control results are represented. It can be seen that the optimal solution of Method 3 brings a total saving of 29.831 MWh in EES over the last 14 days, while the saved EES from the baseline strategy is only 25.249 MWh. This indicates an increase of 18.15 % in energy savings due to the advertisement control strategy. Using the assumed electricity tariff in Section 4.1, the electricity bill reduced for the network over the whole 28-day period with Method 3 is £7,049.8 which is smaller than the total budget (£40 k) that is spent using advertisement for product promotion.

4.4.5. Method 4: Maximise the adoption rate

It is observed from Table 4 that the optimal solution on the daily impressions of Method 4 is similar to Method 3. The adoption rate of Method 4 is shown in Fig. 10 with violet dashed curve, and the adoption rate reaches 0.1349 % on Day 28, which is above the programme target of 0.13 %. The cost of this method is the £40 k, the total budget allowed. The number of product installations for the whole network is 1,349. With this design, most of the advertisement investment is used for the first day of the design period (Day 15), which is likely due to the diminishing return effect.

For large population networks, the advertisement investment seems to have more effective influence on the adoption rates compared to the small population network. It can be seen from Fig. 10 that the adoption rates are significantly increased through advertisement control, and Method 3 achieves the largest total energy savings among the four design methods (see Fig. 11).

5. Conclusions

In this work, we explore energy savings in residential sector from a unique perspective – looking at the impacts of advertisement control to energy savings through (large) social networks. The mathematical model is developed to quantify diffusion of energy product information

Table 3
Original impression data in large population network (from survey).

Day	1	2	3	4	5	6	7
Impressions (1e3)	7,247	7,316	6,506	4,250	4,157	2,768	7,798
Day	8	9	10	11	12	13	14
Impressions (1e3)	7,358	64,900	12,851	32,333	21,386	10,676	11,258
Day	15	16	17	18	19	20	21
Impressions (1e3)	8,626	11,158	10,989	10,986	12,283	9,651	10,606
Day	22	23	24	25	26	27	28
Impressions (1e3)	8,587	9,531	10,508	12,027	9,030	10,303	10,315

Table 4
Optimal advertisement investment of different methods in large population network.

Impressions (1e3) \ Days	15	16	17	18	19	20	21	
Method 1	155,598	37	1,762	341	260	1,742	408	
Method 2	1	0	3	374	1	0	0	
Method 3	192,935	3,153	372	93	303	27	1,914	
Method 4	198,844	277	79	0	0	0	0	
Impressions (1e3) \ Days	22	23	24	25	26	27	28	**Total**
Method 1	69	306	1,169	2,668	38	366	0	**164,664**
Method 2	0	1	198,470	0	0	1	0	**198,851**
Method 3	358	7	21	4	11	2	0	**199,200**
Method 4	0	0	0	0	0	0	0	**199,200**

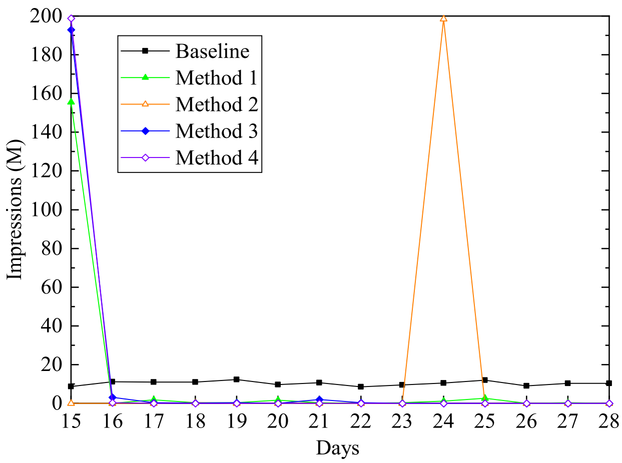

Fig. 9. Daily impressions for different strategies in large population network.

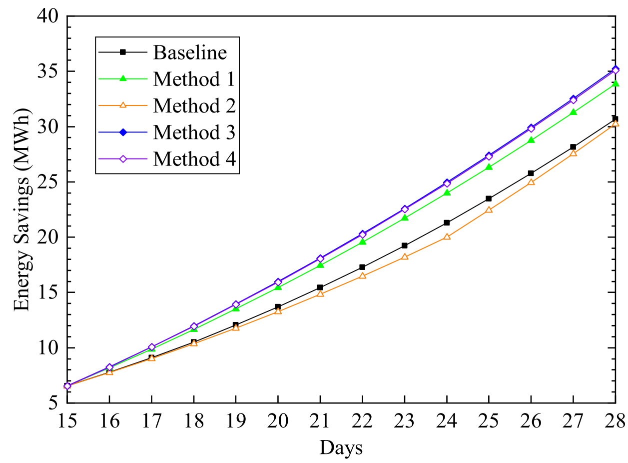

Fig. 11. Daily energy savings of large network (baseline strategy and four design methods).

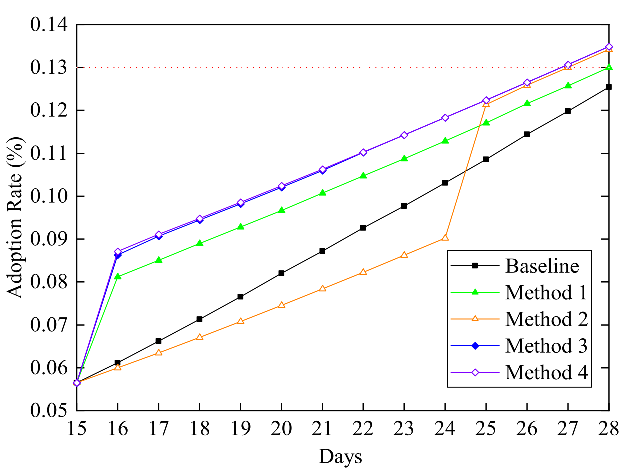

Fig. 10. Adoption rate of four designs for large population network (four optimal design results and the baseline result).

in a large network under the advertisement control. The model is a first of this kind, based on which the advertisement control is determined through optimisation design. The model and the optimal advertisement control will be useful for improving energy savings scheme in a systematic way.

The dynamic network model is established following the epidemics theory, the small-world network theory, and the Bayesian forecasting method to quantify energy savings without using the detailed connection information of individuals within the network. We start from a small network to explore the technical route of the new efforts on modelling and optimisation design for energy saving targets. This provides understanding necessary for the follow-on investigation to large networks.

Four optimisation design methods are proposed to achieve the target adoption rate under the given budget and the time period. Results from the designed advertisement control strategies are compared with each other and also with the baseline programme that has no advertisement control. The period used for case studies is chosen to be 28 days in total, among which the data collected from the first 14 days are used for modelling and the optimisation designs are conducted over the last 14 days.

The first design method targets at the lowest advertisement cost. The optimal solutions obtained for both networks demonstrate that, among the four design methods, Method 1 achieves the smallest advertisement investment. See the total impressions over the last 14 days as listed in Table 2 for the small network and Table 4 for the large network.

With the shortest time objective used in Method 2, the design results show that the large network reaches the targeted adoption rate one day ahead of the full period, and the small network reaches the target four days ahead of the end of the program. Among the four methods, Method 2 has the shortest time required to achieve the target adoption rates. See Fig. 6 for the small network and Fig. 10 for the large network.

In the third method with the objective to maximise the total energy savings, the small network has achieved an increase of 32.21 % in total energy savings compared to the baseline plan, while for the large population network, it has an increase of 18.15 % in energy savings compared to the baseline strategy. The optimised solutions in Method 3 have the largest EES for both small and large networks compared to other methods (see Fig. 7 for small network and Fig. 11 for large network).

In Method 4 that aims at achieving the largest number of installations, the optimal solutions compared with the baseline strategy lead to an increase of adoption rate of 15.48 % and 0.0095 % for the small and large population networks, respectively. Compared with the other three methods, Method 4 obtains the largest adoption rate at the end of the program (see Fig. 6 and Fig. 10 for small and large networks). The increased levels compared to Methods 1, 2 and 3 are 2.70 %, 0.50 %, 2.24 % for the small network, and 4.92e-5, 6.71e-6, 7.22e-8 for the large network, respectively. The optimisation design studies show that the proposed model can be applied to large-scale mass rollout programme to forecast the energy savings and predict the impact of advertisement control to energy savings.

This interdisciplinary research integrates methods from systems engineering and social sciences methods to achieve the goal of energy savings through a large social network. The proposed methodology can be improved from further investigation on modelling and design. In an energy saving scheme applied to a population network, each participant's income, age, education level, etc. can be considered in the modelling as they are related to users' energy consumption behaviours [13]. In practice, a mass rollout programme usually runs for several years, during which factors such as energy product price variations and holiday sales may significantly affect the adoption rate. These non-routine changes are not included in the current short-period design, but can be involved in a design aiming for energy savings over a long period of time.

CRediT authorship contribution statement

Feng Du: Investigation, Methodology, Software, Formal analysis, Writing – original draft. **Hong Yue:** Methodology, Formal analysis, Validation, Writing – review & editing, Supervision. **Jiangfeng Zhang:** Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Feng Du reports financial support was provided by UK EPSRC.

Data availability

The survey data has been shared in appendix.

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Appendix. . Large population network campaign data (population 1 million)

Date	Impression	Visitor	Deal amount	Visitor/ Impression	Deal amout/ Impression	Deal amount/ Visitor	Deal amount/ Population	Visitor/ Population
03/12/14	7,246,843	8522	0	0.117596 %	0	0.000000 %	0	0.008522
04/12/14	7,316,070	5,775	6	0.078936 %	8.20112E-07	0.103896 %	0.000006	0.005775
05/12/14	6,506,708	5,565	9	0.085527 %	1.38319E-06	0.161725 %	0.000009	0.005565
06/12/14	4,250,657	5,109	4	0.120193 %	9.41031E-07	0.078293 %	0.000004	0.005109
07/12/14	4,156,518	4,291	7	0.103235 %	1.6841E-06	0.163132 %	0.000007	0.004291
08/12/14	2,767,515	4,337	5	0.156711 %	1.80667E-06	0.115287 %	0.000005	0.004337
09/12/14	7,798,623	11,266	16	0.144461 %	2.05164E-06	0.142020 %	0.000016	0.011266
10/12/14	7,358,586	6,825	10	0.092749 %	1.35896E-06	0.146520 %	0.00001	0.006825
11/12/14	64,900,395	112,905	105	0.173967 %	1.61786E-06	0.092999 %	0.000105	0.112905
12/12/14	12,851,081	7,172	71	0.055809 %	5.52483E-06	0.989961 %	0.000071	0.007172
13/12/14	32,333,011	13,269	64	0.041039 %	1.9794E-06	0.482327 %	0.000064	0.013269
14/12/14	21,386,124	12,893	65	0.060287 %	3.03935E-06	0.504150 %	0.000065	0.012893
15/12/14	10,676,755	8,681	65	0.081307 %	6.08799E-06	0.748762 %	0.000065	0.008681
16/12/14	11,258,100	7,176	59	0.063741 %	5.24067E-06	0.822185 %	0.000059	0.007176
17/12/14	8,626,184	13,052	60	0.151307 %	6.95557E-06	0.459700 %	0.00006	0.013052
18/12/14	11,157,634	14,460	87	0.129597 %	7.79735E-06	0.601660 %	0.000087	0.01446
19/12/14	10,989,131	18,621	52	0.169449 %	4.73195E-06	0.279255 %	0.000052	0.018621
20/12/14	10,986,393	15,083	28	0.137288 %	2.54861E-06	0.185639 %	0.000028	0.015083
21/12/14	12,283,494	15,250	40	0.124150 %	3.2564E-06	0.262295 %	0.00004	0.01525
22/12/14	9,651,261	15,296	67	0.158487 %	6.9421E-06	0.438023 %	0.000067	0.015296
23/12/14	10,605,578	15,872	60	0.149657 %	5.6574E-06	0.378024 %	0.00006	0.015872
24/12/14	8,586,888	15,302	76	0.178202 %	8.8507E-06	0.496667 %	0.000076	0.015302
	9,531,478	21,465	71	0.225201 %	7.449E-06	0.330771 %	0.000071	0.021465

(continued on next page)

(*continued*)

Date	Impression	Visitor	Deal amount	Visitor/ Impression	Deal amout/ Impression	Deal amount/ Visitor	Deal amount/ Population	Visitor/ Population
25/12/14								
26/12/14	10,507,586	19,670	60	0.187198 %	5.71016E-06	0.305033 %	0.00006	0.01967
27/12/14	12,026,972	14,172	25	0.117835 %	2.07866E-06	0.176404 %	0.000025	0.014172
28/12/14	9,030,185	18,872	55	0.208988 %	6.09068E-06	0.291437 %	0.000055	0.018872
29/12/14	10,303,387	15,764	34	0.152998 %	3.29989E-06	0.215681 %	0.000034	0.015764
30/12/14	10,314,633	15,367	63	0.148983 %	6.10783E-06	0.409969 %	0.000063	0.015367
31/12/14	5,465,951	11,415	55	0.208838 %	1.00623E-05	0.481822 %	0.000055	0.011415

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