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Modelling the impact of social network on energy savings

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HIGHLIGHTS

- Energy saving propagation along a social network is modelled.
- This model consists of a time evolving weighted directed network.
- Network weights and information decay are applied in savings calculation.

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ABSTRACT

It is noted that human behaviour changes can have a significant impact on energy consumption, however, qualitative study on such an impact is still very limited, and it is necessary to develop the corresponding mathematical models to describe how much energy savings can be achieved through human engagement. In this paper a mathematical model of human behavioural dynamic interactions on a social network is derived to calculate energy savings. This model consists of a weighted directed network with time evolving information on each node. Energy savings from the whole network is expressed as mathematical expectation from probability theory. This expected energy savings model includes both direct and indirect energy savings of individuals in the network. The savings model is obtained by network weights and modified by the decay of information. Expected energy savings are calculated for cases where individuals in the social network are treated as a single information source or multiple sources. This model is tested on a social network consisting of 40 people. The results show that the strength of relations between individuals is more important to information diffusion than the number of connections individuals have. The expected energy savings of optimally chosen node can be 25.32% more than randomly chosen nodes at the end of the second month for the case of single information source in the network, and 16.96% more than random nodes for the case of multiple information sources. This illustrates that the model presented in this paper can be used to determine which individuals will have the most influence on the social network, which in turn provides a useful guide to identify targeted customers in energy efficiency technology rollout programmes.

1. Introduction

In the UK, the residential sector accounts for 31% of total energy consumption except non-energy use in 2013 [1]. It is predicted that domestic energy use will increase more than two times in the UK in 2025 comparing to the amount of energy use in 2013 [2]. Thus, residential areas are important targets for energy consumption reduction, and different aspects of residential energy consumption characteristics are investigated. For instance, Ref. [3] studies the relations between residential energy consumption and building characteristics, socio-demographics, occupant heating behaviour, etc. Embodied and controlled energy consumptions of urban areas are studied from network control perspective [4]. A novel 3-level emergetic evaluation framework is presented in [5] to investigate energy efficiency and sustainability of complex biogas systems with the aid of time-series ecological-economic behaviours. Dynamic and embodied energy for water and water for energy are also calculated in the study of energy-water nexus [6]. It is also noted that residents' personal preferences and habits have a strong influence on energy use in residential homes [7–10]. In [8], the result shows that the operational behaviour of domestic hot water supply system can have influence on the energy use efficiency. Ref. [9] studies the impact of compact development on energy consumption by households' consumption behaviour simulation. The results in [10] show that the energy consumption

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patterns of a building is affected by not only the behaviour of its own occupants, but also by occupants from neighbouring buildings. Previous studies provide evidence that lifestyle changes can lead to savings in overall energy use [11–13]. It is found in [12] that changing the habit to use an electric kettle can save an average of 40 kW h per household per year. Ref. [14] discusses how change and continuity in practices can be understood by applying practice theory in residential energy consumption. Studies in [15] reveal that collective behaviour change, even within a small network, can provide a large amount of energy savings. Note the connections between people in a community, researchers have studied the impact of social network to energy consumption [13,16,17]. Reduction of energy use can be achieved by residents sharing energy efficiency information in a social network. The results in [13] indicate that energy consumption can be reduced by sharing energy efficiency information between families. A Facebook application for energy consumption information sharing is designed in [18] to promote energy savings.

This paper focuses on the influence of social network to human behaviour. In a social network, different individuals usually have direct or indirect connections with each other. The influence of people from direct connected individuals is easy to understand, and the influence from indirect connections is based on the knowledge of small world phenomenon [19–23]. This paper studies how interactions between individuals among social network will influence the energy savings of the whole network. In order to analyse information diffusion within a social network, complex network theory is applied. In a network graph, an individual can be considered as a node, and the connection between two individuals can be seen as node connection.

Fig. 1 is a diagram which shows the impact of interactions between individuals in social network to the mass rollout of energy efficiency technologies. In the mass rollout of energy efficiency products, such as the rollout of solar water heaters in many countries, there are some selected nodes within the social network with earlier installation of efficient products earlier than others for various reasons, say, a positive response to new technologies or free trial provided by suppliers. These nodes will benefit from the new energy efficient products and will therefore spread such information among their friends and relatives. Thus, other nodes within the social network will get to know the energy saving information, and would potentially purchase the new product. These users will further spread the energy saving information along the social network. In this way more energy savings are expected through the interactions of people within the social network. A challenging problem will be qualitatively determining such expected energy savings.

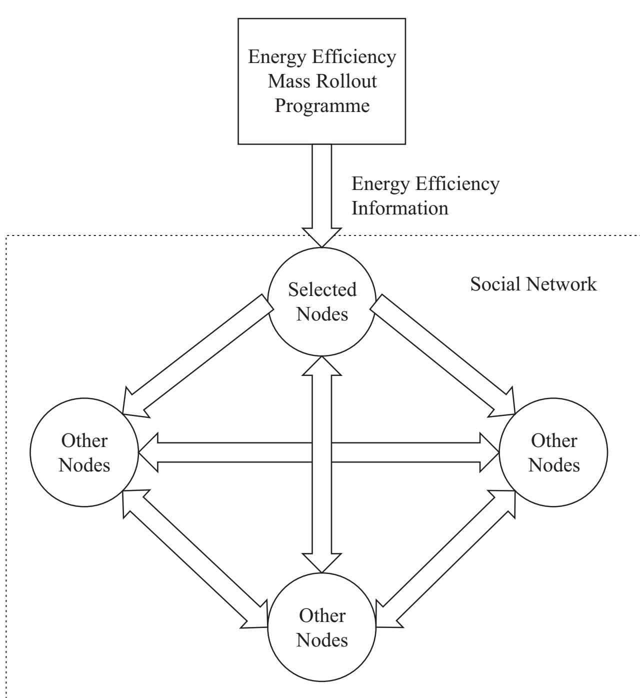

Fig. 1. Impact of interactions of social network to energy efficiency programme.

The connections of a social network are explored in [24,25], where the expected energy savings through interactions under small degree of separation are quantified using information entropy theory. However, the model in [24,25] assumes that an individual has an equal impact to all of his/her friends, neighbours, or family members, and also assumes such an impact does not change against time. The strength of interactions between individuals is considered equal and symmetric in both directions in [26–28]. This paper considers more practical situations where an individual has different and time varying impacts to his contacts. With the aid of weighted directed graph, a mathematical model is developed to calculate the expected energy savings within a social network. Considering data requirement for variable validation in designed model, a survey is designed. This survey investigates the relationship of 40 participants and their response to recommendation of energy saving product within the social network. Then the designed model is further validated by the results collected from the survey.

The remainder of the paper is structured as follows, a mathematical model quantifying energy savings achieved through network interaction and the case study is provided in Section 2, the calculation results from a survey is discussed in Section 3, and some conclusions are made in the last section.

2. Mathematical model

2.1. Weighted social network

Individuals in a social network are represented as nodes in a complex network [19,29], and the connections between people who know each other are represented as edges between nodes.

Consider a weighted directed network with N nodes, assume that node i is connected to k_i neighbours, where $i = 1, \ldots, N$. The weight of an edge in the network is defined as the strength of influence of one node to the other, and this weight is assumed to be an integer between $[0, 5]$ in this paper. A zero value of strength means no effect, while a positive value indicates positive effect between the two nodes.

It is noted that the influence from node i to node j may not be equal to the influence from node j to node i. Thus, this network is generally an unbalanced digraph [30,31] with $W_{ij} \neq W_{ji}$, where W_{ij} is the weight from node i to node j, W_{ji} is the weight from node j to node i [32,33]. In order to represent the dynamic changes of people's relations against time, the weights are assumed to be functions of time t. The weight from node i to node j during time period t is therefore denoted by $W_{ij}(t)$, where $0 \leqslant W_{ij}(t) \leqslant 5$, $t \geqslant 0$. The exact value of $W_{ij}(t)$ depends on the frequency of communications per month between the two nodes.

$$W_{ij}(t) = \begin{cases} 1, & 0 \leqslant f < 1.25; \\ 2, & 1.25 \leqslant f < 2; \\ 3, & 2 \leqslant f < 4; \\ 4, & 4 \leqslant f < 10; \\ 5, & f \geqslant 10; \end{cases} \tag{1}$$

where f is the frequency of communications per month. When node i and j are not directly connected, there will be no direct communication between these two nodes, therefore define $W_{ij}(t) = 0$.

2.2. Propagation of network links

The probability $p_{ij}(t)$ refers to the probability that the information regarding an energy efficiency project is transferred from node i to its neighbour node j at time period t. The relation of probability $p_{ij}(t)$ with weights is given as follows:

$$p_{ij}(t) = W_{ij}(t)\alpha_{ij}(t), \tag{2}$$

where $\alpha_{ij}(t)$ is the coefficient between the probability and weight at time period t, $0 \leqslant p_{ij}(t) \leqslant 1$, $\alpha_{ij}(t) \geqslant 0$. Note that (2) is only applicable to nodes that are directly connected. A formal definition to facilitate the calculation of $p_{ij}(t)$ is given later in this section by knowledge from epidemic theory. The propagation coefficient $\alpha_{ij}(t)$ will be determined through surveys or experiments. From epidemic theory [19,34], the changing rate of probability can be assumed as a decreasing exponential function. Then the coefficient $\alpha_{ij}(t)$ is expressed as

$$\alpha_{ij}(t) = a_{ij}e^{-\mu_j t}, \tag{3}$$

where a_{ij} is the propagation factor, μ_j is the decaying factor of the receiver node j, $t \geqslant 0$.

It is noted that the propagation coefficient decays from time t = 0. However, the probability can only decay after information is received at node j from node i. Therefore, the time delay of communication must be considered in the calculation of $\alpha_{ij}(t)$. Note that the communication delay, denoted by Δt_{ij}, is defined only for directly connected nodes and can be determined through surveys or experiments for a particular social network.

Then the propagation coefficient is modified as

$$\alpha_{ij}(t) = \begin{cases} a_{ij}e^{-\mu_j(t-\Delta t_{ij})}, & t \geqslant \Delta t_{ij}, \\ 0, & 0 \leqslant t < \Delta t_{ij}. \end{cases} \tag{4}$$

2.3. Information diffusion

Initially, an information source is a specific node in the network. Only those nodes which are directly connected to this information source node can receive energy saving information from it. Fig. 2 shows the diffusion of information spreading out from source node i in a network with the maximum degree of separation to be 5. Note that i is directly connected to $q^{(1)}, q^{(2)}, q^{(3)}$ and thus information is transferred directly from i to them. Nodes $r^{(l)}$, $l = 1, 2, 3, 4$, are not directly connected to i, and they can only receive information after certain $q^{(k)}$, $1 \leqslant k \leqslant 3$, receives information from i.

The diffusion of energy saving information in a social network has certain similarity to infectious disease spreading. In fact, the energy saving information itself can be understood as a virus, and individuals in the network are considered as susceptible or infected [19]. In epidemic theory, an individual can only infect other people in the network when he/she is already infected. In the social network, people may not purchase the energy saving equipment even though they are informed, and they can spread out energy saving information to their contacts before they actually purchased/adopted the energy saving equipment. However, the impact to their contact will be much weaker if they do not physically install the energy saving facilities. Therefore, the energy saving information from a friend who does not actually install the energy saving equipment is assumed to be negligible. Under this hypothesis, individuals can only spread out information after the adoption of the energy efficient product. Additionally, when a node

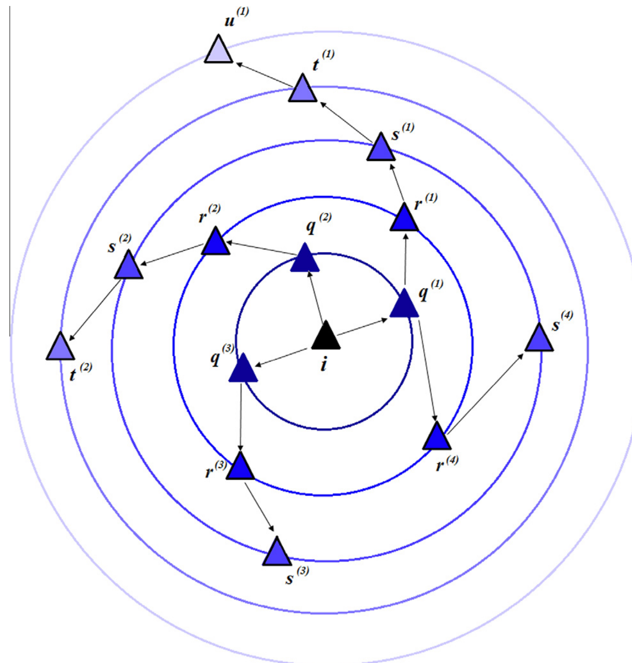

Fig. 2. Information diffusion by number of degree separation.

adopts the energy saving product, it will be treated as a new information source node. Thus, for any node which has a degree of separation larger than one to the nearest information source node, then the information it receives cannot directly come from the source node, but from a neighbour and only after the neighbour adopts the energy efficient product. This adoption time delay for any node j is denoted by T_j and can be determined by the equation below,

$$\sum_{t=1}^{T_j} W_{ij}(t)\alpha_{ij}(t) = 1 \tag{5}$$

where i is an information source node connected directly to node j, and the value of 1 in the right hand side in (5) represents that the accumulated probability of node j to adopt the energy efficient product. In case T_j in (5) is calculated to be infinite, then it means that node j will not adopt this product.

Since there will always be people immune to virus, individuals in a social network are possible to ignore the energy saving information. This set of immune targets ignoring energy saving information is represented by the notation G. Nodes in this set will not transfer information and can be ignored in the calculations of energy savings. The group of people that recovered from virus attack is represented by the notation K, and it corresponds to the case that these nodes in K will not transfer energy saving information after their adoption of energy saving products. The sets G and K can usually be determined through surveys.

Following the ideas of virus transmission, the probability $p_{ij}(t)$ is calculated in the following equation,

$$p_{ij}(t) := W_{ij}(t)\alpha_{ij}(t), j \notin \mathrm{G}, j \notin \mathrm{K}, j \in \prod(i,t), \tag{6}$$

where $\prod(i,t)$ is the set of all the nodes that are directly connected to node j at time period t.

Theoretically, information will keep on being propagated along the social network after adopted nodes become new information sources. Eventually, all nodes will have energy saving product installed except for immune ones. However, in practice, information will decay as Fig. 2 shows, where the triangles represent the information transferred from the information source. When the information transfers further away from initial information source i, its impact to target nodes becomes smaller, as indicated by the decay of the colours of the triangles in Fig. 2. The amount of information transferred reduces sharply with the increase of the degree of separation between source and target.

With the aid of probability theory, the information that spread by information sources can be quantified as mathematical expectations. Thus, the amount of information spread by initial information source i to its neighbours during time period t can be calculated as below,

$$I(i,t) = \sum_{j \in \prod(i,t) \setminus G} p_{ij}(t). \tag{7}$$

Then the total information diffusion from the beginning $t = 0$ to time $t = T$ can be calculated as,

$$S_i(T) = \sum_{t=1}^{T} \sum_{j \in \prod(i,t) \setminus G} p_{ij}(t). \tag{8}$$

It is important to note that Eq. (8) can only be applied to the case where the network has only a single information source. If multiple information sources appear in the network, the information diffusion by all information sources will be the sum of all information transferred,

$$M_T = \sum_{t=1}^{T} \sum_{i \in M(t)} \sum_{j \in \prod(i,t) \setminus (G \cup M(t))} p_{ij}(t), \tag{9}$$

where $M(t)$ is the set of all information source nodes in the network at time t. Note that information exchange between source nodes are excluded in (9) since these source nodes already have full information and the impact from other source nodes will not increase their total amount of information.

2.4. Energy savings forecast

According to Ref. [24], the expected energy savings can be divided into direct and indirect energy savings. The former savings are contributed by individuals who are implementing the energy efficiency project. These individuals are identified as information sources. The latter savings are contributed by other people within the social network who adopt the energy efficiency project after information diffusion. Assume the i-th end user is the only person that implements an energy efficiency measure in his/her network, then the expected energy savings of node i during the time period from time $t = 1$ to $t = T$, which is denoted by $F_i(T)$, is

$$F_i(T) = \sum_{t=1}^{T} \left(E_i(t) + \sum_{1 \leqslant j \leqslant N, j \neq i} E_{j,i}^{indirect}(t) \right), \tag{10}$$

where $E_i(t)$ is the direct energy savings of i-th user at time t that implements the energy efficiency measure, $E_{j,i}^{indirect}(t)$ is the indirect savings in additional to $E_i(t)$ which is achieved through information transformation to node j and it satisfies the following relation,

$$\sum_{1 \leqslant j \leqslant N, j \neq i} E_{j,i}^{indirect}(t) = I(i,t) E_i(t). \tag{11}$$

2.5. Case study

A survey is carried out on a group consisting of 40 people in an apartment building. Everyone is given a questionnaire that has a list of all other people's name. Participants are asked to write the strength of relationship from zero to five depending on the frequency of communications per month. This value of strength a participant filled in represents the influence of other people to him. For example, if participant A fills 5 for the strength of B to him/her, then the weight notation W_{BA} is introduced, which represents the impact from B to A, and it is evaluated as $W_{BA} = 5$. From the survey data, the communication delay Δt_{ij} between two directly connected nodes i and j is calculated as

$$\Delta t_{ij} = \begin{cases} 30, & W_{ij}(t) = 1; \\ 21, & W_{ij}(t) = 2; \\ 14, & W_{ij}(t) = 3; \\ 7, & W_{ij}(t) = 4; \\ 3, & W_{ij}(t) = 5; \end{cases} \tag{12}$$

where the unit of Δt_c is day.

At the second part of the questionnaire, questions about the response on recommendations of changing incandescent light bulbs to LED light from friends on the list. The details of the two kinds of light bulbs are shown in Table 1. The annual electricity bill and payback period are calculated by assuming an average of 3 h usage per day. These details are listed in the questionnaire to help participants making decisions when they receive this information.

All the weights between nodes are obtained from the survey data, and the network graph is shown in Fig. 3. The 40 red dots with labelled numbers represent individuals in the social network. The grey lines with arrow between these dots represent directed impact between the nodes. To indicate the number of connections a node has, the sizes of the nodes are properly chosen so that bigger size nodes have more edges connected.

In order to calculate information propagation, values of the propagation coefficient α_{ij} and decay coefficient μ_j need to be identified. Theoretically, there are 1600 α_{ij}'s and 40 μ_j's to be identified. In practice, there will be less unknown coefficients to be identified as some of them are zero. To determine these unknown coefficients, least square method data fitting is applied. The objective function is shown below,

$$\min \sum_{i \in M} \sum_{1 \leqslant j \leqslant N, j \notin M} \left(\left(\sum_{t=1}^{T} p_{ij}(t) \right) - y_i(T) \right)^2, \tag{13}$$

where the minimisation variables are the α_{ij}'s and μ_j's, $y_i(T)$ is obtained from survey data, and is the installations at time period T when node i is taken as the information source.

The expected energy savings can be calculated by Eq. (10) under the following assumptions.

1. Only one piece of energy saving information is considered in the network.
2. Individuals can only transfer information to those they have connections.

Table 1
Comparison of LED and incandescent light bulbs.

Product type	Price (£)	Power (W)	Lumen (amount of visible light)	Lifetime (h)	Annual electricity bill (3 h usage per day)	Payback period (Months)
LED	4.97	4.6	470	15,000	£ 0.81	10
Incandescent	1.13	40	630	2000	£ 7.01	–

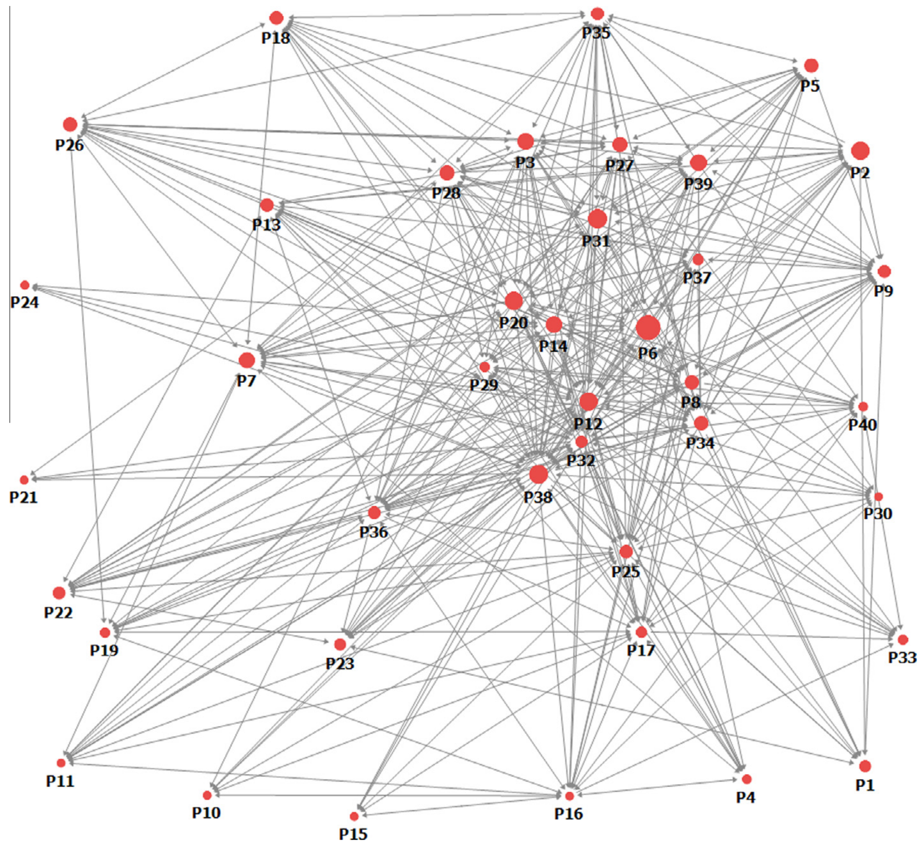

Fig. 3. Graph representation of the social network.

3. There are 12 incandescent light bulbs having 3 h daily usage in each people's home within the building, and these homes are using the same electricity supplier.

3. Results and discussions

There are 639 nonzero squared items in the objective function (13). Two Matlab functions 'fmincon' and 'ga' are applied to solve (13), where fmincon applies a gradient based searching algorithm while ga uses the popular genetic algorithm. The results from either fmincon or ga on its own are not good, however, the solution provided by fmincon can be substituted to ga as an initial value, and then the solution from ga is further substituted back to fmincon as a new initial value. After several rounds of computation by the two functions, the final solution obtained gives the objective function (13) the value of 7.2612×10^{-7}, which is very small and is acceptable comparing to 639 nonzero items in the objective function. After the identification of these unknown coefficients, the energy saving information propagation can be quantified.

3.1. Single information source

Assume that only one person has changed all the light bulbs to LED in the beginning. In order to calculate the expected energy savings with single information source of all 40 people within this social network, Eqs. (8) and (10) are used.

The expected energy savings of the whole social network is calculated separately for the 40 cases in which each node is assumed to be the unique information source in the network. The results are shown in Tables 2–6 are the savings over the time duration over 1 month, 2 months, 3 months, 6 months, and 12 months, respectively. Note that the savings in these tables are listed in descending order, and node degree means the number of connections a node has.

It can be seen in Table 2 that the largest amount of EES (expected energy savings) for the first month is 644.56 kW h when node 6 is taken as information source. This saving is over five times larger than 123.1 kW h for which node 10 is taken as the information source. This indicates that the impact of node 6 is much larger than node 10, and in case an energy efficiency product needs to be advertised, then node 6 is the most favourable target to be approached as this node will bring the highest possible energy savings from the whole network. Table 2 also shows that the adoption rate, i.e. expected savings, which depends roughly but not strictly on information source's node degree. For example, node 6 and 38 are the top two nodes with higher EES than other nodes, and their node degrees are 31 and 32 respectively. Although node 38 has a slightly bigger node degree than node 6, its EES is lower than node 6 because this EES is the accumulated effect over a period of 30 days when the information flows evolve differently over the two nodes' contact networks.

In Table 3, source node 6 still has the largest EES for the first two months, while the smallest amount of EES is achieved by node 24 who has the least node degree. EES for the first two months achieved by source node 6 is twice the amount gained by source node 24. Node 6 achieves 1147.74 kW h expected savings at the end of the second month, which is much larger than its savings 644.56 at the end of the first month. This indicates that from the first month to the second month, the adoption rate within the network is still increasing rapidly.

Table 4 is the EES for single information source in 3 months. It can be seen that node 6 still has the largest amount of EES. However, it should be noted the increased EES at the third month of

Table 2
Expected energy savings for a single information source in 1 month.

Source node	6	38	5	3	28	26	2	20	39	31	23
Node degree	31	32	18	24	22	16	14	19	23	26	17
EES (kW h)	644.56	589.28	579.02	553.59	550.33	548.09	533.04	525.95	525.81	524.74	521.81
Source node	27	8	22	33	19	14	25	18	40	12	9
Node degree	23	29	19	20	15	22	22	13	24	28	23
EES (kW h)	520.26	519.39	503.12	500.28	498.62	494.79	486.67	476.98	474.55	472.43	470.39
Source node	35	36	4	7	37	21	34	16	15	1	17
Node degree	21	20	14	18	20	11	25	15	9	10	19
EES (kW h)	469.24	467.92	464.26	457.65	453.54	450.49	444.56	428.21	422.90	418.69	415.90
Source node	30	29	11	32	13	24	10				
Node degree	12	20	15	19	14	6	10				
EES (kW h)	409.28	372.73	363.92	324.73	212.94	206.67	123.10				

Table 3
Expected energy savings for a single information source in 2 months.

Source node	6	5	26	39	28	2	8	27	3	35	20
Node degree	31	18	16	23	22	14	29	23	24	21	19
EES (kW h)	1792.3	1695.9	1630.4	1623.6	1622.7	1614.6	1601.4	1591.6	1589.9	1587.1	1580.7
Source node	31	34	12	9	14	25	19	18	38	36	4
Node degree	26	25	28	23	22	22	15	13	32	20	14
EES (kW h)	1577.3	1572.5	1537.5	1519.1	1510.3	1501.2	1492.8	1488.5	1487.0	1483.3	1473.2
Source node	40	33	21	29	30	1	16	7	23	37	15
Node degree	24	20	11	20	12	10	15	18	17	20	9
EES (kW h)	1468.4	1453.2	1449.6	1429.4	1421.5	1421.4	1414.4	1403.3	1395.3	1389.1	1380.8
Source node	11	22	17	32	13	10	24				
Node degree	15	19	19	19	14	10	6				
EES (kW h)	1349.5	1334.7	1329.6	1265.4	1088.6	993.17	893.26				

Table 4
Expected energy savings for a single information source in 3 months.

Source node	6	5	26	2	39	8	27	20	31	34	35
Node degree	31	18	16	14	23	29	23	19	26	25	21
EES (kW h)	2947.7	2897.5	2891.4	2876.2	2846.9	2826.5	2814.8	2803.4	2800.5	2795.8	2775.5
Source node	28	3	9	25	19	18	12	36	38	40	4
Node degree	22	24	23	22	15	13	28	20	32	24	14
EES (kW h)	2768.5	2748.0	2713.2	2697.8	2694.4	2683.0	2682.1	2676.1	2676.0	2669.9	2669.8
Source node	33	1	14	21	29	16	30	37	7	11	15
Node degree	20	10	22	11	20	15	12	20	18	15	9
EES (kW h)	2654.8	2653.6	2645.5	2644.6	2629.9	2625.2	2584.8	2576.6	2565.6	2551.1	2544.2
Source node	17	22	23	32	13	10	24				
Node degree	19	19	17	19	14	10	6				
EES (kW h)	2514.9	2503.3	2494.3	2457.0	2257.0	2184.4	2031.0				

Table 5
Expected energy savings for a single information source in 6 months.

Source node	5	35	8	6	34	16	27	28	2	19	4
Node degree	18	21	29	31	25	15	23	22	14	15	14
EES (kW h)	6813.5	6779.4	6672.5	6659.4	6645.2	6618.9	6609.8	6602.9	6596.4	6595.1	6585.8
Source node	40	21	33	31	14	3	29	12	26	39	30
Node degree	24	11	20	26	22	24	20	28	16	23	12
EES (kW h)	6570.6	6560.5	6555.5	6554.7	6551.3	6548.0	6540.8	6534.5	6523.6	6506.0	6485.5
Source node	9	11	15	22	37	38	32	20	18	10	7
Node degree	23	15	9	19	20	32	19	19	13	10	18
EES (kW h)	6455.7	6451.7	6444.8	6419.3	6403.0	6399.1	6357.7	6302.6	6108.9	6048.1	6033.5
Source node	36	1	25	24	23	17	13				
Node degree	20	10	22	6	17	19	14				
EES (kW h)	6018.5	5996.6	5868.3	5837.4	5701.8	5673.9	5164.3				

source node 6 is 1155.4 kW h. This amount of increase is smaller than many other source nodes in the third month, for instance, node 5 has an increase of 1201.6 kW h in the third month. This means that the increasing rate of source node 6 is smaller than some other nodes after the second month. Due to this phenomenon, it can be seen that source node 6 has the 4th largest EES for the first half year as shown in Table 5. It should be noted from Tables 5 and 6 that the increasing rate difference of EES

Table 6
Expected energy savings for a single information source in 12 months.

Source node	8	35	4	19	16	14	33	6	38	5	30
Node degree	29	21	14	15	15	22	20	31	32	18	12
EES (kW h)	15,526	15,466	15,461	15,449	15,443	15,416	15,415	15,310	15,268	15,229	15,163
Source node	34	12	15	3	27	9	40	28	20	22	31
Node degree	25	28	9	24	23	23	24	22	19	19	26
EES (kW h)	15,155	15,151	15,123	15,092	15,089	15,071	15,056	15,051	15,011	15,007	15,006
Source node	39	32	37	11	10	26	21	7	2	18	25
Node degree	23	19	20	15	10	16	11	18	14	13	22
EES (kW h)	14,994	14,976	14,948	14,898	14,876	14,852	14,709	14,696	14,694	14,556	14,539
Source node	29	36	23	1	17	13	24				
Node degree	20	20	17	10	19	14	6				
EES (kW h)	14,489	14,272	14,218	14,203	12,585	12,063	9965.7				

between different source nodes becomes similar after the first half year. This is due to the reason that almost every individual in the social network who has the probability to adopt energy saving product has already installed it. In Table 6, it can be seen that the source node which has the largest amount of EES for the first year is not the node with the largest node degree. Additionally, node degrees do not seem to have any direct link with the EES, and a node with higher node degree does not automatically imply it will have a higher EES. Therefore, EES is not much related to the value of node degree of the information source but it is likely to be influenced more by the time varying node connection weights.

Fig. 4 is a graph on product installations of the whole social network when node 6 is taken as a source node. It is observed that the number of installed products increases rapidly for the first twenty days. Then it slows down at the end of the first month. In the second month, the number of installations increases from 25 to over 30 in 10 days, and it eventually stabilises at 32. The reason for the rapid increase of the number of installations in the initial 20 days is that node 6 has a very large node degree and with some strong weighting on its connection edges.

The maximum value reached by node 6 in 90 days is 32, this value increases with time, and eventually get saturated at 34.6 after 180 days. The saturation points for all source nodes appear after 180 days, and there is almost no change to these values even at the end of a 360 day period. Node 8, 16, 26 and 35 have the highest saturated number of installations, and these values are all equal to 35.6. The remaining nodes will saturated at 34.6 installations. This indicates that the saturation point of a network is not highly related to source node. For most of the source nodes within a network, they have roughly the same maximum number of installations after a sufficiently long time period.

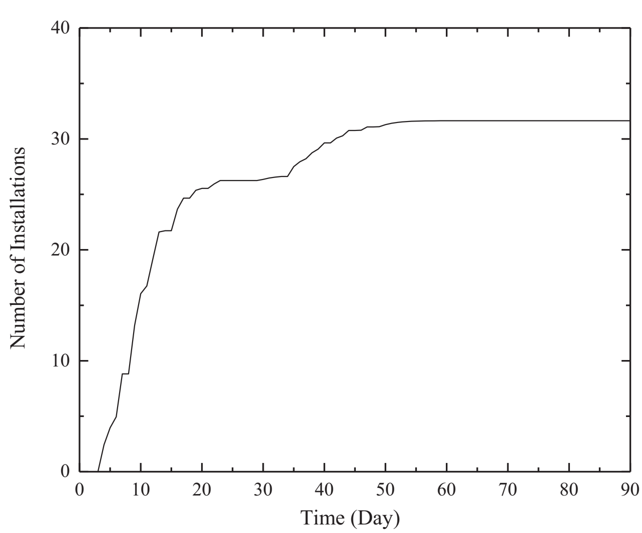

Fig. 4. Number of installations while node 6 is taken as the information source.

Table 7 shows a comparison of the expected energy savings for the best node with the average savings from 10 randomly chosen nodes in 1, 2, 3, 6, and 12 months. In the first month, the best node achieves 12.98% more savings than the average of the 10 random nodes. This figure turns to be 25.32% at the end of the second month. At the end of the 12th month, the optimal node has 5.64% more savings than the random nodes, and this figure turns to be smaller due to the gradual saturation of the expected energy savings.

3.2. Multiple information sources

Now consider the case where there are two people in the network whom have renovated their inefficient lighting systems into LED. In order to calculate the expected energy savings from the two nodes to the whole social network, Eqs. (10) and (11) are applied.

The expected energy savings of the whole social network is accumulated over each day during the calculation period of 1 month, 3 months, and 12 months and the corresponding results are given in Tables 8–10 respectively. In the calculations, all the possible combinations of any two nodes to be used as the information sources are calculated. The results can be seen in columns 'Combination' in Tables 8–10 respectively where the best 10 solutions and worst 10 solutions are listed.

In Table 8, the best combination is source node 16 and 38 which create 691.15 kW h energy savings in one month. On the other extreme node 13 and 24 are the worst combination in the first month with 230.30 kW h EES. Comparing Table 8 to Table 2, it can be seen clearly that two information sources have higher EES than a single source situation. It is noted that although source node 6 is the best one in a single source situation, it does not appear in the best combination when two source nodes are considered. This is because that the combination of node 16 and 38 create more connections to the rest of the social network in comparison to the combination of node 6 with any other node. However, source

Table 7
Comparison of expected energy savings of best node with the average of 10 random nodes.

Month	EES (kW h)		Percentage of improved savings (%)
	Best node	Average of 10 random nodes	
1	520.26	460.49	12.98
2	1792.3	1430.2	25.32
3	2947.7	2657.4	10.92
6	6813.5	6398.5	6.49
12	15,526	14,697	5.64

Table 8
Expected energy savings of best and worst 10 combination of information sources in 1 month.

Rank	Best combinations		Worst combinations	
	Combination	EES (kW h)	Combination	EES (kW h)
1	16,38	691.15	13,24	230.30
2	6,17	689.00	10,13	236.57
3	5,16	687.71	10,24	251.31
4	6,34	686.38	10,32	304.58
5	6,8	682.08	10,11	310.62
6	6,16	681.99	1,10	315.02
7	5,6	681.59	10,30	331.78
8	33,38	677.80	10,15	334.10
9	6,40	675.68	24,32	343.15
10	38,40	675.06	1,32	347.21

Table 9
Expected energy savings of best and worst 10 combination of information sources in 3 months.

Rank	Best combinations		Worst combinations	
	Combination	EES (kW h)	Combination	EES (kW h)
1	6,8	3057.1	10,24	2139.9
2	5,16	3048.3	13,24	2241.8
3	6,9	3038.4	10,13	2307.1
4	2,6	3030.6	24,32	2380.2
5	8,35	3026.3	10,15	2380.3
6	2,8	3024.6	10,11	2380.6
7	16,38	3022.4	10,32	2401.3
8	6,34	3013.3	1,10	2411.4
9	6,17	3007.8	10,30	2412.0
10	2,5	3005.8	22,23	2440.7

Table 10
Expected energy savings of best and worst 10 combination of information sources in 12 months.

Rank	Best combinations		Worst combinations	
	Combination (nodes)	EES (kW h)	Combination (nodes)	EES (kW h)
1	8,35	15,808	13,24	12,136
2	6,8	15,713	16,24	12,241
3	8,26	15,708	17,24	12,411
4	16,38	15,688	16,17	12,477
5	8,31	15,657	13,17	13,004
6	2,8	15,651	13,16	13,234
7	8,38	15,601	10,24	13,421
8	8,28	15,581	10,13	13,796
9	8,12	15,573	10,17	13,957
10	8,39	15,508	1,24	14,006

node 6 still appears six times in the list of the 10 best combinations in Table 7 and when longer term is considered, for 3 months savings, a combination of node 6 and 8 is the best resulting in 3057.1 kW h of savings (see Table 9). The best combination in 1 month becomes the 7th at the end of 3 months. It is also noted that the difference between the best 10 combinations is very small. Additionally, the difference of EES increasing rate between the best and worst combinations is decreasing as well. This indicates that the social network with two information sources is likely to become saturated shortly after 3 months. Table 10 shows that the best combination of node 8 and 35 can save 15,808 kW h in a whole year, which is 30% more than the worst combination of node 13 and 24.

Table 11 is a comparison of the expected energy savings between the best combination and the average of 10 random combinations. It can be seen that in the first month, the best combination has 47.40% more savings than the random cases. At the end of one year, it is still 6.77% higher than the random average. This implies that the optimal combination will provide a quick win to achieve targeted savings.

Table 11
Comparison of the best combination with the average of 10 random combinations.

Month	EES (kW h)		Percentage of increased savings (%)
	Best combination	Average of 10 random combinations	
1	691.15	468.91	47.40
2	1833.8	1567.9	16.96
3	3057.1	2722.7	12.28
6	7137.4	6594.5	8.23
12	15,808	14,806	6.77

3.3. Applications in heat pump rollout

The model obtained for the energy information propagation in the above two subsections does not depend on particular energy technologies, and thus can be applied to calculate expected energy savings for other types of energy efficient technologies. As an illustration, consider its applications in the savings calculation of heat pumps. When compared to electric water heaters air source heat pumps can heat water more efficiently when the ambient temperature is not too low. An assumption that the electric water heater under consideration consumes 4 kW power in each home, and its average working time is 1 h per day is used. The average coefficient of performance, which is defined as the average ratio of generated thermal energy to the input electrical energy, is 4. Assume also that two homes are selected to install heat pumps at a discounted rate in order to attract more homes to purchase heat pumps. The objective is to find the most appropriate two individuals to receive discounted heat pumps in the social network which would create the largest expected energy savings. The expected energy savings over a 6-month period for the best and worst 10 combinations of two possible receivers are shown in Table 12.

In Table 12, the best combination of information source nodes is node 8 and 35. The 6-month expected energy savings for this pair is 16,803 kW h which is about 42% larger than the worst combination of node 13 and 24.

Fig. 5 shows the expected daily energy savings of the beginning 6 months when node 8 and 35 are taken as information sources. The EES increases rapidly from the beginning till the end of the second month. The daily EES becomes steady after about 100 days.

3.4. Implications

This paper uses the expected energy savings to evaluate the impact of human connections on energy consumption within a social network. Although [24,25] use this indicator as well, the

Table 12
Expected energy savings of best and worst 10 combination of information sources in 6 months.

Rank	Best combinations		Worst combinations	
	Nodes	EES (kW h)	Nodes	EES (kW h)
1	8,35	16,802	13,24	11,851
2	6,8	16,604	17,24	12,967
3	8,26	16,566	23,24	13,054
4	2,8	16,542	10,25	13,186
5	16,38	16,478	13,17	13,292
6	8,31	16,461	15,25	13,364
7	2,16	16,421	25,30	13,416
8	5,16	16,394	24,25	13,426
9	8,28	16,341	10,13	13,458
10	9,26	16,334	1,10	13,492

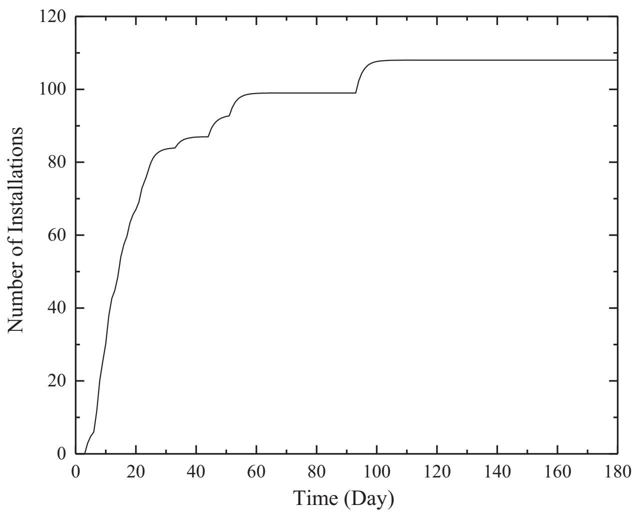

Fig. 5. Daily energy savings with node 8 and 35 are taken as information sources.

model in those papers assumes the impact between individuals is equal which is not realistic. While in this paper, by introducing node weight, the connections between individuals become diverse, and the quantified influence from individuals is more reliable. Additionally, the applied undirected network can simulate a more realistic and accurate social network connections. The model designed in [14,15] can be used to study how households' habits can influence energy consumptions, however, it does not consider the interactions between households, and cannot quantify savings from human interactions. The designed model in this paper quantifies the impact between individuals and uses the expected energy savings as a comparable indicator to evaluate the impact of human interactions on energy consumption. The Facebook tool developed in [18] relies on inaccurate verbal descriptions to find the impact of network interactions on savings, and it is only verified on a small network of 8 people. In [26–28] the probability to adopt new efficient product is described as an individual's characteristic, and it focuses on the dynamic population adoption rate. However, the results are limited to homogenous networks in which connections between individuals are the same, and energy savings are not explicitly quantified. While in this paper, connections between individuals in the social network can be different, and thus the model will be closer to the real situation; furthermore, the model also forecasts the expected energy savings by calculating the impact of the social connections. Therefore, the results in this paper will be more practicable and reliable to guide energy efficiency technology mass rollout programmes and projects.

3.5. Limitations

The modelling method presented in this paper has a few limitations. Firstly, the method requires survey data including details of social network connections. This narrows the scale of the targeted social network. In future studies, epidemic theory will be applied to minimise the requirement of network connection details. Sampling techniques from statistics can also be combined to reduce the number of people involved in a survey. Secondly, there are large amount of parameters about the network to be determined in the presented model, which brings a lot of computational challenges to identify these parameters by least square methods. The current approach in the case studies of this paper is to select sufficiently large populations in the generic algorithm to solve the least square optimisation problem, and more advanced optimisation algorithms need to be identified if the size of the network is very big. Thirdly, the reliability of the expected energy savings depends on whether the sampled social network is representative enough. Inappropriately selected network will cause the results less representative. Advanced sampling techniques in [35,36] can be applied to guide the selection of individuals and the corresponding network.

4. Conclusions

A mathematical model to calculate the expected energy savings is obtained in this paper by studying interactions within a social network. Decayed propagation of information along the social network is modelled by an exponential function. With the aid of probability theory, the obtained mathematical model can calculate both the direct and indirect energy savings. This model can also help to decide which individuals will have the most influence on the rest of the social network. The model is tested by a social network with 40 participants and network data is collected from survey questions. The results on a social network with a single information source show that the influence of an individual is not only related to its connectivity but it is also strongly affected by node to node weights. The best chosen information source can have about 25% more energy savings in the first two month compared to randomly chosen nodes. In the end of a year, it still can have 5.64% more energy savings than random nodes. Therefore, the best node chosen by the model can achieve significant amount of extra energy savings in a very short time period. When the network has multiple information sources, the influence of these multiple source nodes depends on the connections and weights of the network, and the combination of the two most influential single information source nodes may not provide the greatest influence to the network. The best combination of information sources can have about 47% more energy savings in the first month compared to random combinations. This again illustrates the usefulness of the obtained results in guiding energy efficiency technology rollout projects.

The obtained model can be further implemented in many large scale energy related programmes and projects, for example, the rollout of smart metres, electric vehicles, etc. The model will help to monitor the progress of the installations and calculate if the targeted progress can be achieved. A future work will study the quantitative impact of customer engagement to help programme organisers and other stakeholders to take further actions in end user engagement should the forecasted progress is slower than expected.

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References

[1] Prime J, Khan S, Wikes E. Energy Consumption in the UK. UK: Department of Energy & Climate Change; 2015 [Online]. Available:Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/337452/ecuk_chapter_1_overall_factsheet.pdf.
[2] Energy Efficiency Statistics Summary. UK: Department of Energy & Climate Change; 2015 [Online]. Available:Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/395007/stats_summary_2015.pdf.
[3] Huebner GM, Hamilton I, Chalabi Z, Shipworth D, Oreszczyn T. Explaining domestic energy consumption – the comparative contribution of building factors, socio-demographics, behaviours and attitudes. Appl Energy 2015;159:589–600.
[4] Chen S, Chen B. Urban energy consumption: different insights from energy flow analysis, input–output analysis and ecological network analysis. Appl Energy 2015;138:99–108.

[5] Chen S, Chen B. Energy efficiency and sustainability of complex biogas systems: a 3-level emergetic evaluation. Appl Energy 2014;115:151–63.
[6] Chen S, Chen B. Urban energy–water nexus: a network perspective. Appl Energy 2016. http://dx.doi.org/10.1016/j.apenergy.2016.03.042 [In Press, Corrected Proof].
[7] Xu X, Taylor JE, Pisello AL, Culligan PJ. The impact of place-based affiliation networks on energy conservation: an holistic model that integrates the influence of buildings, residents and the neighborhood context. Energy Build 2012;55:637–46.
[8] Carlon E, Schwarz M, Golicza L, Verma VK, Prada A, Baratieri M, et al. Efficiency and operational behaviour of small-scale pellet boilers installed in residential buildings. Appl Energy 2015;155:854–65.
[9] Yin Y, Mizokami S, Aikawa K. Compact development and energy consumption: scenario analysis of urban structures based on behavior simulation. Appl Energy 2015;159:449–57.
[10] Peschiera G, Taylor JE. The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems. Energy Build 2012;49:584–90.
[11] Petersen JE, Shunturov V, Janda K, Platt G, Weinberger K. Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives. Int J Sustain High Educ 2007;8:16–33.
[12] Murray DM, Liao J, Stankovic L, Stankovic V. Understanding usage patterns of electric kettle and energy saving potential. Appl Energy 2016;171:231–42.
[13] Shimokawa M, Tezuka T. Development of the "Home Energy Conservation Support Program" and its effects on family behavior. Appl Energy 2014;114:654–62.
[14] Gram-Hanssen K. Understanding change and continuity in residential energy consumption. J Consum Cult 2011;11:61–78.
[15] Gram-Hanssen K. Standby consumption in households analysed with a practice theory approach. J Ind Ecol 2009;14:150–65.
[16] Jain RK, Gulbinas R, Taylor JE, Culligan PJ. Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback. Energy Build 2013;66:119–27.
[17] Chen J, Taylor JE, Wei H. Modeling building occupant network energy consumption decision-making: the interplay between network structure and conservation. Energy Build 2012;47:515–24.
[18] Foster D, Lawson S, Blythe M, Cairns P. Wattsup? Motivating reductions in domestic energy consumption using social networks. In: Proceedings of the 6th Nordic conference on human-computer interaction: extending boundaries. p. 178–87.
[19] Chen G, Wang X, Li X. Fundamentals of complex networks: models, structures and dynamics. first ed. New York: Wiley; 2014.
[20] Milgram S. The small world problem. Psychol Today 1967;2:60–7.
[21] Watts DJ, Strogatz SH. Collective dynamics of 'small-world' network. Nature 1998;393:440–2.
[22] Watts DJ. Network dynamics and small world phenomenon. Am J Sociol 1999;105:493–527.
[23] Travese J, Milgram S. An experimental study of the small world problem. Sociometry 1969;32:425–43.
[24] Ekpenyong UE, Zhang J, Xia X. Mathematical modelling for social impact to energy efficiency savings. Energy Build 2014;84:344–51.
[25] Ekpenyong UE, Zhang J, Xia X. How information propagation in social networks can improve energy savings based on time of use tariff. Sustain Cities Soc 2015;19:26–33.
[26] McCullen NJ, Rucklidge AM, Bale CSE, Foxon TJ, Gale WF. Multiparameter models of innovation diffusion on complex networks. SIAM J Appl Dyn Syst 2013;12(1):515–32.
[27] Bale CSE, McCullen NJ, Foxon TJ, Rucklidge AM, Gale WF. Harnessing social networks for promoting adoption of energy technologies in the domestic sector. Energy Pol 2013;63:833–44.
[28] Bale CSE, McCullen NJ, Foxon TJ, Rucklidge AM, Gale WF. Modeling diffusion of energy innovations on a heterogeneous social network and approaches to integration of real-world data. Compl Sci Soc Pol 2014;19(6):83–94.
[29] Centola D. The spread of behavior in an online social network experiment. Science 2010;329:1194–7.
[30] Milgram S, Bickman L, Berkowitz L. Note on the drawing power of crowds of different size. J Pers Soc Psychol 1969;13:79–82.
[31] Brink R, Grilles R. The outflow ranking method for weighted directed graphs. Eur J Oper Res 2009;193:484–91.
[32] Shannon CE. A mathematical theory of communication. Bell Tech J 1948;27:379–423.
[33] Marsden PV. Homogeneity in confiding relations. Soc Netw 1988;10:57–76.
[34] Newman MEJ. The structure and function of complex networks. Soc Ind Appl Math 2003;45:167–256.
[35] Ye X, Xia X, Zhang J. Optimal sampling plan for clean development mechanism lighting projects with lamp population decay. Appl Energy 2014;136:1184–92.
[36] Cochran WG. Sampling techniques. third ed. New York: Wiley; 1977.