Modeling the Impact of Innovation Diffusion on Solar PV Adoption in City Neighborhoods

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Abstract- This study presents an agent-based model of innovation diffusion for Renewable Energy Technologies (RET) based on the spread of information in social networks within city neighborhoods. Information spread patterns across household and Twitter networks are combined to model the rate of RET innovation diffusion[†]. The resulting approach provides a methodology for capturing how RET innovation diffusion in online social networks and city neighborhood networks may jointly influence the residential adoption of renewable energy technologies. An application of this approach is demonstrated with reference to solar PV adoption in Qatar.

Keywords Diffusion of Innovation, Renewable Energy Technologies, Renewable Energy Adoption, Agent-Based Modeling, Social Network Analysis.

† Social media consists a major domain for the production and dissemination of real-time information. Such flows of information have traditionally been thought of as diffusion processes over social networks by the interactions among numerous participants.

1. Introduction

Qatar's plans to generate 2% of the nation's total electricity production from solar energy by 2020 and 20% by 2030 [1] broach several environmental and economic benefits for the nation. For example, the ensuing saving in natural gas, which is currently the primary source of electricity generation, would lower Qatar's carbon emissions, and could be repurposed for additional trade to increase revenues or left untapped to extend the lifetime of the country's natural gas reserves and lower extraction costs [2], [3]. The development of a solar energy market would also help diversify the national economy through innovation and entrepreneurship to accelerate the ongoing transition from a carbon-based to a knowledge-based economy, as mandated by national development plans [4]. Residential photovoltaic (PV) systems play a crucial role for the achievement of these objectives, because of the difficulty in finding available land suitable for PV installations in the country, and the importance of avoiding additional transmission and distribution costs with utility scale installations in remote areas. Understanding the mechanism that underlie a household's decision to adopt Renewable Energy Technologies (RET) in Qatar is therefore crucial to help policymakers and other stakeholder understand challenges and opportunities in reaping the benefits of solar energy penetration. Understanding the impact of information contagion on residential PV adoption can help policymakers and users assess the risks associated with adoption, and learn how to address challenges and take advantage of opportunities. Economists and behavioral scientist have become increasingly interested in analyzing the impact of social interactions in the diffusion of innovations. A growing body of literature argues that individuals and organizations rarely make decisions solely on the basis of economic factors [5], [6] [31]. Decisions are increasingly shaped by online social network interactions, which have come to play a major role in the spread of information with the rising ubiquity of social media [7], [8]. Consequently, theories of innovation diffusion are increasingly focusing on social network analysis approaches, where a positive feedback loop in the network of initial adopters may create peer pressure effects which promote new adoptions [9] [34].

Online social [29] networks allow hundreds of millions of Internet users worldwide to produce, share and consume content [32] on an unprecedented scale. Social media platforms play a major role in the diffusion of information by increasing the spread of novel information and diverse viewpoints. For example, Facebook and Twitter have proved to be pivotal in shaping the course of political events worldwide, such as the outcome of the 2008 U.S. presidential elections and the outbreak of the Arab Spring in 2010, through the creation of social movements. Analogous impacts have been found on economies worldwide [10], [11].

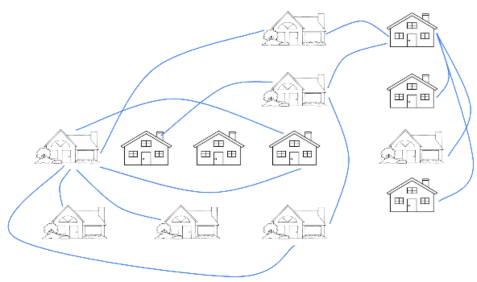
This study uses an agent-based modeling (ABM) to characterize the impact of innovation diffusion on residential PV adoption in city neighborhoods. The paper is organized into six sections. Section 1 introduces the problem. Section 2 describes the proposed model and introduces the terminology used throughout the paper. Sections 3 describes the data used throughout this paper. Section 4 combines the results of the simulations of the innovation diffusion in Twitter and neighborhood networks. In section 5, the evaluation of the impact of the innovation diffusion factor on PV-adoption decision was conducted by integrating the model into an ABM. Finally, Section 6 presents the conclusions of this study.

2. Approach

Our modeling premise is that decision behaviors about residential RET adoption are the outcome of a social process undertaken by motivated stakeholders who exert influence on each other in different spaces. This study investigates the influence of innovation diffusion on RET adoption in two spaces: city neighborhood households and online social networks. The joint spread of new RET ideas in these two spaces is analyzed as contributing to residential RET adoption, in an analogous way to how the neighborhood effect has been proved to influence a household's decision to adopt renewable energy [12][33][35][36].

A novel innovation diffusion algorithm is proposed to characterize the influence that may lead a household to RET adoption. First, a reference network of RET messages on Twitter in Qatar is created using the Barabási Albert [13] model. Then, a network model for a selection of city neighborhoods in Doha-Qatar is developed, where some of the Twitter RET message traffic is geocoded, using spatial analysis methods from Qatar census geography [14].

Next, a linear threshold approach [15] is used to model innovation diffusion in the city neighborhood and Twitter networks. Finally, the influence that may lead a household to RET adoption is characterized as the weighted sum of the influences that the household receives from the two networks.



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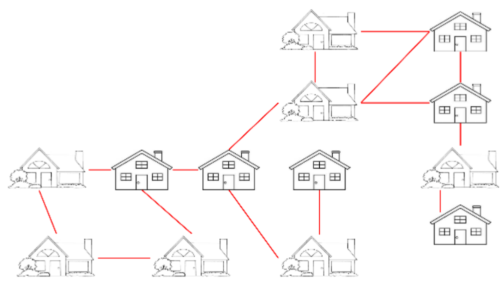

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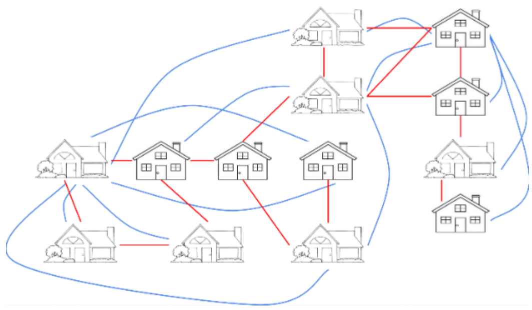


(c)

Fig.1. (a) Twitter Network TN (b) Dwelling Network DN, (c) TN-DN Network.

2.1 Modeling the Social Media Network

The Barabási Albert [16] (BA) algorithm is used to develop a social network that approximates the diffusion of attitudes and ideas about renewable energy in a reference Twitter network. The BA model is an algorithm that generates "scale free" networks, i.e. networks in which vertex connectivity follows a power-law distribution. It incorporates two basic concepts: growth and preferential attachment. Growth means that the number of nodes in the network increases over time. Preferential Attachment (PA) means that the more connected a node is, the more likely it is to form new links. Both growth and preferential attachment are widely observed in real-world networks [16]. In the context of social media networks, a link from A to B means that person A "knows" or "is acquainted with" person B.

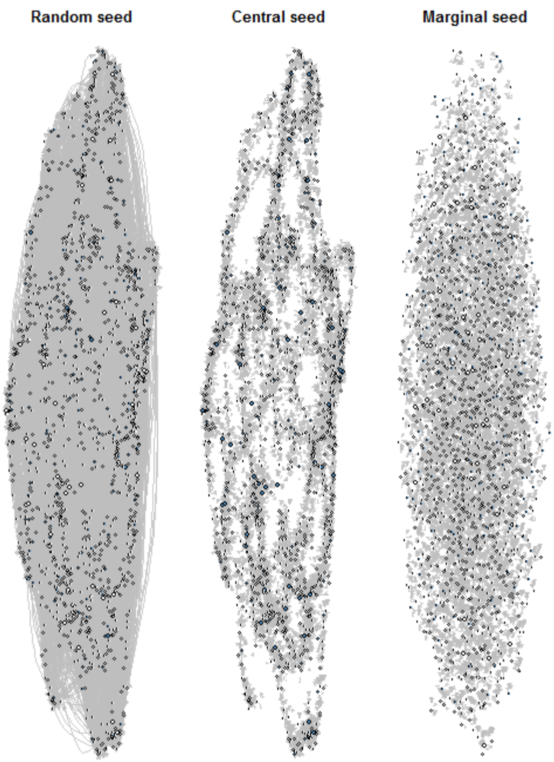


Fig.2. Simulations of the information spread in the Twitter Reference Network, with random, central and marginal configurations. All graphs are "scale-free" and differ only in how the initial seed of informed nodes is chosen. Initial network seeds appear as solid dots.

Heavily linked nodes represent well-known people with lots of relations. According to PA, a newcomer to the network is more likely to form links with nodes that are more heavily connected. We refer to individual nodes in the network as being either active (i.e. participating in innovation diffusion) or inactive, at any given point in the development of the network. Three cohorts of initial active nodes in the reference Twitter network are set: central, random and marginal. Each cohort includes 2.5% of users who twitted about renewable energy in the initial period of network formation (January 2009 through March 2016). The central cohort includes nodes that have the highest number of connections (highest degree), the marginal cohort is formed by nodes that have the lowest degree, while nodes in the random cohort are randomly chosen.

The size of each cohort of initial active users (2.5%) corresponds to the innovators category of adopters in Rogers' innovation curve [17]. According to Rogers, innovators are active information seekers about new ideas who are close to the scientific community and other innovators, have financial liquidity, and are willing to take high risks to pursue their vision. With reference to diffusion of information about solar and renewable energy in Twitter, such a cohort would match the profile of eco-warriors with financial means and high

technology awareness, seeking the advancement of their ecological ideology. The central, random and marginal cohorts are used as seeds for the generation of simulated networks (Fig. 2), to verify which configuration best approximates the diffusion characteristics of the reference Twitter network. Formal details about the BA graph generation are provided through the pseudo-code in Algorithm 1 below, where the *m* parameter determines how quickly a novel piece of information spreads within a network (see Fig. 3).

Algorithm 1 *BA* Graph Generation

Add m nodes to $\mathfrak{G}$

Randomly add edges to $\mathfrak{G}$ until we get a connected graph

for $i \in \{1, \ldots N - m\}$ **do** (where N is # of nodes in $\mathfrak{G}$)

  $\mathfrak{G}.Add\_node(i)$

  while $degree(i) < m$ **do**

    Choose a node j uniformly at random from $\mathfrak{G}$.

    Compute: $p_j = \frac{k_j}{\sum_{1..n} k_n}$ ▷ where p_j is the probability of connecting nodes i and j, k_j is the number of edges connected to node j

    Choose r uniformly at random between 0 and 1

    if $r \le p_j$ **then**

      $\mathfrak{G}.Add\_edge(i, j)$

    end if

  end while

end for

To ensure that the network generation model uses an m parameter that adequately characterizes the flow of information in the reference Twitter network, m is set to a value that captures the degree distribution observed in the reference Twitter network. Trial tests with diverse values for the m parameter and initial active user cohorts indicate that the best fit is obtained using the average degree in the reference Twitter network (m = 15) with central initial active nodes.

2.2 Modeling the City Neighborhood Network

A network model for a selection of city neighborhoods in Doha, Qatar was developed where most geocoded posts in the reference Twitter network occur. Figure 4 shows the specific city area of interest, which is one of the most populated neighborhoods in Doha. Each selected household (represented with a green circle) corresponds to a compound or independent villa-type accommodation. To ensure that our city neighborhood model – the dwelling network (DN) henceforth – preserves the layout of its real world physical counterpart, constraints derived from Qatar's census geography were used in developing the model. More specifically, census blocks were used as the basic unit of DN.

Fig.3. The diffusion spread process in one user network.

Census blocks are statistical areas bounded by visible features, such as streets, roads, streams, and railroad tracks, and by invisible boundaries, such as selected property lines and city, township, school district, and county limits and short line-of sight extensions of streets and roads. Generally, census blocks cover small areas, such as a block in a city bounded on all sides by streets. Census blocks in suburban and rural areas may be large, irregular, and bounded by a variety of features, such as roads, streams, and transmission lines. In remote areas, census blocks may encompass many square miles.

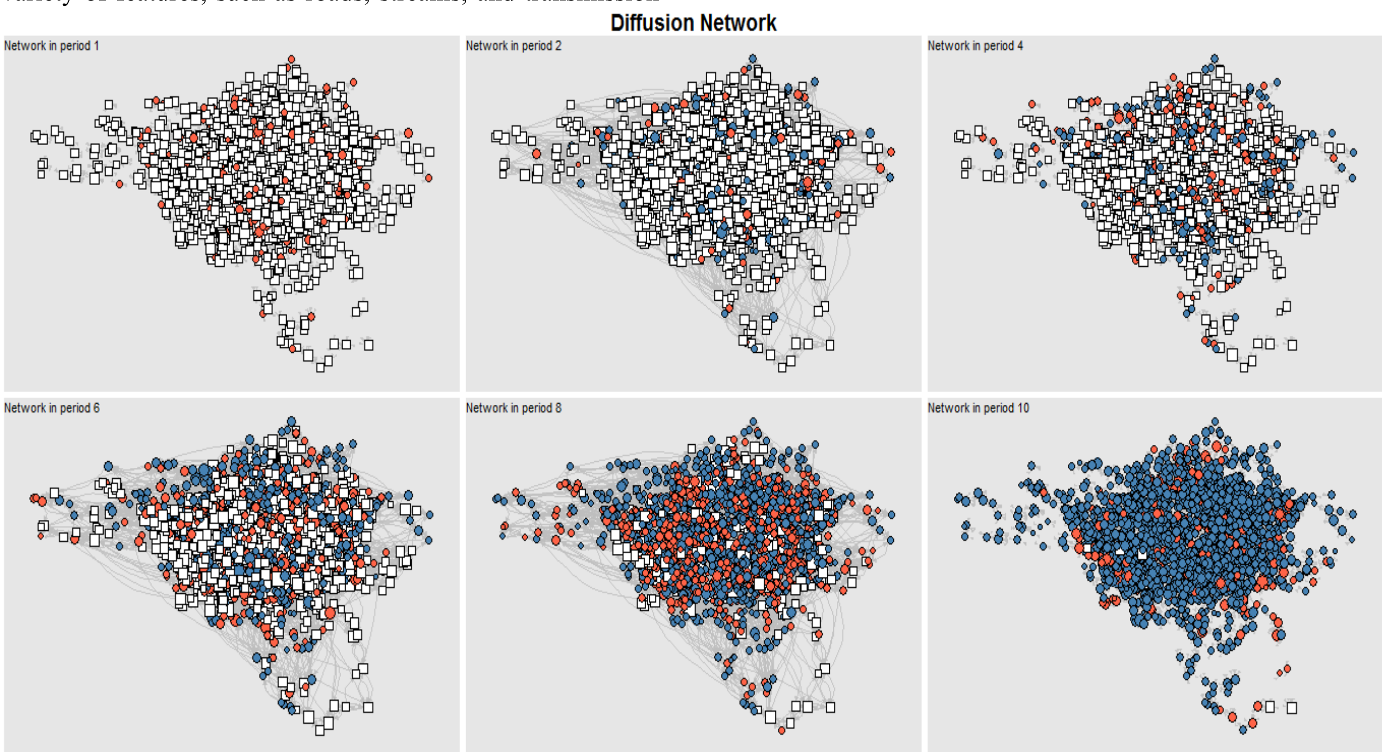


Fig.4. Geographic distribution of selected households (green circles) in Doha.

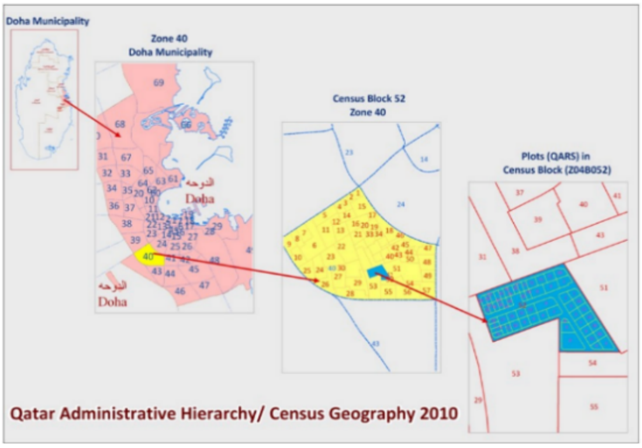


Fig.5. Sample of Qatar's 2010 census geography.

As to Qatar's 2010 census geography, 4345 blocks containing 150,000 building plots are grouped into 90 zones, which in turn are arranged into seven municipalities, as shown in Fig. 5. GIS files providing information about census blocks and building locations were used as reference data for DN. In DN, each node corresponds to a census block. First, a network where each block is connected to an adjacent block was created. Next, a spatial join operation was performed to link each housing unit (represented as a pair of coordinates) to its corresponding block (represented as polygon). Then, housing units were added into the network of blocks as nodes and links were created following these two rules:

- Each housing unit node is connected to its corresponding block node.
- Housing unit nodes within the same block form a fully connected sub-graph.

A network model for the selection of city neighborhoods in Doha (Qatar) shown in Fig. 4 was developed, where most geocoded posts in the reference Twitter network occur.

Figure 6 provides an analysis of structural properties for the real-world dwelling network. Panel (a) shows the distribution of neighboring blocks in the network. One observation is that most of the blocks have between 4 and 8 adjacent blocks, the maximum number of neighbors a block may have being 14. The distribution of the number of villas per block is shown in panel (b). Most of blocks turn out to have less than 20 villas. Very few have more than 50 villas. It is important to notice that over 500 blocks have no villas.

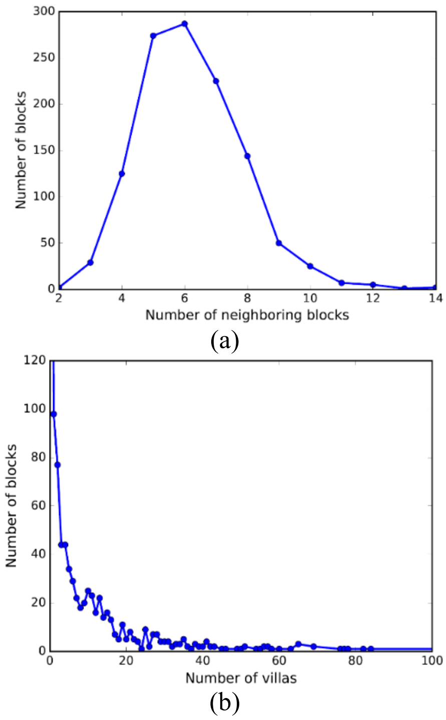


Fig.6. Some structural properties of the real dwelling network. Panel (a) plots the distribution of number of adjacent blocks for each block. Panel (b) plots the number of buildings in each block. Note that there are 521 blocks without any building in them.

Figure 7 shows the distribution of neighboring blocks in the network. The dots in this graph represent the blocks of the k selected zones.

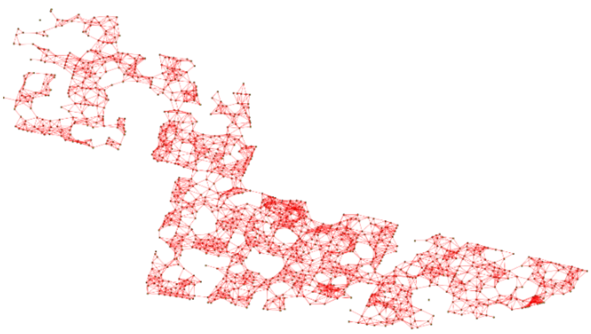


Fig.7. A sub-graph of some blocks from k selected zones

2.3. Linear Threshold Model for Innovation Diffusion

Information may spread through a network in different ways. Accordingly, diverse models of network information spread have been developed in the literature. For example, in the PUSH model, only nodes that have information can contact neighbors to inform them, and an active node can only contact one of its neighbors at a time. This model has been used to transmit information in computer networks [18], [19]. By contrast, linear threshold models allow an active node to contact all its neighbors at once.

Linear threshold models are better suited to characterize the spreading of information in social networks such as Twitter and Facebook, where the content generated by a user is made instantaneously available to all her followers and/or friends. In addition, linear threshold models can factor in two important factors: (i.) the extent to which a user can be influenced by or influence its neighbors, and (ii.) the activation threshold of different users. For example, a user may become active if only one of its neighbors is active, whereas another user may require 50% of its neighbors be active before it activates. The pseudo-code in Algorithm 2 describes the linear threshold-based diffusion process that has been adopted in this paper.

Since the same linear threshold algorithm can be applied to the Twitter network (TN) and the dwelling network (DN), Innovation Diffusion (ID[‡]) can be characterized in combined TN and DN networks jointly (ID (TN, DN)), as shown in 1, where: (a) α is the weight[§] given to the social network influence; (b) β = 1−α is the weight of the dwellings network influence; (c) t_{s_i,s_j} (d_{s_i,s_j}) is the influence that stakeholder s_j exerts on s_i in TN (DN).

$$\mathrm{ID}(\mathrm{TN},\mathrm{DN}) = \alpha \times (\sum_{s_j \epsilon TN(s_i)} t_{s_i,s_j} + \beta \times \sum_{s_j \epsilon DN(s_i)} d_{s_i,s_j} \tag{1}$$

The joint TN-DN innovation diffusion function was used in (1) to calculate innovation diffusion jointly in the Twitter and dwelling networks. Algorithm 2 presents a pseudo-code of the adaption of linear threshold model to deal with multigraphs.

Algorithm 2 Linear Threshold Diffusion for Multi-Graphs

Let $\mathcal{G}$ be a multi-graph with two types of links ▷ social links and dwelling neighborhood links
Choose $(\alpha, \beta) \in ([0,1],[0,1])$ ▷ importance weights for social network and dwellings network
Set A_0 to be 2.5% of nodes in $\mathcal{G}$ ▷ early adopters
for all $n_i \in \mathcal{G}.nodes()$ **do**
  Set activation threshold $\theta_i \in [0,1]$ ▷ uniformly at random
end for
for all $(u,v) \in \mathcal{G}.edges()$ **do**
  Set influence weight $b^{sn}_{u,v} \in [0,1]$ ▷ Influence in TN
  Set influence weight $b^{dn}_{u,v} \in [0,1]$ ▷ Influence in DN
end for
$A = A_0$
for $t \in timesteps$ **do**
  $A_{new} = \emptyset$
  for $n_i \in \mathcal{G}.nodes() - A$ **do**
    if $\alpha \times (\sum_{s_j \in TN(s_i)} b^{sn}_{s_j,s_i}) + \beta \times (\sum_{s_j \in DN(s_i)} b^{dn}_{s_j,s_i}) \geq \theta_i$ **then**
      $A_{new} = A_{new} \cup \{n_i\}$
    end if
  end for
  $A = A \cup A_{new}$
end for

3. Data

For the dwelling network DN, reference GIS data has been used, which where kindly made available by Qatar Ministry of Development Planning and Statistics. For the creation of the renewable energy social network, information about the interest of people living in Qatar towards renewable energy was collected from Twitter.

The process for extracting Twitter message reflecting users's interest towards renewable energy is described below, and the results are shown in Fig. 9.

(a) *Identifying users of Qatar:* First, a gazetteer of locations in Qatar was created including the names of main cities and districts in both English and Arabic, and under different spellings. This list was matched to a 45 day sample of the Twitter Decahose API[**] - a sample of 10% of the entire Twitter stream - to identify users of Qatar. This list was expanded by iteratively analyzing profiles of the friends and followers until no more users were identified. The result consists of 117K users who claim to live in Qatar.

(b) *Collecting User Tweets:* Twitter Historical API[††] was used to collect up to 3,200 tweets posted (the maximum allowed by Twitter API) for each of the users. This collection generated a total of 109.6 million tweets posted by more than 98,066 different users over a

‡ ID is the factor measuring how the information spread through the network.

§ α is the relative importance assigned to each network.

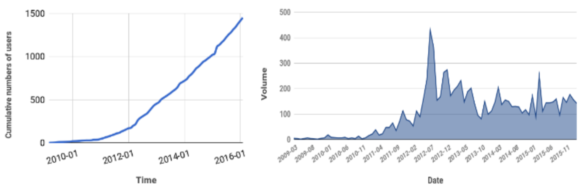
**https://developer.twitter.com/en/docs/tweets/samplerealtime/overview/decahose , last accessed on Dec 2017

†† https://developer.twitter.com/, last accessed on Dec 2017

period of nine years (from 2007 to 2016). As Twitter was launched in 2006 only, the activity of the users in Qatar was very marginal before 2011. Therefore, we focus on the time period spanning from January 1st, 2009 to January 1st, 2016.

(c) *Filtering for Renewable Energy:* Next, a filtering process has be run to retrieve tweets that match one of the following keywords: solar and renewable energy (see Fig. 8). The keyword solar is used as a wild card to catch several solar energy related technologies such as solar panels, solar energy, solar electricity, solar power, and solar PV. By doing so, we obtained a list of 8,681 tweets posted by 1,570 unique users (see Table. 1).

(d) *Building Follow-ship Network:* data from step (a) has been used to connect the 1,570 users to their friends and followers. This resulted in a unified network of 8,181,998 nodes (users) and 11,040,652 links. As our only focus point is on the network linking the 1,570 users, all links to users who are not in that list were filtered out. Hence, a smaller network has been obtained– represented as a directed graph – with 1,471 nodes and 22,217 links.



(a) (b)

Fig.8. (a) Cumulative number of users who twitted about solar and renewable energy in Qatar. (b) Monthly time line of tweets referring to renewable energy posted by users of Qatar.

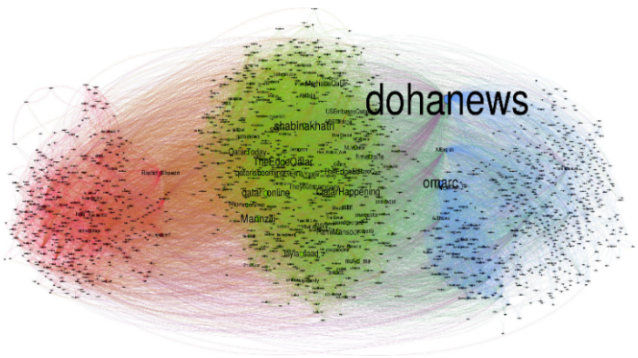


Fig.9. Topology of *Twitter Close-Net* network connecting users in Qatar interested in *renewable/solar energy*. One observation is that the network is strongly connected and has three distinguishable communities.

Table1. Twitter Follow-Ship Network Statistics. CLOSE-NET is the Subset Network Made for the 1,417 Users.

Relationship	#Links	#Users	Avg. links/user
Followers	10,0.30,279	7,927,366	6,388,71
Friends	1,030,270	581,826	656,22
Closed-Net	22,217	1,417	14,27

4. Results

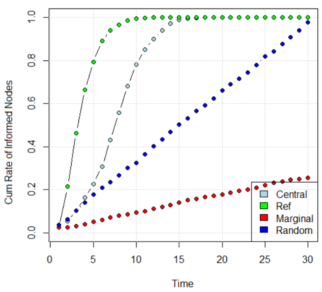
First, the best performing Twitter network model was selected in terms of its ability to match a real-world model of the reference Twitter network. Then, the selected Twitter network model was used to calculate the combined rate of diffusion for renewable energy innovation across the Twitter and dwelling networks.

A real-world model of the reference Twitter network was first created through 30 simulated iterations of the linear threshold spreading algorithm, with an initial seed cohort equal to 2.5% of the reference Twitter user network, as shown in Fig. 10. Then the analogous simulations were performed using the BA model with random, central and marginal configurations of the initial seed cohort, using different values for graph density parameter ($m \in \{5, 10, 11, 15\}$). This allowed us to verify which of the three configuration comes the closest to the reference Twitter network – see [20] for a similar study. As shown in Fig. 10, the closest approximation of the simulated networks to the reference Twitter model is obtained with the highest degree of graph density (m = 15) in the central configuration.

Since all buildings within a census block form the smallest neighborhood unity within a municipality, we hypothesize that innovation diffusion can spread in parallel across households within a census block, so that buildings belonging to the same census block activate together within the innovation diffusion model. Therefore, census blocks were used as the basic unit of the dwelling network networks of buildings instead of using individual buildings. This reduces significantly the size of the dwelling network with substantial ensuing efficiency in the computations needed to carry out this study.

After simulating the Twitter network TN in the configuration which best fits the reference Twitter network (using the BA model with the graph parameter m = 15), the combined TDN network was created by mapping each user captured in Twitter network to a census block. The activation threshold for all nodes was set in both TN and DN to 1/10, meaning that a node will activate if at least one tenth of its neighbors are activated. The scores that quantify the influence nodes exert on each other (i.e. edge weights) are assigned randomly, so that influence scores of all incoming edges of any node sum up to 1.

Figure 11 shows how information started at a random node spreads in the reference Twitter and simulated networks. The diffusion of innovations in this model are consequently parameterized by a threshold of adoption. The key variable here is the initial distribution of thresholds across a social network, which describes in totality the final extent of the behavior. Results show that news spreads much faster in the real world networks and the central graphs than in the random and marginal graphs. Early potential adopters in the real network and potential adopters in the central configuration are the most favorable to have a high exposure‡‡, as they have many connections.



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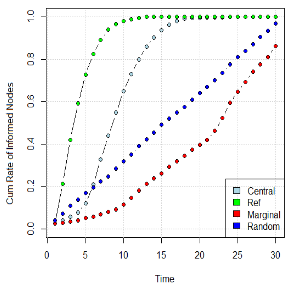

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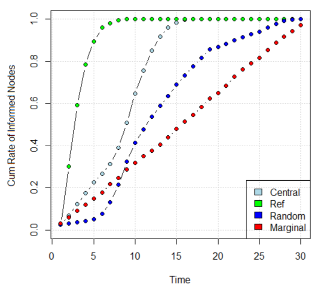

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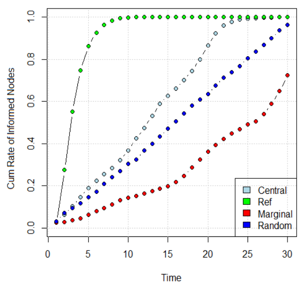
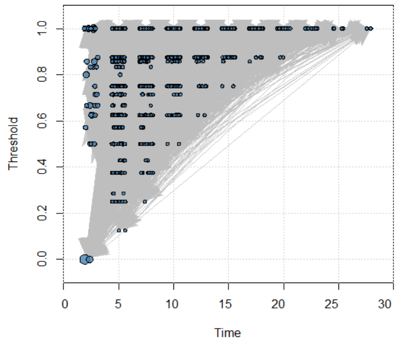


(d)

Fig.10. Informed nodes average rate over time for the Twitter-Real-Network and random, central and marginal attachments of the initial seed cohort of users. Simulations were run using the same number of nodes (# of nodes=1451) and density parameter m ∈ {10, 11, 15}. Both the real network and the central attachment show better and faster contagion spread in comparison with the others processes.



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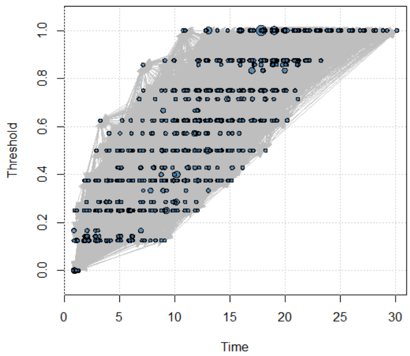

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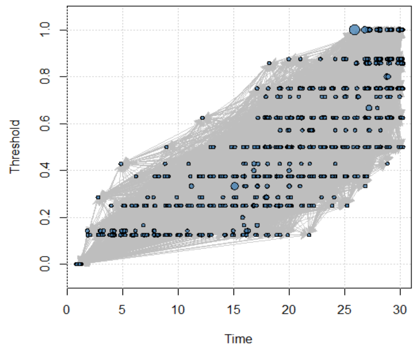

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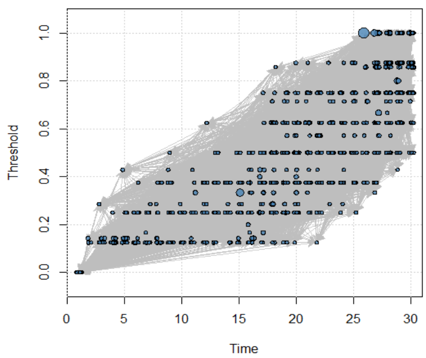

(d)

Fig.11. Time of Topic Spread by Network Threshold. # of nodes=1451 and density parameter m=10 (a) *Ref-Twitter*, (b) *Central*, (c) *Random* and (d) *Marginal*.

‡‡ The exposure of a node is the fraction of their neighbors who are already informed and that must be reached before they will adopt the innovation.

The linear threshold spreading algorithm was simulated on TDN until convergence was achieved (i.e., no more nodes can be activated) with the initial seed cohort of active nodes (equal to 2.5% of the reference Twitter user network, see section 2.1 for details). In order to allow a better understanding of the impact of the choice of initial active nodes on the diffusion process, two different scenarios were simulated:

- Random cohort, in which the initial active nodes are selected at random from the set of all nodes.
- Central cohort, in which the initial active nodes with the highest degree (number of connections in the network) are selected.

α, β parameters were varied to take values in the interval {0, 0.25, 0.5, 0.75, 1} with the constraint $\alpha + \beta = 1$.

Fig.12 reports the results for the different experimentation configurations. Note that when $\alpha = 1$ and $\beta = 0$, then TDN reduces to the Twitter network TN. Similarly, the combined network TDN reduces to the dwellings network for $\alpha = 0$ and $\beta = 1$. The results for these two special cases are plotted in sub-figures (a) and (b) respectively. The main observation here is that innovation diffusion spreads much faster in TN (where convergence is achieved in 3 steps for the central cohort, and 5 for the random cohort) compared to DN (where convergence is achieved in 8 steps for the central cohort, and 11 for the random cohort). This is mainly due to the presence of more highly connected nodes in the Twitter Network than there are in the dwelling Network.

The remaining sub-figures (c), (d) and (e) in Fig. 12 show the behavior of innovation diffusion with values for the α, β parameters in the interval {0.25, 0.5, 0.75}, i.e. when both TN and DN determine the level of diffusion jointly. The main result here is that TN somewhat dominates the diffusion process. The lower the weight α is, the higher the number of steps required for the diffusion algorithm to converge. Finally, the central cohort of initial active nodes (curves in green) leads to faster innovation diffusion when compared to the random cohort of initial active nodes (curves in blue) in all cases. This is mainly due to the fact that highly central nodes are connected to more neighbors, and thus allow the activation of more nodes.

5. Integrating Innovation Diffusion Factor in a Multi-agent Residential PV Adoption Model

Agent-based modeling (ABM) is recognized as a powerful tool to understand and analyze phenomena in complex systems [21]. It's one kind of micro-scale model, bottom-up approach that captures the simultaneous interactions of multiple agents [30] in an attempt to recreate and predict macro system-level events [22]. ABM was used to demonstrate the impact of our approach to innovation diffusion on residential PV adoption. Our starting point is the residential PV adoption model developed in [23], where agents represent residential households whose decision to adopt PV is driven by economic factors.

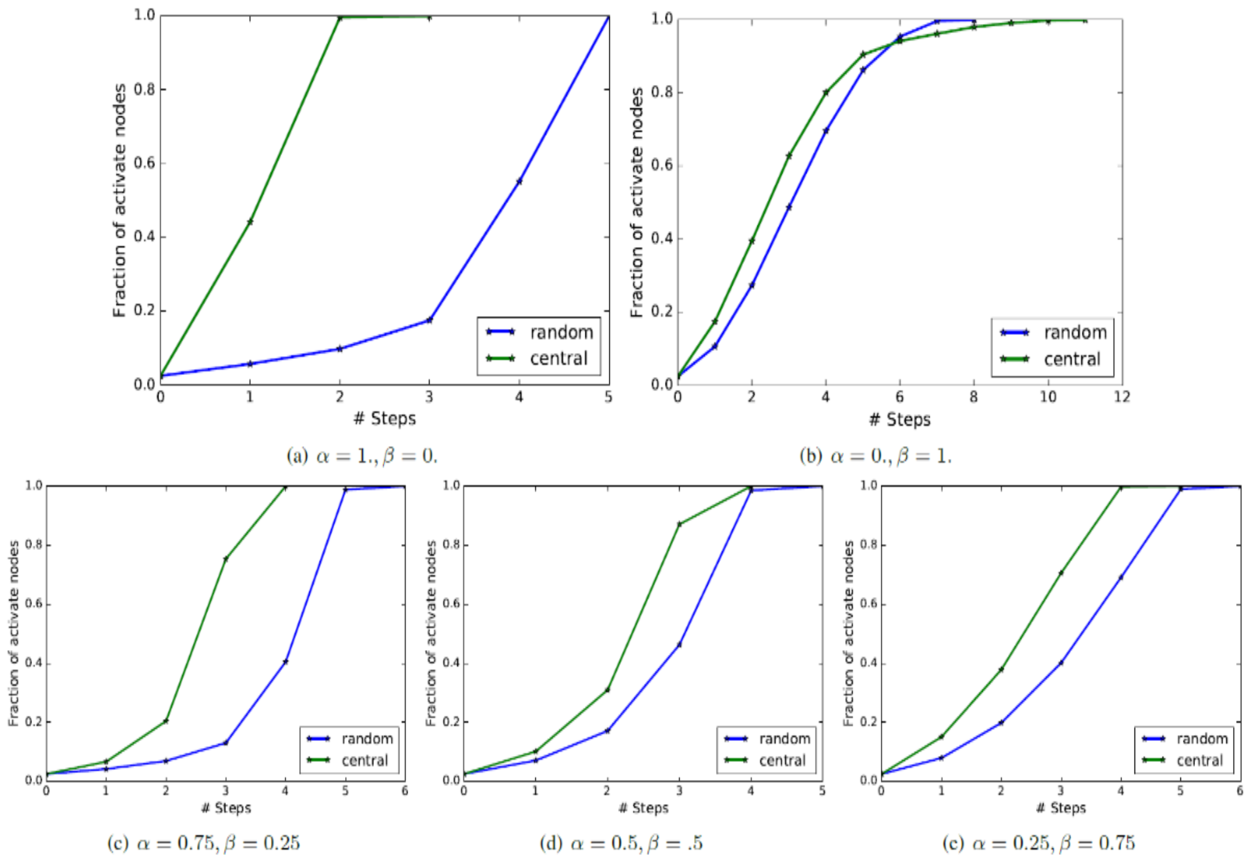

Fig. 12. Innovation diffusion results for the combined TN-DN network with different influence weights for the two networks.

Households adopt solar PV with a probability established by the logistic function in (2), where L is a scaling constant, e is the natural logarithm, x is the cost of PV minus the cost of electricity, and k is a parameter which determines the slope of the adoption curve. Following [23], L was set to 1 to normalize the output of the logistic function as a probability. For the k parameter, a value was selected that yields a PV market share of 2.5% at the end of the simulation in a scenario where the cost of PV stays constant through time. This market share is equivalent to the number of innovators in Rogers' innovation adoption curve, who by disposition are willing to adopt novel technology at a premium price. At each simulation tick, each household agent that has not adopted yet, is presented with the opportunity of doing so. Adoption is determined randomly in terms of the output of the logistic function in (2): a random probability p_r is generated, and if

the probability of adoption as calculated by (2) is greater or equal to p_r, adoption occurs.

$$f(x) = \frac{L}{1+e^{-k*x}} \tag{2}$$

Using the Netlogo environment [28], three scenarios were simulated: one with ID in the Twitter network TN, one with the ID factor simulated in the Dwelling network DN and one with the ID simulated in both TN+DN. Each scenario was simulated for 14 years starting from 2016, with each simulation tick corresponding to a year. Simulations are iterated 200 times for each year, and the adoption rate for the year was calculated as the average adoption for the year.

To quantify the falling cost of PV, the US Department of Energy SUNSHOT Initiative targets [24] has been used, according to which residential PV costs in 2020 and 2030 are respectively expected to be 50% and 70% less that PV costs in 2016 [23]. The SUNSHOT targets have been adopted as reference points and use interpolation to calculate PV costs in the intervening years, as shown in Table 2. Following [25], residential PV cost was set by doubling a utility PV solar plant in the 300MW scale. Given our focus on the Arabian Gulf Region, the 2015 award by the Dubai Electricity and Water Authority to Acwa Power for a 200MW solar plant, at a fixed rate of 5.84c/kWh over 25 years [26] was used as the reference cost for utility-scale PV. The price of residential PV in 2016 was therefore set at 11.68c/kWh. The price of electricity was calculated as the average ongoing KAHRAMAA tariff for residential villas, of 3.555c/kWh [27]. The analysis is presented in two portions. First, we present a comparative analysis focused on identifying descriptive differences between the different networks: TN, DN and TN+DN. Then, an analysis of the PV total adoption rate (i.e. cumulative adoption rate) was provided for the three networks.

Table 2. Estimated Residential PV costs 2016-30 in Qatar using DOE SUNSHOT Initiative targets.

Year	PV Cost (¢/kWh)	Calculated as
2016	11.68	Initial PV Cost
2017	10.22	Interpolate
2018	8.76	Interpolate
2019	7.30	Interpolate
2020	5.84	50% less than initial PV cost
2021	5.61	Interpolate
2022	5.37	Interpolate
2023	5.14	Interpolate
2024	4.91	Interpolate
2025	4.67	Interpolate
2026	4.44	Interpolate
2027	4.20	Interpolate
2028	3.97	Interpolate
2029	3.74	Interpolate
2030	3.50	70% less than initial PV cost

5.1 Comparative analysis of the TN, DN and TN+DN Networks

This analysis highlights both similarities and differences between the TN, DN and TN+DN networks in terms of two main outcomes: the rate of total and new adopters per year. In Fig.13, simulation results were reported relative to the rate of total and new adopters for two scenarios: PV Adoption with and without Innovation Diffusion (PVA-ID, PVA-No-ID).

Figures 13c-e show the impact of the Innovation Diffusion factor (ID) simulated in the Twitter network TN and the Dwelling network DN for new and total adoptions rates per year using the DOE Sun Shot targets for falling PV costs. The PVA-No-ID is the basic scenario where ID factor is not taken into account in the ABM. For the PVA-ID, two special cases are plotted in Fig. 13a and Fig. 13b. Different PVA-ID scenarios are provided by varying the α and β parameters in the interval {0.25, 0.5, 0.75}, i.e. when both TN and DN determine the level of diffusion jointly. The main result here is that TN somewhat dominates the diffusion process. The lower the weight α is, the higher the number of years required for the PV adoption decision to be positive. The combined network TN+DN leads to faster PV adoption when compared to the two special cases plotted in Fig. 13a-b.

The analyses show that total adoption rate is higher and grows faster in TN compared to DN. These results are expected according to the results presented in section IV, which demonstrate that innovation diffusion ID spreads faster in TN compared to DN. This is mainly due to the presence of more highly connected nodes in the Twitter network than there are in the Dwelling network. Another explanation is that the social network TN is denser and more interconnected than the Dwelling network DN.

5.2 Analysis of the PV total adoption rate for the TN, DN and TN+DN Networks

Table 3 provides simulation results for the total PV adoption rate, which appear to be growing faster in the combined network TN+DN than other networks. This can be explained by the fact that the PV adoption decision tends to grow faster in households networks that are more connected in social media network and are situated in the same district or area. The results suggest small, but positive and significant social effects that can be exploited to promote adoption: at the average installation rate of 0.3 installations per 1,000 owner-occupied households. At the average number of 37,565 owner-occupied households within a postcode district, this implies an increase in the number of new installations in the neighborhood by 0.05. The resulting approach shows how online social networks and city neighborhood networks may jointly influence the residential adoption of RET.

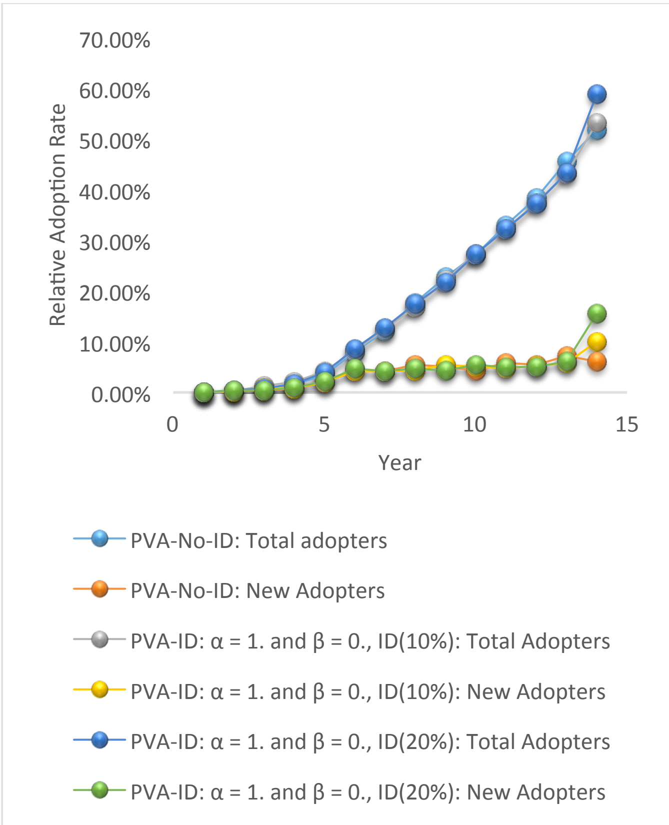

Fig. 13a α = 1 and β = 0, TDN reduces to the TN.

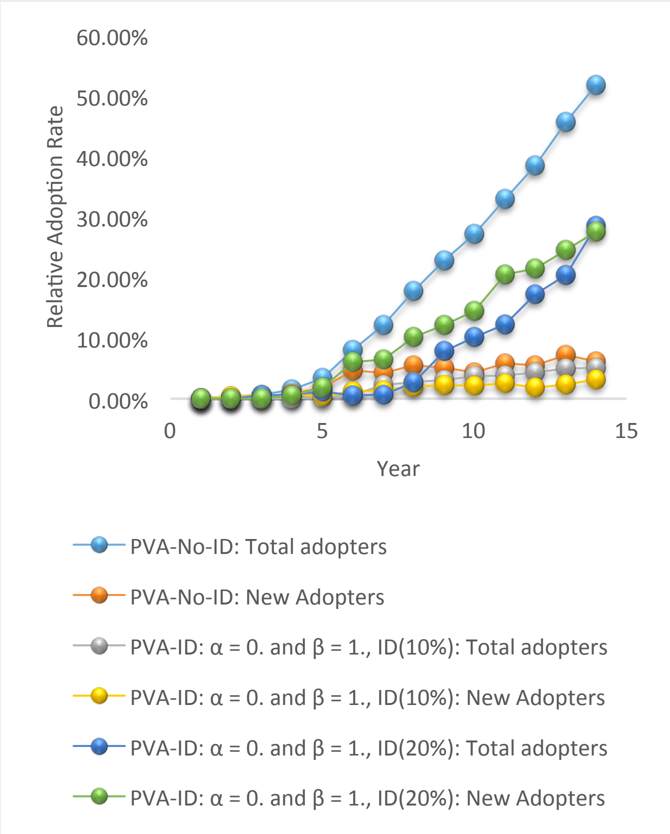

Fig. 13b α = 0 and β = 1, TDN reduces to the DN.

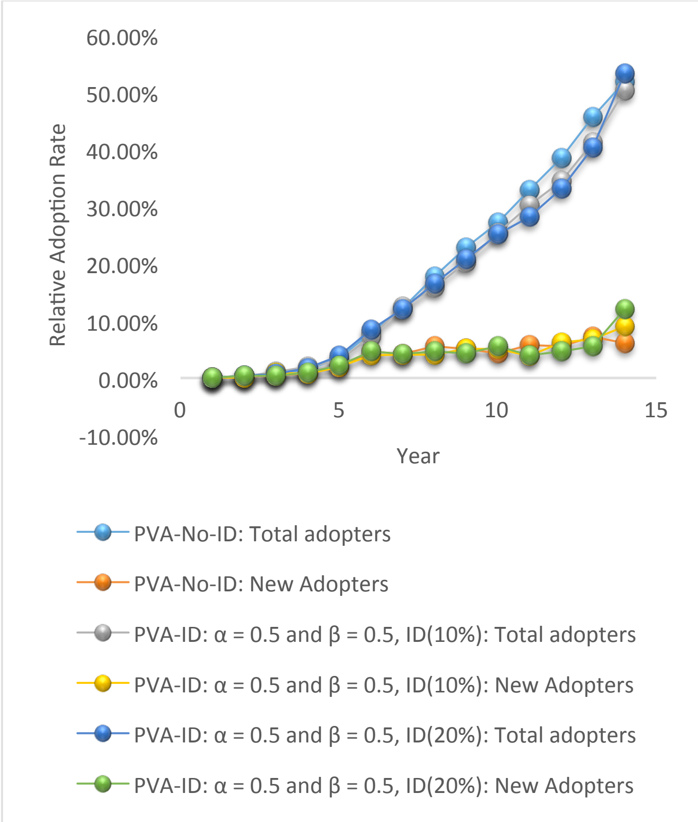

Fig. 13d α, β ∈ {0.25, 0.5, 0.75}, i.e. joint TN-DN ID.

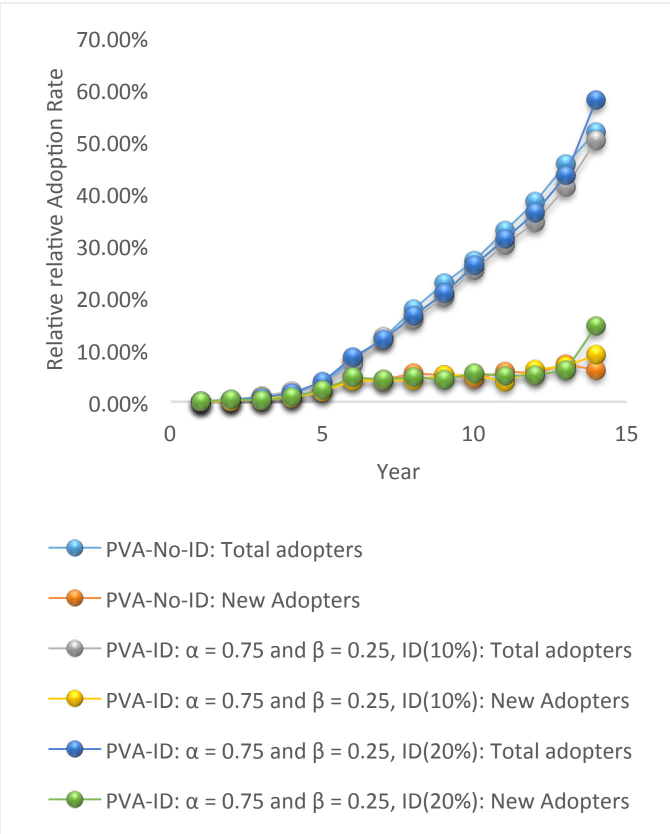

Fig. 13c α, β ∈ {0.25, 0.5, 0.75}, i.e. joint TN-DN ID.

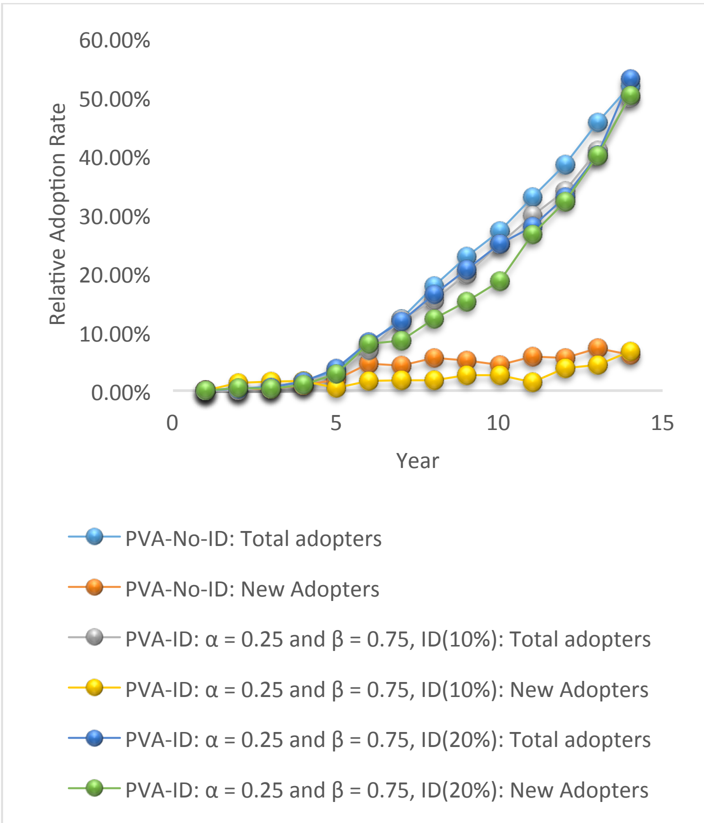

Fig. 13e α, β ∈ {0.25, 0.5, 0.75}, i.e. joint TN-DN ID.

Fig.13. The impact of the Innovation Diffusion factor (ID) simulated in the Twitter network TN and the Dwelling network DN, on *new* and *total adoptions* rates per year.

Table 3. Estimated rates of total PV adopters in TN, DN and TN+DN networks for 2016-30 in Qatar using DOE SUNSHOT Initiative targets.

Year	TN		DN		TN+DN	
1	0.21%	114	0.16%	104	0.21%	126
2	0.41%	240	0.29%	223	0.40%	251
3	0.97%	489	0.68%	473	0.74%	537
4	2.03%	1023	1.04%	1008	1.70%	1071
5	4.52%	2223	2.37%	2206	3.91%	2336
6	7.89%	4869	5.35%	4820	8.51%	5051
7	15.23%	7808	9.85%	7766	12.02%	8154
8	19.42%	11141	12.94%	11099	16.51%	11614
9	24.63%	14903	19.45%	14714	20.78%	15485
10	32.41%	18899	21.59%	18734	28.29%	19475
11	37.32%	23306	22.11%	23004	37.25%	23831
12	45.47%	27856	35.99%	27519	46.35%	23342
13	54.52%	32533	41.06%	32151	47.42%	32981
14	60.20%	37321	46.05%	36731	63.92%	37565

6. Conclusion

Understanding the innovation diffusion mechanism that underlie a household's decision to adopt Renewable Energy Technologies (RET) is crucial to help policymakers and other stakeholder understand challenges and opportunities in reaping the benefits of renewable energy penetration. This study shows that a model of RET innovation diffusion can be developed by combining information diffusion patterns derived from online social network and city neighborhood networks. The resulting approach provides a methodology for capturing how online social networks and city neighborhood networks may jointly influence the residential adoption of renewable energy technologies. Our future goals are to evaluate the contribution of information diffusion to PV adoption when combined with other factors in diverse regulatory frameworks, as an augmentation of a PV adoption model.

Acknowledgements

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