Modelling social networks in innovation diffusion processes: the case of electricity access in rural areas

Fabio Riva[a], Emanuela Colombo[b], Carlo Piccardi[c]

[a]Politecnico di Milano, Department of Energy, via Lambruschini 4, Milan 20156, Italy; +39 02 2399 3866 – fabio.riva@polimi.it

[b]Politecnico di Milano, Department of Energy, via Lambruschini 4, Milan 20156, Italy; +39 02 2399 3820 – emanuela.colombo@polimi.it

[c]Politecnico di Milano, Department of Electronics, Information and Bioengineering, via Ponzio 34/5, Milan 20133, Italy; +39 02 2399 3566 – carlo.piccardi@polimi.it

DIGEST OF THE FULL PAPER[1]

1. Introduction

In rural contexts, long-term evolutions of electricity demand can be explained as a diffusion of new electrical appliances and an increase of their ownership and use by local people. By relying on classical innovation diffusion models, it would be possible to simulate eventual scenarios of electrical appliances diffusion. However, following the recommendations of Bhattacharyya [1], reliable models should capture some of the specific socio-economic dynamics of developing countries, especially in rural context that are affected by high uncertainty, strong non-linear phenomena, complex diffusion mechanisms, time-adjustments of technology perceptions.

As a first step to deal with all such complexities, with this work we start trying to introduce an extra complexity in innovation diffusion models, *i.e.* the modelling of social networks. We adopt a speculative approach: we rely on an ideal case of innovation diffusion in a rural community and we design some experiments to describe the effect of introducing social networks in the process. Network-based diffusion scenarios are developed through discrete agent-based modelling (ABM) approaches, and results are then compared to classical continuous diffusion models simulated through a system-dynamics (SD) approach.

2. Material and methods

2.1. Network models

For modelling social networks in diffusion processes, we start representing an ideal rural community through 3 types of networks: (i) Random, (ii) Barabási & Albert, and (iii) Social.

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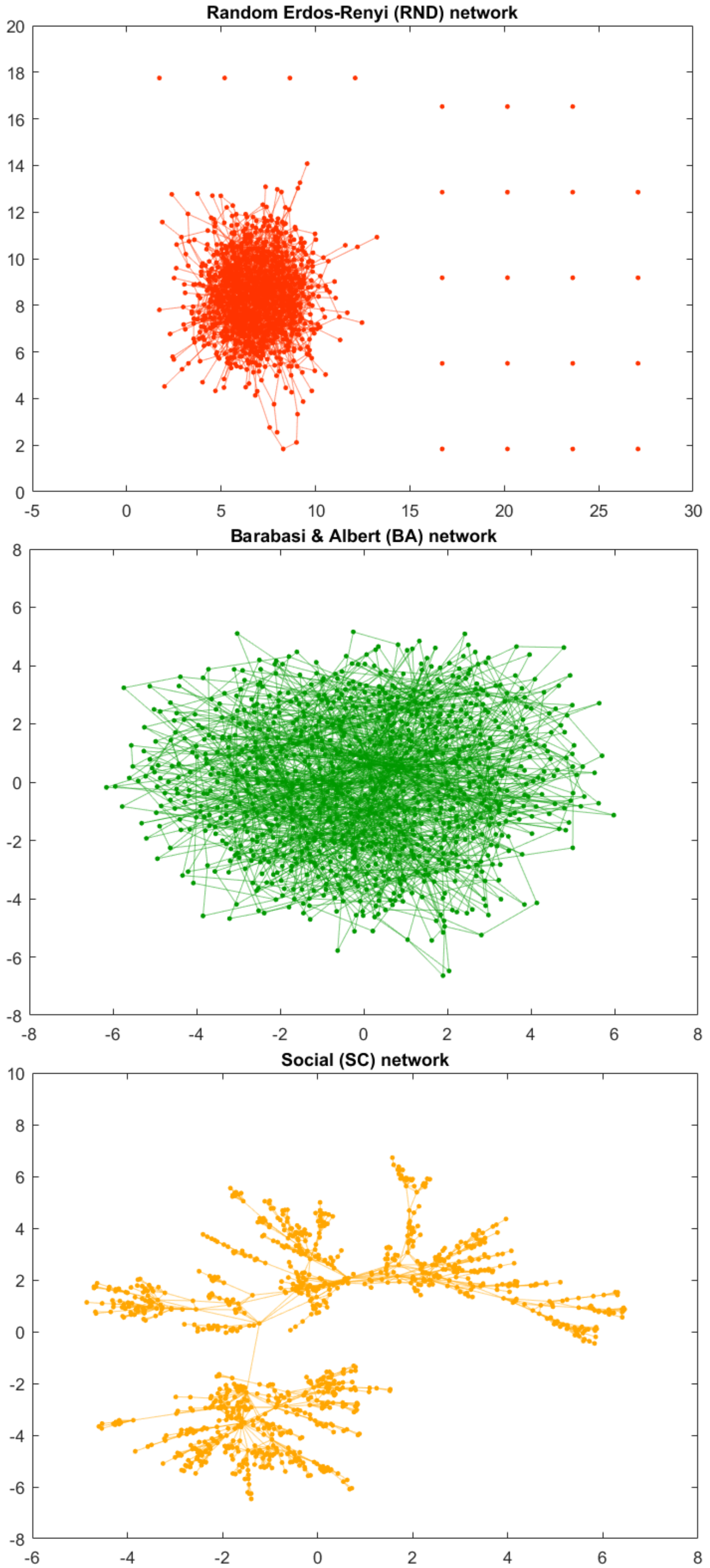
[1] The full paper is available under request to the main author: fabio.riva@polimi.it



k_{max}=11
k_{min}=0
$k_{avg,eff}$=4.000
C_{avg}=0.0033

k_{max}=63
k_{min}=2
$k_{avg,eff}$=3.994
C_{avg}=0.0153

k_{max}=34
k_{min}=1
$k_{avg,eff}$=3.916
C_{avg}=0.652

Figure 1. Plots of RND, BA and SC graphs for k_{avg}=4 and N=1000.

2.2. Diffusion models

The main hypothesis at the basis of the Bass model is that the social network where the spread of an innovation takes place is assumed to be fully connected and homogenous. The diffusion process based on this "fully connected and homogenous" hypothesis is suitable to be formulated and simulated with the classical stock and flow diagrams of system-dynamics (SD), as confirmed by a number of studies and books coming from SD-based literature [2]–[11].

When investigating factors that drive the growth of energy demand, Rai and Henry [12] suggest that «Agent-based modelling (ABM) is a powerful tool for representing the complexities of energy demand, such as social interactions and spatial constraints». They suggest how SD-based models may reveal some limitations in modelling the complexity of consumer energy behaviours, referring mainly to a lack of representation of social interactions that ensue within social networks. Many Authors focused their research on proposing improvements and solutions to the main limitations of the continuous Bass model. Trying to pursue the same final modelling goal and to contribute to the same effort of other researchers, our work investigates and discusses the hypothesis of "perfect-mixing" of adopters and non-adopters within innovation diffusion mechanisms. In particular, we try to reject the Bass' assumption that individuals reveal the same behaviours with respect to their social contacts, and we report the results by modelling an ideal case of diffusion of "electric appliances" in rural contexts of the world.

2.2.1. Modelling scenarios

In this work, we propose three cases for testing some hypothesis of diffusion mechanisms within agent-based and SD models. Agent-based simulations have been tested for all the three types of network (*viz. RND*, *BA*, *SC*), while the hypothesis at the basis of each simulated mechanism in the three cases has been also modelled in the equivalent SD model. Within each of the three cases, we simulated some different scenarios; each scenario within each case accounts for 20 simulations per type of network, for a total of 61 simulations per scenario: 20 for RND, 20 for BA, 20 for SC and 1 for the deterministic Bass model simulated through a SD-based approach. In this way, our simulations statistically embrace the stochasticity due to the process of networks creation and discrete diffusion.

For each case, the total population has been fixed equal to $N = 1000$; each agent represents a household of a typical rural community in a developing country, which has received potential access to electricity at time $t = 0$. The simulation horizon has been set equal to $T = 240$ months, that is 20 years, which roughly corresponds to the lifetime of a typical off-grid system composed by photovoltaic panels and batteries. The diffusion mechanism here refers to the diffusion of a general type of electrical appliance, once people have received electricity connection, or also the "decision to ask for grid connection in the house".

Case 1. In the first case, we simulated the classical Bass model from a SD perspective and the equivalent agent-based discrete models with the RND, BA and SC networks. We created 5 scenarios by varying the average degree (k_{avg}) of the network (*i.e.* the "contact rate" c for the Bass model) – 4, 6, 8, 10 and 12.

Case 2. In the second case, based on the experience of the authors in the access to energy-related research, we introduce some hypotheses that may fit with the contexts under study: in rural areas, the effect of advertising is supposed to be minimal, especially where people lack electricity and consequently TV, radios, mobile phones, *etc.* To allow the diffusion mechanism to start and spread, and to solve the start-up problem, we consider to "seed" some initial adopters (*i.e.* a portion A_0 of the N agents) at time $t = 0$. We develop 6 scenarios: for k_{avg} equals to 4 and 8, we set an initial portion of adopters A_0 equals to 1, 5 and 10% of N. As per the previous case, we introduce the adoption fraction i equals to 0.02.

Case 3. The last case simulates the effect of splitting the entire population among two different classes of potential adopters: the *influentials* and the *imitators*. From a modelling point of view, Van den Bulte and Joshi [13] describe influentials as people who are more in touch with new developments (*i.e.* affected by external influences as advertising), who in turn affect both other influentials and the imitators.

In our work, we implement the simulations by relying on MATLAB-Simulink © computing environment. For SD simulations, we create the stock-and-flows model by using Simulink, while we develop specific MATLAB scripts for the agent-based diffusion models and for generating the graphs of the networks. We firstly run the scripts for network formation, in order to generate pools of graphs to use then within the agent-based diffusion models.

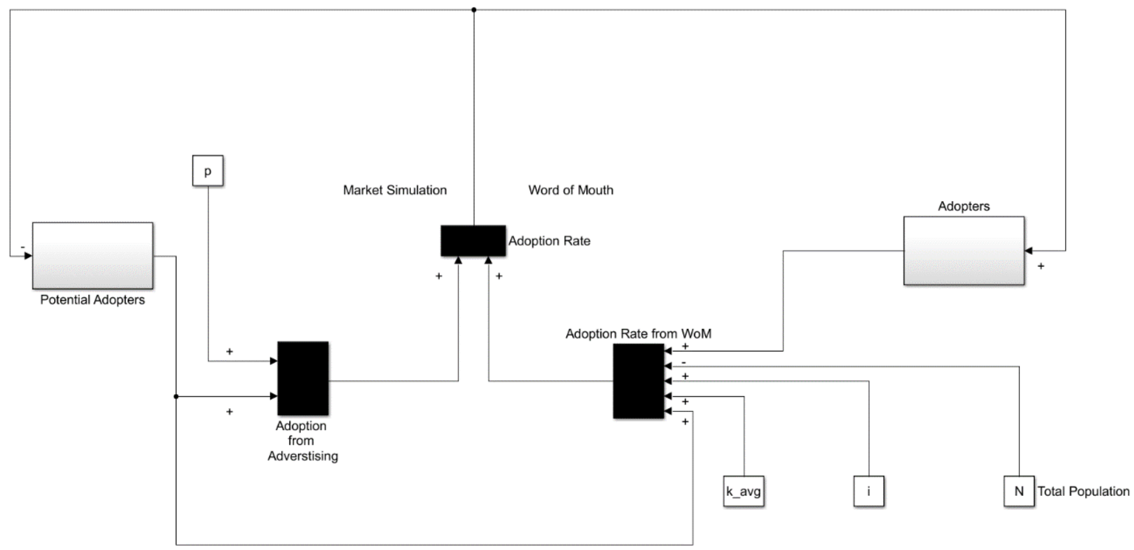


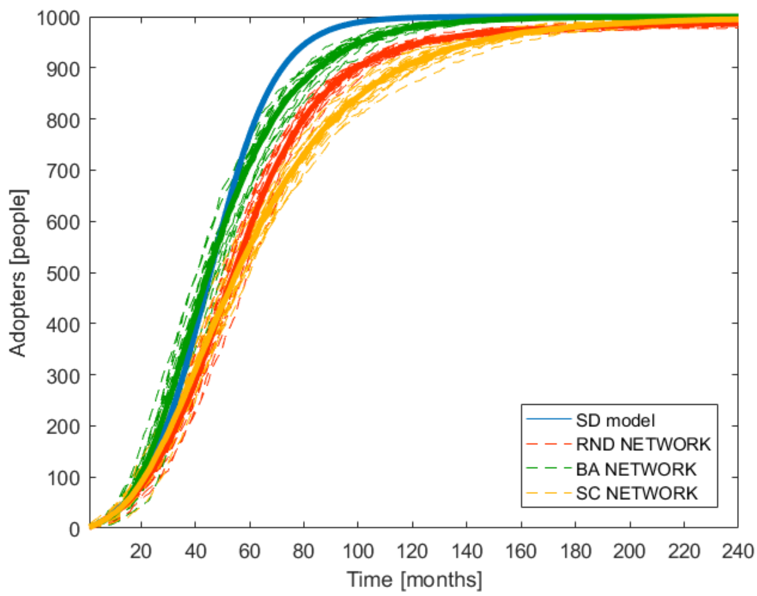
Figure 2. Example of stock and flows diagram developed in Simulink © for Case 1 and Case 2.

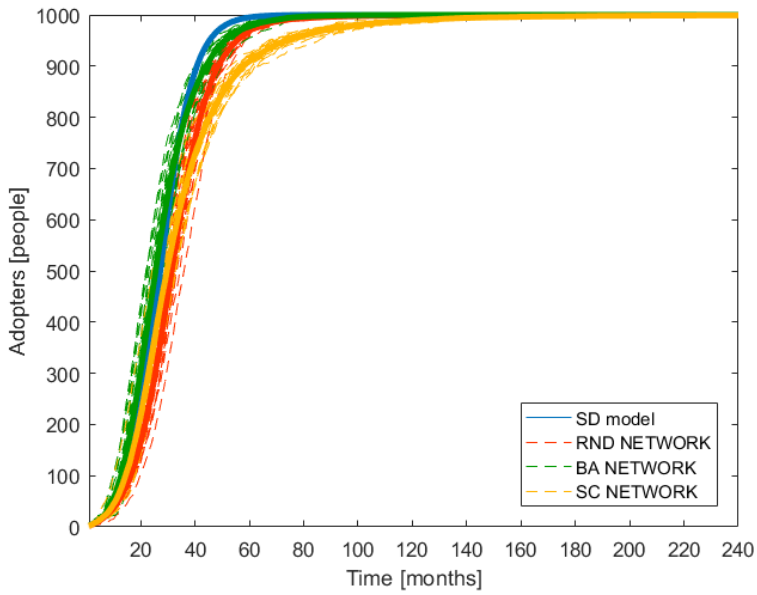
3. Results and discussion

In this section, we report the results of the simulations performed in the three cases. For each simulation of each scenario, we plot the "electricity adoption curves" representing the total number of adopters of electrical appliances $A(t)$ at time t. The blue curves represent the SD model, while red, green and yellow curves represent respectively the result of the diffusion process on RND, BA and SC networks. For the AMB simulations with the three types of network, the dashed lines represent the 20 simulations per scenario, and the bold line highlights the average of the simulations. The results are then discussed by comparing the stochastic agent-based adoption curves with the related SD model: for each scenario of the three cases, we compare the min and max time interval needed by the agent-based stochastic curves to reach 50% and 95% of diffusion, and we compare these values to that of the SD model.

3.1. Case 1

For Case 1, we created 5 scenarios by varying the average degree (k_{avg}) of the network (viz. the "contact rate" c for the Bass model). Results for k_{avg} equals to 4, 8 and 12 are plotted in Figure 3.





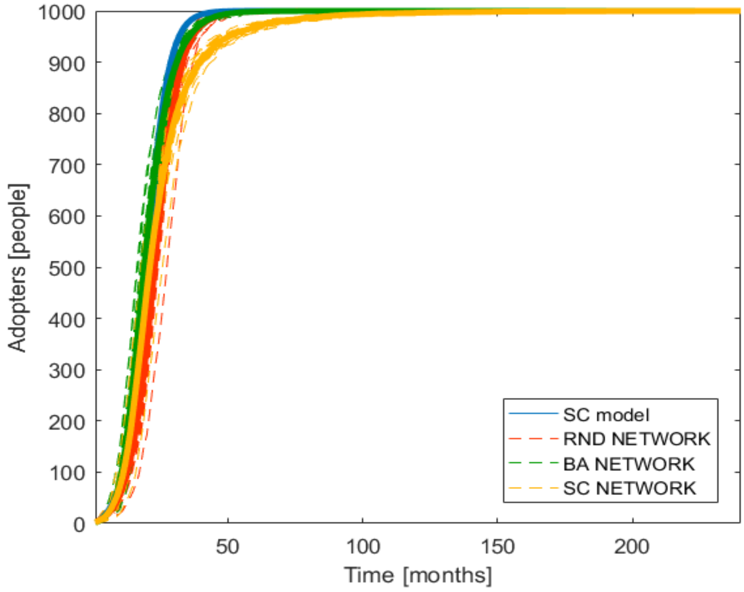
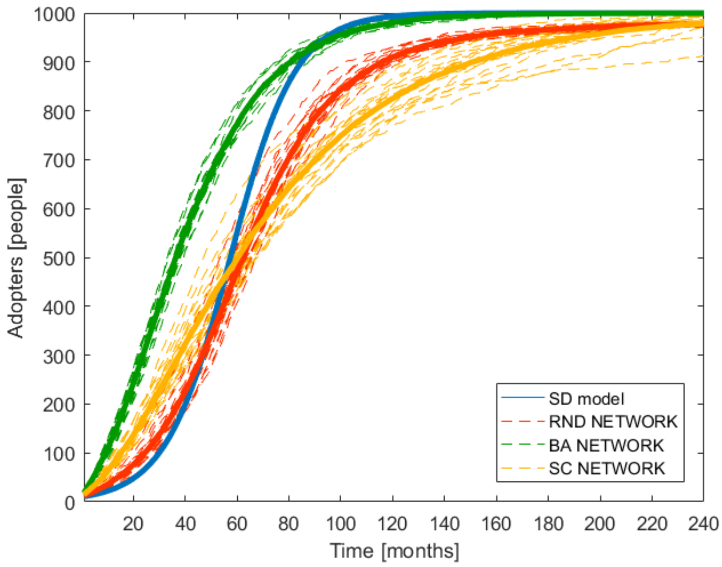


Figure 3. Diffusion curves for *Case* 1: results for k_{avg}=4, 8 and 12.

3.2. Case 2

For Case 2, we created 6 scenarios by varying the values of initial adopters for all the diffusion processes with k_{avg} of the network (*viz.* the "contact rate" c) equals to 4 and 8. Results for k_{avg} equals to 4 and A_0 = 1%, 5%, 10% of N are plotted in Figure 4.



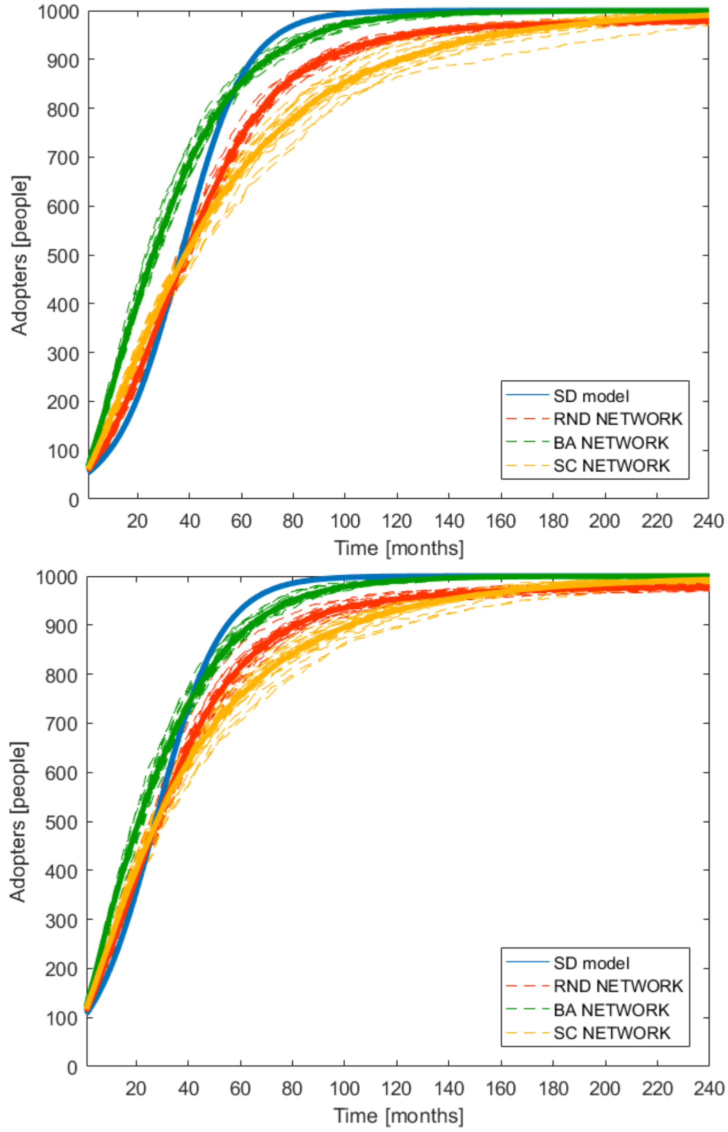


Figure 4. Diffusion curves for *Case* 2: results for k_{avg}=4 and A_0 = 1%, 5%, 10%.

3.3. Case 3

For Case 3, we created 6 scenarios by varying the value of w – *i.e.* the relative importance that imitators attach to influentials' versus other imitators' behaviour ($0 \leq w \leq 1$) – for all the diffusion processes with k_{avg} of the network (*viz.* the "contact rate" c) equals to 4 and 8. Results for k_{avg} = 4 and w = 0.03, 0.15, 0.75 are plotted in Figure 5, left side, while results for k_{avg} = 8 are on the right side.

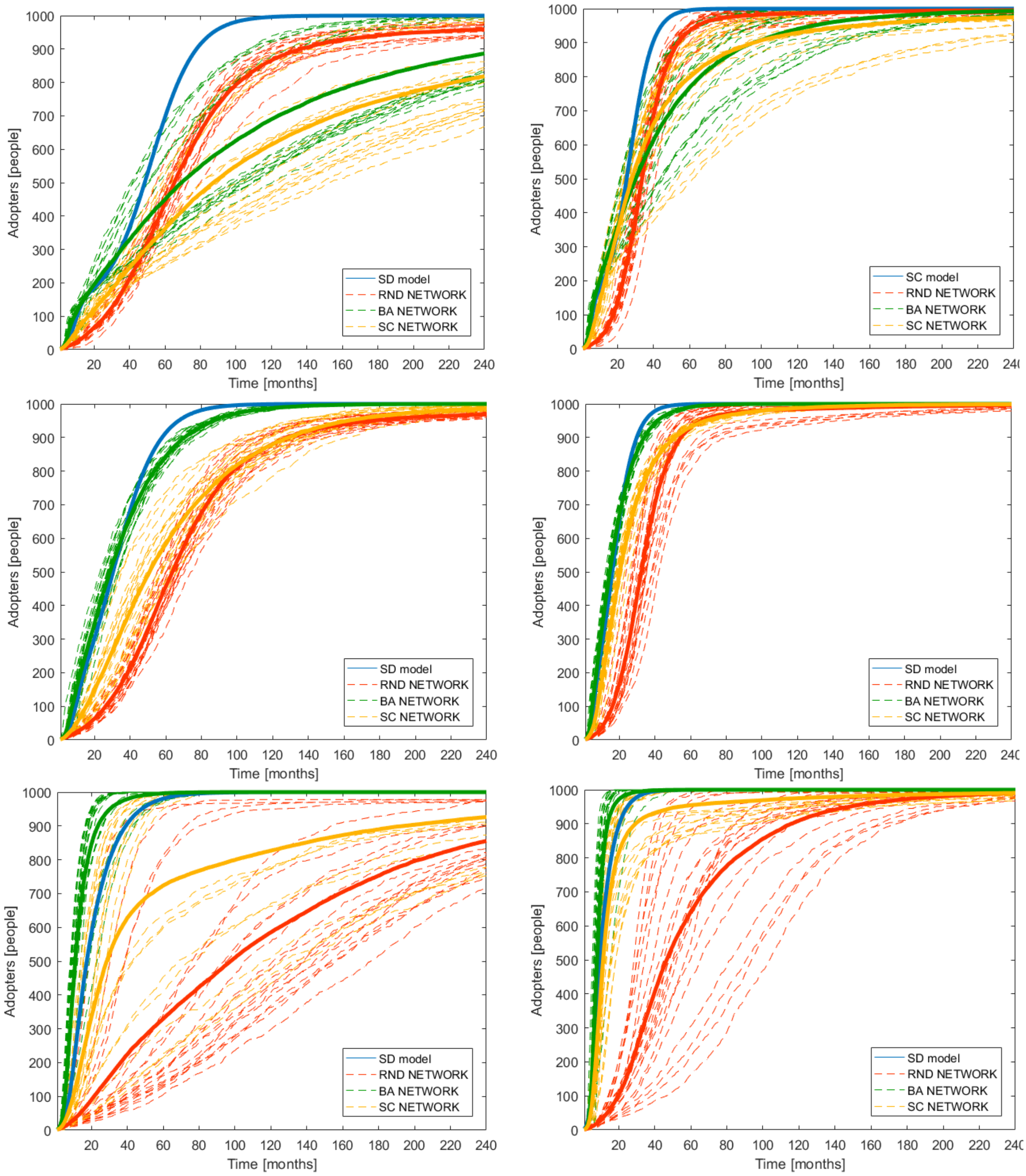


Figure 5. Diffusion curves for *Case 3*: results for k_{avg}=4 (left) and 8 (right). From top to bottom, w=0.03, 0.15, 0.75.

The next Figure 6 represents the fraction of the population adopting over time t for the 4 diffusion processes when k_{avg} is equals to 4, to highlight some particular patterns due to the subdivision of the population among influential and imitator households.

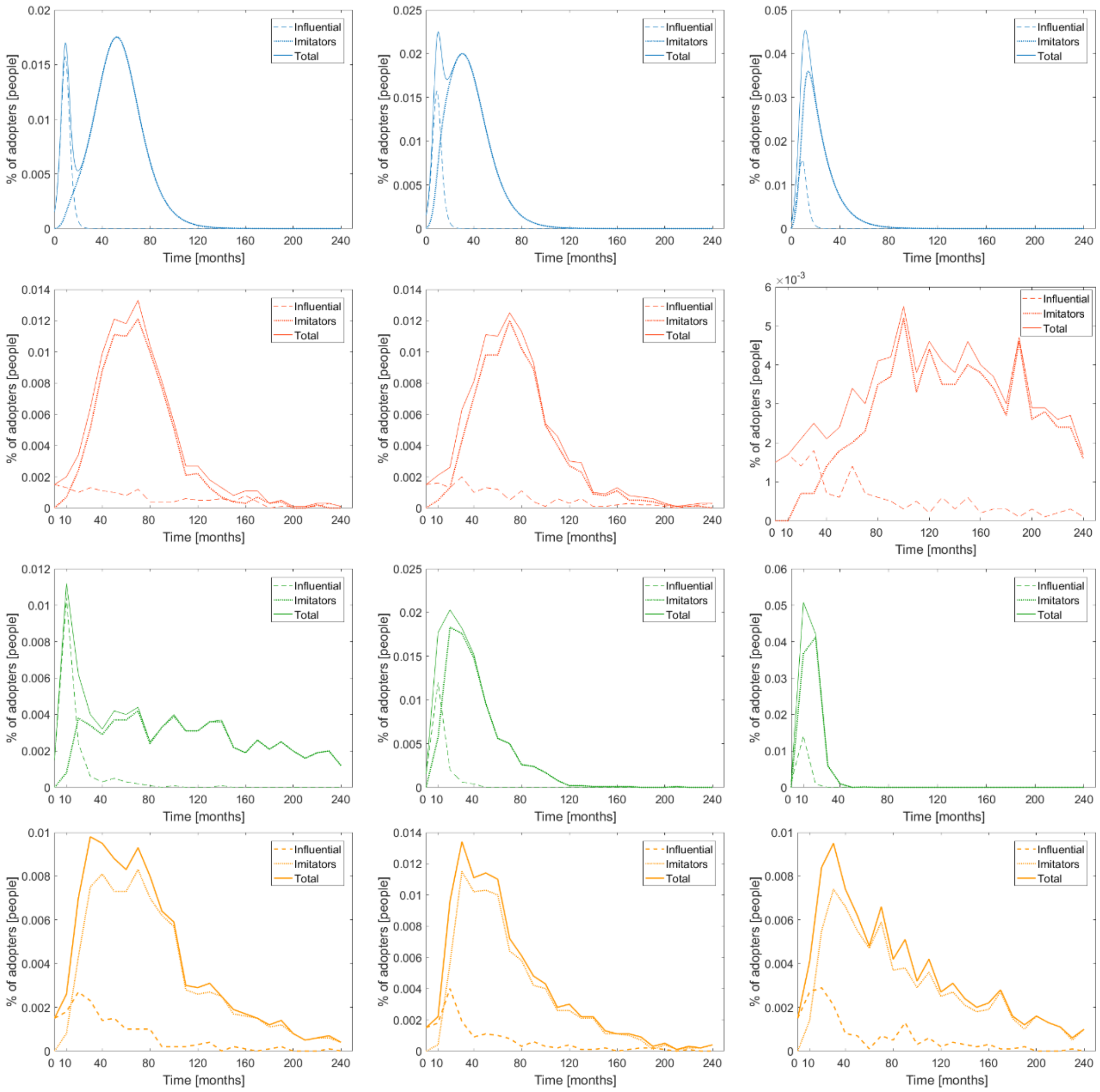


Figure 6. Adoption fraction over time t for the diffusion process of Case 3 when k_{avg}=4. From top to bottom: SD model, ABM on RND, BA, SC networks, and w=0.03 (left), w=0.15 (centre), w=0.75 (right).

In many simulations, the agent-based processes do not reach 100% of adoption for k_{avg} = 4, and the relative portion of population is numerically relevant in the cases resumed in Table 1. While RND-networks present some isolated nodes that prevent complete adoption, the lacking adoption by some agents in case of BA- and SC-network processes is due to the too short simulation horizon.

Table 1. Percentage of maximum adoption at t=241 months for RND, BA and SC processes at k_{avg}=4

	max adoption		
	w=0.03	*w=0.15*	*w=0.75*
RND	93.2-98.0	95.7-97.9	71.6-97.8
BA	79.0-99.9	-	-
SC	91.3-99.5	97.2-99.6	75.2-100

In case of k_{avg} = 8, the maximum adoption fraction is less than 100% in 16 simulation of SC model, and the final adopters range from 909 to 1000.

4. Conclusion

Since electricity use in remote contexts reveal many complex dynamics to deal with, we start investigating the effect of social network by relying on an ABM approach. We introduced 3 types of networks – (i) Random (RND), (ii) Barabási & Albert (BA), and (iii) Social (SC) – and we simulated 3 different *Cases* of diffusion processes, designing many experiments and different scenarios for each one, and finally comparing the results with the corresponding diffusion model simulated through a system-dynamics (SD) approach in continuous time. We adopt a speculative approach, being the final aim of the paper to investigate how the modelling of social network may impact of diffusion process.

In *Case 1*, the diffusion curves generated with both the AMB and SD approaches show all the same trend, that is the typical S-curve trend of classical continuous diffusion models. However, the agent-based diffusion processes take longer to complete, especially the SC-based processes, with some processes reaching 95% of diffusion from 6 to 77 months later the SD one.

In *Case 2*, the agent-based processes nose up in the first months, sometimes reaching 50% of adoption till 24 months before the Bass model – in the case of BA networks –, while they slowly approach the plateau at the end, sometimes reaching 95% of adoption till 136 months later the SD model, or even without reaching it – in the case of SC networks.

In *Case 3,* the ABM processes presents high variability and stochastic uncertainty, and the final diffusion curves highly depend on the initial assignment of roles of influential and the relative importance that imitators attach to influentials' versus other imitators' behaviour. The agent-based diffusion processes take longer to complete, specifically the SC- and BA-based processes when influentials have low importance – with some processes reaching 95% of diffusion till 136 months later the SD model, or even without reaching it –, and the RND-based processes when influentials have high importance – with some processes reaching 95% of diffusion till 183 months later the SD model, or even without reaching it.

The results obtained in this paper confirm how the ABM of social networks in diffusion processes may considerably impact on diffusion mechanisms, leading to unexpected agents' rates of adoption and timing to complete the process. Such understanding may be pivotal for local electricity utilities, which manage off-grid systems, especially when they make their investment plans, and define the electricity tariffs for guaranteeing a positive return of investment. Indeed, unreliable prediction may have an unpredictable ruinous impact on utilities' financial resources and stability, since they may overestimate or underestimate the amount of energy that people are forecasted to consume at time *t*.

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