HSC Research Report

HSC/17/04

The role of educational trainings in the diffusion of smart metering platforms: An agent-based modeling approach

Tomasz Weron[1]
Anna Kowalska-Pyzalska[2]
Rafał Weron[2]

[1] Faculty of Pure and Applied Mathematics, Wrocław University of Science and Technology, Poland
[2] Department of Operations Research, Wrocław University of Science and Technology, Poland

Hugo Steinhaus Center
Wrocław University of Technology
Wyb. Wyspiańskiego 27, 50-370 Wrocław, Poland
http://www.im.pwr.wroc.pl/~hugo/

The role of educational trainings in the diffusion of smart metering platforms: An agent-based modeling approach

Tomasz Weron[a], Anna Kowalska-Pyzalska[b], Rafał Weron[b,*]

[a]*Faculty of Pure and Applied Mathematics, Wrocław University of Science and Technology, 50-370 Wrocław, Poland*
[b]*Department of Operations Research, Wrocław University of Science and Technology, 50-370 Wrocław, Poland*

Abstract

Using an agent-based modeling approach we examine the impact of educational programs and trainings on the diffusion of smart metering platforms (SMPs). We also investigate how social responses, like conformity or independence, mass-media advertising as well as opinion stability impact the transition from predecisional and preactional behavioral stages (opinion formation) to actional and postactional stages (decision-making) of individual electricity consumers. We find that mass-media advertising (i.e., a global external field) and educational trainings (i.e., a local external field) lead to similar, though not identical adoption rates. Secondly, that spatially concentrated 'group' trainings are never worse than randomly scattered ones, and for a certain range of parameters are significantly better. Finally, that by manipulating the time required by an agent to make a decision, e.g., through promotions, we can speed up or slow down the diffusion of SMPs.

Keywords: Smart meter, Smart metering platform (SMP), Behavioral strategy, Demand response, Diffusion of innovations, Agent-based model
PACS: 87.10.Rt, 88.05.Gh, 88.05.Lg, 89.65.Gh

1. Introduction

Nowadays, the energy system faces a lot of challenges. On one hand, energy demand is increasing rapidly and – according to experts – further growth will be observed due to increased 'electrification' of our lives and population growth. On the other hand, due to the constantly decreasing natural resources, the generation may face problems of scarcity of fossil fuels. The increasing presence of *renewable energy sources* (RES), like wind and solar, may help to provide the demanded power, but its non-dispatchable (non-controllable) character negatively influences power system stability. These challenges, as well as the ambitious goals set by the European Commission and other international organizations, e.g. CO_2 reduction and a significant increase

*Corresponding author

Email addresses: `tomek.weron@gmail.com` (Tomasz Weron), `anna.kowalska-pyzalska@pwr.edu.pl` (Anna Kowalska-Pyzalska), `rafal.weron@pwr.edu.pl` (Rafał Weron)

of energy efficiency, will have a great impact not only on electricity generation but also on consumption. The consumers will need to decrease their consumption and shift loads to off-peak hours, which may involve changes in everyday behavior and routines [1, 2].

As a remedy, the *smart grid* (SG) concept has been proposed recently. SGs use modern communication technologies to exchange information between market agents (generators, market operators and end-users) in order to improve power system efficiency [3–5]. However, the basic requirement for the success of this approach is the roll-out of *smart meters* (SMs) among electricity end-users [6, 7].

The diffusion of smart meters is usually combined with offering an access to so-called smart metering information systems or platforms (SMPs) [2, 8, 9]. For instance, the local *distribution system operator* (DSO) in Wrocław (Poland) is planning to install SMs at all households by the end of 2017. The households will get access to the information about their energy consumption via a web-based SMP called *e-licznik*, that runs on smartphones and tablets, and will receive alerts when the targeted energy consumption level is exceeded. However, as the literature suggests, the potential success of the smart meters' roll-out is combined with consumer awareness of the potential technologies and their engagement [4, 5, 7]. Particularly, the regular use of SMPs is found to be related with consumer willingness to optimize their energy consumption [8].

Recently a number of field experiments, research surveys and pilot programs have been conducted in order to analyze the determinants of successful diffusion of SMs [1, 6, 8, 10, 11]. As it turns out, there is a great discrepancy between consumer opinions and their behaviors towards various innovations in the energy market [3, 12]. For example, even if consumers declare their willingness to save energy, they do not even try to reduce their electricity consumption [13]. Such an *intention-behavior gap* is often responsible for slow or unsuccessful adoption of innovative technologies or behaviors [14]. Among the reasons for this gap the literature usually mentions unstable consumer opinions, lack of knowledge and skills, lack of professional advice, general confusion of choice, distrust in new technologies and energy providers [13].

In a parallel stream of literature, *agent-based models* (ABMs) have been used to investigate the diffusion of smart technologies, for a review see [15]. For instance, the diffusion of smart meters has been examined in [16], but from a different perspective – the authors used ABMs to analyze what regulatory interventions induce the diffusion of SMs. In [9], the agent-based model proposed in [17] and built around the concept of the reservation price (representing product appraisal), has been used to analyze the diffusion of SMPs. It has been shown that social influence can either increase or decrease adoption rates and the market share of SMPs, dependent on their market value [9].

Somewhat surprisingly, most innovation diffusion models make no distinction between opinions and decisions – opinions are identified as final decisions whether to adopt an innovation or not. Yet, the literature suggests that opinions do not have to and in case of eco-innovations often are not followed by the decisions [12, 18]. To address this feature, Kowalska-Pyzalska et al. [14] have proposed an ABM to study the temporal dynamics of consumer opinions regarding switching to dynamic electricity tariffs and the actual decisions to switch. The model is built on the assumption that the decision to switch is based on the unanimity of τ past opinions and offers a hypothetical, yet plausible explanation of why there is such a big discrepancy between consumer opinions and adoption rates.

In this paper, we build on and modify the ABM proposed in [14, 19, 20] with an objective of examining the impact of educational trainings and programs offered by energy utilities on the diffusion and adoption of the SMPs. In particular, we analyze how opinions and decisions depend on (i) social responses, like conformity or independence, (ii) skills (or know-how) required for everyday use of the SMPs, and (iii) stability of consumer opinions.

The paper's contribution is threefold. Firstly, we observe that the positive effect of educational programs and trainings depends on the level of independence in the society and agent *decision* and *memory times*. Secondly, we show that spatially concentrated 'group' trainings, e.g., for all households in a given area or district, are never worse than randomly scattered ones. Finally, we find that for intensive mass-media advertising, the type of educational trainings – spatially concentrated or randomly scattered – does not matter.

The remainder of the paper is structured as follows. In Section 2 we discuss the role of interventions on consumer behavior. In particular, we focus on the evidence from pilot programs and field experiments showing that a successful diffusion of smart technologies is not possible without a certain level of consumer knowledge and awareness. In Section 3 we introduce our agent-based model and present the Monte Carlo simulation scheme, then in Section 4 discuss the results of our simulation study. Finally, in Section 5 we conclude and discuss policy implications.

2. The role of interventions in adoption of SMPs and other eco-innovations

2.1. Slow diffusion of SMPs

The prospect of an effective roll-out of smart meters seems optimistic. It may bring a lot of advantages both for energy suppliers and consumers. From the consumer point of view the main advantage is direct access to real-time consumption data via a SMP. Using such information a consumer may optimize the energy consumption and achieve financial savings or personal satisfaction, e.g., from being pro-environmental. As Good et al. [7] emphasize, there is a great number of incentives and barriers of successful adoption of SM technologies.

Financial savings and social and personal norms are the most important incentives [10, 11]. On the other hand, the major obstacles include confusion of choice and consumer resistance to behavioral change, e.g., rescheduling the daily routine in response to electricity prices dictated by a variable electricity tariff [1, 4, 11, 12]. To reduce the latter disadvantage a typical energy consumer would like to have enabling technologies, that adjust the work of home appliances according to the prevailing electricity price. Moreover, to increase the participation and engagement rates, the non-economic or one-off incentives, like an offer of a free programmable thermostat, would be helpful.

Finally, we cannot forget that most consumers are not interested in the energy market at all. They are unaware what opportunities SMs offer, largely due to the scarcity of educational campaigns and programs [21]. To reach a high level of enrollment, the design of the pricing rate, education and marketing of new solutions and offerings must be appropriate. Without that, there will be no significant demand response as a result of the lack of knowledge, high level of indifference and ignorance of the consumers.

Table 1: Examples of behavioral interventions.

Behavioral strategies (interventions)		
Antecedent	**Consequence**	**Structural**
Tailored marketing	Direct, indirect and inadvertent feedback	Price policies
Educational campaigns and programs	Rewards	Subsidies
Interpersonal word of mouth		Loans
Demonstration		Legislation
Goal-setting		

2.2. *Behavioral interventions*

Based on the findings from the pilot programs and field experiments, as well as social and economic theories explaining the process of opinion formation and decision making, behavioral strategies – so-called *interventions* – have been proposed to overcome or limit consumer reluctance to behavioral change [8, 22]. These strategies can be divided into three categories: antecedent, consequence and structural interventions, see Table 1.

Antecedent interventions propose various information intensive tools, like educational campaigns and trainings, aim at increasing consumer awareness and knowledge [22]. They are preliminary and crucial for the diffusion, since they impact opinion formation towards an innovation [23]. *Consequence interventions* offer numerous ways to motivate behavioral change via feedback and rewards. Dependent on how information is spread, on its type, quality and quantity of data presented, direct, indirect and inadvertent feedback can be defined [6, 22]. In the context of energy conservation, it has been found that installation of SMs should be followed by access to SMPs and in-home displays. These tools should be used as a source of information for customers about their energy consumption. This information could be also provided to the clients in an indirect way, via billing. It has been shown that energy conservation and reduction of peak demand increases because of receiving better information about electricity consumption (in a direct or/and an indirect way) [11]. Finally, *structural interventions* include price policies, subsidies, loans, a choice of different program structures and legislation [22].

2.3. *Self-regulated behavioral change*

A behavioral change, especially in case of innovative products, services or ideas, is a process which takes some time and effort. There is a variety of theories and models that aim to investigate and explain the complex process of human decision making and its influence on innovation diffusion [23, 24].

This study is motivated by the model of *self-regulated behavioral change* [25], which describes a person's transition through a temporally ordered sequence of different stages: a predecisional stage, a preactional stage, an actional stage and a postactional stage. Transitions between the stages is provoked by the formation of a *goal intention* (predecisional → preactional), a *behavioral* *intention* (preactional → actional) and an *implementation intention* (actional → postactional). According to Bamberg's [25] model, these transitions can be encouraged by certain interventions tailored to the current behavioral stage, e.g., sharing information and advice, forming a social or a personal norm, offering feedback, etc.; we elaborate more on this topic in Section 3.

We should emphasize, however, that we do not investigate the effectiveness of various interventions on stage transition. We rather focus on one particular intervention, i.e., educational campaigns and trainings, and study how such an intervention can impact the diffusion and adoption rate of SMPs. We have decided to limit our analysis to educational campaigns and trainings, because we believe that raising awareness of smart technologies and learning certain skills (e.g., knowledge of how to download a SM application to a smartphone, skills needed to navigate the SMP, etc.) are basic requirements for a successful adoption of SMPs.

3. The model

We build on the agent-based model of opinion formation proposed in [19], later extended in [20] to different network structures and in [14] to incorporate a decision-making mechanism and applied to studying the adoption of dynamic electricity tariffs. Compared to the latter paper, the decision-making process considered here is based on a coincidence of two factors – a stable positive opinion over a certain time interval and *operational knowledge* (gained through education) – not just a stable opinion. As a consequence of introducing this 'innovation', the new model allows to obtain more realistic results. Most importantly, the level of adoptions (decisions to adopt) does not exceed the level of positive opinions.

Like in [14, 19], we consider a system of $N \times N$ agents on a square lattice with periodic boundary conditions and use Monte Carlo simulations to study innovation diffusion. Most of the simulations have been performed on a 100×100 lattice (i.e., $N^2 = 10,000$ agents). However, also larger and smaller systems have been tested; qualitatively the results are the same. Each site $i = 1, ..., N^2$ of the lattice is occupied by an agent (representing a household) that is characterized by three variables:

- *Opinion* or *attitude* $S_i \in \{-1, 1\}$ towards the SMP. If $S_i = -1$ the agent is not interested in a regular use of the SMP and if $S_i = +1$ the agent has a positive opinion towards using it.
- *Knowledge* $K_i \in \{0, 1\}$ required to use the SMP on a regular basis. If $K_i = 0$ the agent is uneducated and if $K_i = +1$ the agent possesses the skills needed to operate the SMP.
- *Adoption state* $SM_i \in \{0, 1\}$. If $SM_i = 0$ the agent is not using the SMP and if $SM_i = +1$ the agent is an adopter.

Following Nyczka and Sznajd-Weron [26] and Przybyła et al. [19], we also call these agents *spinsons* (= 'spin' + 'person') to reflect their dichotomous nature originating in spin models of statistical physics and humanly features and interpretation.

A single simulation run or experiment consists of $T = 2000$ Monte Carlo steps (MCS), which can be interpreted in terms of time intervals. Assuming that one MCS represents a day, the simulation corresponds to a period of ca. 5.5–8 years depending on whether we consider all days of the year or only business days. It should be emphasized that we are interested here in system evolution over a finite time period and not the stationary state, since the latter is irrelevant from the perspective of a utility investing in a SMP and expecting a return on investment in a reasonable time frame.

Within each MCS, N^2 elementary sub-steps are repeated to ensure that on average each agent is chosen once. As the outcome of the mth experiment we compute the ratio of agents with a positive opinion towards using the SMP after time T, i.e., $c_{S,m}(T)$, and the ratio of SMP adopters, i.e., $c_{SM,m}(T)$:

$$c_{S,m}(T) = \frac{\#\{i : S_i(T) = 1\}}{N^2}, \qquad c_{SM,m}(T) = \frac{\#\{i : SM_i(T) = 1\}}{N^2}, \tag{1}$$

where $m = 1, \ldots, M$. Next, we average them across $M = 100$ Monte Carlo experiments:

$$c_S(T) = \frac{1}{M}\sum_{m=1}^{M} c_{S,m}(T), \qquad c_{SM}(T) = \frac{1}{M}\sum_{m=1}^{M} c_{SM,m}(T). \tag{2}$$

We assume that initially all agents $i = 1, ..., N^2$ are unaware of the SMP, hence have a negative opinion towards using it ($S_i = -1$), are uneducated ($K_i = 0$) and consequently are unadopted ($SM_i = 0$). In Sections 3.1-3.3 we discuss in detail the three phases of a single MCS: opinion formation, training and decision-making.

3.1. Opinion formation

The evolution of a spinson's opinion is governed by two different processes: (i) independence and (ii) social and mass-media influence. We introduce independence in a similar way as was done in [27, 28], i.e., each spinson behaves independently with probability p and forms an opinion solely on the basis of individual judgment, see the left part of the flowchart in Fig. 1. Similarly as in [19, 27], we assume that this behavior is characterized by the flexibility parameter, $f \in (0, 1]$, describing how frequently the spinson changes its opinion. For simplicity we set $f = 0.5$ in our simulations, but for any value of $f > 0$ the results can be rescaled using the remaining model parameters, see [19, 27] for details. One could argue that assigning the same value of p to each agent is not realistic. However, the distribution of independence in the society is not known [29]. In the absence of this knowledge, Sznajd-Weron et al. [30, 31] have considered two extreme approaches – *situation* (homogeneous agents; as used, e.g., in [14, 19, 32, 33]) and *person* (a binomial distribution of independence; as used, e.g., in [34, 35]) – and shown that the former better reflects reality. Therefore, for simplicity, we also use it here. Nevertheless, we are aware that probably something in between would be more appropriate.

Then, with probability $(1 - p)$ the agent is exposed to social influence (i.e., word-of-mouth, WOM) and advertising, see the left part of the flowchart in Fig. 1. *Social influence* is a result of interactions between the agent and a group of neighbors in a given time step. Following [14, 19], we assume that the spinson interacts with a randomly chosen neighboring panel of 2×2 spinsons (i.e., a *q-lobby* with $q = 4$); note, that there are eight equally probable choices. When the agent is confronted by a unanimous panel of agents sharing the opposite opinion, it will conform to peer pressure [36].

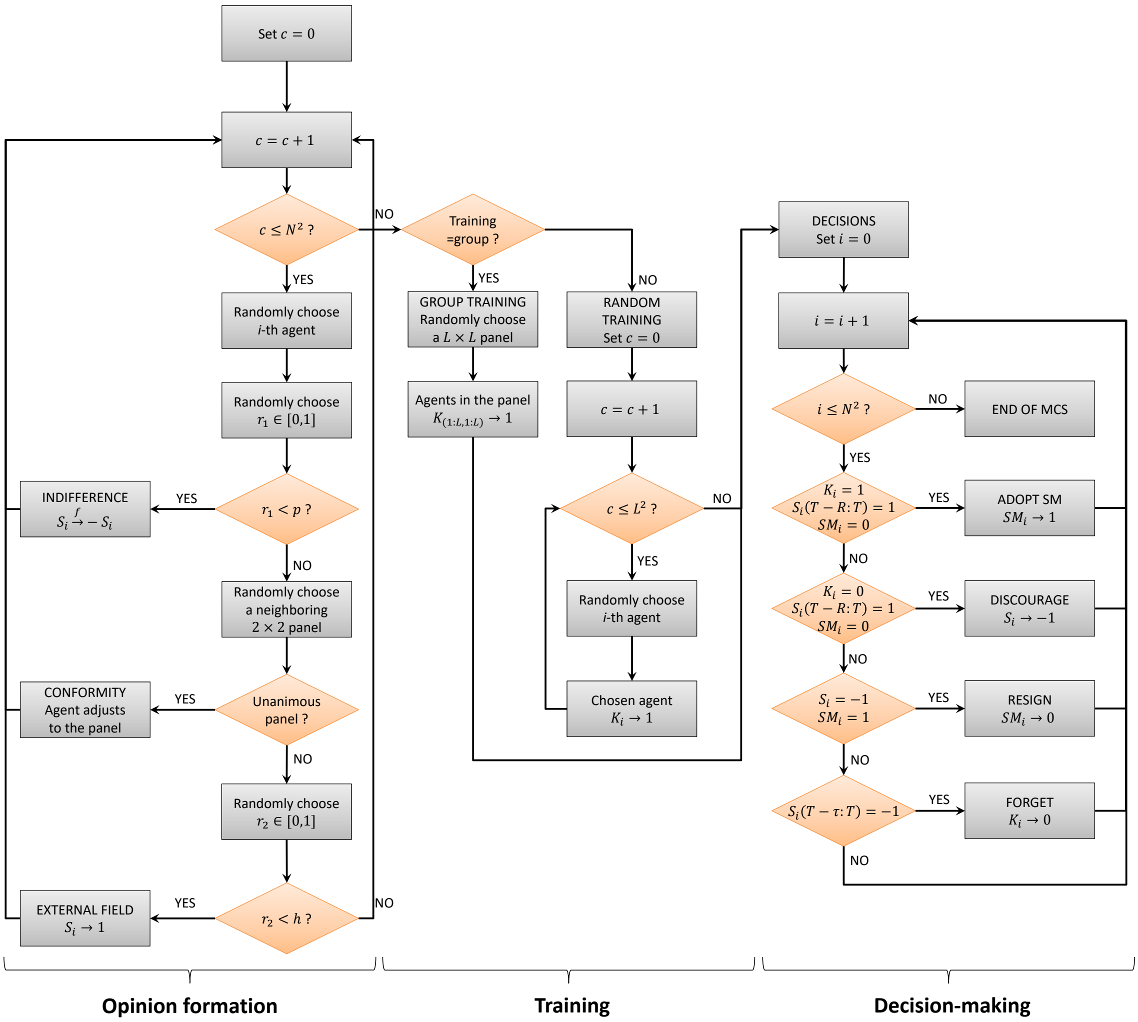

Figure 1: A flowchart of a single Monte Carlo step (MCS) in our model. The model dynamics can be divided into three phases discussed in Sections 3.1-3.3: opinion formation, training (at the end of a MCS or a certain number of MCS steps) and decision-making (at the end of a MCS).

On the other hand, if the panel is not unanimous, WOM will have no effect and the agent is exposed to *advertising*. This rule is motivated by a number of social experiments, which show that for social influence to prevail it is not only essential for the majority to be of sufficient size but also unanimous [37]. The impact of advertising is expressed by parameter h, i.e., the probability that the spinson changes its evaluation of the innovation and becomes interested in a regular use of the SMP ($S_i \to S_i = +1$), for instance, due to new information obtained from mass-media. We assume that the external (advertising) field is uniform and can affect all agents in the same way. As a result of this part of the model, each spinson can have a positive or a negative opinion towards the SMP.

3.2. Training

At the end of a MCS (or a certain number of MCS) selected agents undergo training, see the central part of the flowchart in Fig. 1. In this study we consider two variants of education, however, in a single simulation run we only use one type of training. In the *spatially concentrated* ('*group*') training we randomly choose a panel of $L \times L$ spinsons and set their knowledge variable to one, i.e., $K_{(1:L,1:L)} \to +1$. In the *randomly scattered* ('*random*') training we randomly choose (with possible repetition) L^2 spinsons and set their knowledge variables to one, i.e., $K_i \to +1$, $i = 1, ..., L^2$. Agents educated via such trainings become viable to adoption in the decision-making phase.

3.3. Decision-making

At the end of a MCS all spinsons enter the decision-making phase, see the right part of the flowchart in Fig. 1. During this phase not only can they change their adoption state, but also become discouraged or loose the skills needed to operate the SMP. The reason is that we allow for a temporal decay of both the positive attitude towards the SMP (governed by variable R called the *decision time*) and the education effect (governed by variable τ called the *memory time*). Namely, the ith spinson can:

- *become an adopter*, i.e., $SM_i \to +1$, if it has a positive opinion ($S_i = +1$) that has not changed over the last R MCS steps, is educated ($K_i = +1$) and is not an adopter ($SM_i = 0$),
- *become discouraged*, i.e., $S_i \to -1$, if it has a positive opinion ($S_i = +1$) that has not changed over the last R steps and has not already become an adopter ($SM_i = 0$), but does not possess the required knowledge ($K_i = 0$),
- *resign from using the SMP* (or *unadopt*), i.e., $SM_i \to 0$, if the spinson is an adopter ($SM_i = +1$), but its opinion is negative ($S_i = -1$),
- *forget the knowledge*, i.e., $K_i \to 0$, if it has had a negative opinion ($S_i = -1$) over the last τ MCS steps.

If none of the above conditions is satisfied the spinson takes no action. Snapshots of a sample evolution of the system for nine different time steps are presented in Fig. 2.

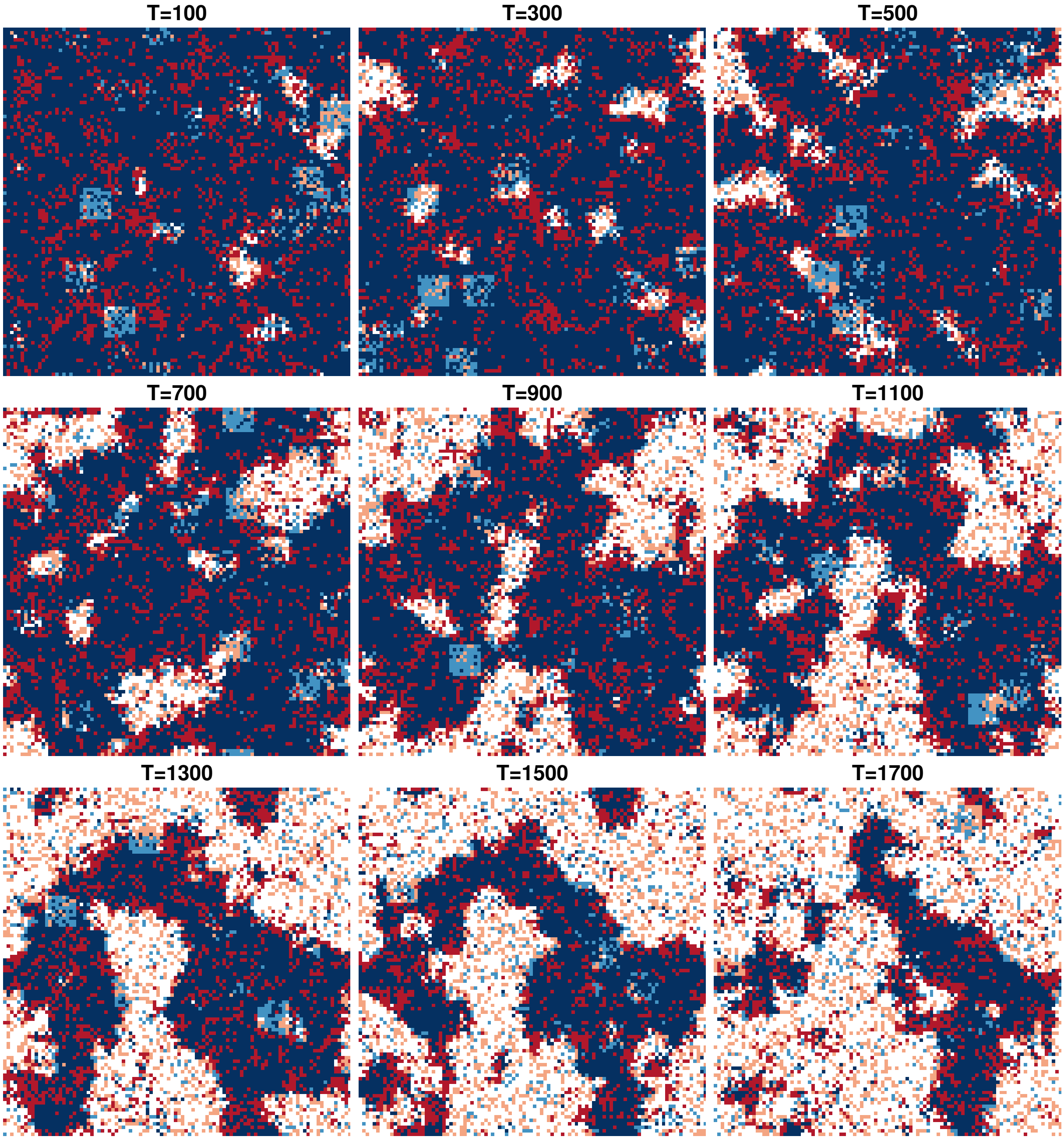

Figure 2: Snapshots of a sample evolution of the system at time $T = 100, 300, ..., 1700$ for size $N^2 = 10,000$, independence $p = 0.1$, advertising $h = 0.09$, decision and memory times $R = \tau = 5$, and spatially concentrated trainings of size $L^2 = 81$. Color scheme: white – adopted agents (educated and with a positive opinion), light red – unadopted agents (educated and with a positive opinion), dark red – uneducated agents with a positive opinion, light blue – educated agents with a negative opinion, and dark blue – uneducated agents with a negative opinion. Note the light blue trained ‘squares’ of educated agents in a sea of dark blue agents with a negative attitude towards the SMP (visible for low values of T).

3.4. Self-regulated behavioral change and our model

Our ABM is motivated to some extent by the model of self-regulated behavioral change of Bamberg [25]. Initially all agents have a negative opinion ($S_i = -1$), do not possess skills to use the SMP ($K_i = 0$), hence are unadopted ($SM_i = 0$). We assume that to encourage an agent to move from the *predecisional* stage to the *preactional* one, the opinion has to become positive ($S_i \rightarrow +1$), for instance, due to agent's independence, social influence or advertisement. Having a positive opinion about the SMP is a preliminary condition to formulate the so-called *goal intention*. Then, in the preactional stage the agent is considering a regular use of the SMP (i.e., formulates the so-called *behavioral intention*), but is not sure how to achieve this goal. For a transition from the preactional to the *actional* stage to be possible, the agent needs to undergo training. If the following conditions are jointly met: $S_i = +1$, $K_i = 0$, $SM_i = 0$, the agent formulates the so-called *implementation intention* and is ready to start using the SMP. The formation of this intention is equivalent to a transition to the last, *postacional* stage ($SM_i = 1$).

4. Results

In this Section we report the most interesting results obtained within our model. We start with the influence of advertising and trainings, then comment on the differences between spatially concentrated and randomly scattered trainings, and finally discuss the dependence on the decision (parameter R) and memory (parameter τ) times.

4.1. Advertising and training

Advertising (governed by parameter h) and trainings (parameter L) have a similar impact on the state of the system. Both are needed for the diffusion of smart meters, but a lower value of one variable may be compensated by a higher value of the other, as shown in Fig. 3. Because a lack of knowledge leads to discouragement and changes the opinion to negative, education supports positive opinions and so does advertising. We can also observe the so-called *intension-behavior gap*, i.e., the difference between public opinion (PO) measured by $c_S(T)$ and adoption ratio (SM) measured by $c_{SM}(T)$, as a function of independence p and after $T = 2000$ MCS. The higher the independence, the larger the intension-behavior gap. This can be explained by the fact that it is harder for an agent to maintain its stable positive opinion when independence is high.

4.2. Spatially concentrated vs. randomly scattered trainings

We have observed that spatially concentrated ('group') trainings are never worse in terms of public opinion (PO) or adoption ratio (SM) than randomly scattered ('random') trainings of the same size (L^2 spinsons). What is more, for a wide set of parameters the former are far more efficient, see Fig. 3. For a relatively small intensity of advertising ($h = 0.09$) and training only $L^2 = 49$ agents (ca. 0.5% of the population) both variants function almost the same, as such values of parameters are too low to support innovation diffusion. Similarly, for parameters exceeding $h = 0.12$ and $L^2 = 100$ there is little difference between the training variant, because these values are high enough to allow for the diffusion. However, for parameters between those mentioned above, group trainings foster the diffusion, while random trainings do not.

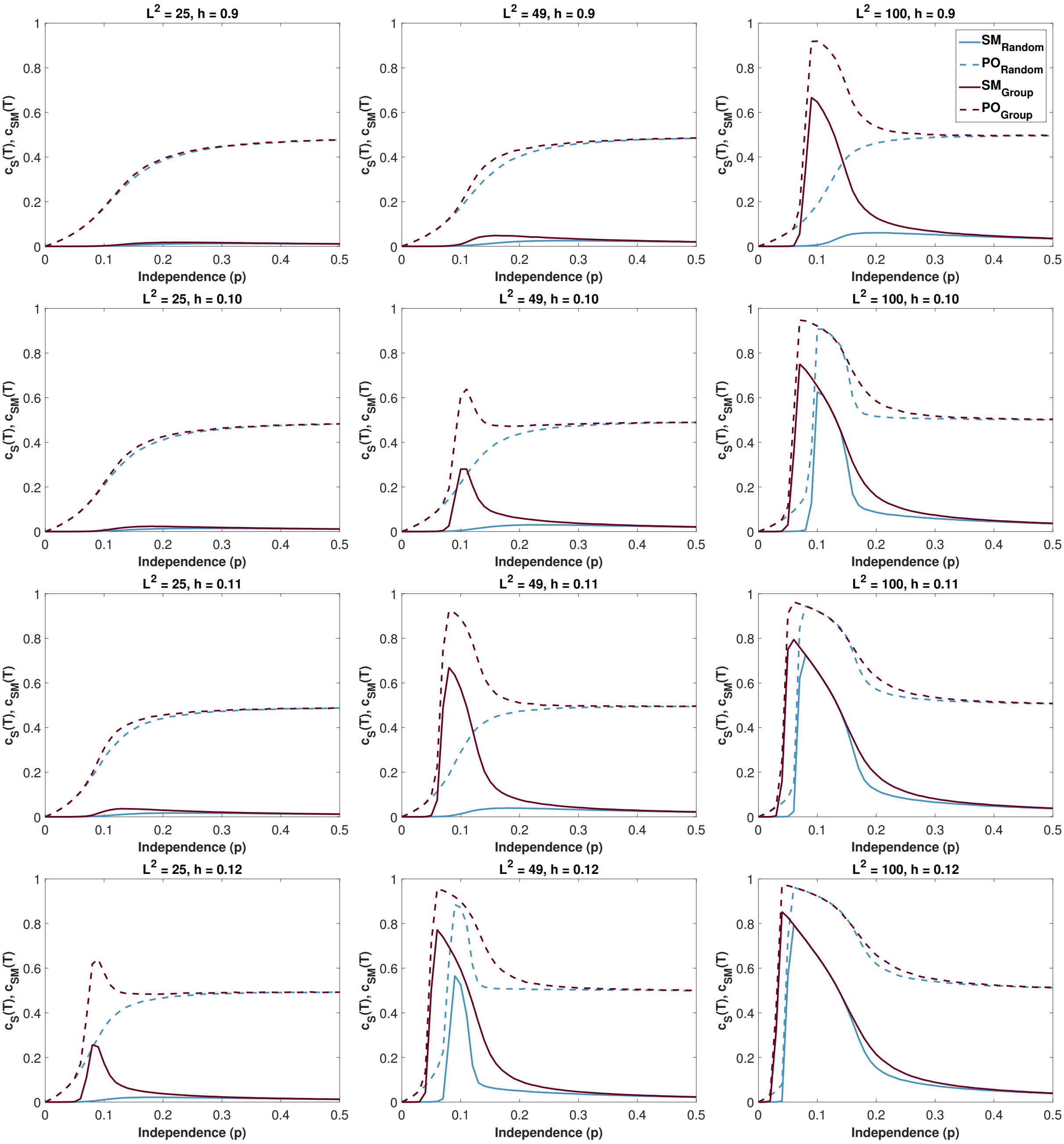

Figure 3: Public opinion (PO), measured by $c_S(T)$, and adoption ratio (SM), measured by $c_{SM}(T)$, as a function of independence p for both variants of trainings, three values of training size $L^2 = 25, 49, 100$ and four values of advertising $h = 0.09, 0.10, 0.11, 0.12$. The plots depict the state of the system after $T = 2000$ MCS, averaged after $M = 100$ independent runs, with system size $N^2 = 10,000$ and equal decision and memory times $R = \tau = 5$.

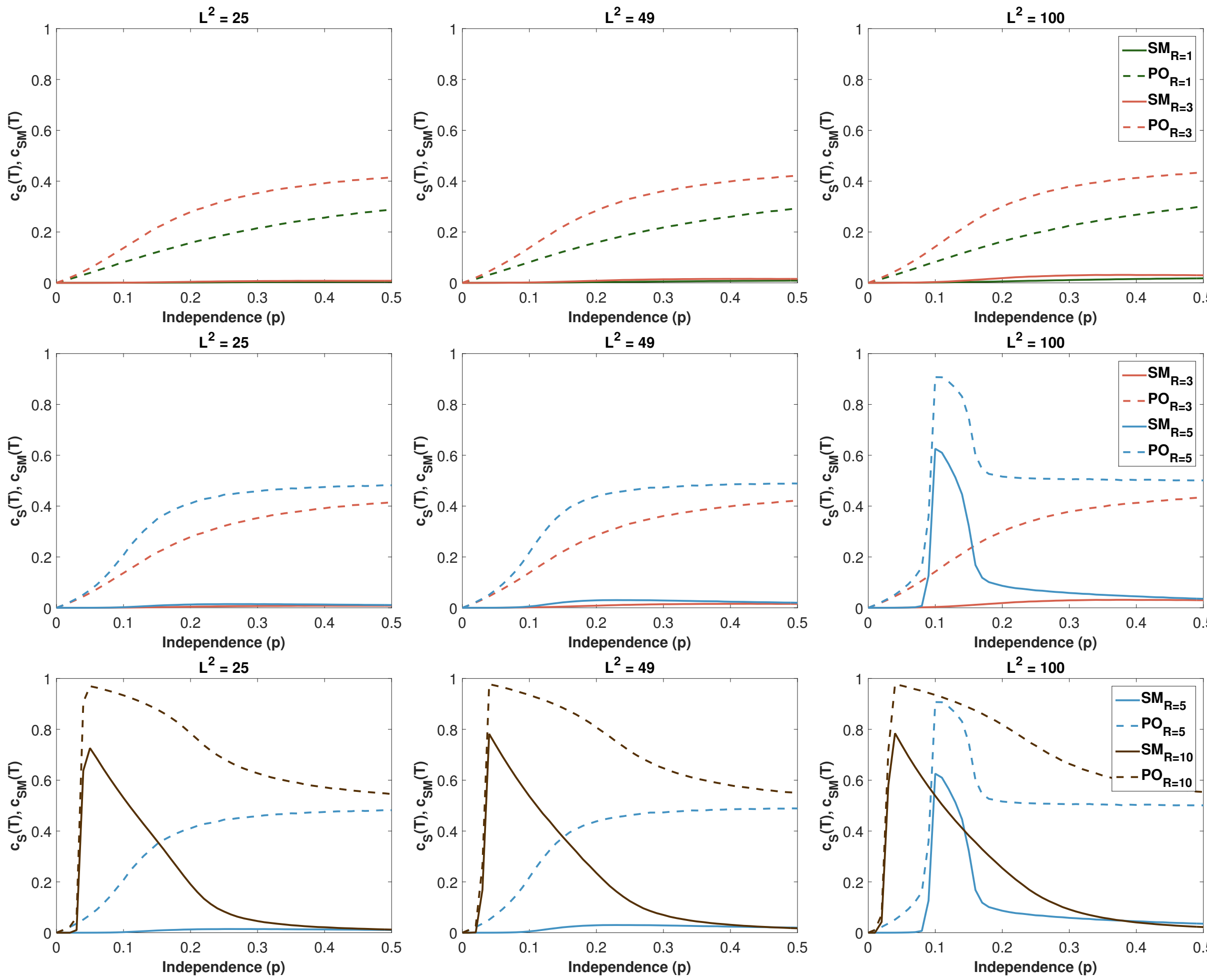

Figure 4: Public opinion (PO), measured by $c_S(T)$, and adoption ratio (SM), measured by $c_{SM}(T)$, as a function of independence p for four values of decision and memory times $R = \tau = 1, 3, 5, 10$ and three values of training size $L^2 = 25, 49, 100$. The plots depict the state of the system after $T = 2000$ MCS, averaged after $M = 100$ independent runs, with system size $N^2 = 10,000$, advertising $h = 0.1$ and randomly scattered ('random') trainings.

A viable explanation for this outcome is that due to the opinion dynamics in our model, the lack of knowledge has the ability to prevent the diffusion, discouraging agents and changing positive opinions into negative. It can literally shatter clusters of agents with positive opinions. Group trainings are less vulnerable to this effect, since clusters of educated agents cannot be discouraged that easily. On the other hand, random trainings lead to a lattice with educated agents scattered all around, hence much more susceptible to a social pressure from neighboring agents with a negative opinion.

4.3. *Length of the decision and memory times*

The length of the decision time R and the memory time τ have a significant impact on system evolution, as shown in Fig. 4. While longer decision and memory times are always preferable for the diffusion of public opinion (PO), their influence on the adoption of the SMPs (SM) is less obvious. Explanation of first phenomenon is rather trivial. The longer the decision and memory times, the higher the chance that an agent has been trained before it is ready to adopt the SMP, so discouragement occurs less often. The second relation is less straightforward. Most likely, it is due to the fact that the concentration of adopters has the same characteristics as public opinion, but the diffusion is hampered by the so-called intention-behavior gap (which grows with independence p). Moreover, a longer decision time makes the influence of p on the intension-behavior gap greater, because for a longer period of time an agent needs to have a stable opinion.

5. Conclusions and policy implications

Using an agent-based modeling approach we have examined the impact of educational programs and trainings on the diffusion of smart metering information systems (or platforms, SMPs). Our ABM is based on the model of Kowalska-Pyzalska et al. [14], but the decision-making process considered here relies on a coincidence of two factors – a stable positive opinion over a certain time interval and operational knowledge (gained through education) – not just a stable opinion. As a consequence of introducing this change, our model allows to obtain more realistic results. In particular, the level of adoptions does not exceed the level of positive opinions, i.e., the so-called intention-behavior gap is always positive.

The paper's contribution is threefold. Firstly, we observe that the positive effect of educational programs and trainings depends on the level of independence in the society and agent decision and memory times. Secondly, we find that mass-media advertising (i.e., a global external field) and educational trainings (i.e., a local external field) lead to similar, though not identical adoption rates. Thirdly, we find that for intensive mass-media advertising, the type of educational trainings – spatially concentrated or randomly scattered – does not matter, but for a certain range of parameters 'group' trainings, e.g., for all households in a given area or district, are significantly better than 'random' trainings. Interestingly, an opposite relationship – but with respect to the initial state, not the local external field as here – was found in [38]. Martins et al. studied adoption of new products within a CODA-type model [39], i.e., with agents characterized by continuous opinions and discrete actions (decisions). They compared the case where initial adopters were clustered to the case where they were randomly scattered around the social network and found that the process of innovation diffusion from an initial cluster was much slower than in the case of randomly spread adopters.

Our findings provide important guidelines for utilities, SMP suppliers and regulatory authorities interested in the diffusion of SMPs. In particular, we find that it is more efficient (in terms of the adoption ratio per number of agents trained) to offer and conduct spatially concentrated (i.e., group) trainings rather than to invest in general mass-media advertising or system-wide educational trainings. Moreover, by manipulating the time required by an agent to make a decision, e.g., through promotions, we can speed up or slow down the diffusion of SMPs, depending on the independence level in the society. Finally, it may be worthwhile to encourage consumers not to forget the knowledge and skills gained through training, e.g., by reminding about the SMP by texting, mailing or sending informational brochures.

Acknowledgement

This work was supported by the National Science Centre (NCN, Poland) through grants 2013/11/B/HS4/01061 and 2016/23/B/HS4/00650, and by the Ministry of Science and Higher Education (MNiSW, Poland) core funding for statutory R&D activities.

Bibliography

[1] A.-G. Paetz, E. Duetschke, W. Fichtner, Smart homes as a means to sustainable energy consumption: A study of consumer perceptions, Journal of Consumer Policy 35 (2012) 23–41.

[2] G. Papachristos, Diversity in technology competition: The link between platforms and sociotechnical transitions, Renewable and Sustainable Energy Reviews 73 (2017) 291–306.

[3] T. Zhang, W. J. Nuttall, Evaluating government's policies on promoting smart metering diffusion in retail electricity markets via agent-based simulation, Journal of Product Innovation Management 28 (2011) 169–186.

[4] T. Krishnamutri, D. Schwartz, A. Davis, Preparing for smart grid technologies: A behavioral decision research approach to understanding consumer expectations about smart meters, Energy Policy 41 (2012) 790–797.

[5] A. Kowalska-Pyzalska, What makes consumers adopt to innovative energy services in the energy market? A review of incentives and barriers, Renewable and Sustainable Energy Reviews (2018) doi: 10.1016/j.rser.2017.10.103.

[6] S. Darby, Smart metering: What potential for household engagement?, Building Research and Information 38 (2010) 442–457.

[7] N. Good, K. Ellis, P. Mancarella, Review and classification of barriers and enablers of demand response in the smart grid, Renewable and Sustainable Energy Reviews 72 (2017) 57–72.

[8] M. Nachreiner, B. Mack, E. Matthies, K. Tampe-Mai, An analysis of smart metering information systems: A psychological model of self-regulated behavioral change, Energy Research & Social Science 9 (2015) 85–97.

[9] A. Kowalska-Pyzalska, An analysis of factors enhancing adoption of smart metering platforms: an agent-based modeling approach, 13th European Energy Market (EEM) Conference, Porto, Portugal, 6-9 June 2016 (2016).

[10] T. Gerpott, M. Paukert, Determinnants of willingness to pay for smart meters: An empirical analysis of household customers in Germany, Energy Policy 61 (2013) 483–495.

[11] F. Gangale, A. Mengolini, I. Onyeji, Consumer engagement: An insight from smart grid projects in Europe, Energy Policy 60 (2013) 621–628.

[12] D. Gadenne, B. Sharma, D. Kerr, T. Smith, The influence of consumers' environmental beliefs and attitudes on energy saving behaviors, Energy Policy 39 (2011) 7684–7694.

[13] A. Kowalska-Pyzalska, Social acceptance of green energy and dynamic electricity tariffs – a short review, International Conference on Modern Electric Power Systems (MEPS'15), 6-9 July 2015, Wroclaw, Poland (2015).

[14] A. Kowalska-Pyzalska, K. Maciejowska, K. Suszczyński, K. Sznajd-Weron, R. Weron, Turning green: Agent-based modeling of the adoption of dynamic electricity tariffs, Energy Policy 71 (2014) 164–174.

[15] P. Ringler, D. Keles, W. Fichtner, Agent-based modelling and simulation of smart electricity grids and markets - a literature review, Renewable and Sustainable Energy Reviews 57 (2016) 205–215.

[16] M. Rixen, J. Weigand, Agent-based simulation of policy induced diffusion of smart meters, Technological Forecasting & Social Change 85 (2014) 153–167.

[17] A. Kowalska-Pyzalska, K. Ćwik, A. Jędrzejewski, K. Sznajd-Weron, Linking consumer opinions with reservation prices in an agent-based model of innovation diffusion, Acta Physica Polonica A 129 (2016) 1055–1059.

[18] I. Diaz-Rainey, D. Tzavara, Financing the decarbonized energy system through green electricity tariffs: A diffusion model of an induced consumer environmental market, Technological Forecasting & Social Change 79 (2012) 1693–1704.

[19] P. Przybyła, K. Sznajd-Weron, R. Weron, Diffusion of innovation within an agent-based model: Spinsons, independence and advertising, Advances in Complex Systems 17 (2014) 1450004.

[20] K. Sznajd-Weron, J. Szwabiński, R. Weron, T. Weron, Rewiring the network. What helps an innovation to diffuse?, Journal of Statistical Mechanics: Theory and Experiment (3) (2014) P03007.

[21] M. Claudy, C. Michelsen, A. O'Driscoll, M. Mullen, Consumer awareness in the adoption of microgeneration technologies. An empirical investigation in the Republic of Ireland, Renewable and Sustainable Energy Reviews 14 (2010) 2154–2160.

[22] M. Lopes, C. Antunes, N. Martins, Energy behaviors as promoters of energy efficiency: A 21st century review, Renewable and Sustainable Energy Reviews 16 (2012) 4095–4104.

[23] E. M. Rogers, Diffusion of Innovations, The Free Press, 2003.

[24] D. G. Myers, Social psychology (11th ed.), New York: Free Press, 2013.

[25] S. Bamberg, Applying the stage model of self-regulated behavioural change in a car use reduction intervention, Journal of Environmental Psychology 8 (2013) 331–354.

[26] P. Nyczka, K. Sznajd-Weron, Anticonformity or independence? Insights from statistical physics, Journal of Statistical Physics 151 (2013) 174–202.

[27] K. Sznajd-Weron, M. Tabiszewski, A. Timpanaro, Phase transition in the Sznajd model with independence, EPL 96 (4) (2011) 48002.

[28] P. Nyczka, K. Sznajd-Weron, J. Cisło, Phase transitions in the q-voter model with two types of stochastic driving, Physical Review E 86 (2012) 011105.

[29] K. Byrka, A. Jędrzejewski, K. Sznajd-Weron, R. Weron, Difficulty is critical: The importance of social factors in modeling diffusion of green products and practices, Renewable and Sustainable Energy Reviews 62 (2016) 723–735.

[30] K. Sznajd-Weron, J. Szwabiński, R. Weron, Is the person-situation debate important for agent-based modeling and vice-versa?, PLoS ONE 9(11) (2014) e112203.

[31] A. Jędrzejewski, K. Sznajd-Weron, Person-situation debate revisited: Phase transitions with quenched and annealed disorders, Entropy 19 (8) (2017) 415.

[32] S. Galam, Contrarian deterministic effects on opinion dynamics: "the hung elections scenario", Physica A: Statistical Mechanics and its Applications 333 (1-4) (2004) 453–460.

[33] A. Jędrzejewski, Pair approximation for the q-voter model with independence on complex networks, Physical Review E 95 (1) (2017) 012307.

[34] S. Galam, F. Jacobs, The role of inflexible minorities in the breaking of democratic opinion dynamics, Physica A: Statistical Mechanics and its Applications 381 (1-2) (2007) 366–376.

[35] P. Sobkowicz, Agent based model of effects of task allocation strategies in flat organizations, Physica A: Statistical Mechanics and its Applications 458 (2016) 17–30.

[36] P. Nail, K. Sznajd-Weron, The diamond model of social response within an agent-based approach, Acta Physica Polonica A 129 (2016) 1050–1054.

[37] R. Bond, Group size and conformity, Group Processes & Intergroup Relations 8 (2005) 331–354.

[38] A. Martins, C. Pereira, R. Vicente, An opinion dynamics model for the diffusion of innovations, Physica A: Statistical Mechanics and its Applications 388 (15-16) (2009) 3225–3232.

[39] A. Martins, Continuous opinions and discrete actions in opinion dynamics problems, International Journal of Modern Physics C 19 (4) (2008) 617–624.

HSC Research Report Series 2017

01 *Variance stabilizing transformations for electricity spot price forecasting* by Bartosz Uniejewski, Rafał Weron and Florian Ziel

02 *On the importance of the long-term seasonal component in day-ahead electricity price forecasting. Part II – Probabilistic forecasting* by Bartosz Uniejewski, Grzegorz Marcjasz and Rafał Weron

03 *Importance of the long-term seasonal component in day-ahead electricity price forecasting revisited: Neural network models* by Grzegorz Marcjasz, Bartosz Uniejewski and Rafał Weron

04 *The role of educational trainings in the diffusion of smart metering platforms: An agent-based modeling approach* by Tomasz Weron, Anna Kowalska-Pyzalska and Rafał Weron