Agent-based Simulation Design for Technology Adoption

Christensen, Kristoffer; Ma, Zheng; Værbak, Magnus; Demazeau, Yves; Jørgensen, Bo Nørregaard

Published in:
Proceeding of 2020 IEEE/SICE International Symposium on System Integration (SII)

DOI:
10.1109/SII46433.2020.9025823

Publication date:
2020

Document version:
Accepted manuscript

Citation for pulished version (APA):
Christensen, K., Ma, Z., Værbak, M., Demazeau, Y., & Jørgensen, B. N. (2020). Agent-based Simulation Design for Technology Adoption. In *Proceeding of 2020 IEEE/SICE International Symposium on System Integration (SII)* (pp. 873-878). IEEE. https://doi.org/10.1109/SII46433.2020.9025823

Agent-based Simulation Design for Technology Adoption

Kristoffer Christensen, Zheng Ma, Magnus Værbak, Yves Demazeau, and Bo Nørregaard Jørgensen, *Member, IEEE*

***Abstract*— The global consequences of climate change calls for adoption of new technologies across all sectors of society. However, it is important to know how fast new technologies are adopted to reach the political climate goals. This paper presents a method for designing agent-based simulations for studying technology adoption. The method includes the design of simulation population, agent adoption logic, and external factors influencing agents' adoption decisions. A case study of the Danish commercial greenhouses' adoption of a smart energy solution is investigated. The result is presented with Roger's technology adoption curve which can be used to demonstrate the desired adoption rate by regulating different simulation parameters. The adoption rate of 50% with the return on the investment of 3 and 5 years is investigated. The greenhouse segment of growing pot plants with an area of more than 20,000 m2 is found to be the innovators. The simulation result shows that the population categories of the 'innovators', 'early adopters', and 'early majority' don't change between the return on investment time of 3 and 5 years. Furthermore, the relation of the return on investment time and the initial cost is close to linear. Hence, a lower/higher initial cost will result in a shorter/longer return on investment time.**

I. Introduction

As part of Denmark's climate goals, Denmark aims to supply electricity from 100% renewable energy sources by 2030 [1]. This goal calls for adoption of innovations that can support this green transition. These innovations are smart energy solutions, e.g. solutions which provide more intelligence and efficiency to electricity management. Smart grid is considered to be one of these innovations. A smart grid can manage electricity efficiently and allow more fluctuating power in the system [2]. A key element in the smart grid is the smart meters which allow two-way communication [3]. With smart meters, it is possible to gather better information from consumers which can lead to energy savings and utilization of consumers' energy flexibility [2]. Another direction for innovation is the utilization of energy flexibility in buildings. Energy flexibility in buildings is defined by IEA Energy in Buildings and Communities Program (EBC) Annex 67 "Energy Flexible Buildings" as "the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements" [4]. Industrial consumers with high electricity consumption may have an incentive to provide their energy flexibility to the grid.

Although there are several innovative smart energy solutions for supporting the green transition, many adoption barriers, e.g., economic risks, have to be addressed [5]. Therefore, it is important to identify adoption barriers to find the adoption triggers which can be used to overcome barriers. By simulating the adoption behaviors, an adoption rate can be found. The adoption rate (percentage and speed) is important in achieving climate goals because the climate challenges are time-dependent. Simulations of consumers adoption behaviors can be used to design and test business models for smart energy solutions to keep an adoption rate that meets the timeline of climate goals. Agent-based simulation can define and program agents' behaviors in a given environment. Therefore, agent-based simulation can simulate consumers' decision triggers and adoption behaviors. This paper uses agent-based simulation to investigate the adoption rate of a smart energy solution that allows Danish commercial greenhouses participation in an implicit Demand Response (DR) program. The adoption rate includes the ROI (Return On Investment) time and the corresponding maximum cost of the adopted solution. Commercial greenhouses are chosen due to their large electricity consumption. In 2017, 0.7% of the total Danish electricity consumption came from only 436 commercial greenhouse growers [6, 7]. 75% of the consumed electricity is estimated to come from artificial lighting [8]. Therefore, commercial greenhouses have a potential in helping to balance the electricity grid and thereby achieve large savings.

This paper first gives an overview of the background in section II- research background followed by section III- methodology. Section IV introduces the simulation design and its logic. The case study section describes the specific case followed by section VI- simulation results. Last, the conclusion section summarizes the research findings.

II. Research Background

A. Demand Response in the Danish Context

In the traditional Danish electricity value chain, the grid companies have only one job, which is to transport electricity from A to B [9]. In the traditional value chain, the supply matches demand by up-regulating production when consumption increases. This regulation is typically done by fast responding production units such as gas turbines which, however, are expensive to run [10]. The increasing share of renewable energy, such as wind and solar, increase the complexity and costs of following the demand. This is due to the fact that wind and solar energies depend on weather conditions, thus the energy production fluctuates. This calls for a paradigm shift where demand follows supply. This can be done through the smart grid which among other things support a two-way power and information flow [11]. With a well-designed DR program, consumers can be motivated towards modifying their demand to the electricity prices and thereby help to balance the grid [12]. DR is defined by the European Commission as voluntary changes in consumers' electricity usage patterns, in response to market signals [13]. DR can be divided into two categories: explicit and implicit DR.

Explicit DR is a program that gives the end-users the possibility to compete in the wholesale market with producers, balancing and ancillary services. This is possible with services provided by aggregators or single large consumers. Aggregators trade aggregated load in the electricity markets, receive payment comparable with the generation, and consumers receive direct payment in the explicit DR [14, 15]. Today, DR aggregation only takes place through the electricity suppliers, and independent aggregators are not allowed in Denmark. Therefore, Danish consumers only have the opportunity to participate in the implicit DR program. *Implicit DR* program refers to consumers being exposed to time-varying electricity prices that reflect electricity prices in different time periods. Consumers react to those price differences without commitment [14, 15].

B. Innovation Adoption

Innovation adoption means that consumers make full use of the innovation [5]. The adoption process includes several decision stages. According to [5], the whole decision process consists of a knowledge stage (i.e., awareness of the innovation), a persuasion stage (i.e., evaluation of the innovation), a decision stage (i.e., intention to adopt or not), an implementation stage (i.e., actual behavior), and a confirmation stage. Consumers are considered as an adopter when all the stages have been achieved.

It is important to identify the adoption barriers and to find the triggers to overcome the barriers. The *barriers* can be divided into two categories; Functional- and psychological barriers [5]. *Functional barriers* consist of usage- and risk barriers. *Usage barriers* are when the technology solution is not compatible with existing workflows. The *risk barriers* have three subcategories; economic, functional and social. *Economic risk barrier* is defined as the uncertainty about the costs for the technology solutions. *Functional risk* is the uncertainty about if the technology may not function as expected. The *social risk* concern the risk of being ridiculed by peers [5]. *Psychological barriers* consist of image-, tradition-, and norm barriers. That is when the technology solution is perceived in a negative way and the technology conflicts with the adopter's traditions and norms [5].

A reason why it can be difficult to identify the barriers is that customers have a different view from the innovators regarding the benefits and costs when adopting an innovation. According to [16], innovators only see the total benefit and the purchase price for the users, whereas the users include other costs (e.g. the cost for retraining, equipment upgrades, etc.) and only see the relative benefit i.e. the benefit differences between the old and the new solutions. Hence, the relative benefit and the total cost decide if customers adopt or not. Fig. 1 illustrates the customers' and innovators' different views on costs and benefits.

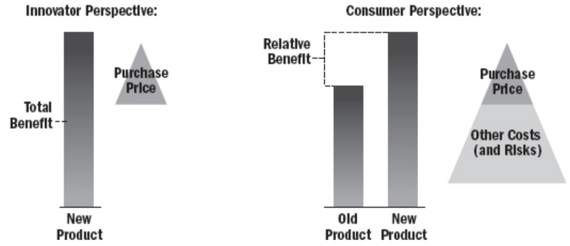

Fig. 1. The consumer and innovator's perspective of "benefits" and "costs" [16].

This paper aims to find the adoption rate. The *adoption rate* indicates if the innovation requires regulatory changes to meet the climate goals or if it can diffuse itself under the current system structures. According to [17], the adoption rate is defined as: "the relative speed with which an innovation is adopted by members of a social system. It is generally measured as the number of individuals who adopt a new idea in a specific period, such as a year. So, the rate of adoption is a numerical indicator of the steepness of the adoption curve for an innovation." The adoption rate is determined by different variables such as relative advantages (e.g. economic profitability), compatibility, complexity, trialability, and observability [17]. However, this paper mainly focuses on the economic aspects of innovation adoption. Fig. 2 illustrates adoption distributions [17], and Fig. 3 shows a normal distribution divides the adopters into five categories: innovators, early adopters, early majority, later majority, and laggards. The criterion for the adopter categorization is innovativeness, the degree to which an individual or another unit of adoption is relatively earlier in adopting new ideas than other members of the social system [17]. Therefore, it is possible to simulate consumer adoption behaviors with the above theories and real data of consumers and their environment.

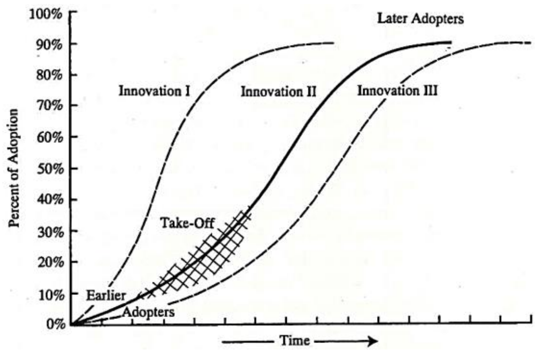

Fig. 2. The adoption process [17].

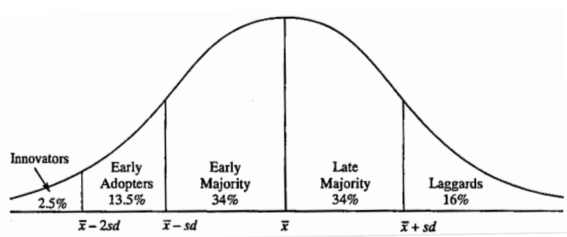

Fig. 3. Rogers' adoption curve with adopter categorization [17].

III. Methodology

Agent-based simulation is used in this paper to simulate innovation adoption. Agent-based simulation is a relatively new method to simulate real-life systems compared to system dynamics and discrete event modeling. The increase in practicing agent-based simulation occurs due to growth in CPU power (agent-based models demand high CPU power capacity), the desire to get deeper insights into simulated systems, etc. Agent-based simulation allows finding the system behavior with the possibility of applying several agents in an environment and interact with each other (multi-agent systems [18]). There is no direct definition for an agent, but agents can represent many different things in an agent-based model like vehicles, projects, products, people in different roles, ideas, investments [19].

Agent-based simulation is an artificial intelligence method which allows software agents to behave close to real-life entities. Agents operate in a certain environment and behave and react to different changes. This behavioral knowledge is fed into the agent logic through data (e.g. historical data for how an agent behaves to a specific change in the environment) [20].

In the agent-based simulation of consumer's energy choices, energy technology adoption is the most commonly studied subject [21]. The studies of agent-based simulation focus on questions about policy design and evaluation. Researchers analyze how variations in policy instruments and marketing or communication strategies impact the rate and scale of adoption [21]. The emergence of agent-based modeling in energy-related studies is driven by the advantages of agent-based modeling that offers simulations through dynamic interactions of agents.

IV. Simulation design

This paper uses a multi-agent simulation tool named AnyLogic. AnyLogic is a simulation software tool that supports three simulation modeling methods: system dynamics, discrete event, and agent-based modeling and allows to create multi-method models [22].

The first step of the agent-based simulation design is the identification of the agents that are subjects of the research. Next, the agents have to be divided into groups based on their different behavior and will represent an agent population.

The agent population in this paper is the Danish commercial greenhouse growers. The designed population includes the Danish commercial greenhouses' size, type of plant species, power of installed artificial lighting, and light sum (the plant's daily required amount of light). The data input for the population is provided by a plant expert, Prof. Carl-Otto Ottosen, Department of Food Science, Aarhus University, and Statistics Denmark (the national authority on Danish statistics). The designed population includes growers' types of tomatoes, cucumbers, herbs, pot plants, and salad. The example of the designed population for tomatoes and pot plants greenhouses is shown in TABLE I.

The simulation design in this paper aims to find the savings achieved by adopting a new solution relative to the old solution and based on this, to find the adoption rate. To specify, the old solution corresponds to how Danish greenhouse growers managed their artificial light before adopting an automatic DR-enabled light control system.

Information regarding how the commercial greenhouse was managed before was given by Knud Jepsen a/s (one of the biggest Danish commercial greenhouse growers). The new solution is an automatic system that controls the light after the hours when the plants get the highest photosynthesis gain per spot price unit. The new solution uses the weather forecast and the announced electricity spot prices for the next day to calculate and create a forecast for the photosynthesis gain per spot price unit for using artificial light. Based on this forecast a time schedule is created for using artificial light, such that the artificial light is turned on in the necessary number of hours where the plants get the highest photosynthesis per spot price unit. The designed light schedule always meets the plants' requirements.

Fig. 4 illustrates the described solution design: 1) is the simulation times and dates including information of the adopting agents when adoption occurs. 2) are the parameters which are editable for simulating different scenarios. 3) is a curve of the 24-hour solar irradiance forecast. 4) is the spot price curve. 5) represents the calculated photosynthesis gain per spot price. The two curves illustrate the fact that the photosynthesis gain as a function to natural light level is non-linear.

TABLE I. Agent population design

Grower type	***Greenhouse segment area [m^2]***	***Number of growers***	***Area per grower [m^2]***	***Installed art. light [W/m^2]***	***Light sum [Wh/m^2]***
Tomatoes	<1000	47	71.51	140	2240
	1,000 – 1,999	10	1,000		
	2,000 – 4,999	5	2,000		
	5,000 – 9,999	4	5,000		
	10,000 – 14,999	2	10,000		
	15,000 – 19,999	0	0		
	20,000<	7	40,766.9		
Cucumbers				120	1920
Herbs				100	1600
Pot plants	<1000	18	416.61	110	1760
	1,000 – 1,999	13	1,138.46		
	2,000 – 4,999	45	2,677.67		
	5,000 – 9,999	37	5,741.89		
	10,000 – 14,999	20	10,000		
	15,000 – 19,999	6	17,100		
	20,000<	27	51,496.8		
Salad				90	1440

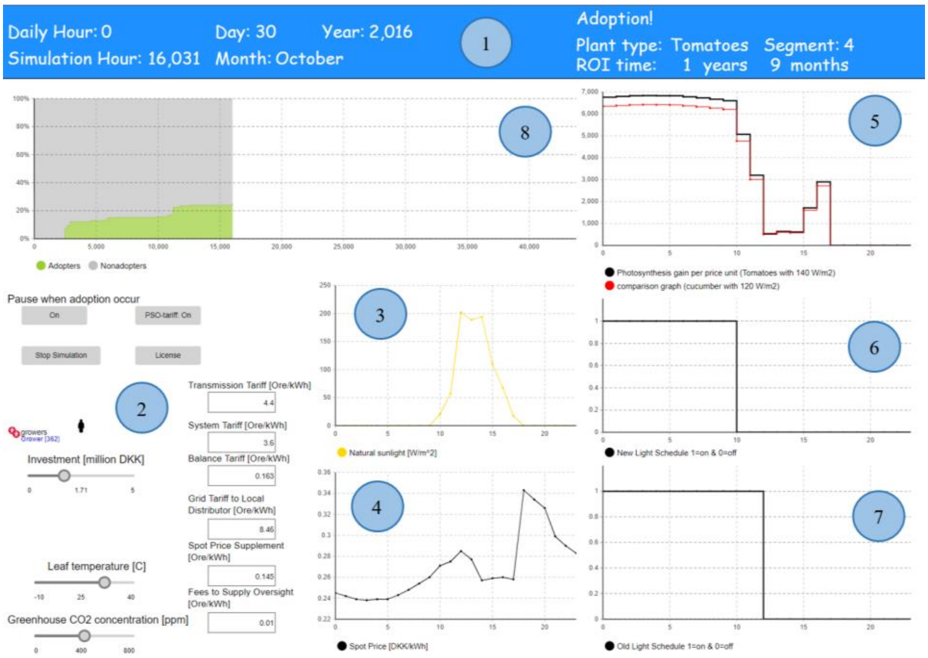

Fig. 4. Screenshot of the interface from the developed solution design in AnyLogic.

The two curves have a difference of 20 W/m2 and have a noticeable difference in photosynthesis per spot price during the night whereas the difference is very small when there is natural light. Hence, using artificial light in bright daylight will only result in a small amount of additional photosynthesis. 6) is the light schedule for the new solution where the light is turned on when '1' and off when '0'. 7) is how the light was operated before implementing the new system. 8) illustrates the adoption curve.

The solar irradiation forecast and spot prices are based on the available historical data from 2015 to 2019. Therefore, the simulation starts in 2015 and use a retro-perspective approach to decide when to adopt. The adoption decision uses the historical data to find possible savings. When the accumulated savings for an agent equals the monetary cost for adoption, the agent adopts and the ROI time for the adopted innovation equals the simulation time when the adoption occurs. The agents' decision of adopting or not is entirely based on the monetary benefits in this simulation. The simulation stops when 50% of the population has adopted as that equals the average adoption time according to Fig. 3. There are five logic designs in this simulation: 1) overall simulation, 2) decision, 3) overall domain, 4) new DR-enabled light control system, and 5) old solution before adopting the new solution. As an example of how these logics are built and implemented, a flowchart of the decision and simulation logic can be seen in Fig. 5.

The simulation investigates what the maximum one-time payment cost is for a 50% adoption rate with a ROI of 3 and 5 years. Two adoption rates are chosen:

- Adoption rate of 50% in 5 years under the current electricity price structure. It has been estimated that an ROI time of 5 years is reasonable for medium-sized industries such as commercial greenhouses.
- Adoption rate of 50% in 3 years.

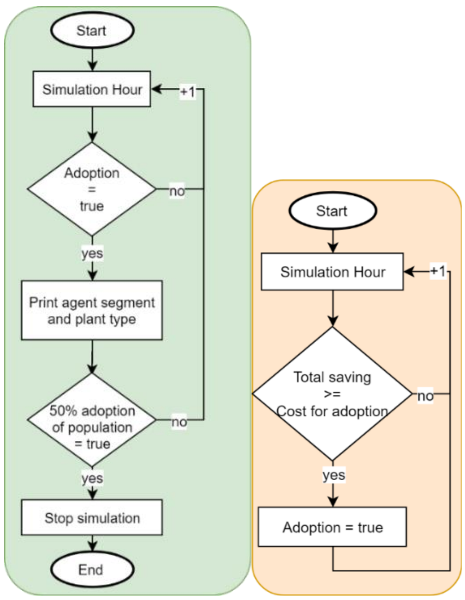

Fig. 5. Flowcharts of the model simulation logic. [Green: Simulation logic][Orange: Decision logic].

TABLE II. REALITY-EXPERIMENT TABLE

Real-life data	***Parameters in simulation***
Spot-price from Nordpool	Daily Nordpool spot prices for DK-West
Fees, tariffs and taxes	• Spot supplement • Fees to supply oversight • Transmission tariff

	• Balance tariff • PSO tariff • Grid tariff to a local distributor • System tariff
The reduction in PSO	The PSO value is reduced per quarter (based on [23]) until zero in the year 2022
Solar irradiation	Weather station data
Plants light sum	Plant species' light sum in W/m2
Photosynthesis gain	The calculation based on leaf temperature, CO_2 concentration, and solar irradiation.
Cost for adoption	The initial cost for new technology implementation.
Dark hours requirement for plants	5 PM to 12 midnight
Light schedule before the new solution	Light can be turned on from 12 midnight and until 5 PM, in the condition of the light is turned on until a setpoint and turn off when the light sum is reached

Furthermore, the populations of 'innovators', 'early adopters', and 'early majority' (from Fig. 3) are identified by analyzing the simulation output.

Several parameters are set up in the simulation to represent the real-life data (shown in Table II). The parameters are designed to be as close as possible to real-life data. TABLE II lists all the real-life data included and how they are used in the simulation.

V. Case Study and Results

Fig. 6 illustrates the adoption curve for the Danish commercial greenhouses, and it is found that a maximum one-time payment cost of 1.765 million DKK results in an adoption rate of 50% in 4 years 10 months and 19 days. TABLE III provides the information behind the curve and shows the categorization of the greenhouses that the green-colored greenhouses are the innovators, yellow represents the early adopters, and red is the early majority.

The parameter for the one-time payment cost was changed to achieve an adoption rate of 50% within 3 years. The outcome of the simulation can be seen in Fig. 7 and TABLE IV. The found maximum cost is 1.148 million DKK. The same as TABLE III, the adopters are categorized in innovators, early adopters, and early majority as green, yellow, and red, respectively.

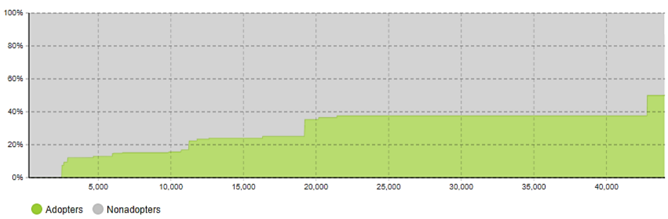

Fig. 6. The adoption curve for commercial greenhouses' adoption of DR (with an initial cost of 1.765 million DKK). [X-axis: Hours] [Y-axis: Adoption percentage of the population]

It can be seen from TABLE III and -IV that the categories are represented by the same greenhouses. However, the ROI time has shortened with 38.7% when the initial cost for adoption has been reduced by 35%. Hence, the case study further investigates the sensibility of the initial cost relative to the ROI time of 50% adoption. Fig. 8 shows the curve of the ROI time of 50% adoption as a function to the initial costs for adopting the automatic DR-enabled light management system. The curve can be used to determine the maximal initial cost if a specific ROI time is required. It is found that by reducing the initial cost from 3 million DKK to 0.25 million DKK, which corresponds to a reduction of 91.7%, results in a reduction of 93.9% in the ROI time. This means the function is not linear as evidenced on the curve in Fig. 8.

TABLE III. Adoption information table (with an initial cost of 1.765 million DKK)

Plant type	*Grower segment [m²]*	*ROI time: years*	*ROI time: months*	*ROI time: days*
Pot plants	>20,000	0	3	14
Tomatoes	>20,000	0	3	20
Cucumber	>20,000	0	4	1
Herbs	>20,000	0	6	13
Pot plants	15,000-19,999	0	8	6
Cucumber	10,000-14,999	1	2	22
Pot plants	10,000-14,999	1	3	13
Herbs	10,000-14,999	1	4	6
Tomatoes	5,000-9,999	1	10	10
Pot plants	5,000-9,999	2	2	11
Cucumber	5,000-9,999	2	3	20
Herbs	5,000-9,999	2	5	11
Pot plants	2,000-4,999	4	10	19

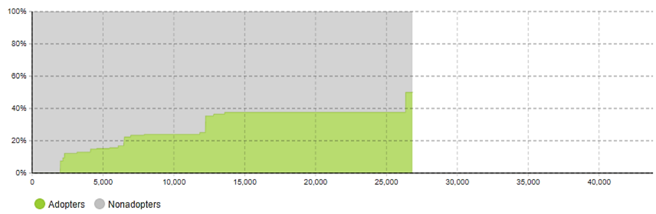

Fig. 7. The adoption curve for commercial greenhouses' adoption of DR (with an initial cost of 1.148 million DKK). [X-axis: Hours] [Y-axis: Adoption percentage of the population]

TABLE IV. Adoption information table (with an initial cost of 1.148 million DKK)

Plant type	*Grower segment [m²]*	*ROI time: years*	*ROI time: months*	*ROI time: days*
Pot plants	>20,000	0	2	24
Tomatoes	>20,000	0	3	0
Cucumber	>20,000	0	3	5
Herbs	>20,000	0	4	12
Pot plants	15,000-19,999	0	5	21
Cucumber	10,000-14,999	0	8	10
Pot plants	10,000-14,999	0	8	28
Herbs	10,000-14,999	0	9	17
Tomatoes	5,000-9,999	1	4	7
Pot plants	5,000-9,999	1	4	24
Cucumber	5,000-9,999	1	5	17
Herbs	5,000-9,999	1	6	18
Pot plants	2,000-4,999	2	11	28

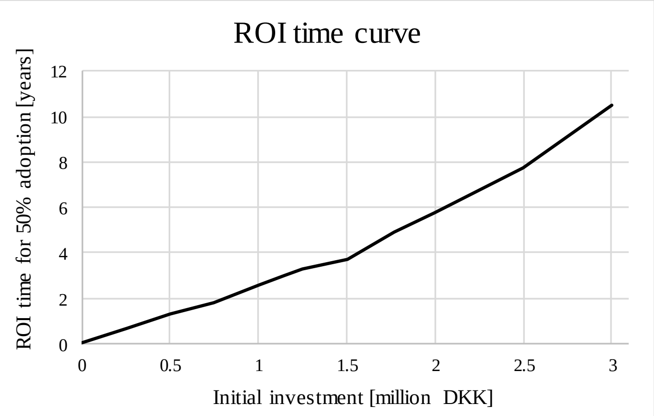

Fig. 8. Curve of the ROI time for 50% adoption as a function to the initial investment cost.

VI. Conclusion

This paper presents a methodology of designing an agent-based simulation to simulate technology adoption behaviors. The simulation design includes population creation and the decision logic design. A case study of the Danish commercial greenhouses' adoption of an automatic DR-enabled light control system to participate in the implicit DR program is used for this paper. This simulation finds that with a maximum one-time payment cost of 1.765 million DKK for adopting an automatic DR-enabled light control system, 50% of the Danish commercial greenhouses will adopt within 5 years, and with a maximum one-time payment cost of 1.148 million DKK 50% will adopt within 3 years. Furthermore, it is found that a lower/higher initial cost will result in a shorter/longer ROI time. This finding can, for example, be used by politicians to subsidize implicit DR programs to achieve the desired adoption time which can meet the climate goals.

The simulation result shows that there are population categories of the 'innovators', 'early adopters', and 'early majority' among the Danish commercial greenhouses and the categories do not change between the ROI time of 3 and 5 years. Innovators are defined as the first 2.5% of the populations [17]. The greenhouse segment of growing pot plants with an area of more than 20,000 m2 is the innovators in this case. This finding can be used for technology providers to target the consumers who are the early adoption, and to determine what the maximum cost can be. The paper also contributes to the agent-based research area with a special focus on innovation adoption in the smart energy sector. For simplicity, the simulation has been investigating the adoption behavior in relation to the monetary factors with a focus on the initial one-time payment cost. As mentioned in this paper many factors influence the adoption rate, and the more factors implemented in the simulation the closer it can reach the reality. Therefore, factors related to compatibility, complexity, trialability, and observability are suggested to be included in future research.

References

[1] Danish Energy Agency. "Energiaftale - af 29. juni 2018." https://efkm.dk/media/12222/energiaftale2018.pdf

[2] E. a. B. Danish_Ministry_of_Climate. "Smart Grid Strategy." https://ens.dk/sites/ens.dk/files/Globalcooperation/smart_grid_strategy_eng.pdf

[3] K. T. Raimi and A. R. Carrico, "Understanding and beliefs about smart energy technology," *Energy Research & Social Science*, vol. 12, pp. 68-74, 2016, doi: 10.1016/j.erss.2015.12.018.

[4] K. Foteinaki, R. Li, A. Heller, and C. Rode, "Heating system energy flexibility of low-energy residential buildings," *Energy & Buildings*, vol. 180, pp. 95-108, 2018, doi: 10.1016/j.enbuild.2018.09.030.

[5] R. Reinhardt, N. Hietschold, and S. Gurtner, "Overcoming consumer resistance to innovations – an analysis of adoption triggers," 2017.

[6] Danmarks Statistik. "Energiforbruget i væksthuse halveret på 15 år." https://www.dst.dk/da/Statistik/nyt/NytHtml?cid=25153 (accessed 04/09/2019).

[7] Energistyrelsen, "Energistatistik 2017," pp. 1-58, 2017. [Online]. Available: https://ens.dk/sites/ens.dk/files/Statistik/pub2017dk.pdf.

[8] J. C. Sørensen, K. H. Kjaer, C.-O. Ottosen, and B. N. Jørgensen, "DynaGrow – Multi-Objective Optimization for Energy Cost-efficient Control of Supplemental Light in Greenhouses," *8th International Joint Conference on Computational Intelligence (IJCCI 2016)*, vol. 1: ECTA, pp. 41-48, 2016.

[9] Energinet, "Introduktion til elmarkedet," April 14, 2016. Accessed: June 11, 2019. [Online]. Available: https://www.google.com/url?sa=i&source=images&cd=&cad=rja&uact=8&ved=2ahUKEwjKw4rgq-HiAhUD2qQKHdRrBSkQ5TV6BAgBEAs&url=https%3A%2F%2Fenerginet.dk%2F-%2Fmedia%2FEnerginet%2FEl-RGD%2FEl-BSJ%2FDokumenter%2FIntroduktion-til-elmarkedet.pdf&psig=AOvVaw2LSPm54TvGQ3OK0CBy4dN0&ust=1560337628780077

[10] S. Segantin, R. Testoni, and M. Zucchetti, "The lifetime determination of ARC reactor as a load-following plant in the energy framework," *Energy Policy*, vol. 126, pp. 66-75, 2019, doi: 10.1016/j.enpol.2018.11.010.

[11] J. Stoustrup, A. Annaswamy, A. Chakrabortty, and Z. Qu, *Smart Grid Control: Overview and Research Opportunities* (no. Book, Whole). Cham: Springer International Publishing, 2019.

[12] S. Bahrami, M. H. Amini, M. Shafie-khah, and J. P. S. Catalao, "A Decentralized Electricity Market Scheme Enabling Demand Response Deployment," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 4218-4227, 2018, doi: 10.1109/TPWRS.2017.2771279.

[13] Z. Ma, J. D. Billanes, and B. N. Jørgensen, "Aggregation Potentials for Buildings-Business Models of Demand Response and Virtual Power Plants," *energies*, pp. 1-19, 2017. [Online]. Available: https://www.mdpi.com/1996-1073/10/10/1646.

[14] P. Bertoldi, P. Zancanella, and B. Boza-Kiss, "Demand Response status in EU Member States," *EUR 27998 EN*, pp. 1-140, 2016, doi: 10.2790/962868.

[15] SEDC, "Mapping Demand Response in Europe Today 2015," *Smart Energy Demand Coalition (SEDC)*, pp. 1-187, 2015.

[16] R. Adner, *The wide lens: a new strategy for innovation*. Portfolio/Penguin, 2012.

[17] E. M. Rogers, *Diffusion of Innovations*, Fifth ed. Free Press, 2003, p. 551.

[18] J. Ferber, *Multi-agent systems: An introduction to distributed artifial intelligence*, 1st ed. Addison-Wesley Proffessional, 1999.

[19] I. Grigoryev, "Anylogic 7 in three days," pp. 1-256, 2016.

[20] A. Wodecki, *Artificial Intelligence In Value Creation - Improving Competitive Advantage*. 2019, p. 340.

[21] V. Rai and A. D. Henry, "Agent-based modelling of consumer energy choices," *Nature Climate Change*, vol. 6, no. 6, pp. 556-562, 2016, doi: 10.1038/nclimate2967.

[22] I. Grigoryev, "Anylogic in three days," 2016.

[23] Energistyrelsen. "PSO-tariffen for 2. kvartal 2019." https://ens.dk/service/statistik-data-noegletal-og-kort/aktuel-pso-tarif (accessed May 14, 2019).