A Simulation-Game for Resilience Assessments in a Payment System Disruption Scenario

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ABSTRACT

This paper presents a quantitative agent-based simulation model of the everyday payment system used to simulate the business and consumer consequences of loss of functionality, or disruptions of the payment system for the food and fuel retailing markets as well as the bank sector in order to address resilience. The simulation model is used in a gaming simulation approach that couples a role-playing game with the simulation model in order to provide crisis management team-training to decision-makers in a multi-organisational context. Drawing primarily on resilience engineering and crisis response, the concepts of core values, coping strategies, and resilience value networks were used to guide the design of the simulation model. The ultimate aim of this study is to explore the collaborative responses from the key actors during the disruption scenario in order to evoke and facilitate collective resilience.

KEYWORDS

Disruption, Payment System, Resilience, Serious Games, Simulation

1. INTRODUCTION

During the latter decade, the literature on critical infrastructure has emphasized that more awareness should be put on digital vulnerabilities, and expressed a need to educate professionals and citizens on these matters, enabling for a society to become more resilient to disturbances in digital infrastructures and the functions dependent on these (Hagen, 2016). Resilience in a society with a high degree of interdependency between the functions of critical infrastructures depends on collaborative responses from the actors involved, who might have diverse backgrounds and differing responsibilities, not familiar with cascade effects into areas beyond and outside their own organisation or sector. In such circumstances, there is a risk that the responses of the individual actors are sub-optimal or counteract each other due to limited understanding of the interdependencies and constraints of other actors (Ansell et al., 2010). Studying escalations and cascading effects is not an easy task, thus there exists very few empirical studies of these matters across many infrastructures, making it difficult to predict...
necessary interactions between sectors in crisis management, cf., e.g., (Boin, and McConnell, 2007; van Eeten et al., 2011).

Gaming simulation encompass roles to be played by participants of a game where the outcomes or their actions are simulated, and the interactions between the participating “players” and their actions made in order to reach goals are also part of the simulation, see (van Laere et al., 2006). The approach is particularly relevant when studying interactions between the participants, such as deliberative processes on possible actions to take and negotiations about which action to take and how to interpret simulation outcome as a consequence of the action taken. As the participants literally are active participants, and not merely observers, it may facilitate learning of both the context simulated and of other participants’ constraints, see, e.g., (Mayer, 2009).

This paper reports upon a study conducted within a research project aiming to develop a gaming simulation environment that enables for a greater understanding how resilience against disruptions in the payment system is to be improved. For clarity, when referring to the “payment system” we refer to the means by which consumers may initiate a transaction to business in exchange for goods or services, with a focus on food, medicines, and fuel supply. Some attempts towards modelling and simulation of the payment system have been made, primarily focusing on the banking sector. For instance, Galbiati, and Soramäki (2011) constructs a multi-agent system where the agents represents banks, simulating how the banks manage delays and liquidity acquisitions resulting in equilibrium states. With respect to simulation for risk assessment purposes, Bedford et al. (2005) investigates worst-case scenarios as a consequence of the inability of one part to send and receive payments in a large-value context. By constrast, the ultimate purpose of the project is to provide team training to decision-makers in inter-organisational crisis management when the common means for transactions suddenly become limited or non-existing. A number of data collections such as document studies, interviews and workshops with experts from the food, fuel and financial sectors, reveal seven challenges for collective cross-functional critical infrastructure resilience that need to be dealt with: 1) Shortage of food, fuel, cash, medicine; 2) Limited capacity of alternative payment solutions; 3) Cities are more vulnerable than the countryside; 4) Economically vulnerable groups in society are more severely affected; 5) Need to maintain trust and prevent panic; 6) Crisis communication needs; 7) Fragmentation of responsibility for critical infrastructures across many actors. For a detailed description, see (van Laere et al., 2017; Johansson et al., 2017; Johansson et al., 2018).

1.1 Systemic Resilience

Bergström et al. (2015) describes what the term ‘resilience’ can refer to within the domain of safety and crisis response: bouncing back to a previous state, or bouncing forward to a new state, or both; absorbing variety and preserve functioning, or recovering from damage, or both; and being proactive and anticipating, or being reactive (when recovering during and after events), or both. The variety of interpretations of resilience that have been identified makes it difficult to operationalize resilience into measurable indicators.

Lundberg and Johansson (2015) developed the Systemic Resilience (SyRes) model as a step towards better metrics and a more comprehensive understanding for determining the resilience of a system in crisis management. The SyRes model consists of four different sections: Event-based constraints, Functional Dependencies, Adjustment of capabilities and Strategy (see Figure 1).
(i) **Event-based constraints** can be viewed as latent conditions (vulnerabilities), event onset cues, direct and indirect effects of the event, and damages to the system. Indirect effects may be in the form of side effects of a response to an event. The effects may be direct, delayed, or causing new latent conditions/vulnerabilities.

(ii) **Functional dependencies** refer to six functions that a system may employ to cope with events: *anticipation*, *monitoring*, *response*, *recovery*, *learning*, and *self-monitoring*; and core functional dependencies between them. The six functions are arranged in a circular fashion, placing the functions where their output can be used at the earliest, in relation to events, thereby clarifying the relation between functional dependencies and event-based constraints.

(iii) **Adjustment of capabilities** is done through establishing and mobilizing modes. Establishing represents deciding what the resources should do. Mobilization represents actually getting resources deployed and active.

(iv) **Strategy**, the execution of resilience functions may manifest in the form of basic strategies, including: *immunization* (e.g., moving a city from above a slowly collapsing mine, to a different location), *avoidance* (e.g. evacuation), *control* (e.g. attempting to control water flowing toward a city), *rebuilding* (e.g. repairing damaged buildings), or through *knowledge* (e.g. making sure every part of a community knows about threats and coping strategies).

In the SyRes model, anticipation is a pre-requisite for the ability of establishing functions for monitoring the onset of events, functions for event detection, preparing suitable modes of operation during response, and immunizing against avoidable threats. Monitoring is a pre-requisite for detecting the onset of events. Subsequently, abilities to detect effects of events may be adjusted and mobilized, response capabilities may be adjusted and mobilized, and effects may, in some cases, be entirely avoided by some manoeuvre. Initiating response is a pre-requisite for the ability to detect direct effects of events, respond to events through the current repertoire of action, to take control of events.
Initiation of recovery is a pre-requisite for detection of effects and damages and for re-establishing damaged functions. Learning is then a pre-requisite for adjusting functions for event detection and damaged modes of operation. Finally, at the core of this model, self-monitoring refers to the ability to monitor and adjust all other functions continuously, a prerequisite for the ability to maintain the core abilities of the model.

1.2 Agent-Based Simulation and Modelling

The use of agent-based simulation (ABS) models as a facilitator for involving stakeholders and supporting collective decision making training has been shown to be a valuable approach, cf. (Gilbert, 2008). In particular, the joint use of ABS and role playing games (RPG) to develop and investigate collective management scenarios has been promoted in previous research (Barreteau et al., 2001; Etienne et al., 2002; Dray et al., 2006), where the approach ‘companion modelling’ has been coined. This approach specifically couples ABS and RPG, see, e.g., (Barreteau et al., 2003) for an introduction, and a main objective of the approach is to enable for both researchers and field actors to gain insights and understanding of a (social) phenomena through interaction with a simulation model.

With respect to ABS and multi-agent systems in general, the concept of an ‘agent’ is of central concern. An agent can be viewed as an entity (or a piece of code) that can act autonomously, interact and communicate with other agents in the system, change its internal state over time, has a boundary, and being unique within its system or environment, cf. (Macal and North, 2010). Different types of agents can be defined depending on their properties. Following Wooldridge (2000), we can define an agent’s capabilities. Let \( x \) be an agent, and let \( S = \{s_1, s_2, \ldots\} \) be the state space of \( x \)’s environment, so that at any given instance the environment of \( x \) is in one of these states. The capabilities of \( x \) is then represented by the possible actions \( Ax = \{a_1, a_2, \ldots\} \) of \( x \). Now, \( x \) is categorized as a simple reactive agent if its behavior is simply characterized by an action function \( (A_1) \) mapping a state to an action.

\[
\text{action: } S \rightarrow Ax \quad (A1)
\]

When an agent is limited in the sense that it cannot perceive its full environment, a perceive function mapping the environment state to a percept is required \( (A2) \)

\[
\text{perceive: } S \rightarrow Px \quad (A2)
\]

where an action becomes a function from the perception set \( Px \) to \( Ax \) such that

\[
\text{action: } Px \rightarrow Ax \quad (A3)
\]

A perceptually bounded agent entails that \( Px \not\rightarrow S \), i.e. the agent \( x \) cannot perceive all states of the environment (or distinguish between all of them). An agent can also have a set \( Ix \) of internal states, and an action function

\[
\text{action: } Ix \rightarrow Ax \quad (A4)
\]

and it may change internal state depending on current state and a perception by means of a next-function

\[
\text{next: } Ix \times Px \rightarrow Ix \quad (A5)
\]

An agent that reacts upon perceived changes in its environment and acts in different ways depending on its internal state are reactive agents. Reactive agents can be modelled in a so-called finite-state model, defining the possible (finite) states of the agents’ attributes and scripted rules or conditions when they change state. Adam and Gaudou (2017) describe a finite-state model for simulation of population behaviour during bushfire incidents, however with a significantly smaller population size (200) compared to our case (440,000). In a subsequent paper, Adam et al. (2017) compares the belief-desire-intention (BDI) model against the finite-state model (FSM) when conducting agent-based simulation of populations under a crisis scenario and conclude that the BDI architecture in general offer better properties for flexibility and extensibility of the simulation. Our case, with 440,000 population size and the necessity for running the simulation on ordinary desktop computers when being used in games at different locations implied that, due to memory restrictions, consumer agents and vehicle agents are generated as, in relation to the environment, non-persistent.
objects at food stores and gas stations (who are persistent objects) according to a calibrated arrival rate. This also renders the BDI model infeasible for our purposes.

2. CONTEXT AND MODEL DESCRIPTION

When a longer payment disruption would occur, the responses of food stores, gas stations, pharmacies, transport companies, security companies, local government and media need to be well-aligned. In the simulation-game, participants discuss how to tackle the disruptions collectively through actions taken at different time points of the disruption scenario. The actions selected are represented in the simulation, and the consequences of their actions are provided to the participants instantly leading to a new collective decision on the next actions until the simulation terminates after a pre-defined number of simulated days. The participants can re-play the scenario several times and learn how different strategies have different impacts on the payment disruption scenario and leads to different consequences. The simulation-game challenges the participants to address the interaction between the payment system, food and fuel retailing markets and supply chains, security problems and communication challenges. A simulation-game created with the intention of addressing resilience towards an event must therefore reflect the complexity and interdependencies of a real world system. Within its context, it should encompass the event-based constraints, the functional dependencies, the adjustment of capabilities, and the strategies. At the same time, the simulation-game must provide well-structured and accessible feedback allow the participants in the simulation-game to explore the consequences of different actions as well as understand the consequences of non-actions.

The proposed model is set to simulate the flow of payments caused by consumer’s needs for purchasing foodstuffs and gasoline and the payment settlements. Payment requests are generated by purchase transactions made by consumers at food stores and gas stations. In addition, the circulation of cash within the system is simulated - collecting cash from stores, cash withdrawals, and refilling of ATMs. The payment types of main concern to model then include: Card purchases (debit/credit cards, typically Mastercard or Visa), ATM cash withdrawals, and payments through direct debiting and Real Time Gross Settlement (RTGS) (FSPOS, 2012). The payment types available to a consumer is calibrated from a 2019 report from the Swedish National Bank (Riksbanken, 2019), for instance, that 70% of the consumers has the ability to pay with Swish and that about 13% of the consumers use cash. As for the modelled region and market and its calibration, the total population for the modeled region is 440,000 inhabitants. Based on a data set of household characteristics and food shopping behavior used in (Lundberg and Lundberg, 2010), distributions of household categories (single, single father/mother, couple with/without children), number of persons in a household, and ownership of cars were set. Further, estimates of daily consumer purchase (household representative), visits for each food store and gas station (depending on the size) could be done using the data set.

The Swedish food-retailing and the retail fuel market are concentrated, where four trade groups account for 90% of the former (Hafgren and Wikander, 2015) and four companies, with both integrated retail and wholesale activities, account for approx. 90% of the total retail market for foodstuffs. In 2016, four companies controlled more than 99% of the retail Gasoline and Diesel markets and where automated stations has about 66% market share1. The model development was done using the simulation software AnyLogic2. It enables building an architecture for large-scale complex systems incorporating agent-based, discrete event, and system dynamics simulation. Each AnyLogic model has a built-in database. The database enables to:

(i) read input data and write simulation outputs,
(ii) create parameterized agent populations
(iii) import data from other databases or spreadsheets and store it in the readily available form
(iv) store and export statistics, datasets, and logs, and
(v) export data to spreadsheets, and restore data.
The AnyLogic Process Modeling Library supports a process-centric modeling paradigm where you can model the real-world systems in terms of agents (transactions, customers, vehicles, etc.), processes (queues, delays, resource utilization), and resources. The processes are specified in the form of flowcharts. The model uses a Geographic Information System (GIS) space to visualize the locations of food stores, gas stations and ATMs in a region that covers four municipalities (Lund, Malmö, Lomma and Staffanstorp) in Scania county, southern Sweden. (See Figure 2).

Figure 2. Visualization of food stores, gas stations and ATM:s using a GIS space

2.1 Crisis Dynamics

The dynamics of main interest is how the purchasing behaviour of citizens (as consumers) affects the flow of goods and money between them and the suppliers, and how the inability to pay due to payment system disruptions affects the behaviour and sentiment of the citizens triggering the suppliers and other societal actors to act. If no actions are taken from these societal actors, there is an escalation of both problematic behaviour such as hoarding, thefts, and robbery, as well as other problematic consequences such as lack of supplies and liquidity issues. In system dynamics, such a crisis scenario can be captured by means of escalating feedback loops, cf. (Mrotzek & Ossimitz, 2008). In our agent based model this is represented by a function in the generation of consumer agent making the internal state of the agent consumer when emerging at food stores and gas stations dependent on the state of a set of global static environmental parameters and global environmental variables. These variables, in combination with so-called plausibility effect variables determine the actions of a generated consumer agent.

The static environmental parameters consists of the distributions of household category, household income and expenditure, as well as the payment means available to the consumer. Further, each generated consumer has a probability of certain behaviours such as hoarding or stealing, which
increase with consumers’ perception of scarcity and future inabilities to overcome, cf. (Gupta and Gentry, 2019).

The global environmental variables are increments of the consumer agents’ fates when emerging at a food store or gas station, ending in either a successful purchase or a disappointment due to inability to pay or a lack of products at the store, as well as the number of hoarding and stealing incidents emerging from actions of the agents. The likelihood of a consumer agent to hoard or steal is affected by the magnitude and increase of these variables together with the “plausibility effect” environmental variables have on a consumer’s disposition for hoarding and stealing, see Figure 4. Thus, the fates of the non-persistent consumer agents affects the environment, which in turn affects the state of newly generated consumers, creating a feedback loop that may escalate while simulating a persistent population with non-persistent agents. The plausibility effect variables controls the strength of the feedback loops, while also enabling for runtime calibration of the population’s sensitivity towards disturbances and they can therefore be used to increase or decrease the difficulty of a game session.

2.2 The Crisis Scenario

The modelled crisis scenario is a disruption that stops at-store card payments, while cash withdrawals, internet- and tele-bank and online payments are functioning normally. Each simulation run starts at 06:00 am, continues for 11 days, from Day 0 to Day 10. A gaming session involves three simulation runs:

- A baseline (business-as-usual) simulation run considers 11 days with normal operation of card payments at food stores and gas stations.
- A worst-case simulation run, considers a disruption of card payments to occur on Day 1, at 12:00 pm, (i.e., after 30 hours using the model time), continues till end of the simulation run with no response actions taken by the participants (crisis management team from different organizations).
- Finally, a gaming simulation run that considers the same card payment disruption on Day 1, at 12:00 pm and multiple pauses for response actions on Day 1, at 15:00 pm (3 hours after disruption), Day 2, at 6:00 am (next morning) and every two days till end of the scenario (i.e., Day 4, Day 6, Day 8 and Day 10 at 6:00 am).

An event is the simplest way to schedule some action in the model. There are several timeout triggered once occurring events used to schedule the card payment disruption and the different pauses for action. In addition, there are two timeout triggered cyclic events. One is used to store and retrieve simulation outcomes (in terms of indicators) for the three different simulation runs, with recurrence time of three hours. Another is used to dynamically calculate the arrival rates of consumer agents at food stores and gas stations process models with recurrence time of one hour.

The model provides an architecture with three main components: the retailing market offer, the consumers’ behaviour and the payment system, including the following populations of agents, processes and response actions.

2.2.1 Consumer Agents

Individual consumer agents are household representatives with aggregated expenditure for family food supply. Consumer agents are modeled with several socio-economic characteristics and shopping properties.

Parameters:

- Household category (single/cohabiting, with/without children) and no. of persons.
- Household aggregated monthly income (SEK)
Household expenditure for food (SEK): Swedish consumers spent about 12% of their household budget on food and beverages in 2014, about the same as the EU average [30].

Bank account: Bank (agent) ID
Card, cash, Swish, and credit payment alternatives
Purchase quantity and Price sensitivity for each product group

State variables:

Knowledge about card payment disruption (true or false)
Knowledge about Swish payment possibility (true or false)
Knowledge about offline payment possibility (true or false)

2.2.2 Food Store Agents
A population with a total of 77 food stores loaded from a database table that provides the following parameters:

Retailer category: (4 leading retail groups, discount chains and others).
Store size: (3 Hypermarkets, 3 Megastores, 45 Supermarkets, 12 Minimarkets and 14 convenience stores)
Opening and closing times weekdays, Saturdays and Sundays: To reflect household preferences for timewise accessibility.
Store information, location, latitude and longitude.
Average daily consumer visits.
Store bank account

State variables:

Availability of payment options: card, cash, Swish and offline payment
Status (open, closed, temporarily unavailable, out of business)
Number of security guards

We consider the following food product groups:

i. Dairy products, fats and eggs
ii. Fruit and vegetables
iii. Baked and cooked products
iv. Beverages including alcoholic
v. Cereals, coffee, tea and cocoa
vi. Ready-to-eat, frozen, canned, dried and other convenience food products
vii. Meat products
viii. Fish and seafood

Relative to each product group a set of variables exist, assigned initial values based on the store size and average daily consumer visits, including:

Offered: true if the store offers a food product group.
Sales price per unit (kg / Liter)
Purchasing cost per unit
The following running variables are generally used to store the results of model simulation or to model some data units or object characteristics, changing over time. Food store agent contain the following running variables:

- Generated consumers count, Food store visits count and ATM visits count.
- Store account balance (aggregated card/Swish payments)
- Amount of cash in a store (aggregated cash payments)
- Store credit balance (aggregated offline/credit transfer payments)
- Available cash at near-by ATMs
- Successful purchases count
- Payment disappointments count
- Product disappointments count
- Cash disappointments count
- Hoarding and stealing incidents count
- Number of supplies, sold and expired quantities, and stock levels for each product group.

Figure 3, shows the flowchart of food store process (modelling of consumer visits). The flowchart starts with a Source block to generate consumer agents arriving to the store, uses a number of Delay and Service blocks and ends with a Sink block to destroy the consumer agents.

The process in the food store is described as follows:
Consumers are generated with an arrival rate based on the average daily consumer visits of each store. The arrival rate varies according to time of the day and equals zero out of the store opening times. Dynamics include disposition for stealing and hoarding in a systems dynamic model, see below and Figure 4.

Based on the availability of payment options and the communication of information about the disruption and response actions, generated consumers either continue to enter the store or move to one of the near-by ATMs to collect cash. If it is possible to get cash, the consumer continues to enter the store, otherwise, it leaves and a cash disappointment is added to the corresponding global variable.

Collecting products has a minimum duration of 5 minutes, a maximum of 20 minutes, and a most-likely duration of 10 minutes. The purchase quantities from different product groups are determined based on the shopping properties of the consumer agent, products offered at the store and their stock levels (allowing to identify product disappointments – if the purchase quantity of any of the food products is less than stock level), pricing and price sensitivity (promotions on perishable items during disruption), and possible hoarding behaviour based on consumer’s food expenditure and possibility to store food.

The circulation of cash, (i.e., removing cash from the store and refilling of ATMs), is modeled using two timeout-triggered cyclic events with a recurrence time that is defined and controlled on the system level and varies randomly between different stores.

Payment options are modeled by four Service blocks with various triangularly distributed service times, queue times and a ResourcePool (staff or cashiers) with a capacity depending on the store size.

The process for a consumer agent ends as a successful purchase if the consumer is able to pay using one of the available options, otherwise, it ends as a payment disappointment and added to the corresponding global variable.

2.2.2.1 Related Dynamics

Figure 4 illustrates a systems dynamics involved in consumer generation and their arrival rates at open food stores. The amount of closed stores has a positive but delayed impact on the arrival rate together with an aggregate of cumulative disappointments in the environment. This aggregate also has a positive impact on both the probability for a generated consumer to hoard and steal. As a note, these probabilities can be affected by communication actions, here represented by binary variables in the bottom right of Figure 4.

Figure 4. Systemic effect on arrival rates for food stores and consumer behaviour
As for stock levels, a schedule is defined to check the stock levels of products three times per day, if the stock level is below the reorder level, products are supplied with a reorder size depending on store size. A source block is used to inject initial stock levels and the supplied products (as entities). Stocks are modelled using queue blocks, the queues for perishable food products, enable ‘exit on a timeout’ to model expiry of products. Figure 5, shows the flow chart logic for the supply food products group “Fish and seafood”.

**Figure 5. Flowchart of the food supply process**

![Flowchart of the food supply process](image)

The dependency of available fuel for suppling stores with products and the dynamics involved is illustrated in Figure 6. The effect of lack of availability of fuel (due to the payment disruptions) and increased number of food products deliveries to stores on the probability of a delivery to reach its destination. As the number of gas stations that cannot serve its customers increases, the available fuel decrease and the delivery probability along with it.

**Figure 6. Systemic effect on food supplies delivery. The aggregate variable “deliveryProb” is the probability of a delivery to a food store to reach its destination**

![Systemic effect on food supplies delivery](image)

Figures 7 below show some of the statistics on the food store level; cumulative amounts of payment disappointments, product disappointments, successful purchases and cash, Swish and offline payments made over time (top), and details for sold, expired, and stolen amounts (bottom).
2.2.3 Gas Station Agents

A total of 58 gas stations, loaded from a database table that provides the following parameters:

- Retailer category: (4 leading retail groups, others).
- Type of station: (Service – gas station – of which 29 are automated/unmanned)
- Opening and closing times (manned stations).
- Station information, location, latitude and longitude.
- Average daily traffic / visits.

Additional parameters:

- Bank account (bank agent)
- Capacity (Gasoline95, Gasoline 98, Diesel)
- Retail (pump) price (Gasoline95, Gasoline 98, Diesel)
- Reorder level (Gasoline95, Gasoline 98, Diesel)
- Reorder size (Gasoline95, Gasoline 98, Diesel)

State variables:

- Status (open, closed, temporarily unavailable, out of business)
- Availability of payment options: card, cash, Swish and offline payment
- Number of security guards.
Running variables:

- Generated vehicles (station visits) count.
- Station bank account balance (aggregated card/Swish payments)
- Amount of cash in a store (aggregated cash payments)
- Store credit balance (aggregated offline/credit transfer payments)
- Quantity stored (Gasoline / Diesel).
- Successful fueling count
- Disappointments count (vehicles have fuel)
- Disappointments count (vehicles with no fuel)
- Number of supplies, sold quantities, and stock levels (Gasoline95, Gasoline 98 and Diesel).

Figure 9, shows the flowchart of the gas station process, in which supply and fueling is modeled using the Fluid Library, while generation of vehicles and fuel tankers is modelled using the Process Modeling Library.

Figure 8. Flowchart and visualization of the gas station process

- Consumer vehicles are generated with an arrival rate based on the average daily traffic/visits for each gas station. The arrival rate varies according to time of the day and it equals zero out of the opening times (for manned stations).
- In the baseline scenario, we assume that all consumers can pay by card, about a 10% use cash (available in manned stations). In the worst-case scenario, no payment options are available at unmanned stations, so all visits end as disappointments, where some vehicles are already out of fuel and get stuck at the station (for one day). The same for manned stations, except that it is possible to pay with cash. The probability to get cash changes between a maximum of 0.6 and a minimum of 0.1 during the recurrence time of refilling ATMs and removing cash from stations. Figure 9 shows the system dynamics model for the probability of a vehicle owner getting cash.
Figure 10, shows the fuel supply model, with a reorder level of 3m³ for the gasoline/diesel tank and Figure 11, shows the gas station statistics, including: (a) Vehicles count (gas station visits), count of successful fueling and disappointments; (b) numbers of card, cash, Swish and offline payments made; and (d) Stock levels and sold amounts of fuel (Gasoline 95, Gasoline 98, Diesel).
2.2.3.1 Related Dynamics

Figure 12 illustrates a systems dynamics involved in consumer generation and their arrival rates at open gas stations and that an increased number of non-serving gas stations pushes the customers to other open stations, i.e. the aggregate of cumulative disappointments due to inability to fuel in the environment has a positive but delayed effect on the arrival rate.

Figure 12. Systemic effect on arrival rates for gas stations. The aggregate “disappointmentG” affects the arrival rate at gas stations
### 2.2.4 Response Actions

The store strategy is defined by the relative importance of three factors: profits, sales volume (market share) and customer satisfaction. The appropriate weights are determined by the store management (Baydar, 2003). Figure 15, shows the implemented response actions for food stores, including:

(a) Closing and opening stores  
(b) Changing opening times  
(c) Adding payment alternatives (Swish, Offline/Invoice payments)  
(d) Changes in supply of specific food products (reorder size or stop supply) and changing pricing (making promotions or raising prices).

These actions can be implemented in various food stores sizes; large stores (Hypermarkets, Megastores and supermarkets) or small stores (Minimarkets and convenience stores), and for a selected percentage of these groups.

**Figure 13. Food store actions**

Gas station actions:

(a) Closing and opening stations  
(b) Adding payment alternatives (Swish, Offline/Invoice payments)  
(c) Changing fuel prices (either promotions or increasing price)

These actions can be implemented in Manned or Unmanned gas stations, Stations belonging to different fuel retailing companies, and for a selected percentage of these groups.

Communication actions:  
Public communication of information with some presumed efficiency.

(a) Information about the card payment disruption
(b) Information about availability of Swish as an alternative payment method
(c) Information about availability of Offline/Invoice payment.

Security-related action:
Increasing the number of security guards at food stores and gas stations.
Figure 16, shows gas station actions, communication actions and security-related actions.

Figure 14. Gas station actions

RESULTS AND DISCUSSION

The design of the simulation model involves an implementation of impacts of each and every action, based on interviews and discussions with key representatives from the different societal processes simulated. Even as we as designers know the expected impact of an action, the playing sessions should reveal how the different actions in combination fall out. In addition, actions can be implemented at different points in time (pauses for action – Day 1 to Day 10 of the scenario), which results in a large number of alternative strategies.

The whole idea behind involving real societal actors in role-playing game is to let their expertise and value frames guide the selection and time-planning of combinations of actions.

Moreover, not only the selection of actions as such is of interest, but also the motivation and reasoning behind. Therefore, the teams who play need to motivate the timing and selection of actions before they are implemented in various playing rounds and the collection of these motivations is seen as a crucial element of the simulation-game.

By coupling a role-playing games and a computer simulation, a powerful gaming simulation environment is created. Actors, as game participants, can collaborate or compete with each other in different rounds, enter their decisions in the simulation and receive the output of the simulation as input in their next playing round. As such, participants can experience role play and impacts of their decisions over time. The participating decision makers can compare intended consequences with
unintended and unexpected consequences and create a deeper understanding of the system as a whole and the behaviour of other game participants.

The model has direct correspondence between the agents in the model and real-world actors. This would also support the design of the role-playing game and the conversion of objects, agents and rules included in the ABM into the game support, players and roles. The agents in each agent set reflect a variety in parameters, preferences and rules of action to allow for different behaviours by different agents.

3.1 Simulation Outcomes and Resilience Assessments

Based on the SysRes model, resilience assessments are guided by identification of the vulnerabilities of the system, effects of events and actions and assessment of damages resulting from payment disruption. Resilience functions of anticipation, monitoring, response, recovery, learning, and self-monitoring, aim to cope with the disruption scenario and protect the core values of the system. An evaluation of these function is based on comparing the outcomes of the gaming simulation run with the outcomes of both the baseline and the worst-case simulation runs.

Table 1, provides a sample action plan for the gaming simulation run- a list of actions chosen by the team at various decision pauses or different points of simulation time in hours.

| DecisionPause | Time (Hours) | Action description                                | Value |
|---------------|--------------|---------------------------------------------------|-------|
| Day 1 – 15:00 | 33           | Municipality comm. info. about disruption          | 70%   |
| Day 2 – 06:00 | 48           | Use Swish - Hypermarkets                          | 100%  |
| Next morning after disruption | | Use Swish – Megastores                           | 100%  |
|               |              | Use Swish - Supermarkets                          | 100%  |
|               |              | Use Swish – Minimarkets                           | 100%  |
|               |              | Use Swish - Convenience stores                    | 100%  |
|               |              | Use Swish - Manned stations                       | 100%  |
|               |              | Municipality comm. info. Swish availability       | 80%   |
| Day 4 – 06:00 | 96           | Close unmanned stations                           | 100%  |
|               |              | Use Offline payment - Manned stations             | 100%  |
|               |              | Use Offline payment - Minimarkets                | 100%  |
|               |              | Use Offline payment - Convenience stores          | 100%  |
|               |              | Increase security guards - large food stores to: | 60    |
|               |              | Increase security guards - small food stores to:  | 10    |
| Day 6 – 06:00 | 144          | Use Offline payment - Hypermarkets                | 100%  |
|               |              | Use Offline payment - Megastores                  | 100%  |
|               |              | Use Offline payment – Supermarkets                | 100%  |
|               |              | Open unmanned stations                            | 50%   |
|               |              | Use Cash – Unmanned stations                      | 50%   |
|               |              | Municipality comm. info. Offline availability     | 70%   |
|               |              | Increase security guards - gas stations to:       | 30    |
|               |              | Increase security guards - large food stores to:  | 90    |
|               |              | Increase security guards - small food stores to:  | 20    |
Figures 17 and 18 provide the simulation outcomes on Day 4, 06:00, for food stores and gas stations respectively.

Figure 15. Food stores indicators – Day 4

Figure 18 (top), provides a record of Open/Closed food stores, availability of payment options, consumers visits, and a number of security-related indicators (e.g., number of stores with large amount of cash and number of security guards).

Figure 18 (bottom), provides outcomes of the baseline simulation run (in green color), worst-case simulation run (in red color), and the current simulation run (in black color).

We can notice the effects of the implemented actions so far, as follows:

- Increase in store visits and successful purchases compared to worst-case scenario
- Much less payment disappointments due to introduction of Swish payment option.
- More product disappointments because of less product supplies (as a consequence to unavailability of fuel).
- Purchases made using Swish payments, which experienced a breakdown at simulation time of 84 hours, due to its limited capacity (when the number of simultaneous Swish transactions reaches some threshold).
- Improvement in sales, amount of sold products and expired products comparing to worst-case simulation run.
Similarly, from Figure 19, we can notice the effects of the implemented actions, as follows:

- Less visits to unmanned stations, leading to less disappointments, while more visits to manned stations and less disappointments because of introduction of Swish payment option.
- Sales improved slightly compared to worst-case scenario.

Food stores indicators and gas stations indicators of the simulation outcome on Day 10, 06:00, are presented in Figures 19 and 20 respectively.

Figure 16. Gas stations indicators – Day 4

Figure 17. Food stores indicators – Day 10
3. CONCLUSIONS

In this paper we have presented a design and an implementation of an agent-based simulation model of the everyday payment system, simulating the consequences on food stores and fuel supply in the case of payment system disruption. Consumer agents are, relative to the simulated environment, non-persistent agents and generated at the entries of food stores and gas stations based upon dynamic arrival rate parameters, simulating cascading effects of payment system disruptions throughout the supply chain of food, cash, and fuel. The payment disruption is modelled as an escalating crisis scenario, where an escalation feedback loop between global environment variables and the fates and emergence of the generated consumer agents. This is a promising approach for societal simulation, enabling for simulation of an escalation crisis scenario with relatively large simulated populations running on conventional desktop computers.

The simulation model is implemented in the AnyLogic software, enabling for a group of human game players to control actions of food and gas station agents in order to collectively remediate the situation and investigate collective resilience of various strategies. The societal resilience is reflected by comparing environmental running variables over time in the simulated society under a disruption scenario against the same variables in a simulation run when there is no disruption. This enables for resilience assessment to the degree of to what extent actions made by game playing actors facilitates the environment variables to close in upon their values in a no-disruption scenario. It is the ambition of the project which within the developments reported on in this paper, that the organizations and actors that need to collaborate and coordinate their activities to cope with disturbances in the payment system can utilize the simulation as a foundation for effective learnings on the complexities of collective resilience consistent with the SyRes model.

DATA AVAILABILITY

AnyLogic cloud is an online platform to access, run and download the model source files. The simulation model is available on AnyLogic cloud and can be accessed via the URL: https://cloud.anylogic.com/model/61d56c76-3cf3-448f-9ec7-834a94e04dd6?mode=SETTINGS

Figure 18. Gas stations indicators – Day 10
CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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REFERENCES

Adam, C., & Gaudou, B. (2017). Modelling human behaviours in disasters from interviews: Application to Melbourne bushfires. *Journal of Artificial Societies and Social Simulation*, 20(3), 12. doi:10.18564/jasss.3395

Adam, C., Taillandier, P., Dugdale, J., & Gaudou, B. (2017). BDI vs FSM agents in social simulations for raising awareness in disasters: A case study in Melbourne bushfires. *International Journal of Information Systems for Crisis Response and Management*, 9(1), 27–44. doi:10.4018/IJISCRAM.2017010103

Ansell, C., Boin, A., & Keller, A. (2010). Managing transboundary crises: Identifying the building blocks of an effective response system. *Journal of Contingencies and Crisis Management*, 18(4), 195–207. doi:10.1111/j.1468-5973.2010.00620.x

Barreteau, O. et al. (2003). Our companion modelling approach. *Journal of Artificial Societies and Social Simulation*, 6(1).

Baydar, C. (2003). Agent-based modeling and simulation of store performance for personalized pricing. In *Proceedings of the 2003 Winter Simulation Conference*, 1759-1764. doi:10.1109/WSC.2003.1261630

Bedford, P., Millard, S., & Yang, J. (2005). Analysing the impact of operational incidents in large-value payment systems: A simulation approach. In *Liquidity* (pp. 247–274). Risks and Speed in Payment and Settlement Systems – A Simulation Approach.

Bergström, J., van Winsen, R., & Henriqson, E. (2015). On the rationale of resilience in the domain of safety: A literature review. *Reliability Engineering & System Safety*, 141, 131–141. doi:10.1016/j.ress.2015.03.008

Boin, A., & McConnell, A. (2007). Preparing for critical infrastructure breakdowns: The limits of crisis management and the need of resilience. *Journal of Contingencies and Crisis Management*, 15(1), 50–59. doi:10.1111/j.1468-5973.2007.00504.x

Dray, A., Perez, A., & Jones, P. (2006). The AtollGame experience: From knowledge engineering to a computer-assisted role playing game. *Journal of Artificial Societies and Social Simulation*, 9(1).

Etienne, M., Cohen, M., & Le Page, C. (2003). A step-by step approach to build-up land management scenarios based on multiple viewpoints on multi-agent system simulations. *Journal of Artificial Societies and Social Simulation*, 6(2).

FSPOS. (2012). *The flow of payments in Sweden – How it works*. FSPOS.

Galbiati, M., & Soramäki, K. (2011). An agent-based model of payment systems. *Journal of Economic Dynamics & Control*, 35(6), 859–875. doi:10.1016/j.jedc.2010.11.001

Gilbert, N. (2008). *Agent-based models*. SAGE Research Methods (No. 153).

Gupta, S., & Gentry, J. W. (2019). ‘Should I Buy, Hoard, or Hide? Consumers’ responses to perceived scarcity. *International Review of Retail, Distribution and Consumer Research*, 29(2), 178–197. doi:10.1080/09593969.2018.1562955

Hafgren, H., & Wikander, S. (2015). Market Report, Food – Focus on the Swedish market. Chamber Trade.

Hagen, J. M. (2016). Cyber security – The Norwegian way. *International Journal of Critical Infrastructure Protection*, 14, 41–42. doi:10.1016/j.jcip.2016.05.002

Johansson, B., Jaber, A., & van Laere, J. (2018). The lack of preparedness for payment disruptions in local community core businesses. *Proceedings of the 15th International Conference on Information Systems for Crisis Response and Management*, 904-913.

Johansson, B., van Laere, J., & Berggren, P. (2017). Using simulation games to assess critical infrastructure resilience in case of payment disruptions. *Proceedings of the 7th Resilience Engineering Association (REA) Symposium.*
Lundberg, J., & Johansson, B. (2015). Systemic resilience model. *Reliability Engineering & System Safety, 141*, 22–32. doi:10.1016/j.ress.2015.03.013

Lundberg, J., & Lundberg, S. (2010). Retailer choice and loyalty schemes—Evidence from Sweden. *Letters in Spatial and Resource Sciences, 3*(3), 137–146. doi:10.1007/s12076-010-0044-6

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation, 4*(3), 151–162. doi:10.1057/jos.2010.3

Mrotzek, M., & Ossimitz, G. (2008). Catastrophe archetypes - using system dynamics to build an integrated systemic theory of catastrophes. *Proceedings of the 2008 International Conference of the System Dynamics Society.*

Riksbanken. (2019). *Så betalar svenskarna* [How Swedes pay]. https://www.riksbank.se/sa-betalar-svenskarna-2019

van Eeten, M., Nieuwenhuis, A., Luijf, E., Klaver, M., & Cruz, E. (2011). The state and the threat of cascading failure across critical infrastructures: The implications of empirical evidence from media incident reports. *Public Administration, 89*(2), 381–400. doi:10.1111/j.1467-9299.2011.01926.x

van Laere, J., Berggren, P., Gustavsson, P., Ibrahim, O., Johansson, B., Larsson, A., Lindqwister, T., Olsson, L., & Wiberg, C. (2017). Challenges for critical infrastructure resilience: cascading effects of payment system disruptions. *Proceedings of the 14th International Conference on Information Systems for Crisis Response and Management*, 281–292.

van Laere, J., de Vreede, G. J., & Sol, H. G. (2006). A social simulation game to explore future coordination in knowledge networks at the Amsterdam police force. *Journal of Production Planning and Control, 17*(6), 558–568. doi:10.1080/09537280600866611

Walker, W. E., Giddings, J., & Armstrong, S. (2011). Training and learning for crisis management using a virtual simulation/gaming environment. *Cognition Technology and Work, 13*(3), 163–173. doi:10.1007/s10111-011-0176-5

Wooldridge, M. J. (2000). *Reasoning about rational agents*. MIT Press.

**ENDNOTES**

1. http://spbi.se/statistik/volymer/marknadsandelar/, http://spbi.se/statistik/forsaljningsstallen/
2. Anylogic 8.3.3 University Researcher Edition https://www.anylogic.com/downloads/
3. Runtime calibration can be used to increase the difficulty of the game play in a sequence of games.
4. Swish is a mobile app launched through a collaboration between the Swedish major banks. It allows consumers to use their mobile phones to make payments and transfer money to someone else’s bank account.
Aron Larsson was born in Umeå, Sweden, in 1976. He is MSc in computer engineering and PhD in computer and systems sciences from Mid Sweden University, Sundsvall, Sweden, from 2004 and 2008 respectively. His primary research interest is computer-based decision support for complex societal problems involving uncertainty and goal conflicts.

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