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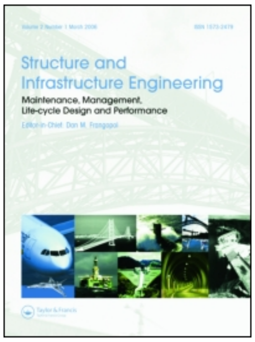
DOI
10.1080/15732479.2016.1212902

Publication date
2016

Document Version
Final published version

Published in
Structure and Infrastructure Engineering

Citation (APA)
van Riel, W., Post, J., Langeveld, J., Herder, P., & Clemens, F. (2016). A gaming approach to networked infrastructure management. *Structure and Infrastructure Engineering*, *13*(7), 855-868. https://doi.org/10.1080/15732479.2016.1212902



Structure and Infrastructure Engineering
Maintenance, Management, Life-Cycle Design and Performance

ISSN: 1573-2479 (Print) 1744-8980 (Online) Journal homepage: http://www.tandfonline.com/loi/nsie20

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STRUCTURE AND INFRASTRUCTURE ENGINEERING, 2017
VOL. 13, NO. 7, 855–868
http://dx.doi.org/10.1080/15732479.2016.1212902

A gaming approach to networked infrastructure management

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ABSTRACT
Operational decision-making processes for networked infrastructure management often occur as a multi-actor planning problem, implying these are based on negotiations between different stakeholders in addition to available system quality information. As such, does more accurate data about actual structural condition lead to other or better decision-making? A serious game is introduced, Maintenance in Motion, aiming at investigating the influence of information quality on rehabilitation decisions, for single- and multi-actor decision-making. Players manage drinking water, gas, sewer and street infrastructures. They are to balance their individual goal, cost-effectiveness, with their team utility, increasing overall infrastructure quality to minimise failure while minimising overall public costs. The game design, calibration and solution space are presented.

ARTICLE HISTORY
Received 5 January 2016
Revised 26 February 2016
Accepted 21 May 2016
Published online
8 August 2016

KEYWORDS
Decision-making; maintenance and inspection; conceptual design; cost–benefit ratios; probabilistic models

1. Introduction

Among engineers, it is generally considered that extensive and good quality data about infrastructure performance are most important for making sound decisions regarding infrastructure maintenance. Multiple decision support systems have been developed for various infrastructures to assist managers in optimising their maintenance planning. These systems generally contain a mathematical optimisation procedure (single or multi-objective), a deterioration process and maintenance strategies. These normative decision support tools propose maintenance strategies over time to help the actual infrastructure managers with their decision-making (e.g. Egger, Scheidegger, Reichert, & Maurer, 2013; Liu & Frangopol, 2005; Lounis & Daigle, 2013; Marzouk & Omar, 2012; Sægrov et al., 2006; Tscheikner-Gratl, Sitzenfrei, Rauch, & Kleidorfer, 2015).

The operational decision process, however, often occurs as a multi-actor planning problem, because of preferred integrated rehabilitation of adjacent infrastructures, motivated by reduction of costs and nuisance to traffic and citizens. Each infrastructure has its own technical and functional lifetime, and corresponding rehabilitation strategy in space and time. Nonetheless, these are located on top of or right next to each other. The combination of an overall preference for integrating public works and differences in spatio-temporal rehabilitation strategies causes the involved decision-makers to make compromises about whether, where and when they cooperate. This implies decision-making is based on negotiations between different stakeholders in addition to the data (Allison, 1971; Lindblom & Woodhouse, 1993; Stone, 1988; Sylvan, Goel, & Chandrasekaran, 1990).

As a result, the influence of available information about an infrastructure's performance might become subordinate to other criteria during negotiations (Van Riel, Langeveld, Van Bueren, Herder, & Clemens, 2016). The quality of the underlying data itself, for example, closed circuit television footages to determine structural condition of sewer pipes, has been shown to be error prone (Dirksen et al., 2013; Van der Steen, Dirksen, & Clemens, 2014) and does not allow to predict structural condition. As a consequence, it leaves the involved managers to rely on intuition (Van Riel, Langeveld, Herder, & Clemens, 2014). This leads to the question, does more accurate data about actual a system's structural condition lead to other or better decision-making?

This question has been quantitatively addressed for individual decision-making (Chorus, Arentze, & Timmermans, 2007; Keller & Staelin, 1987), but not for multi-actor settings. Since sewer rehabilitation works are often combined with other public works, a research tool has been developed that incorporates both the concepts of information quality and human interaction. To that end, this paper introduces a first suggestion for such a research instrument in the form of a serious game, 'Maintenance in Motion'. The presented serious game should not be seen as a normative decision support tool to support infrastructure management in practice. Instead, the game is a descriptive instrument to analyse the influence of information and cooperation in the decision-making of infrastructure managers in reality.

2. Serious games: what and why?

The previously portrayed decision-making for urban infrastructures occurs within a complex system. Complexity is defined as consisting of a high number of interacting physical and social elements (Bar-Yam, 1997; Sterman, 2000). This complexity can

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be separated in two types: system and process complexity. System complexity refers to the many interactions between physical infrastructure components and their direct surrounding. System complexity often results in difficulties for structural condition prediction and assessing full effects of decisions being made. Process complexity refers to the many interactions between relevant stakeholders and their interests. Process complexity may cause unpredictable project progress over time due to changing actor interests and opportunities (Mayer, van Bueren, Bots, van der Voort, & Seijdel, 2005).

In order to increase understanding in such complex decision-making environments, methods are needed that incorporate both the concepts of system and process complexity. Serious gaming (or gaming simulation) is a method that allows to do so, where the term 'serious' refers to 'gaming with a purpose beyond pure entertainment'. The game itself can be defined as a rule-based formal system with a variable and quantifiable outcome, where different outcomes are assigned different values, the player exerts effort in order to influence the outcome, the player feels attached to the outcome, and the consequences of the activity are optional and negotiable. The term 'quantifiable outcome' means that the game outcome is unambiguous (Juul, 2003).

Simulation games are a simplification of a part of reality, allowing participants to experiment with decision-making and reflect on the outcomes. These experiences are relevant for a better understanding of how complex social–technological systems work. In such games, multiple people enact a part of reality in order to gain understanding and learn from their experience. This notion of understanding and learning leads to a typology of three game types (De Caluwé, Geurts, & Kleinlugtenbelt, 2012; Mayer & Veeneman, 2002):

- research: the game is a research environment that allows experimental manipulation and observation of players. The game initiator is focused on learning through the game in order to get empirical data or develop theory. The game presented in this paper is a research game,
- learning: the game is an experiential environment that allows the players to learn about the system at hand and
- intervention: the game is an experimental environment in which both researchers and participants can make inferences for real decision-making.

Games have been particularly developed to increase understanding of land-use planning problems for research or training purposes, for example, in agricultural contexts (e.g. Martin, Felten, & Duru, 2011; Speelman, García-Barrios, Groot, & Tittonell, 2014) or urban contexts (e.g. Cecchini & Rizzi, 2001; Mayer, Carton, de Jong, Leijten, & Dammers, 2004; Mayer et al., 2005; Wärneryd, 1975). The game presented in this paper is an urban planning research game. Typically, urban planning games support decision-making in reality, and thus provide a learning environment. These games are usually open games, in which the game outcome is not predefined but discovered during interactions (Mayer et al., 2005).

Open research games typically have an almost unknown solution space, requiring interpretive analysis methods like observations or group discussions. Yet, this hampers reproducibility, systematic comparison and testing of hypotheses about the relation between game outcomes and player behaviour. Closed research games, on the other hand, typically contain relatively small solution spaces, measurable variables and quantitative outcome analysis. These characteristics are relevant for experimental game purposes. Experimental gaming research differs from game theoretical research. Game theory is concerned with the, usually mathematical, analysis of interacting decision-makers. Game theory assumes the decision-makers act perfectly rational and strategically by taking into account their expectation of other decision-makers' behaviour, in order to maximise some utility function (Osborne & Rubinstein, 1994). In contrast, gaming assumes agents are not rational, goals are partly unknown and agents display opportunistic behaviour (Mayer & Veeneman, 2002).

According to game theory, games are competitive or cooperative. Competitive games require players to form strategies that directly oppose the other players in the game, for example, chess. In contrast, cooperative games model situations involving two or more individuals whose interests are neither completely opposed nor completely coincident. The word cooperative is used because the two individuals are supposed to be able to discuss the situation and agree on a rational joint plan of action (Nash, 1953). A third category exists, collaborative games, in which all the participants work together as a team, sharing the pay-offs and outcomes. The game presented in this paper includes collaborative simulation. Collaboration as a team differs from cooperation among individuals in that cooperative players may have different goals and pay-offs where collaborative players have only one goal and share the decision rewards. The challenge for players in a collaborative game is working together to maximise the team's utility (Zagal, Rick, & Hsi, 2006, p. 26).

3. Game design

This section includes a description of the game design process and game calibration methods. Both aspects are commonly absent in literature containing game development.

Designing a simulation game essentially consists of the following steps: analysing the system and problem being addressed, transforming this analysis into a conceptual framework of reality and transforming this framework into a game (Duke, 1980, 2014).

3.1. System analysis and conceptual model

The system and problem to address were analysed from a sewer system perspective, consisting of two steps. First, an overview of current decision-making for sewer pipe replacement was obtained by literature review and interviewing sewer asset managers at Dutch municipalities. Emphasis was put on retrieving the variety of motivations for deciding upon sewer pipe replacement (Van Riel et al., 2014). Second, actual sewer pipe replacement projects were analysed, through interviews, in terms of decision argumentation and decision-making process. This analysis illustrated the variety of trade-offs sewer asset managers had to make, especially when integrating their works with other public works. The most relevant actors were urban planners, street managers, flora and fauna managers and utility service managers. It was found that decision-making in reality for replacing sewer

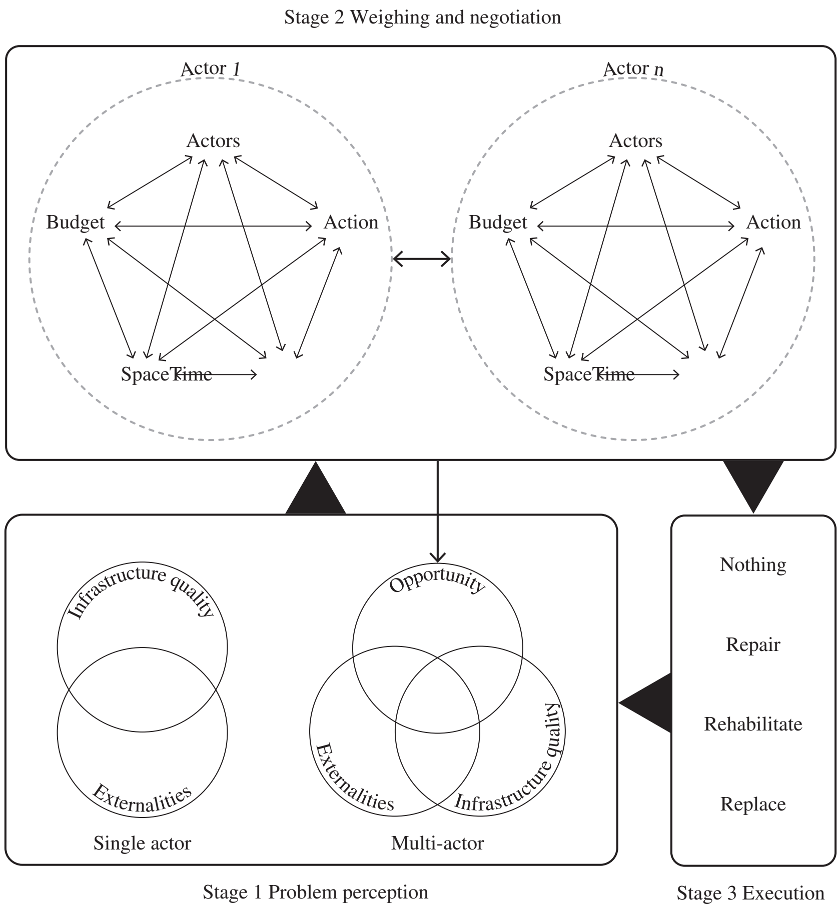

Figure 1. Conceptual model of decision-making for urban infrastructure rehabilitation.

pipes has both rational and political characteristics (Van Riel et al., 2016).

From a rational point of view, decision-making is portrayed as choosing the alternative that reduces the perceived problem most. The political point of view on decision-making focuses on multi-actor settings and processes. Thus, a hybrid conceptual model for the game design is needed that contains both perspectives, reflecting the concepts of system and process complexity. Figure 1 shows this model, combining a rational single-actor model and a multi-actor political model for operational decision-making. Whenever one actor is involved, the model is rational. As soon as two or more actors become involved, the model reflects dynamics of multi-actor decision-making (negotiations, making compromises and seeking opportunities).

Problem perception starts with a combination of analysis of infrastructure quality and externalities such as organisational strategy or national legislation. When a manager perceives a problem in light of his organisational strategy, i.e. presumed or projected insufficient system performance, works are planned. This planning can be time or condition dependent. Then, a weighing and negotiation stage is entered in which the planned work is prepared for potential execution. The involved infrastructure manager balances five interacting elements to choose some action. These elements are:

- actors: Who is available to integrate works with,
- action: What action is needed,
- time: When is an action needed,
- space: How much action is needed and
- budget: What is the available budget?

These five elements are weighed, in light of the problem perception, from which a choice for some action is determined and executed in the last stage. Multiple actors may be involved, possibly influencing each other's weighing process, which causes an actor's problem perception to be redefined through opportunity to integrate works. For example, a sewer manager did not plan any replacement works at a particular location, but still decides to so when he notices road rehabilitation is to be executed there. In other words, actors could display opportunistic behaviour.

3.2. Building the game model

The game's objective is to answer two main questions regarding operational decision-making for public infrastructures. First, what is the influence of information quality on decision outcome? And second, what is the effect of cooperation between involved actors on decision outcome? To answer these questions, an experimental research set-up was chosen that allows hypotheses testing about the relation between game outcome and player behaviour. The core idea of the game is that the players have complete freedom in how to manage their infrastructure, given their predefined objective. Analysis of the positioning and spread of the player performance scores answers the two research questions.

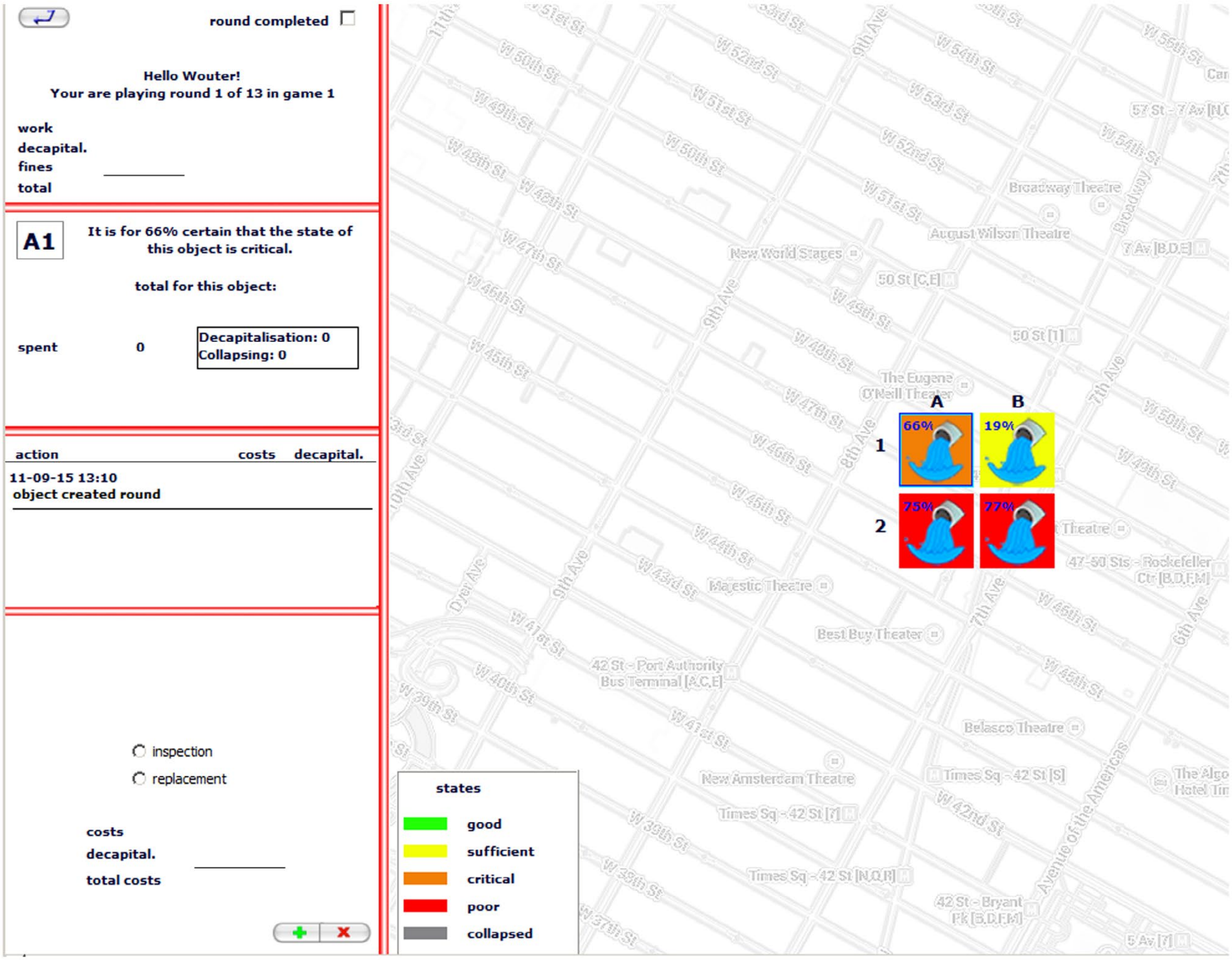

Figure 2. Maintenance in Motion, example of sewer player.

Due to the experimental set-up, the game needs a relatively small solution space, measurable variables and a quantitative outcome analysis. The players should let go of their own day-to-day frameworks for reasoning, in order to focus their decision-making on what is presented in the game itself and limit the influence of intuitive reasoning. In order to maximise the future player sample size, it should be possible to play the game with people with different levels of knowledge or experience in infrastructure management. These considerations for research set-up, framework for reasoning and maximising sample size require the game to be an extensively simplified reality. Moreover, increasing complexity by including a large number of interacting components would put a relatively high cognitive load on the players, which would be unbeneficial for gameplay and results (Sweller, 1988).

Building a game model involves developing a variety of elements. From all game design elements (Duke, 2014), the most relevant for this game are presented here. These are game scenario, game procedures (rules and mechanics) and player involvement techniques.

3.2.1. Game scenario

The game simulates operational decision-making regarding management of an imaginary infrastructure. The game world contains four infrastructures managed by four individual players: gas, sewer, street and drinking water. Each infrastructure consists of separate objects that deteriorate and require management over time. Each object is associated with a random initial quality level, which in turn is associated with a cost for rehabilitation. The goal of each player is to manage its infrastructure as cost-effective as possible. Figure 2 shows a screenshot of Maintenance in Motion.

Since the game intends to address the combined influence of information quality and player negotiations, reflecting system and process complexity, four gaming simulations were set up that are played sequentially:

(1) single-player game with perfect information about infrastructure quality,
(2) single-player game with imperfect information about infrastructure quality,
(3) multi-player game with perfect information about infrastructure quality and
(4) multi-player game with imperfect information about infrastructure quality

The term 'single-player game' means non-cooperation: players play without coalitions, i.e. they are assumed to act independently, without collaboration or communication with any of the others (Nash, 1951, p. 286). In the multi-player or collaborative games, players

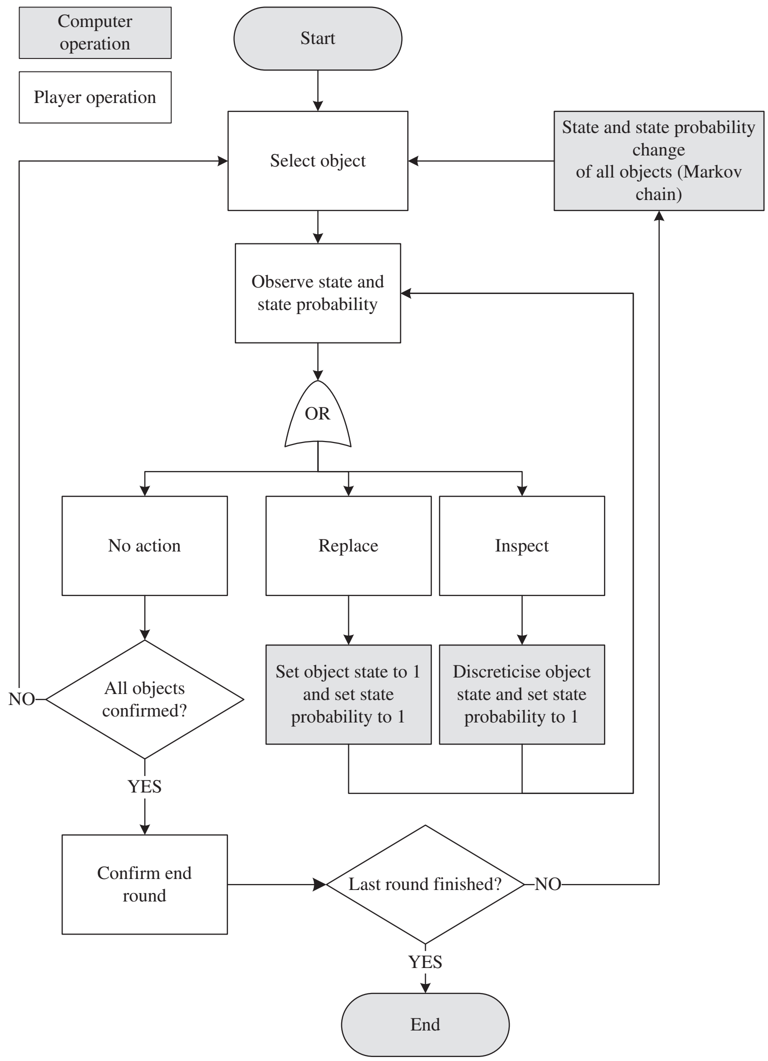

Figure 3. Game flowchart of single player game.

first make non-cooperative choices (planning stage) and then enter a collaborative phase where they discuss potential collective rehabilitation on equal locations in the grid (execution stage). This sequential process is based on the conceptual model in Figure 1.

A detailed version of the gameplay sequence is depicted in Figures 3 and 4, showing the game flow charts for the single- and multi-player simulations. In the multi-actor games, the players are explicitly explained upfront to operate as a single entity, e.g. a municipality, to manage their infrastructure from a public point of view in order to address the main game objective. This concept of a single entity may differ from reality, where multiple entities can have different objectives, and where water companies, sewer operators and gas utilities each aim at achieving their own goals most cost-effectively, despite higher public costs.

Information about infrastructure quality is reduced to an aggregate variable, a colour, which in reality consists of a variety of underlying information sources. The primary function of information about an infrastructure's quality is to plan actions in time to manage its functioning. Information quality is defined as 'the information inherent usefulness to consumers in assessing the utility of an alternative' (Keller & Staelin, 1987, p. 200). As such, perfect information would be 100% certain about both the current and future state of an object in order to time replacement perfectly.

Nevertheless, in order for the game to reflect reality in this regard, perfect information is defined here as having 100% certain information about the objects' current state only, i.e. the observable state equals the actual state. The players can only guess the future state, based on the given information about the deterioration process. Imperfect information is defined here as having uncertain information about the objects' quality, i.e. the observable quality may differ from the actual quality. Note that these definitions of perfect and imperfect differ from the game's theoretical definitions, where perfect information assumes the game participants are fully informed about each other's moves (Osborne & Rubinstein, 1994).

In the multi-player games, useful information to a player relates to the actions of other players as well, next to object state. Therefore, players are informed about each other's actions by a 'joint checkbox' (Figure 5), which facilitates collaboration. Checked implies a player prefers to replace; unchecked implies a player prefers not to. Players can check or uncheck their own checkbox as many times as needed to assess whether cooperation is worthwhile or not.

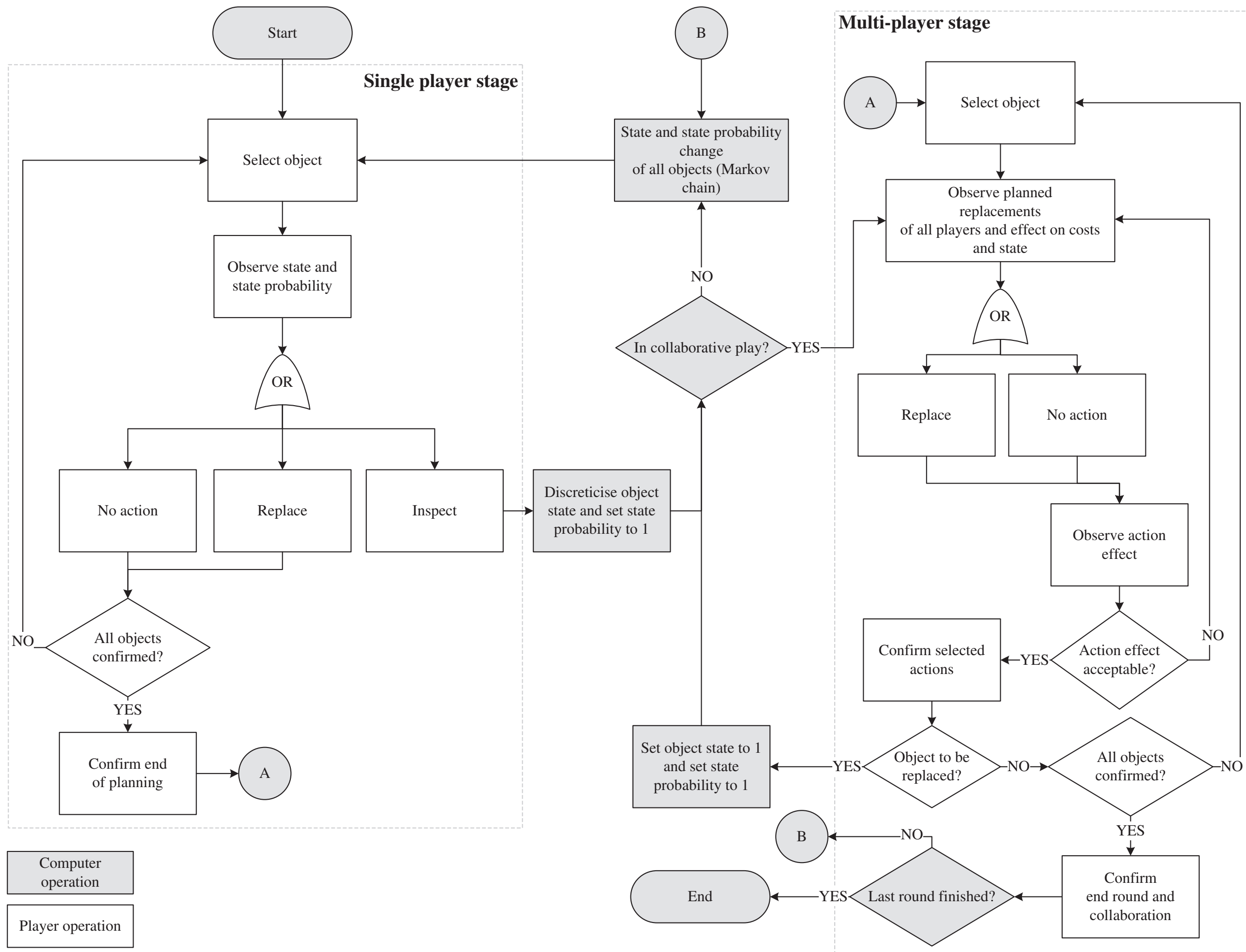

Figure 4. Game flowchart of multi-player game.

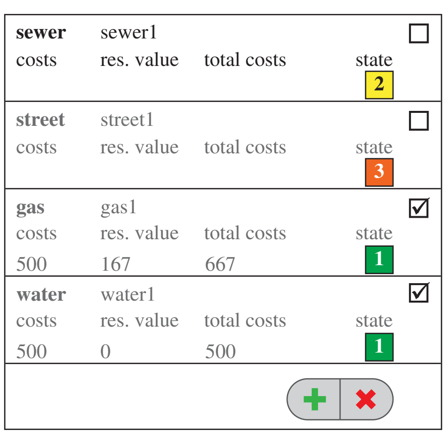

Figure 5. Joint checkbox for group decision support.

A typical Dutch residential street is used as a reference system, which serves as the basis for the physical and financial infrastructure interactions. Figure 6 shows a cross section of this reference system. Gas, drinking water, roads and sewers are considered to be the most important infrastructures in this system. This reference system to base the game on has the following characteristics:

- the total street is approximately 12 m wide,
- gas pipes and water with diameters between 60 and 150 mm, located away from the street axis at 60 to 100 cm below street level and
- sewer pipes with a 300-mm diameter, located at the street axis at least 1 m below street level.

In this reference system, sewer replacement causes the street to be rehabilitated as well, because of the depth and width of the excavated trench and additional works on replacing gully pots and house connections. Street rehabilitation costs amount to 40 to 60% of the total costs. Replacement of gas pipes and water mains often occurs through smaller trenches at which the street is locally repaired, inducing an increased deterioration rate of the corresponding street section. Table 1 lists the included physical and financial interactions. The numbers in Table 1 are generalisations from practical experiences. This reference system is expected to be simple enough for the players to comprehend most interactions, while including enough complexity and dynamics to mimic decision-making in reality. The included complexities are uncertainty about current object state (when presented with imperfect information), an unknown deterioration process, physical interactions between infrastructures and negotiations among the players.

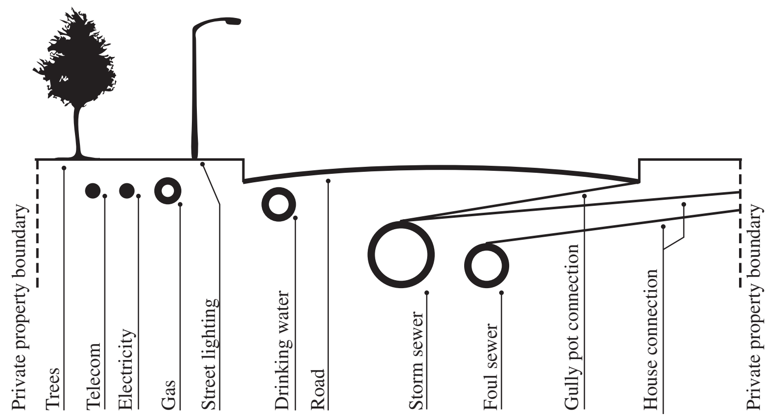

Figure 6. Several networked infrastructures beneath a typical Dutch residential street.

Table 1. Player interaction matrix with financial and physical effects.

	Street replacement	
Combined with	Yes	No
Gas	10% reduction of street replacement costs	Faster object deterioration
Sewer	60% reduction of street replacement costs	600 (fine), street object gets s_1
Water	10% reduction of street replacement costs	Faster object deterioration

3.2.2. Game procedures

3.2.2.1. Deterioration model and available actions. Infrastructures are inspected in practice, according to a predefined frequency, to observe their current condition and deterioration over time. The inspection data are usually summarised as discrete condition classes, underlying a variety of statistical infrastructure deterioration models. Infrastructure deterioration is complex and not completely understood, calling for a stochastic model. Examples are cohort survival models, (semi-)Markov models, logistic regression models and Poisson models (Ana & Bauwens, 2010; Black, Brint, & Brailsford, 2005; Egger et al., 2013; Scheidegger, Hug, Rieckermann, & Maurer, 2011). A Markov model was chosen to model deterioration in the game, because of its general application to a variety of infrastructures, applicability for individual objects, relative simplicity of condition state transition and availability of a condition state probability that is useful for risk-based decision-making (Ana & Bauwens, 2010).

A system containing decision-makers, a set of actions and a state transition function can be described by a Markov decision process (MDP). An MDP is a mathematical model that is concerned with optimal strategies of a decision-maker who must make a sequence of decisions over time with uncertain outcomes. In MDPs, the sequence of actions taken to make decisions assumes that the environment is completely observable and the effects of actions taken are deterministic. If this assumption does not hold, the effects of actions taken are nondeterministic. Decision-making in such environments can be modelled by a partially observable Markov decision process (POMDP). The involved agent cannot observe the actual state, but maintains a probability distribution over the hidden states. This is referred to as the 'belief state'. The basic mechanics for both the MDP and POMDP is that an agent takes a set of actions to control the system at each state in order to maximise some expected reward (Ibe, 2013).

The MDP here is a discrete-time discrete-state probabilistic system that is represented by the tuple (S; A; R; P), where:

- S is a finite set of N states (i.e. condition classes), in this case, $S = \{1, 2, 3, 4, 5\}$. s_1 resembles 'new', s_5 resembles 'failure',
- A is a finite set of K actions that can be taken at any state, in this case $A = \{a_0, a_1, a_2\}$, where a_0 represents 'no action', a_1 represents 'rehabilitate' and a_2 represents 'inspect',
- $\mathbf{R}$ is the reward matrix that varies per action. In this case, no reward is associated with a_0 and negative reward (costs) is associated with a_1 and
- $\mathbf{P}$ is the transition matrix that varies per action. A transition matrix contains the probabilities p_{ij} by which the process moves from state s_i to state s_j in one step. It is assumed that applying action a_1 results in the process moving from a state s_i to s_1 with probability 1. The transition matrix for action a_0 models the autonomous infrastructure deterioration process. Section 4.1 describes the set-up of the transition matrix in more detail.

Time inside the game is modelled as rounds, during which game time stands still. In each round, players can opt for three choices per infrastructure object: inspect, replace or do nothing. Deterioration of the infrastructure objects occurs when going to the next round. This process is unobservable for the players. For the game with imperfect information, an object's true state is also unobservable for the players, leaving the player to rely on the visualised state. Inspection allows them to see the real state.

The state per object that is visualised on the computer screen is a discretisation of the state probability vector $\mathbf{u}$. This discretisation occurs by uniform sampling from the inverse cumulative state probability vector. The state that corresponds with that particular interval is the visualised state for that object.

In simulations with imperfect information, the cumulative state probability is visualised in each object as a percentage. Inspecting objects discretises the state, equally to the aforementioned process, and sets the state probability of the discretised state to 1. Such a process is referred to as a wave function collapse (Stamatescu, 2009). This assumes inspection gives perfect information about the actual object state. For simulations with perfect information, the state probability of the visualised state is always 1. The initial state of each object per infrastructure is randomly drawn from a uniform state distribution, excluding the last state (collapse). This gives an initial state probability vector **u** = [0.25 0.25 0.25 0.25 0].

The game includes a limited number of physical interactions between infrastructures, listed in Table 1. Whenever a sewer object is replaced, the street object is replaced as well. Since the street is locally repaired after gas or drinking water pipe replacement, it is assumed this causes a faster deterioration of the corresponding street section. In the game, this is modelled by equally dividing the first entry in **u** over the other four entries. This change in **u** is attributed once; after running the Markov chain, a new **u** is produced and the object deteriorates at its original rate. In the single-player games, these physical interactions cause the street player to be confronted with random changes to his objects, because he does not have information about the actions of the other players.

3.2.2.2. Rewards. Three types of rewards are included in the game: replacements costs, collapse costs and inspection costs. Replacement costs for the included infrastructures were obtained from unit costs listings as described in practical guidelines for managers to approximate budget levels (CROW, 2004; Grontmij, 2005; RIONED Foundation, 2007). The associated costs ratios were used to set the replacement costs at 500, 500, 1000 and 750 for gas, drinking water, sewers and streets, respectively. Collapse costs were approximated to be five times the replacement costs. Inspection costs were modelled as a percentage of the replacement costs (see Section 4.2), since inspection is not worthwhile if replacing an object would be cheaper.

3.2.2.3. Individual and team performance. A player's objective is to manage his infrastructure as cost-effectively as possible, i.e. ratio input versus effect (Katz & Kahn, 1978). In reality, cost-effectiveness is a multi-dimensional evaluation criterion. In this game, it is limited to the relation between expenditures and object failure, resulting in a two-dimensional player performance or solution space. To mutually compare player performance, the expenditures are not analysed in terms of absolute costs, but by determining the mean residual value of all rehabilitated objects. To do so, a linear residual value scheme per object state is assumed: s_1 1, s_2 2/3, s_3 1/3, s_4 and s_5 0. The number of collapses is normalised as well over the number of objects and played rounds, giving the failure probability. It is assumed that both the residual value score and failure probability score have equal weight.

In the multi-actor simulations, a criterion is needed to reflect team utility or group pay-off. Cost-effectiveness becomes unsatisfactory as performance criterion, because the best strategy per actor depends on the choices of others (Kraus, 1997; Parsons & Wooldridge, 2002; Sandholm, 1999). To this end, the included criteria to reflect group pay-off are Δ *costs* and Δ *infrastructure quality*. These variables represent the difference at the planning and execution stage in the multi-actor simulations, reflecting the difference between individual and collective choices (see conceptual model in Figure 1). The cost difference relates to planned and executed replacements. Infrastructure quality is determined by a modification of the 'infrastructure value index' (Alegre, Vitorino, & Coelho, 2014), where instead of object age, the residual value per object is used to obtain a mean infrastructure quality. This method assumes each object, for all players, has equal weight. Both Δ *costs* and Δ *infrastructure quality* are converted to relative changes to obtain a similar two-dimensional player performance space, but then for group pay-off.

Group pay-off or cooperation rewards are attributed at the multi-actor simulations when players prefer to rehabilitate at the same object location. Cooperation effects can be gained through cooperation with the street player. The reason for this is the street infrastructure deteriorates fastest, and consequently, has most cooperation opportunities. Table 1 lists the player combinations and the associated effects included in the game.

A fine of 600 is administered when a sewer object is replaced and the corresponding street object is not, in order to mitigate the street player seeking opportunistic behaviour. This fine forces the group to judge about the best available options: advancing or delaying replacement with associated consequences. If this fine would not be administered, the street player has incentive to not participate in the gameplay since his street object is replaced for free by the sewer player (see physical interactions in Table 1). The fine is administered to the entire group, because they operate as a single entity. The level of this fine was set at 600, resulting in higher total costs with the street object in state s_1 or s_2 and lower total costs when in state s_3, s_4 or s_5, irrespective of the player combination, but assuming the non-street objects to be in s_4 or s_5. Such a fine does not exist in reality however, but it creates a relevant dynamic gameplay here forcing the players to actively engage in the gameplay.

The players are to balance their individual goal, cost-effectiveness, with their team goal, increasing overall infrastructure quality to minimise collapses while minimising overall public costs. It is up to them how to pursue their goal.

3.2.2.4. Data registration system. The data registration system stores the data relevant for further analysis. Each registered data record contains the following items:

- date and time of record creation,
- game type (information: perfect/imperfect and cooperation: yes/no),
- object id,
- user id,
- round number,
- object state modification action, including 'object created', 'inspect', 'replace', 'no action', 'new round', 'planned replace' and 'collapse',
- object state modification action costs,
- object state before and after object state modification action,
- cumulative state probability vector before and after object state modification action and
- visualised state probability before and after object state modification action.

3.2.3. Player involvement techniques

Having players involved is at least of equal importance for research purposes as having an acceptable game model, because it triggers the players to act enthusiastically. To do so, gaminess is to be maximised as reasonably achievable. Gaminess is defined as 'a quality of liveliness that makes a game enjoyable to players' (Duke, 2014, p. 177). Reducing gameplay complexity to an acceptable level is important to increase gaminess. Reducing complexity is an inevitable consequence of the choice for an experimental research set-up, being a limited set of measurable variables. Section 3.2.2 described part of the applied simplifications to build the game, including the game scenario and state transition model. The following additional game design complexity reductions were implemented:

- the city to manage only contains the infrastructure to manage; there is no interaction with other urban objects, for example, inhabitants, traffic or housing and business districts,
- the infrastructures consist of independent objects with equal importance that are homogenously spaced,
- the number of player cooperation effects is limited to interaction with street objects,
- decision-making argumentation. In reality, infrastructure managers make their operational rehabilitation decisions in light of their long-term strategies, and may be influenced by a large variety of information sources on the operational level (Van Riel et al., 2016). This large variety is reduced to a limited set of arguments in order to address the game objective. These arguments are:
  - current object state and associated replacement costs,
  - prediction about future object state and associated replacement costs,
  - synergy from collaboration with the other players in terms of costs and infrastructure quality;
- players have unlimited budgets, indicating all operational decisions are in line with any possible long-term strategy.

Despite unlimited budget and complete freedom in the choices players can make, players are instructed to pursue their objective, being cost-effective, as good as possible. Reference scores (Section 4.3) allow to test the ambiguity of their management strategies.

4. Game calibration and testing: methods

Calibration is defined here as fine-tuning individual components to assess whether these jointly function as expected, within general margins of acceptability (Duke, 2014, p. 99). This definition differs from the usage of calibration in a modelling context, where it can be defined as 'estimating model parameter values that enable the model to closely match the behaviour of the real system it represents' (Gupta, Sorooshian, & Yapo, 1998).

4.1. Transition matrix

The transition matrix determines the deterioration rate and speed of the gameplay. A matrix was set up for this game with the following assumptions:

- state transitions occur in a positive direction only, thus $p_{ij} = 0$ for $i > j$,
- state transition may occur with more than one state per step,
- the final state s_5 (failure) is an absorbing state, thus $p_{55} = 1$,
- the probability the chain remains in any state, i.e. p_{ii}, other than p_{55}, is equal. (thus, $p_{11} = p_{22} = p_{33} = p_{44}$),
- the cumulative probability of going to any other state equals $1 - p_{ii}$, where the probability of moving to the next state, starting from p_{ii+1}, decreases by a factor 10.

These considerations result in the following matrix:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & 0.1p_{12} & 0.01p_{12} & 0.001p_{12} \\ 0 & p_{22} & p_{23} & 0.1p_{23} & 0.01p_{23} \\ 0 & 0 & p_{33} & p_{34} & 0.1p_{34} \\ 0 & 0 & 0 & p_{44} & p_{45} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

with

$$p_{ij} = \frac{1 - p_{ii}}{\sum_{j}^{n} 10^{j-m}}, \; i = j - 1 \text{ and } j = \{2, 3, 4, 5\} \tag{2}$$

where m is the number of states.

An important parameter of interest here is the time to absorption, being the expected number of steps t_i before the process hits an absorbing state, given that the chain starts in a non-absorbing or transient state. An absorbing state is a state from which the process cannot escape, in this case s_5. To get t_i, the 'fundamental matrix' $\mathbf{N}$ must be obtained from the transition matrix. The product of the fundamental matrix and a vector $\mathbf{c}$ of ones gives vector $\mathbf{t}$, whose ith entry is t_i (Ibe, 2013, pp. 74–75).

$$\mathbf{t} = \mathbf{N}\mathbf{c} \tag{3}$$

with

$$N = \sum_{k=0}^{k=\infty} Q^k = (I - Q)^{-1} \tag{4}$$

where I is a k-by-k identity matrix, with k being the number of transient states. Then:

$$Q = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ 0 & p_{22} & p_{23} & p_{24} \\ 0 & 0 & p_{33} & p_{34} \\ 0 & 0 & 0 & p_{44} \end{bmatrix} \tag{5}$$

as such:

$$N = \begin{bmatrix} \frac{-1}{p_{11}-1} & \frac{p_{12}}{(p_{11}-1)(p_{22}-1)} & -\frac{(p_{13}+p_{12}p_{23}-p_{13}p_{22})}{((p_{11}-1)(p_{22}-1)(p_{33}-1))} & \frac{(p_{14}+p_{12}p_{24}-p_{14}p_{22}+p_{13}p_{34}-p_{14}p_{33}+p_{12}p_{23}p_{34}-p_{12}p_{24}p_{33}-p_{13}p_{22}p_{34}+p_{14}p_{22}p_{33})}{((p_{11}-1)(p_{22}-1)(p_{33}-1)(p_{44}-1))} \\ 0 & \frac{-1}{p_{22}-1} & \frac{p_{23}}{((p_{22}-1)(p_{33}-1))} & -\frac{(p_{24}+p_{23}p_{34}-p_{24}p_{33})}{((p_{22}-1)(p_{33}-1)(p_{44}-1))} \\ 0 & 0 & \frac{-1}{p_{33}-1} & \frac{p_{34}}{((p_{33}-1)(p_{44}-1))} \\ 0 & 0 & 0 & \frac{-1}{p_{44}-1} \end{bmatrix} \tag{6}$$

The transition matrix is equal for all four included infrastructures. Yet, in order to reflect differences in deterioration rate, the number of steps through the transition matrix after finishing a round differs per infrastructure. Therefore, the associated state probability vector is:

$$\mathbf{u}_{i+1} = \mathbf{u}_i \mathbf{P}^{\nu}, \ \nu = \{1, 1, 2, 4\} \tag{7}$$

where ν is a set of relative transition speeds, based on infrastructure lifetimes of 120, 120, 60 and 30 years for gas, drinking water, sewers and streets, respectively. These numbers are based on generalisations from utility managers.

It is now possible to set p_{ij} from Equation (2) to a value that lets the game operate at a speed suitable for all infrastructures. Suitable in this sense means that it is not too fast for the street infrastructure and not too slow for the gas and drinking water infrastructure, given the expected available gaming time.

4.2. Inspection costs and effect

Players may have incentive to either inspect all objects if the inspection costs would be a too small percentage of the replacement costs and to inspect none of the objects if the inspection costs would be a too high percentage. Hence, the inspection costs are to be optimised instead of set a priori, matching the game parameters and dynamics. This minimises the influence of inspection costs on player behaviour.

The reasoning is as follows: in the game, the total inspection costs depend on the costs per inspection and the number of inspections. The number of inspections depends on a player's inspection strategy, being some object state uncertainty threshold that needs to be exceeded before inspection is opted for. Given a replacement strategy and a range of inspection thresholds, the distribution of total costs could be determined (replacement, collapse and inspection) for predefined inspection costs as a ratio of replacement costs. This notion allows to set the inspection costs with the objective of making the total costs independent from the inspection threshold, preventing a player from either inspecting nothing or everything in order to reduce costs. To this end, simulated annealing was applied to the optimisation problem. Simulated annealing is a probabilistic heuristic optimisation algorithm for determining the global minimum of a given objective function (Kirkpatrick, Gelatt, & Vecchi, 1983):

$$\min_{x \in (0,1)} \left(\sum_{i=1}^{n} \left(y - f\left(x_i\right) \right)^2 \right) \tag{8}$$

The objective function here is the residual sum of squares. Prediction y is the mean total costs with inspection threshold of zero, normalised for the number of steps through the underlying Markov chain. Prediction y was determined through Monte Carlo simulation, where the number of Monte Carlo simulations was related to obtaining stable y predictions. The following modelling assumptions were applied:

- replacement strategy: replace at s_4 or s_5,
- information is imperfect: state discretisation does not set the state probability in $\mathbf{u}$ to 1,
- number of steps through the Markov chain (with $\mathbf{P}$ from Equation (1)): 100,
- Markov chain transition speed: 1, 1, 2 and 4 for gas, drinking water, sewer and street infrastructure, respectively and
- relative object replacement costs: 1, 1, 2 and 1.5 for gas, drinking water, sewer and street infrastructure, respectively.

Monte Carlo simulation was applied to obtain a distribution of the optima from the simulated annealing procedure, given the random character of the underlying Markov chain. The same modelling assumptions were applied as for obtaining y. 200 simulations were run, each time with a random starting point from a uniform distribution. The lower and upper bounds were set to 0 and 1, respectively. Based on the central limit theorem, the distribution of global minima should approximate normality.

An object's visualised state may be and state probability is affected by inspecting an object, due to the discretisation procedure described in Section 3.2.2.1. Thus, inspecting an object influences the rate at which an object reaches s_5, because the discretisation procedure is random. Hence, the relation between inspection and object failure probability was assessed. Two cases were analysed: with and without physical interactions (see Section 3.2.2.3). The following modelling assumptions were applied:

- replacement strategy: replace in s_5,
- information is imperfect: state discretisation does not set the state probability in $\mathbf{u}$ to 1,
- inspection is applied,
- number of steps through the Markov chain (with $\mathbf{P}$ from Equation (1)): 100,
- Markov chain transition speed: 1, 1, 2 and 4 for gas, drinking water, sewer and street infrastructure, respectively and
- number of Monte Carlo simulations: 200.

Any change in failure probability over inspection threshold could be explained by the state probability distribution of inspected objects.

4.3. Solution space for random replacement

Regarding the player performance score space in Section 3.2.2.3, a reference solution space was computed, to allow comparison with future gaming results. Two cases were assessed: with and without physical interactions (see Section 3.2.2.3). The reference solution space is based on the following modelling assumptions:

- replacement strategy: replace in s_5 and randomly when not in s_5,
- information is imperfect: state discretisation does not set the state probability in $\mathbf{u}$ to 1,
- inspection is applied randomly,
- number of steps through the Markov chain (with $\mathbf{P}$ from Equation (1)): 100,
- Markov chain transition speed: 1, 1, 2 and 4 for gas, drinking water, sewer and street infrastructure, respectively,
- implementation of residual value scheme from Section 3.2.2.3 and
- number of Monte Carlo simulations: 200.

The solution space for street objects was based on an increased deterioration rate whenever drinking water or gas was to be

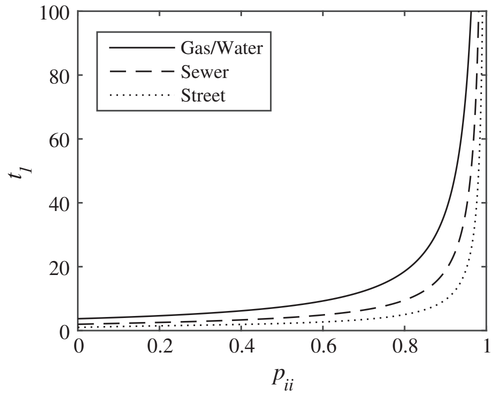

Figure 7. The expected number of steps t_1 before hitting s_5 when starting from s_1 as a function of p_{ii}.

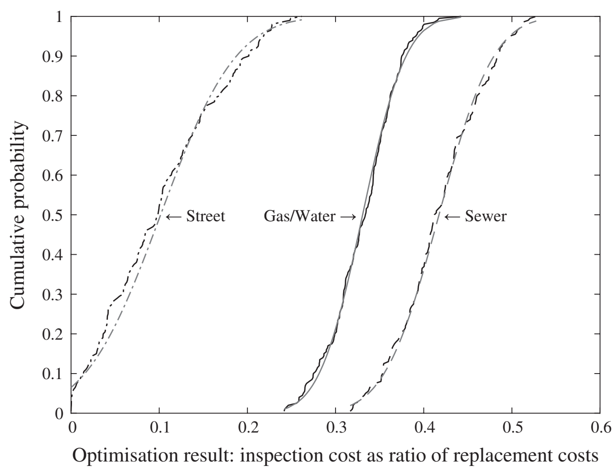

Figure 8. Optimisation result: inspection cost as ratio of replacement costs.

replaced. The increased deterioration rate of street objects due to replacement of gas or water objects was modelled by equally dividing the probability of the object being in s_1 over the probabilities of the other states. The influence of this assumption on the failure probability was determined through sensitivity assessment. To this end, the model output, mean failure probability for street objects, over a range of random replacement probabilities was related to differences in w. w is the state probability vector index, representing the cumulative state probability in $\mathbf{u}$ at s_w. Perturbations were applied one-at-a-time and changes in input were not normalised, because this is ordinal data. The following modelling assumptions were applied:

- $w = \{1, 2, 3, 4\}$,
- replacement strategy: replace in s_5 and randomly when not in s_5,
- information is imperfect: state discretisation does not set the state probability in $\mathbf{u}$ to 1,
- inspection is not applied,
- number of steps through the Markov chain (with $\mathbf{P}$ from Equation (1)): 100,
- Markov chain transition speed: 1, 1, 2 and 4 for gas, drinking water, sewer and street infrastructure, respectively and
- number of Monte Carlo simulations: 200.

5. Game calibration and testing: results and discussion

5.1. Transition matrix

Figure 7 shows the relation between p_{ii} in $\mathbf{P}$ and t_1, where t_1 is the expected number of steps for an infrastructure object to go from s_1 to s_5. A value for all p_{ii}, except p_{55}, of .8 was chosen for the game settings. The combination of the assumed infrastructure lifetimes (see Section 4.1), transition matrix and chosen value of .8 result in each step through the Markov chain resembles approximately six years. This value was obtained by dividing the assumed infrastructures lifetimes (Section 4.1) by t_1 with $p_{ii} = .8$.

5.2. Inspection costs and effect

Figure A1 in Appendix A shows the relation between prediction y and the number of Monte Carlo simulations. From this Figure A1, it can be concluded that 200 simulations are sufficient to obtain stable estimates for y. Figure 8 shows the distribution of the optima per infrastructure, together with the corresponding normal distribution. Based on a visual interpretation, it can be concluded the optimisation results approximate normality, and consequently, the sample mean is the best estimator as a basis for inspection costs. The sample means were .33, .33, .42 and .10 for gas, drinking water, sewer and street infrastructure, respectively (see Figure 8). Consequently, the corresponding inspection costs were set at 165, 165, 417 and 76, assuming replacement costs from Section 3.2.2.2.

The results from Figure 8 are further explained by Figure 9, which shows the relation between the inspection threshold and an object's mean failure probability. Without physical interaction, the mean failure probability decreases with increasing inspection threshold. In other words, a player decreases the deterioration rate when inspecting objects, and consequently, increases inspection costs while decreasing replacement and collapse costs. An optimum for inspection costs exists, as shown in Figure 8, where the total costs are independent from the inspection threshold. In fact, the overall failure probability for street objects is lower when interactions are included, implying that the failure probability for street objects is affected by replacement of sewer objects.

The decrease in failure probability with increasing inspection threshold can be clarified by the state probability distribution of inspected objects, shown in Figure 10. The horizontal axis represents an object's probability of being in the discretised state. The sharp increases in Figure 10 are caused by a relatively large portion (approximately 60%) of state probabilities corresponding with replaced objects. A replaced object has state probability vector $\mathbf{u} = [1\ 0\ 0\ 0\ 0]$. After going through the Markov chain in Equation (7), the first entry in $\mathbf{u}$ of a replaced object becomes approximately .80, .80, .65 and .40 for gas, drinking water, sewer and street infrastructure, respectively. Consequently, given the applied discretisation procedure (Section 3.2.2.1), the probability to remain in s_1 after inspection is .80, .80, .65 and .40 as well for the gas, drinking water, sewer and street object. This explains why the deterioration rate of gas, drinking water and sewer objects decreases with increasing inspection threshold. For street objects, the probability of going to any other state than s_1 is .60, indicating an increase in the deterioration rate due to inspection. On the other hand, the state probability of approximately 25% of the inspected street objects was of .7 or higher. These objects have a .7 probability of remaining in s_1, resulting in a decrease in deterioration rate due to inspection. Overall, the effect of inspection on the failure probability for street objects is small compared with the other infrastructures.

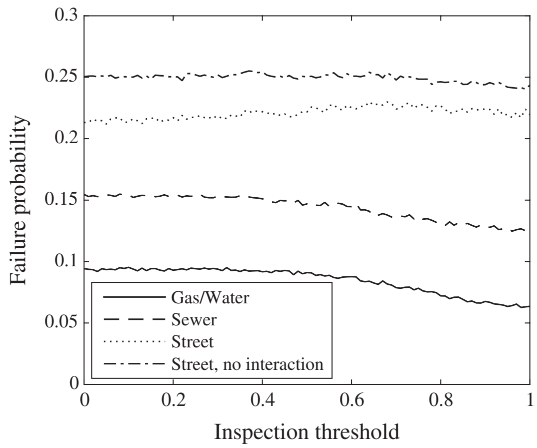

Figure 9. Mean failure probability over inspection threshold from 200 Monte Carlo simulations.

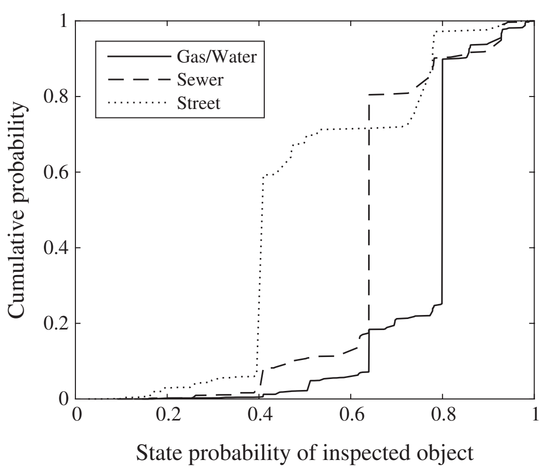

Figure 10. Cumulative state probability distribution of inspected objects from 200 Monte Carlo simulations.

5.3. Solution space for random replacement

Figure 11 shows the two-dimensional solution space for the included infrastructures. Physical interactions cause the solution space of the street player to improve slightly, due to a lower mean failure probability, as also shown in Figure 9. Future gaming results are to be compared with the solution spaces. All future players' scores located in the triangular region left of the confidence interval resemble a more cost-effective management strategy. All future scores located in or right of the confidence intervals resemble an equal or worse strategy than random replacement.

Figure 12 shows the relation between the random replacement probability and a street object's mean failure probability for different w (see Section 4.3). As logically expected, the failure probability increases with increasing w. The results of the sensitivity assessment show changes in w have a relatively small effect on the failure probability, i.e. an alternative solution space would largely overlap the current solution space ($w = 1$ in Figure 11).

6. Lessons learned and future research

The article introduced the serious game Maintenance in Motion. This game intends to investigate the influence of information quality and cooperation between people on operational decision-making for urban infrastructure management. The game design process yielded two main lessons that model or game designers may consider useful.

Lesson 1: 'strip to the bone'. Designing a research game or model calls for identifying most relevant processes needed to answer the research question. This forced the design team to simplify decision-making in reality without omitting its basic elements (information, uncertainty, choice and mutual interaction). This process proved to be challenging and time-consuming, because for each element of decision-making in reality, its core functioning (in itself and in relation to other elements) needs to be understood, checked for relevancy and converted into a conceptual game element. Then it is decided to omit or include it in the game in an alternate manner, simplified even further and connected with the other game elements. As such, simplification of the game, while maintaining its functionality, proved more challenging than increasing complexity.

It is well understood that this particular game simulates an abstraction of reality in which various factors including personal attitude, policies, corporate strategy and budgets are explicitly omitted, in order to force the players to base their choices on

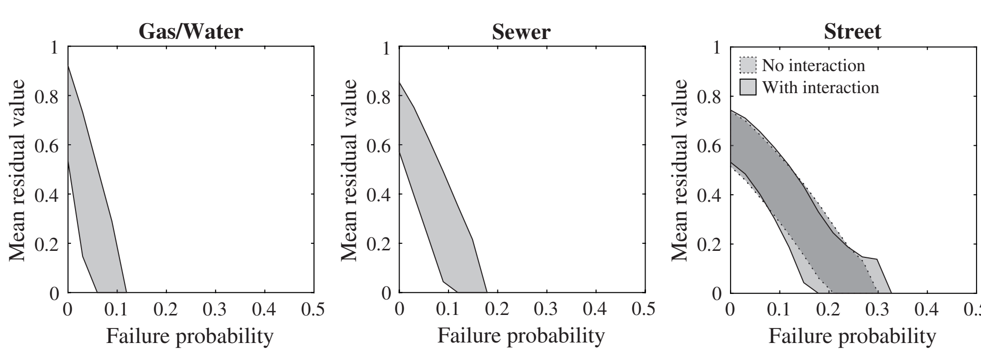

Figure 11. Solution space (95% confidence interval) for random replacement, from 200 Monte Carlo simulations.

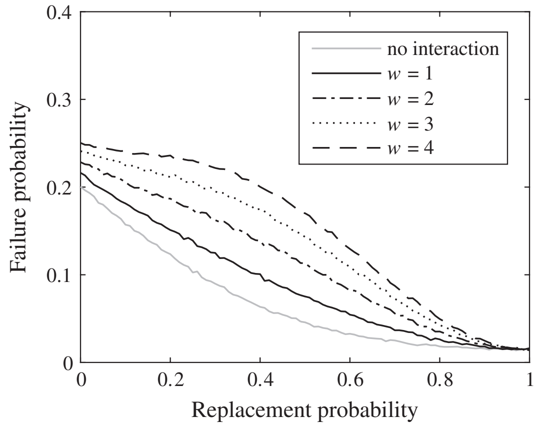

Figure 12. Street object mean failure probability over replacement probability, for random replacement, at different w-values, from 200 Monte Carlo simulations.

presented information and cooperation. Of course, this decreased game realism hampers a player's ability to reflect his gaming experience to his day-to-day work. It is yet unknown whether the future players are willing to accept reality, as presented in the game, before playing according to their objective. Hence, future players require a sound game introduction before playing in order to build trust, acceptance and engagement regarding the game's objective and level of abstraction. An indicator for successively achieving this is to what extent the gained results are explainable or random.

Lesson 2: 'motivate'. Relating to the previous paragraph, all choices for simplification and abstraction of reality should be motivated, because it creates transparency. This is important, because it allows to relate the reliability and validity of game results to the game design. Yet, a detailed game design description is usually neglected or hardly described in literature containing game development and results. Each game is unique in design and outcome generation due to a unique objective and variety of ways to achieve that objective. Thus, consensus about its applicability should not be taken for granted, calling for motivation of game set-up.

Another aspect requiring motivation is parameter settings. Although it is inevitable to assume various parameter values based on experience and intuition, these values do not necessarily match game dynamics. Some game parameters partly lost their physical meaning, because they were tuned according to specific game dynamics. An example from this game is inspection costs. The relation between costs for goods/services in reality is controlled by other processes than it is in the game. Hence, the game requires a relation between costs that matches the dynamics of the game. Parameter calibration and model testing is relevant to foresee the game dynamics and outcome, in order to allow comparison with future results.

Acknowledgements

A special note of thanks goes to Irene Meyer for assisting in developing and programming Maintenance in Motion. The research is performed within the Dutch 'Kennisprogramma Urban Drainage' (Knowledge Programme Urban Drainage). The involved parties are: ARCADIS, Deltares, Gemeente Almere, Gemeente Arnhem, Gemeente Breda, Gemeente 's-Gravenhage, Gemeentewerken Rotterdam, Gemeente Utrecht, GMB Rioleringstechniek, Grontmij, KWR Watercycle Research Institute, Royal HaskoningDHV, Stichting RIONED, STOWA, Tauw, vandervalk + degroot, Waterboard De Dommel, Waternet and Witteveen+Bos.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix A

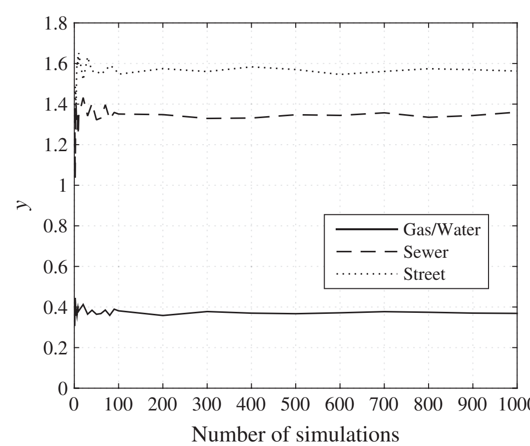

Figure A1. The cumulative mean value for y as function of the number of Monte Carlo simulations (n), as can be seen the values are stable for $n>150$.