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Analysis of information dissemination through direct communication in a moving crowd☆

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ABSTRACT

New generation mobile communication protocols, such as the 5G standards, allow direct communication between devices. This allows to disseminate information directly in a moving crowd. In a safety concept, this information could be used to redirect pedestrians away from danger. We couple state-of-the-art computer models of pedestrian motion and mobile device-to-device communication to build a model of this complex socio-technical system. The model captures the interplay between information dissemination and human behavior. We further harness methods of uncertainty quantification to pinpoint the parameters that most influence the systems functionality for a scenario where pedestrians are redirected. We bundle successful analysis methods to suggest a procedure for future studies. We find that, in our scenario, there are rare cases of information dissemination delayed by shadowing and additional network load from apps, where agents cannot be redirected in time. Our simulation tools and methodology can help to detect such problems and serve as a basis to investigate more complex scenarios and rerouting strategies.

1. Introduction

In urban environments crowds are omnipresent. Guiding them efficiently to ensure their safety and comfort has become one of the pressing problems of traffic engineers, event managers, and other decision-makers. In car-traffic, drivers take an active part by following the advice of navigation systems, and traffic information can be passed from car to car. Pedestrian networking is far less developed. The reasons are many: The system itself is much more complex, e.g. a pedestrian has much more freedom of motion than a road user. Also, there is no mobile application that gathers and transmits information only locally and in a decentralized manner. However, emerging telecommunication standards such as 5G open the opportunity to use local direct communication between crowd members. In this contribution, we want to find out whether or not such direct communication methods are suitable to disseminate saftey-relevant information within a crowd.

This contribution links two areas of research: pedestrian dynamics and mobile communication networks. In the pedestrian dynamics community, terms from the mobile communication area might not be familiar and vice versa. This also entails the possibility of misunderstandings, where technical terms are used differently. Most prominent among those terms is the word ‘mobility’: We are investigating the interaction of human mobility, or locomotion, and communication in ‘mobile’ networks. To avoid confusion, we use the word ‘motion’ as much as possible whenever we refer to the movement of pedestrians in the real world or agents in the simulation. In Table 1, we explain our usage of several key terms.

1.1. State-of-the-art of crowd motion in network simulations

Several authors have investigated crowd motion in the context of network simulations. Grossglauser and Tse (2001) find that the motion of network nodes impacts the performance of wireless communication systems. Bai et al. (2003) introduce a simulation framework which offers the opportunity to analyze the impact of different motion models on information dissemination and routing in mobile ad hoc networks. Two of these models, the random waypoint model and the reference point group mobility model, include motion of pedestrians. In the random waypoint model, agents choose a random destination at every time step, and move towards it. The motion models neither capture the

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Table 1
Key terms for combined crowd locomotion and mobile communication networks.

Term	Meaning
Pedestrian	Person walking through a real world scenario.
Agent	Virtual person walking through a simulated scenario.
Node	Redistribution point for information in a network. In this context, each agent carries one mobile device and thus represents a node.
(Mobile) network	Network with non-stationary nodes. In our scenarios, information is always disseminated from device to device using broadcasts.
Network traffic	Data that is produced by applications that impair the information dissemination of the redirection application in our scenario, e.g. an app for streaming music or videos.
Network load	Synonym for network traffic.
Mobility model	In mobile communication simulation, a mobility model describes the positions and orientations of nodes over time in a Euclidean coordinate system. From this, velocity and acceleration, and also angular position, angular velocity, and angular acceleration data can be computed at the current simulation time.
Dissemination time	Quantity that measures the time until 95% of agents are informed in our example scenario. We use the dissemination time to evaluate the success of our measure to redirect agents.

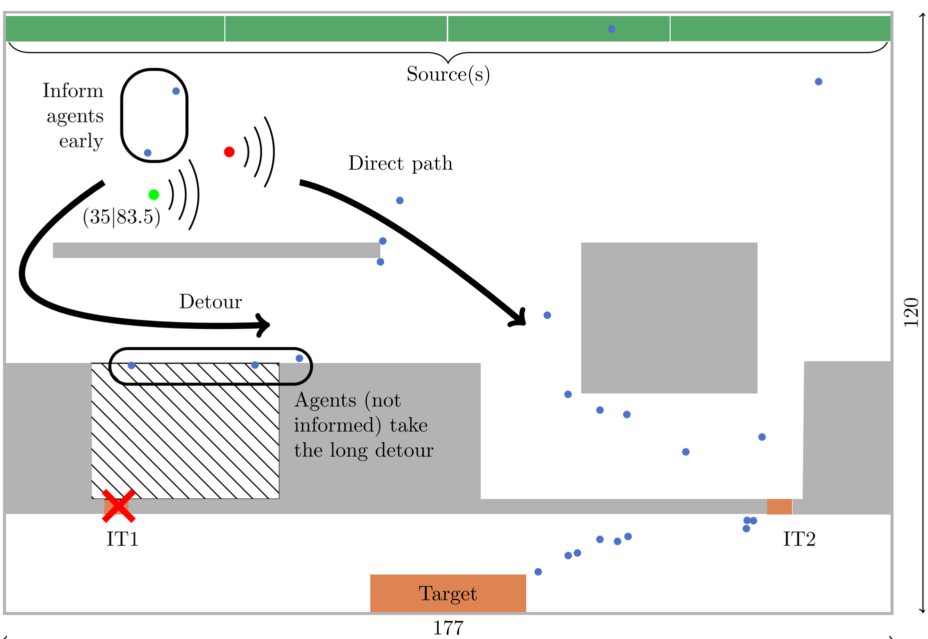

Fig. 1. Research scenario: Agents (dots) coming from a source (top) try to reach a target (bottom). They have a choice between two paths (modeled by the two intermediate targets IT1 and IT2). However, the left pathway is closed (red cross). Agents in line of sight (hatched area) to that pathway become aware of the closure and change their target. Without communication, uninformed agents will continue to follow the unnecessary detour until the closed pathway comes into view. With information through direct wireless communication agents without line of sight are made aware of the closure and directly switch to the right corridor. The simulator does not explicitly model the field of vision or visual perception of an agent, but simply changes the awareness of agents when they reach the hatched area in front of the closure. (Spatial dimensions: $177\,m \times 120\,m$.)

topography, that is, obstacles, nor the interaction between nodes. The reference point group mobility model represents the locomotion of groups, in particular, the motion within a military battlefield where the commander and soldiers form a logical group. In (Bai et al., 2004), the authors find that the path-duration within ad hoc networks is indeed affected by the motion model. At the same time, Jardosh et al. (2003) introduce obstacles in a motion model that affect radio wave propagation. However, they neglect how agents interact. Chaintreau et al. (2007) try to capture the motion behavior of pedestrians in more detail. They use empirical data to model the contact between moving pedestrians gaining a statistical representation of the connectivity pattern of pedestrians from their mobility. Fading, that is, signal attenuation through human bodies in pedestrian crowds, is particularly relevant for communication at high radio frequencies. This has recently been confirmed for 5G mmWave communication in a measurement study and model by MacCartney et al. (2017). Helgason et al. (2014) use LegionSim, a model provided by the pedestrian dynamics community, that reflects the interaction between pedestrians. They analyze the influence of several parameters qualitatively. They find that the topography affects communication within the mobile network. They also find that, in their set-up, the parameters of the motion model, like the free flow speed, have no influence. Chancay-García et al. (2018) use a social force model, a model type that is widely used in pedestrian dynamics research, to generate mobility traces. They observed the number of people arriving and leaving at different times of the day to represent the statistical properties of arrivals in the spawning process. They find that information dissemination depends on the degree of motion and message size. Other approaches to create crowd motion derive microscopic mobility patterns from macro- or mesoscopic view points. Map based models generate trajectories of nodes by intelligent path selections from a map graph that is provided to the system. An example is the working day mobility model (Ekman et al., 2008) in the ONE simulator (Keränen et al., 2009): the shortest paths between two points of interest such as home and work place are selected that match measured mobility patterns of workers. The trajectories are then sampled and some speed distribution along each path is assumed. Hahn et al. (2015) improve the trajectories between two points of interest by, for instance, allowing paths to traverse roads only at designated street crossings. Similar models can be found in Krajzewicz et al. (2014) and in the SUMO simulator as described in Lopez et al. (2018). For further reading we refer to Zhang et al. (2016) who present an overview of mobility models used in communication simulation studies.

Among these contributions, only (Helgason et al., 2014; Chancay-García et al., 2018) profit from the vast progress that has been made in modeling and understanding pedestrian dynamics in the last two decades. The field of pedestrian dynamics offers a number of locomotion models such as social force models, velocity models and optimal steps models that have been validated against empirical data for many relevant scenarios. See (Chraibi, 2012; Dietrich and Köster, 2014; Seer, 2018; Seitz and Köster, 2012; Tordeux and Seyfried, 2014; von Sivers and Köster, 2015) for background reading. Unfortunately, the pedestrian dynamics simulator in Helgason et al. (2014) is not open-source and in Chancay-García et al. (2018) it is not clear whether the simulation model[1] is validated carefully, as it is in the simulation frameworks

Menge (Curtis et al., 2016), *JuPedSim* (Chraibi and Zhang, 2016) or *Vadere* (Kleinmeier et al., 2019). Such validation is necessary to make quantitative predictions (Popper, 2002).

1.2. Guiding crowds through direct communication

So far, however, there has been little discussion about the interaction of crowd motion and mobile networks. Even the more realistic models in Jardosh et al. (2003), Helgason et al. (2014), and Chancay-García et al. (2018) simulate pedestrian locomotion separately and before they simulate the communication in the network. With this, interactions between locomotion and information dissemination cannot be investigated. In particular, one cannot study how information disseminated through the network changes locomotion behavior and vice versa. This is exactly the knowledge gap that we close in this contribution. Our research question is: Is direct device-to-device communication suitable to disseminate information to guide a crowd? Our methods are computer simulation, forward propagation and systematic sensitivity studies on key parameters in the simulation model. These parameters are: the number of agents, the transmitter power and the presence of additional load on the communication system, e.g. from app users.

First, we combine a state-of-the-art open-source mobile networks simulator, OMNeT++, with a state-of-the-art pedestrian locomotion simulator, *Vadere*. The coupling at simulator level through the interface TraCI was recently presented by the authors in Schuhbäck et al. (2019), see Fig. 2. With this, agents could be redirected using information. However, the information dissemination process itself was not captured. For this, one needs to extend the coupling to the model level. In particular, one needs a guidance model, which we will introduce in this contribution. We call the resulting open-source tool *CrowNet* — for **Crow**d **Net**work. It is publicly available at https://github.com/pedestrian-dynamics-HM/crownet-uq-analysis under the following license: GNU Lesser General Public License v2.1.

Second, we construct a scenario where pedestrians are guided away from an exit that might be closed for safety reasons and observe the information dissemination and path changes in the crowd. The goal is to keep the scenario simple while it contains vital aspects of communication: The realistically modeled crowd flow induces an ever changing network. The density of nodes can be varied through the number of agents in the crowd. Walls entail a risk of shadowing. The scale and set-up of our scenario corresponds to a built environment inspired by parts of a train station, see Fig. 1.

Third, we analyze the uncertainties of the simulation model with systematic methods from the field of uncertainty quantification.

The results of our simulations depend on parameters whose exact values are unknown which must be considered when addressing the research question. There are multiple methods to investigate uncertainties (Smith, 2014). In this contribution, we use forward propagation and sensitivity analysis. Forward propagation quantifies the uncertainty of the model output, while sensitivity analysis quantifies the influence of the uncertain parameters (Smith, 2014; Saltelli et al., 2008; Saltelli et al., 2010). Sensitivity indices measure the influence of each parameter on an output quantity of interest. If the index is low, the parameter is not influential. If the index is high, the parameter is influential. So far, quantitative sensitivity analysis has been applied little in the mobile networks and in the pedestrian dynamics community. The use of these methods is limited to some recent studies (Cheng and Monebhurrun, 2017; Dietrich et al., 2018; Gödel et al., 2020; Kurtc et al., 2021). Cheng and Monebhurrun (2017) use sensitivity analysis to gauge the effect of antenna and casing design parameters in a CAD model of a mobile phone on the specific absorption rate (SAR) calculation. SAR is the rate at which energy is absorbed by the phone user's body when exposed to the radio frequency emitted by the phone's antenna. Gödel et al. (2020) and Kurtc et al. (2021) successfully apply sensitivity analysis to identify influential parameters, such as the need for personal space (see Gödel et al., 2020), in pedestrian simulations. We are unaware of any related work where sensitivity analysis has been applied on a mobile network model with direct communication between members of a pedestrian crowd.

Sensitivity analysis as described in Smith (2014), Saltelli et al. (2008), and Saltelli et al. (2010) assumes a deterministic model. Yet, agent-based models of pedestrian motion contain many stochastic elements, from the initial placement of agents to any number of intermediate decisions that simulation tools handle by drawing from some pseudo-random distribution (Kleinmeier et al., 2019). The mobile network models add their own stochasticity. Among the causes are: radio channel modeling based on stochastic radio propagation models, random elements within communication protocols, e.g. random access at the medium access layer, and application layer models, e.g. random inter-transmission intervals of generated data packets. This is indeed a problem for sensitivity analysis, where a deterministic model is assumed. In practice, different approaches can be found to tackle stochasticity in sensitivity analysis. Gödel et al. (2020) and Kurtc et al. (2021) simply eliminate the stochasticity. They (Gödel et al., 2020; Kurtc et al., 2021) repeat the simulation 10 times and average the outcome. The authors (Gödel et al., 2020; Kurtc et al., 2021) state that the number of repetitions (10) was motivated by the results of the convergence analysis method of Ronchi et al. (2014) applied to a simple test scenario. While this approach is pragmatic, it is also computationally expensive. Repeating a coupled crowd-network simulation multiple times becomes infeasible, when the number of samples is large. Also, information may be lost through the averaging process, neglecting once again the variance in model outcomes. What we need is an approach for sensitivity analysis that quantifies stochasticity and, at the same time, reliably quantifies parameter influences.

Hart et al. (2017) differentiates two approaches to considering stochasticity in a sensitivity analysis which are both based on surrogate models. A surrogate model is a simplified version of the simulation model that approximates one or multiple quantities of interest (Smith, 2014). A very simple example is a linear regression. While surrogate models are not new in uncertainty quantification, they have been used little to handle stochasticity. A few specialized approaches for uncertainty propagation have been proposed (Azzi et al., 2019; Binois et al., 2018; Hall et al., 2004; Koenker and Bassett, 1978; Moutoussamy et al., 2015; Plumlee and Tuo, 2014; Zhu, 2020), but none of them has yet become established in practical use. Approaches that quantify stochasticity within a sensitivity analysis are even less available. The authors are only aware of the contributions of Iooss and Ribatet (2009) and Marrel et al. (2012). The idea was firstly presented by Iooss and Ribatet (2009).

The first approach is to, among other things, use the coefficient of determination R^2 of a surrogate model to estimate the influence of stochasticity in the sensitivity analysis. If R^2 is small, stochasticity is large. If R^2 is high, stochasticity is small. Iooss and Ribatet (2009) apply their methodology to an analytical function and nuclear fuel irradiation application using special types of surrogate models, namely, an interlinked generalized linear model and a generalized additive model. Marrel et al. (2012) apply this approach to a biochemistry problem. Unlike (Iooss and Ribatet, 2009), Marrel et al. use Gaussian processes as surrogate models. Although Iooss and Ribatet (2009) and Marrel et al. (2012) apply their approaches successfully to analytical and practical examples, the methodology is not generally applicable. The use of one single surrogate model can lead to loss of information on the system's behavior. This was shown by Hart et al. for an analytic toy example (Hart et al., 2017). This is why Hart et al. propose a second approach,

[1] Chancay-García et al. (2018) refer to the PedSim simulator http://pedsim.silmaril.org which we cannot access (April 2021). However, there are open-source versions of PedSim available, see e.g. https://github.com/srl-freiburg/pedsim_ros (BSD 2-Clause license).

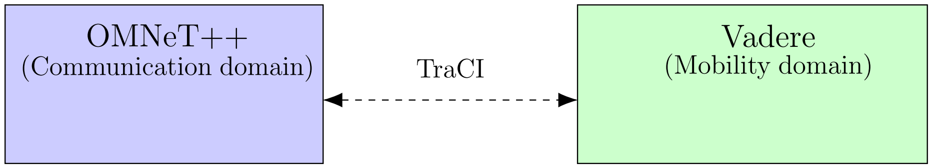

Fig. 2. Simulator coupling (Schuhbäck et al., 2019) of *CrowNet* using Traffic Control Interface (TraCI) to share simulation states. The communication domain is simulated using OMNeT++ in conjunction with the INET framework. The mobility behavior of pedestrians is provided by the *Vadere* framework.

that is, to use multiple surrogate models to compute distributions of the sensitivity indices. Neither of the two approaches (Iooss and Ribatet, 2009; Marrel et al., 2012; Hart et al., 2017) can quantify stochasticity and ensure that the sensitivity indices are indeed reliable at the same time.

We conclude that there is a need for a systematic approach to sensitivity analysis in the fields of pedestrian dynamics and mobile network simulation as well as to their combination. More concretely, we ask: Which methods are suitable to investigate the influence of parameters in our model of reciprocal effects of communication and locomotion? And in particular, how can we deal with the stochasticity of the system? This constitutes a second, methodological research question, which we will tackle. We will scrutinize uncertainty quantification methods from other research fields, modify them where necessary and transfer them to our problem. The goal is to bundle such methods into a sensitivity analysis procedure that works for coupled crowd-network simulators. In particular, we will combine the best of the two approaches that we just discussed.

This paper is divided into six sections: In Section 2, we introduce the simulation framework *CrowNet*. Furthermore, we introduce the methods forward propagation and sensitivity analysis as well as two sub-approaches that handle stochasticity in sensitivity analysis. Section 3 presents the new train station scenario from Fig. 1. We explain the configuration of our new simulation model and how it can be used to analyze information dissemination in a moving crowd. We introduce the three uncertain parameters and the quantity we use to measure the success of the information dissemination. In Section 4, we present and discuss the results of the forward propagation. We use additional simulations to identify possible causes that led to these results. In Section 5, we quantify the influence of the three uncertain parameters. We present a new methodology for sensitivity analysis that is based on bundling existing approches. We apply this methodology to the simulation results from Section 4 and analyze the results in the last part of Section 5. Finally, in Section 6 we interpret our findings, draw conclusions and provide an outlook on future work.

2. Materials and methods

2.1. CrowNet: a coupled crowd-network-simulator

The *CrowNet* simulator couples *Vadere* with OMNeT++ to allow the analysis of interactions between the pedestrian dynamics and mobile networking domains at the simulator level, see Fig. 2.

Vadere offers implementations of several microscopic motion models to simulate crowd behavior. In this contribution we use *Vadere*'s default model: the optimal steps model (OSM), a model type that is well spread within the pedestrian dynamics community. Each agent navigates through two-dimensional space by optimizing a utility function that reflects distance to the agent's target and to other agents. The agent chooses its next foot position at the most favorable location that is within its stride length. 'Stepping' on other agents or obstacles would be heavily punished so that collisions are avoided. See (Seitz and Köster,

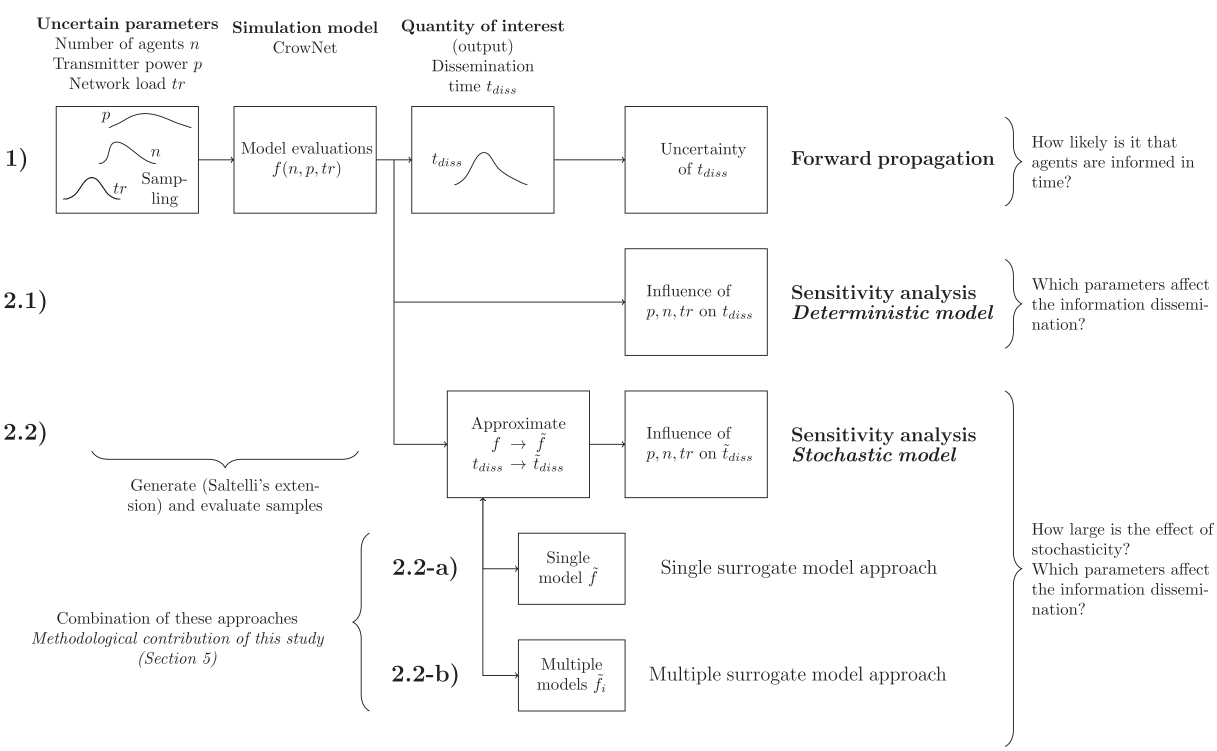

Fig. 3. Method pipeline. We use a bundle of methods to answer the questions: Will agents receive the information in time? How is this affected by uncertain model parameters and stochasticity? For the latter, we propose a new procedure that is based on bundling existing approaches and cross-checking the results.

2012; Kleinmeier et al., 2019) for more detailed descriptions of the model, its verification and validation.

OMNeT++ is a highly modular discrete event simulation library. In conjunction with the INET framework (INET, 2020), it provides a modular communication simulation ecosystem for wired and wirelesses scenarios.

The coupled *CrowNet* simulator is based on our previous work described in Schuhbäck et al. (2019). The basic idea is to use *Vadere* as mobility provider in the mobile networks simulation. This is realized using the 'Traffic Control Interface' (TraCI) (Wegener et al., 2008) provided by SUMO (Lopez et al., 2018). The client-side for interaction with the mobility provider is implemented in the veins project (Sommer et al., 2011). Both simulators run as dedicated processes and communicate via TraCI in a client (OMNeT++) server (mobility provider; here *Vadere*) model. Both simulators retain their simulation loops but synchronize every 400 ms to share their simulation states and thus bidirectionally affect each other. The interval is based on the default update interval of *Vadere*. For a detailed description the reader is referred to Schuhbäck et al. (2019) and Sommer et al. (2011).

The *CrowNet* simulator provides different communication models. Each consists of several sub-models that form a communication stack. In this contribution, we combine established sub-models from the INET framework to model the information dissemination process. We use IEEE 802.11 WLAN in ad hoc mode, the 802.11 DimensionalRadio model, and the corresponding 802.11 DimensionalRadioMedium to simulate the lower layers of the communication stack. To model the path loss, we use the standard log normal shadowing model, implemented in OMNeT++ and cross-validated with the ns-3 simulator (Kuntz et al., 2008). Additionally, we choose the ideal obstacle loss model, where objects in line of sight between nodes block communication entirely. For detailed description of the IEEE 802.11 model, we refer to the corresponding chapters in Virdis and Kirsche (2019) and the INET documentation (INET, 2020).

2.2. Method pipeline

We use a bundle of methods in this contribution. This is necessary, because the information dissemination process is affected by uncertain parameters and stochastic effects. Our quantity of interest is the dissemination time, that is, the time until 95% of the agents in the scenario in Fig. 1 have received the saftey-relevant information. Our parameters are the number of agents in the scenario, the radio transmitter power and the network load, which we will all justify and describe in detail in Section 3. We focus on sampling-based methods only. Forward propagation (Smith, 2014) is used to analyze the uncertainty of the dissemination time t_{diss}, see Fig. 3(1). The influence of the uncertain parameters is quantified in a sensitivity analysis, see Fig. 3(2). Since our simulation model is stochastic, a modified version of sensitivity analysis is used (2.2). In particular, this consists of two sub-approaches (2.2-a and 2.2-b). All of the methods have in common that the simulation model has to be evaluated for different parameter combinations (samples), see Fig. 3. These samples are generated with the robust version of Saltelli's extension (Saltelli, 2002). Saltelli's extension is commonly used to reduce the error of the sensitivity indices (Section 2.2.2) at low sample size. For that purpose, 'cross-samples' are generated from a Sobol sequence. The resulting cross-sampling still represents the initial parameter distributions while correlations between parameters are low (the maximum correlation coefficient is 0.007 in our sampling). We argue that the cross-sampling can be used for forward propagation and sensitivity analysis to reduce the computational effort. Hence, the methods differ in the post-processing only, see Fig. 3.

2.2.1. Forward propagation

Forward propagation determines the uncertainty of the quantity of interest. For a linear function, the uncertainty can be evaluated directly (Smith, 2014). Since our model, *CrowNet*, is neither linear nor available in closed mathematical form, this is not possible. For such models, it is common to use a sampling-based approach (Smith, 2014). That includes sampling the parameter space, running the simulation for each sample, and collecting the quantity of interest for each simulation. The collected model evaluations form an empirical distribution, see Fig. 3. The distribution and its statistical properties are analyzed. The higher the number of samples, the better the true distribution is represented.

2.2.2. Sensitivity analysis

For sensitivity analysis it is assumed that the simulation model is deterministic. That means repeating a sample yields the same results. The simulation model *CrowNet* is stochastic. Repeating a simulation with fixed parameters (but different seeds) yields different results. In this case the model evaluations are not fed directly into the sensitivity analysis, but they are processed in an intermediate step, see Fig. 3. The actual sensitivity analysis remains the same. Before we explain the intermediate step, we briefly introduce the basic idea of sensitivity analysis and the algorithms that we use in this contribution. We are interested in the effect of input uncertainties of the model outcome over the entire range of the parameters, not just the effect of local perturbations. That is, we are interested in global sensitivity analysis. Gödel et al. (2020) gives a brief overview over different types of global sensitivity analysis. So-called variance-based sensitivity analysis is a good choice, if the output does not behave linearly and monotonously on the input (Smith, 2014). The influence of parameters is quantified by so-called Sobol or sensitivity indices. The first-order sensitivity index S_i is defined as ratio of the variance D_i that is caused by the parameter i only, and the total variance of the output D:

$$S_i = D_i / D \tag{1}$$

The total-effect index S_{T_i} is defined as ratio

$$S_{T_i} = D_{T_i} / D \tag{2}$$

where D_{T_i} is the variance caused by the parameter i and its interactions (Saltelli et al., 2010) with the other parameters. If the influence of a parameter is high, the corresponding indices S_i, S_{T_i} are high. The influence is low when the index is low. For the first-order sensitivity index $S_i \in [0, 1]$ holds (Saltelli et al., 2008). For the total-effect index, $S_{T_i} \geqslant 0$ holds (Saltelli et al., 2008).

In a sampling-based procedure, the sensitivity indices are estimated numerically. We approximate the sensitivity indices with the procedure presented in Saltelli et al. (2010). The samples are stored as elements a_{ji} and b_{ji} in the corresponding sample matrices A and $B, i = 1\ldots k, j = 1\ldots N$ where k is the number of parameters, N is the number of simulations. The columns of A and B are used to generate the matrix $A_B^{(i)}$ which contains the columns of A except for column i which is from B. According to Saltelli et al. (2010), D_i and D_{T_i} are estimated with

$$D_i \approx \frac{1}{N} \sum_{j=1}^{N} f(B)_j \left(f(A_B^{(i)})_j - f(A)_j \right) \tag{3}$$

$$D_{T_i} \approx \frac{1}{2N} \sum_{j=1}^{N} \left(f(A)_j - f(A_B^{(i)})_j \right)^2 \tag{4}$$

For these estimates, confidence intervals are bootstrapped (Archer et al., 1997; Saltelli et al., 2010) to get a better understanding on how reliable the estimated indices are. We look at symmetric confidence intervals (Archer et al., 1997).

2.2.3. Approaches to consider stochasticity in sensitivity analysis

Standard sensitivity analysis requires deterministic models. Yet, our simulation model, *CrowNet*, is stochastic. The authors know two approaches (Iooss and Ribatet, 2009; Hart et al., 2017) that try to consider the stochasticity in sensitivity analysis. We briefly introduce the main

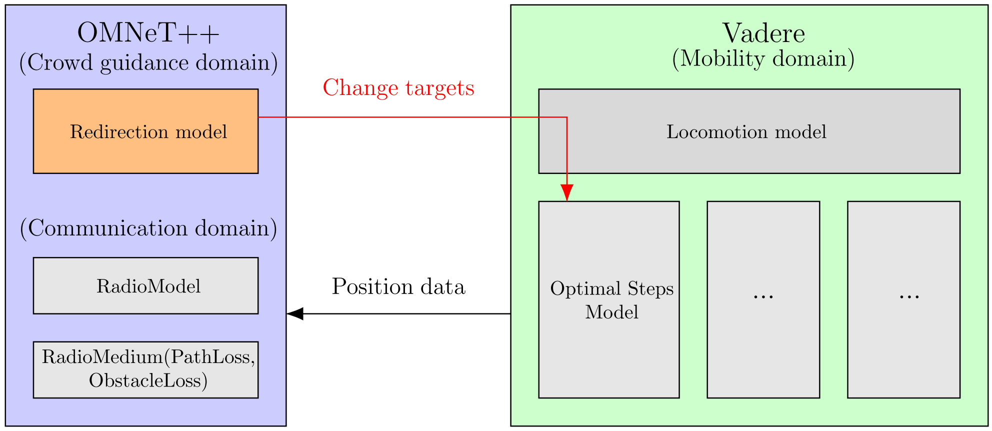

Fig. 4. Modeling interactions between pedestrian dynamics and mobile networks. A new crowd guidance model propagates information that is relevant for pedestrians' path choices through direct communication. Receiving nodes will use this information to trigger a target change of respective agents. This forms a closed loop of mobility and communication models.

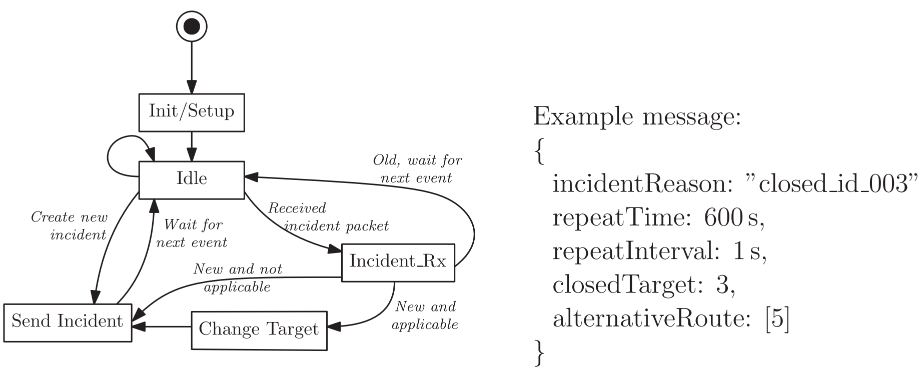

Fig. 5. Simplified finite state machine of application model were some error states are not displayed: The application model waits for an incident message. If an incident is received, the node checks (1) if the specific incident is new or already known, and (2) if the incident is applicable for the current node, that is, if the current target of the agent is mentioned in the incident. If the incident is new and applicable, the node will choose an alternative route that it received in the same message and initialize the re-broadcast process.

ideas of these approaches before we explain, in Section 5, how these approaches can be combined to cross-check the results.

We refer to the first approach as 'single surrogate model approach'. The basic idea is to use a surrogate model instead of the actual simulation model (Iooss and Ribatet, 2009; Marrel et al., 2012). The steps are as follows:

1. Evaluate the simulation model at the sample points (f in Fig. 3).
2. Use these evaluations to construct **one** surrogate that approximates the quantity of interest.
3. Evaluate the surrogate ($\widetilde{f}$ in Fig. 3).
4. Use the surrogate evaluations in sensitivity analysis according to Eqs. (1)–(4).
5. Use the coefficient of determination R^2 to quantify the effect of stochasticity (see e.g. Iooss and Ribatet, 2009; Marrel et al., 2012).

The second approach is presented by Hart et al. (2017). We refer to it as the 'multiple surrogate model approach', because multiple surrogate models are used (Hart et al., 2017):

1. Evaluate the simulation model at the sample points (f in Fig. 3).
2. Use these evaluations to construct $r > 1$ surrogates that approximate the quantity of interest.
3. Evaluate the r surrogates ($\widetilde{f}_i$ in Fig. 3).
4. For each evaluation r_i for $i = 1, \ldots, r$ apply sensitivity analysis according to Eqs. (1)–(4).
5. Analyze the resulting distributions of the sensitivity indices.

Hart et al. (2017) argue that the multiple surrogate model approach is superior, because no information about the stochastic model is lost. They (Hart et al., 2017) show this for an analytical example. However, they do not consider the computational cost to construct multiple surrogate models.

2.3. Software and hardware

The complete source code for the coupled simulator *CrowNet* and the Python code to perform the forward propagation and sensitivity analysis is publicly available on a repository.[2] In our Python code, we use the well tested external python package SALib (Herman and Usher, 2017).

We run 20 simulations in parallel on a server with 80 i7 cores and 250*GB* RAM. The simulation of 2000 samples takes more than 6 days including two restarts of the script that manages the simulations in parallel.

3. A crowd guidance model: interaction between pedestrian locomotion and mobile networks models

The goal of this section is to create a simulation model that redirects a crowd using information disseminated through mobile networks. The model encompasses three steps. First, generate information that is relevant for pedestrian motion. Second, disseminate the information through the mobile network. Third, when information is received, adjust the pedestrians' targets and thus their paths and the motion pattern of the entire crowd. We propose that the three processes each run in a specific domain, see Fig. 4. The crowd guidance domain contains the

[2] https://github.com/pedestrian-dynamics-HM/crownet-uq-analysis.

newly introduced 'Redirection model' that generates messages and triggers the information dissemination process. The actual dissemination process is simulated in the communication domain using established models from the INET module, see Section 2.1. To model the pedestrian dynamics behavior, we use the 'Optimal Steps Model' which is part of the mobility domain. Since the information changes the pedestrians' paths which in turn changes the information dissemination process in the mobile network, the system contains a closed-loop interaction.

3.1. Test scenario: rerouting agents from a closed area

We consider a scenario where pedestrians walk in a built environment that covers an area of size 177 m x 120 m, see Fig. 1. They walk along different routes to reach a destination depicted at the bottom. A gate on one of the paths is suddenly closed which forces agents to detour and use one of the remaining routes. The information of the closure is disseminated through direct communication to all agents, starting from one stationary node[3] in the scenario. Agents receiving this information will re-broadcast the message. This is described in more detail in Section 3.2 and Fig. 5. We assume that agents always change their direction when they have received the information. While this assumption is certainly optimistic, it does not have an effect on whether or not the agents receive the information in time for action. Agents are 'spawned' from four sources (green boxes at the top in Fig. 1). The spawning process follows a Poisson distribution. The Poisson parameter $p = \frac{1}{4}\frac{n}{100s}$ is equal for all four sources. Here n is the average number of agents spawned within 100s. Agents need approximately 100s to reach the target (orange box at the bottom in Fig. 1). After 100s the number of agents in the scenario is almost constant, a steady flow with some fluctuations. At this point, a stationary node (coordinates: x = 35, y = 83.5), starts sending information about the closure to any agent in range. When an agent receives this message, its DetourApp model starts to disseminate the information about the path closure. Also all informed agents change their targets so that they follow an alternative route to the destination. When 95% of the agents have received a text message instructing them to take an alternative route, we consider information dissemination successful, and we stop the simulation to save computational cost.

3.2. A simple redirection model: a crowd guidance model for the test scenario

The communication model consists of several sub-models that form a communication stack. For the lower layers, we use established models from the INET module, see Section 2.1.

The new component is the application model. It manages the logical level of the communication as well as the decision whether agents should change their target or not. Dissemination and interaction are handled in a simple way: we broadcast information without any dedicated ad hoc routing protocol. Messages are passed via a link local broadcast between neighboring nodes. Received messages are passed up to the application model for processing. A finite state machine manages the decisions and triggers re-broadcasts if needed, see Fig. 5. The application model waits for an incident message. If an incident message arrives, the node checks (1) if the specific incident is new or already known, and (2) if the incident is applicable for the current node, that is, if the current target of the node (the destination where the agent is heading) is mentioned in the incident message.

If the incident is new and applicable, the node will choose an alternative route which it received in the same message. Independently, a timer is created for the new incident to be disseminated via broadcast to neighboring nodes. The frequency and number of re-broadcasts is based on the received message parameters. If the received incident is known and the repeat timer is already set no new timer or message is created.

[3] This stationary node could, e.g., be a road-side unit managed by a public transportation company or a local authority.

Table 2
Uncertain parameters. We would like to know how three uncertain parameters affect the dissemination time t_{diss}. We control the packet size s_d to vary the amount of network load tr in our model.

Parameter	Unit	Lower bound	Upper bound	Distribution type	
Number of agents n	1	10	2000	Truncated exponential (Eq. 5)	
Transmitter power p	mW	0.5	2.0	Uniform	
Packet size s_d	B	0	4000	Uniform	
Dependent parameter	Equation	Unit	Lower Bound	Upper bound	Distribution
Network load tr	see Eq. 6	MB/s	0	0.20	Uniform

3.3. Quantity of interest

We measure information dissemination with the dissemination time t_{diss} which is the time between the moment when at least 95% of the agents have been informed and the moment when the information dissemination starts ($t_{start} = 100s$). There are several reasons for this definition. First, the quantity can be easily interpreted by the mobile networks community and the pedestrian dynamics community. Second, it quantifies the success of the redirection measure. If the dissemination time is below $\sim$ 30s, at least 95% of the agents have been successfully redirected. As an alternative, one could count arrivals in the area of the closure. If it is larger than zero, the redirecting attempt failed at least partially. However, if there are more complex guiding strategies in the scenario, the results of the counting procedure might be ambiguous: We would not know whether the agents were in a certain area, because this was their original strategy or because they were redirected. The dissemination time, on the other hand, tells us reliably, whether the agents have a chance to adapt their strategies.

We use 95% instead of 100% in our definition of the dissemination time because new agents are being created continuously throughout the simulation, but not informed immediately after their spawning.

3.4. Parameters

We investigate three uncertain model parameters. The first parameter is the number of agents n, see Table 2. Each agent represents a mobile node in the mobile network. The network is continuously changing, due to the agents' motion, and so is the information dissemination through the network. We decide to use a truncated exponential distribution for the number of agents with lower bound $lb = 10$ and upper bound $ub = 2000$:

$$n(x, b) = \frac{e^{-x}}{1 - e^{b}} \tag{5}$$

We use $b = 4$, shift the distribution by $lb = 10$ and scale it by $(ub - lb)/b$. A histogram for 2000 samples is depicted in Fig. 6. We argue that this type of distribution is especially suited to capture the rare event of shadowing that occurs randomly when the number of agents is low.

We also think that an exponential distribution, while probably not often completely correct, matches certain arrival situations in a train station sufficiently well for our investigation, see Appendix C. Recall that our study scenario was inspired by building blocks that one might find in built environments. The number of agents is extremely high at

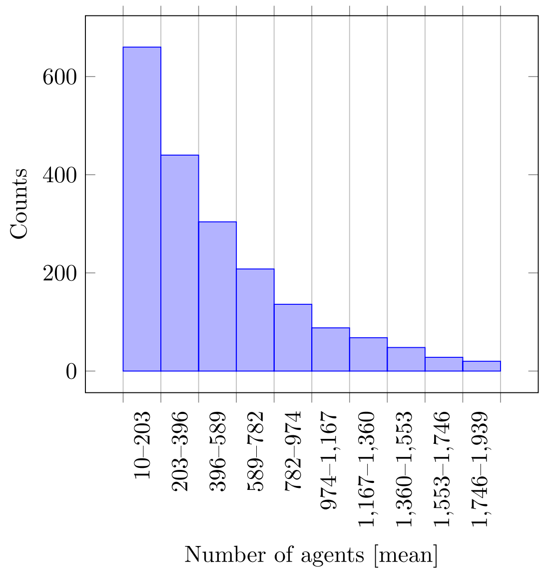

Fig. 6. Histogram of parameter 'number of agents' n as we generate it from a negative exponential distribution. We draw many samples where n is small to detect the effect of shadowing.

certain events, e.g. after a soccer game, it is high during rush hours, but it can be very low during small time intervals during the rest of the day, e.g. between train arrivals. In the future it would be interesting to look into measured distributions in a real built environment.

The second parameter is the radio transmitter power p which affects how far agents can communicate. If the power is low, messages only reach agents that are close by. Information dissemination over large distances fails ('range-problem'). The reception in the deployed model is based on the signal to interference plus noise (SINR) ratio. If the SINR of a given transmission exceeds a threshold, the transmission is correctly received. The default threshold value is 4 dB in the INET framework (INET, 2020). In our safety-relevant scenario, we choose a more conservative threshold of 6 dB. Furthermore, we assume that the radio transmitter power is equal and constant for all mobile phones within a sample. This is a simplification since in reality, p depends on the local situation and the device itself. We vary the transmitter power in the range $0.5\ldots2.0$mW(EIRP[4]).

The third parameter is the network load caused by other apps. While traveling people listen to music, use navigation apps, check their emails. Some even watch movies while walking. To make the simulation more realistic, we assume that agents use apps which produce load in the range of 0…0.20MB/s. This range contains listening to music (0.01‥0.03MB/s), using navigation apps (0.05MB/s) and even streaming videos in low-quality (0.06MB/s). The load tr depends on the packet inter-transmission interval d_{tx} and the packet size s_d

$$tr = s_d \frac{1}{d_{tx}} \tag{6}$$

In our simulation model, we use a constant inter-transmission interval and assume one-packet messages. We control the packet size s_d to vary the amount of load in our model. The inter-transmission interval d_{tx} is defined by the (re-) broadcast interval, which is fixed to 20ms. The corresponding packet size s_d is between 0…4000B. We expect that the information dissemination might be disturbed if the network load is high.

[4] Equivalent Isotropically Radiated Power (EIRP).

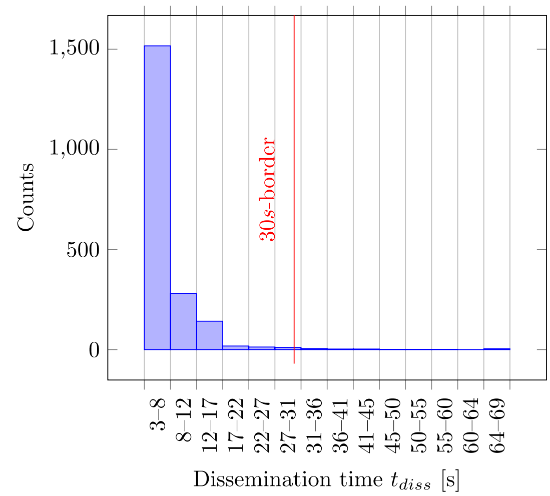

Fig. 7. Empirical distribution of the dissemination time t_{diss} (2000 samples). With a probability of 86.2%, agents are informed within 10s. In some cases (1.1%), the information dissemination takes more than 30s.

4. Simulation results

If we want to use direct communication technologies to safely guide crowds, we need to make sure that the saftey-relevant information is reliably disseminated. In particular, in the case of redirection, the information must reach the pedestrians in time to alter their course. In the following we will analyze this for our benchmark detour scenario described in Fig. 1.

We consider information dissemination to have failed, if the dissemination time is $t_{diss} > 30$s. We determine this value as follows: The redirection measure is only successful, if the information reaches the agents before they have passed the obstacle that hides the closed exit. Once they see the closure, they do not gain anything from using the DetourApp. The distance between the source (green area in upper left corner of Fig. 1) and the obstacle is $ds = 40$m. A typical average walking speed is $v = 1.34$m/s (Weidmann, 1992). Thus the average agent needs $ds/v = 30$s before they pass the obstacle through the passage on the left. Since the walking speed varies within a population (Weidmann, 1992) which we model with a truncated normal distribution, the speed of some persons can be higher. To take into account that some people even run $(4m/s)$ to catch the train, we consider information dissemination to be successful if $t_{diss} < 10$s. With that, even the fastest agent in our simulation is informed in time. We consider the interval $[10\text{s}, 30\text{s}]$ as a transition interval in which information may succeed or fail. If the estimated probability of the dissemination time to be in the transition interval is much smaller than the probability to be below 10 s, $P(10\text{s} \leqslant t_{diss} \leqslant 30\text{s}) << P(t_{diss} \leqslant 10\text{s})$, and if the estimated probability of failure is zero, $P(30\text{s} \leqslant t_{diss}) = 0$, we consider the information transfer to be 'safe'. This pragmatic classification allows us to evaluate the simulation outcomes.

We expect that information dissemination may fail for two reasons: One is shadowing, that is, agents are separated by obstacles that hinder wave propagation. Shadowing occurs seemingly randomly, when agents take up unfavorable positions. We cannot control it directly. If the number of agents is small, it is more likely that information cannot be disseminated due to shadowing. A second effect is interference that occurs when agents try to communicate simultaneously.

4.1. Forward propagation

First, we analyze how likely it is that information dissemination fails. For that purpose, we use forward propagation, see Fig. 7–8. The empirical distribution of the dissemination time t_{diss} from our

Table 3
Statistical properties of the dissemination time depicted in Fig. 7. 1724 of 2000 (86.2%) samples lead to dissemination times $t_{diss} \leqslant 10$s. In 22 out of 2000 cases, the dissemination time is $t_{diss} > 30$s.

Statistical properties of the dissemination time t_{diss}					
Mean	6.9s	Min	2.8s	75%-Percentile	7.2s
Median	4.8s	Max	69.2s	P($t \leqslant 10$s)	86.2%
Mode	4.8s	25%-Percentile	4.8s	P($t \leqslant 30$s)	98.9%

simulations is depicted in Fig. 7. We observe that the dissemination is below 10s for more than 1500 out of 2000 samples, actually it is even below 8s. The probability that the information dissemination time is successful, that is $t_{diss} \leqslant 10$s, is 86.2%. This finding is consistent with the empirical distribution depicted in Fig. 7 which is extremely right-skewed. The mode is 4.8s, the median is 4.8s, and the mean is 6.9s, see Table 3. Hence, we find that in most cases information dissemination is successful.

The probability that information dissemination fails, that is $t_{diss} > 30$s, is 1.1%. We find that information dissemination fails in rare cases. Nevertheless, the information is always disseminated after a certain time: the maximum dissemination time is 69.2s, see Table 3. This is too long for timely information in this scenario, but it might be sufficient when the topography is larger.

4.2. Identifying reasons why information dissemination fails

We use additional simulations to identify reasons why the information dissemination fails. First, we check whether the effect of shadowing, that is, communication between agents is blocked by obstacles, impedes information dissemination. Shadowing is likely if the number of agents is small, see Fig. 10. We remove the obstacle model so that signals are no longer interrupted and rerun all simulations with $t_{diss} > 30$s: Agents get informed more quickly, see Fig. 9. We conclude that shadowing is indeed a problem. Range, and thus the ‘transmitter power’, does not seem to have any effect, because the dissemination time is low even when the number of agents is low.

However, even without obstacles, we see in Fig. 9 that information dissemination can still take longer than 30s for a medium number of agents $n \in [150, 200]$ in samples where app users cause a significant amount of network load. The more agents ($n \in [10, 200]$) there are and the higher the network load (message size), the longer it takes to

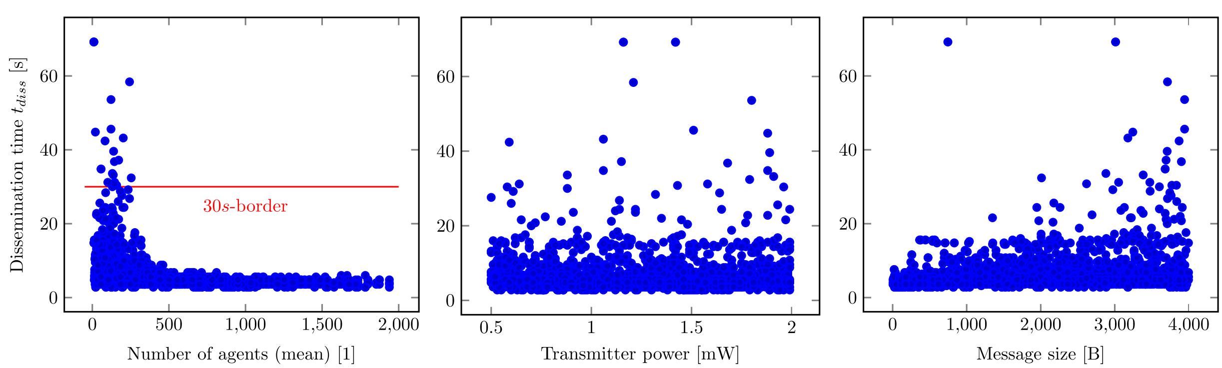

Fig. 8. Dissemination time t_{diss} in dependency of the number of agents (left), the transmitter power (middle), and the packet size (right) that is proportional to the network load. Only 1.1% of the data points exceed the 30s-border. Note: The sample values of the two remaining parameters have been projected in the plane.

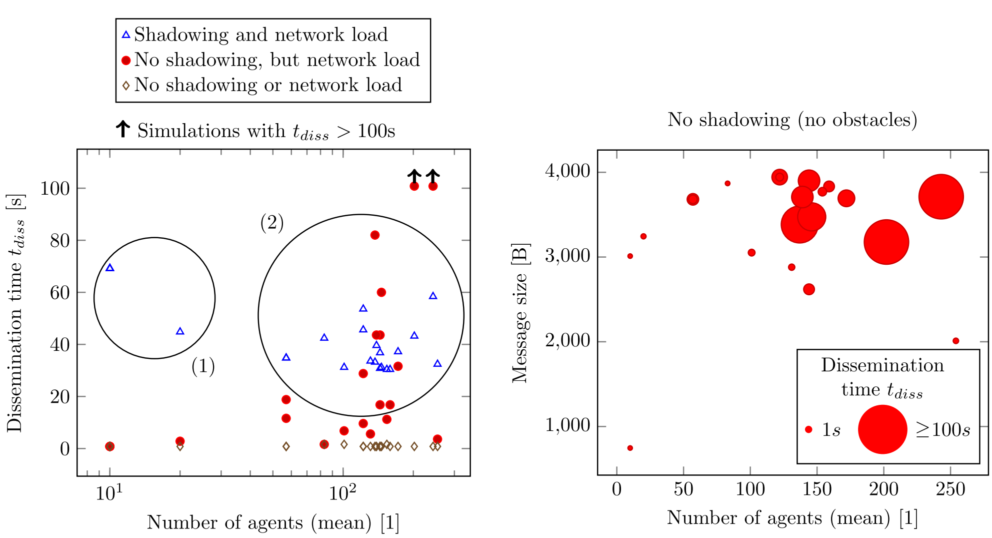

Fig. 9. Additional simulations where the information duration is $t_{diss} > 30$s. There are two causes which lead to information dissemination times $t_{diss} > 30$s. First, the effect of shadowing, that is, communication is blocked by obstacles. If the obstacle model is removed, agents get informed immediately (no shadowing). This means the transmitter power is sufficient and range is not a problem. Shadowing is likely if the number of agents is small (1). Second, the effect of interference when other apps take away resources from the DetourApp (2). This effect occurs in conjunction with shadowing (2). Due to shadowing, agents communicate irregularly and only for short periods. If network load is present during these periods, the information dissemination can be impeded (2). This effect seems to vanish, if the number of agents is large enough, and communication is possible at any time.

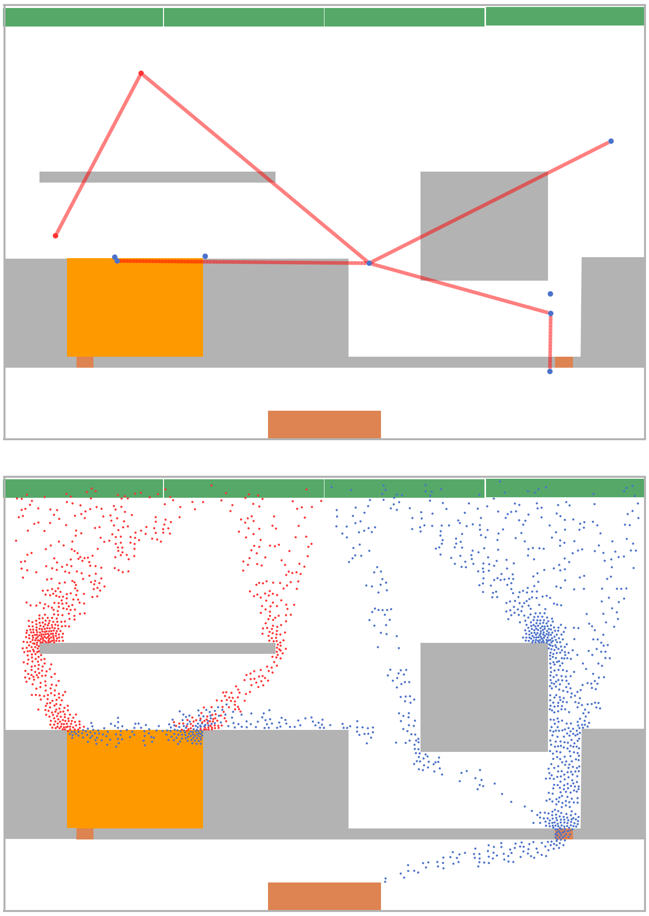

Fig. 10. Effect of shadowing. Agents (marked red) are initially ($t = 100s$) not informed. The effect of shadowing will impede the information dissemination process. Top: Shadowing occurs when agents are separated by obstacles (red lines of sight are cut by obstacles). Bottom: If the number of agents is high, information is disseminated successfully.

disseminate information, see Fig. 9 (right). However, this is only true until the number of agents exceeds a certain threshold. Fig. 8 (left) depicts that information is disseminated quickly ($t_{diss} < 10s$) when the number of agents exceeds $n \approx 500$. In this case, shadowing is present. Note, that the threshold may shift when shadowing is removed.

We also see the combined effect of shadowing with network load. When shadowing occurs, agents communicate irregularly and only for short periods. If network load is present during these periods, the information spread can be impeded. The effect seems to vanish, if the number of agents is large enough, and communication is possible at any time. Fig. 8 supports these hypotheses.

Next, we would like to understand to which extend these effects can be controlled by the choice of our parameters. To quantify the influence of our parameters, we use sensitivity analysis.

5. Sensitivity analysis

The system behavior in a deterministic simulation model is completely controlled by the choice of its parameters. The influence of these parameters is quantified through the size of their sensitivity indices. We use the 2000 samples of the forward propagation to compute the sensitivity indices according to Eqs. (1)–(4). Note that this corresponds to a sample size of $250(=2000/8)$ in Saltelli's sampling procedure at cost $2k+2$ with $k = 3$ parameters (Saltelli, 2002). First we analyze the order of the sensitivity indices of the simulation model. The parameter 'number of agents' is most influential, followed by 'network load', followed by 'transmitter power', see Fig. 13. Since the simulation contains stochasticity, the confidence intervals of the sensitivity indices are large, see Appendix B. With these confidence intervals, drawing reliable conclusions from the index size becomes impossible.

In Section 2.2.3, we presented two approaches where the simulation model is replaced by one or multiple surrogate models. If a Kriging model is used as a surrogate model, one can separate the average from the stochastic model behavior. This allows us to look at the controllable part of the model only. Thus, we hope to reduce the confidence intervals of the sensitivity indices. One might argue that we risk losing information about the system. We mitigate this risk by quantifying the stochastic part of the model with the regression coefficient. This together, with the sensitivity indices of the average model, can help to characterize the system and to draw conclusions.

To tackle the problem of stochasticity in the sensitivity analysis, we combine the two approaches presented in 2.2.3. The basic idea is to cross-check the results of the single surrogate model approach with the multiple surrogate models. This ensures that no relevant information about the system is lost (Hart et al., 2017). Fig. 11 shows how we bundle existing approaches for our purpose. We construct multiple surrogate models by drawing r different sub-sets of samples randomly. This is similar to generating a training-set in a 'Monte Carlo-cross validation' (Kuhn and Johnson, 2013). We will use the terminology from Kuhn and Johnson (2013).

So far, different types of surrogate models have been used in Iooss and Ribatet (2009), Marrel et al. (2012) and Hart et al. (2017). We decide to use a universal Kriging model as surrogate model. Background information for this type of model can be found in Appendix A.

5.1. Applying stochastic sensitivity analysis to information dissemination

The first step is to construct a single universal Kriging model according to Eq. A.1 using the samples from the forward propagation. As parameter values, we feed in the re-scaled sample values that range from $0\ldots1$ (min-max normalization). The re-scaling ensures that each parameter contributes proportionally to the construction of the surrogate model. As quantity of interest, we choose the log-transformed values of the dissemination time and a linear variogram model. The Kriging model is regressed as non-exact interpolator, that is, the sample points are not exactly reconstructed in the surrogate, see Fig. 12. The resulting Kriging model is suitable to model the average dissemination time, because the model is not biased ($Q1 = 0.01 < (2/\sqrt{1999})$). We observe that the dissemination time in the Kriging model evaluation varies less than for the simulation model, see Fig. 12. Rare events are no longer captured.

We evaluate the Kriging model at the 2000 sample points. Other than before, the surrogate allows us to compute a coefficient of determination R^2 to quantify the influence of stochasticity. R^2 is 'the proportion of the information in the data that is explained by the model' (Kuhn and Johnson, 2013). For the single surrogate model, the coefficient of determination is $R^2 = 0.30$. We use R^2 to measure the influence of stochasticity. We find that 70%(=1–0.3) of the variation of the dissemination time is caused by stochastic effects. Hence, the uncertainty in the output caused by stochasticity is larger than the uncertainty caused by parameter variation. This is why we consider the system as difficult to control. Then, we conduct a sensitivity analysis as in Section 2.2.2. As result, we get the first-order and total-effect sensitivity indices and their corresponding confidence intervals computed through a bootstrapping procedure. We call these indices 'surrogate sensitivity indices'.

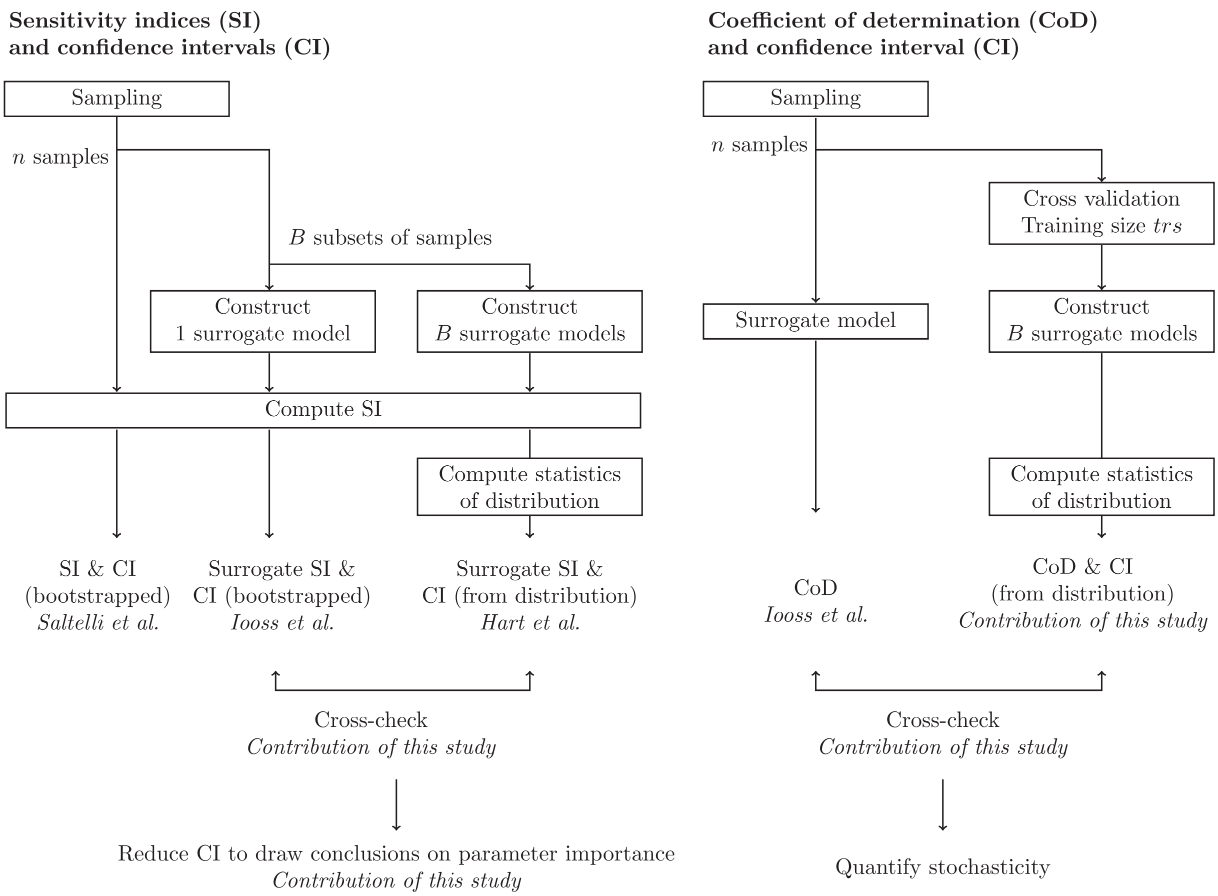

Fig. 11. Overview of approaches to handle stochasticity in sensitivity analysis. We use a surrogate model to smooth the noise caused by stochasticity (rare cases of shadowing). By that, we hope to reduce the confidence intervals of the sensitivity indices. Besides, the coefficient of determination is used to measure the influence of stochasticity. We propose to cross-check the different approaches.

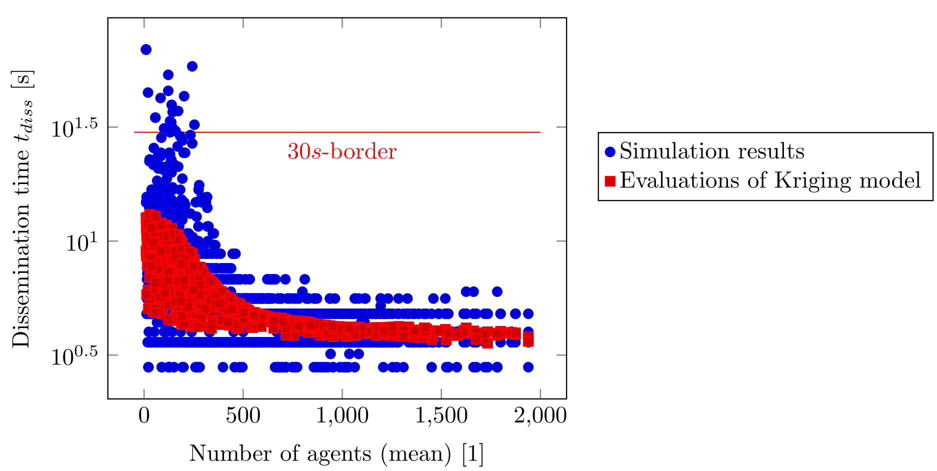

Fig. 12. Dissemination time t_{diss} over the parameter number of agents. The evaluations of simulation model and Kriging model differ. The dissemination time in the Kriging model evaluation varies less than for the simulation model. Rare events ($t_{diss} > 30$s) are no longer captured. Note: the other two parameter dimensions (transmitter power, network load) are projected in the plane.

In a second step, we cross-check the sensitivity indices and the coefficient of determination of the single Kriging model. We produce multiple Kriging surrogate models using different sub-sets of the 2000 samples. We draw these sub-sets randomly as it is done in a Monte-Carlo cross-validation. Except for the type of surrogate model, this is similar to the methodology proposed by Hart et al. (2017). We use three different training sizes $trs \in \{50.0\%, 37.5\%, 25.0\%\}$. For each training size we generate $r = 100$ Kriging surrogates. To evaluate the quality of the model, we use the $Q1$-value, see Appendix A. If $Q1 > (2/\sqrt{1999})$, the model is replaced by a surrogate model that fits the condition. We predict the dissemination time $\widetilde{t}_{diss}$ for the 2000 samples and compute the coefficient of determination. For each surrogate model, we also compute the sensitivity indices. In summary, there are 100 values for the coefficient of determination and each index that form an empirical distribution. We use these distributions to compute symmetric 95% confidence intervals. We compare these results with the results of the single surrogate model, see Fig. 13 and 14. We observe that the confidence intervals of the surrogate models always overlap. Thus, we consider the cross-check as successful. In the following, we do no longer distinguish between the different surrogate model approaches, and refer to the ‘surrogate model approach’ only.

5.2. *Interpretation of results of the stochastic sensitivity analysis*

Our goal was to quantify the effect of stochasticity and the influence of parameters on the parameter-dependent part of the simulation model. By removing the stochastic component of the model, we hoped to reduce the confidence intervals of the sensitivity indices.

First, we look at the size of the confidence intervals. The confidence intervals computed with the surrogate model approaches are smaller than those of the original simulation model, see Fig. 13. Nonetheless, the size of the confidence interval of the first-order index for the parameter ‘number of agents’ is still large. A possible explanation for this is that the sensitivity indices are defined as the ratio between conditional and total variances which may both be reduced when using a surrogate model. For the total effect indices we see a more pronounced shrinking of the confidence intervals.

Second, we look at the order of influence. The order of the parameter influence has not changed, see Fig. 13. The number of agents still has the biggest influence, followed by the network load, followed the transmitter power. The number of agents is indeed dominant, with first-order and total-effect sensitivity indices larger than 0.6. With the reduced confidence intervals, however, the order is now clearly recognizable. Important parameters have become even more important, while the influence of less important parameters has been reduced. The surrogate model seems to work as a filter. A possible explanation for this is, that the surrogate model smooths the noise caused by stochasticity. Hence, parameters that influence the overall system behavior (without stochasticity) become more important while others are ignored.

Third, we look at the parameter ‘transmitter power’. In Section 4.2, we found that this parameter is not influential in the scenario considered in this study. When obstacles are removed, agents are immediately informed. The ‘transmitter power’ does not seem to affect the information dissemination. Hence, the respective sensitivity indices must be zero. However, the confidence interval of the total-effect index ranges from 0 to 0.5 in the standard procedure, see Fig. 13. Only the surrogate model approaches reveal its true lack of influence. Both sensitivity indices of the Kriging models are (numerically) zero with vanishing confidence intervals. This is in agreement with our observations and plausibility arguments from Section 4.2. Thus, we argue that the surrogate model indices which we proposed are more suitable to describe the parameter influence in our model than the indices from the standard procedure.

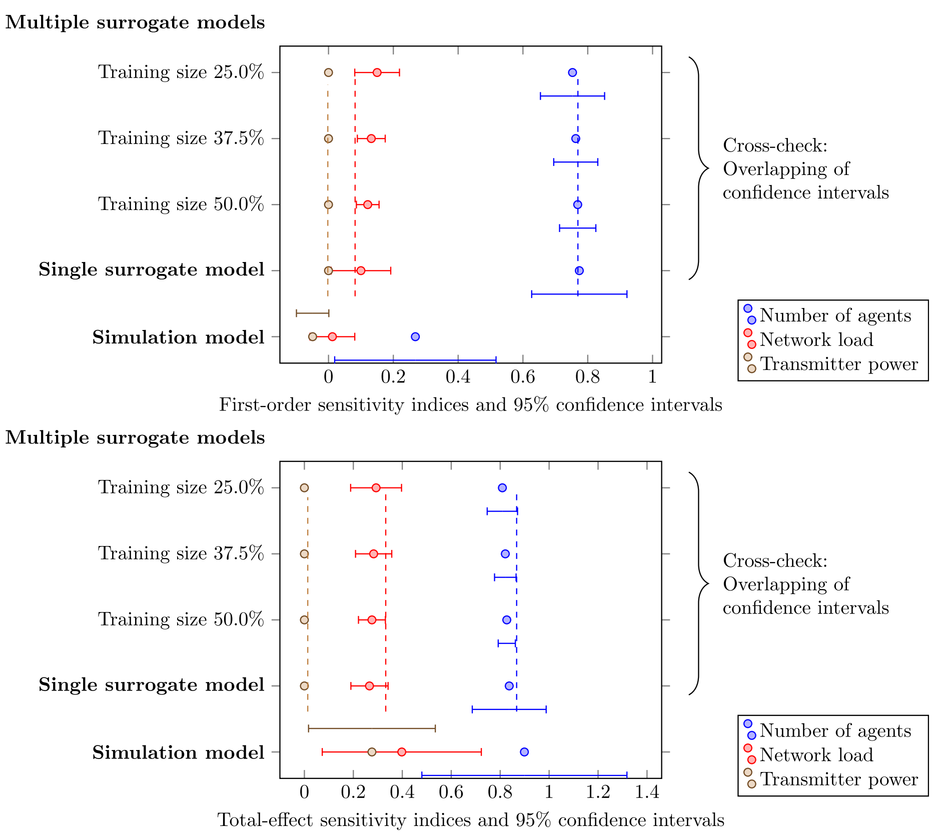

Fig. 13. First-order and total-effect sensitivity indices. The quantity of interest is the information dissemination time t_{diss}. The parameter ‘number of agents’ affects t_{diss} most, followed by ‘network load’, followed by ‘transmitter power’. The confidence interval of the indices of the simulation model are large. The parameters network load and transmitter power might be non-influential, because the confidence intervals contain or are near zero. The surrogate model approaches work as a filter. Through smoothing the data, the confidence intervals are reduced while maintaining the same order. The confidence intervals of the multiple approaches overlap (dashed lines). The influence of important parameters increases (number of agents), while the influence of non-influential parameter decreases (transmitter power). The indices of the single surrogate model approach indicate that the network load is only influential in combination with the parameter number of agents. The confidence interval of the first-order index contains zero, while its total-effect index > 0, and only the parameter number of agents contributes to that. The multiple surrogate model approach indicates that the influence of the ‘network load’ is very low. Note: Negative index values are numerical artifacts.

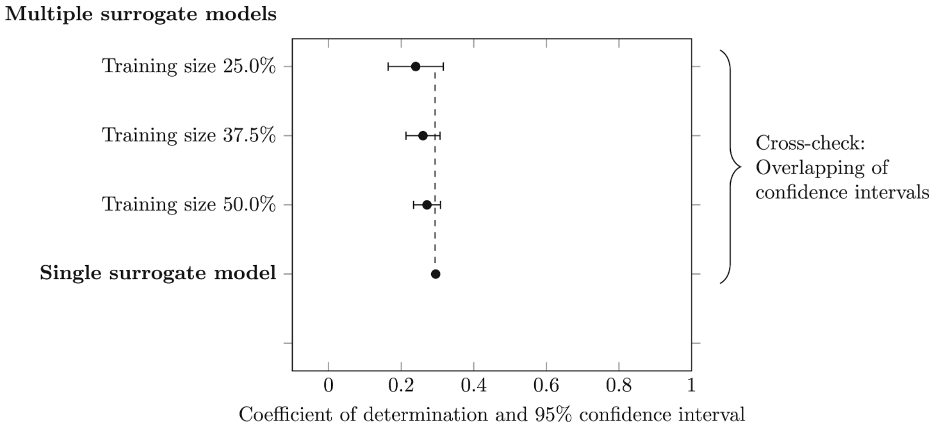

Fig. 14. Coefficient of determination. The coefficient of determination is only 30% (single surrogate model approach). This indicates a large effect of stochasticity on the dissemination time t_{diss}. The results from the cross-check look similar. Three different training sizes are compared: 25.0% of the sample data, 37.5% of the sample data and 50.0% of the sample data (multiple surrogate model approach). For each, 100 surrogate model are constructed. The resulting distribution is represented by the symmetric 95% confidence interval (error bars).

6. Discussion

6.1. Summary

The goal of this study was to find whether or not direct communication as defined in new generation mobile communication protocols, such as the 3GPP Rel. 14 and 5G standards, is suitable to guide pedestrians in safety-relevant situations, for example, when an evacuation route is closed or a certain area should be avoided. Our criterion for success was that pedestrians receive redirection suggestions in time to act on them. We presented a new simulation tool *CrowNet* to analyze this in simulation studies. *CrowNet* is a free and open-source simulation tool that couples a state-of-the-art pedestrian dynamics simulator, *Vadere*, with a state-of-the-art mobile communication simulator, *OMNeT++* with *INET*. It introduces an interaction between pedestrian dynamics and mobile networks on a model level, thus capturing, for the first time, the information dissemination process, the ensuing redirection of the crowd, and the effect on the mobile network. We proposed a simple scenario in a built environment with a structural composition that was inspired by train stations. Pedestrians equipped with mobile devices are redirected from a closed gateway through an app. We analyzed the simulation model with methods of uncertainty quantification to assess how reliable direct communication is and to identify parameters that most influence the functionality of the system. We looked at three parameters: the number of agents, the transmitter power of the mobile devices and additional network load caused by the agents' use of other apps. Our quantity of interest was the dissemination time, that is, the time it took to inform 95% of the agents in the scenario. We propagated 2000 samples and found that information dissemination fails in rare cases. We found strong evidence that the failure is caused by shadowing, that is, agents cannot communicate because they are separated by obstacles. We also found that a high network load can aggravate this effect.

Our observations on the network load improve on former observations by Chancay-García et al. (2018) who used an application to transmit information and varied the message size in the same application to investigate the influence of traffic load. Our approach has the advantage of separating the information dissemination from the additional load through consumer apps. Our findings go beyond those obtained by Helgason et al. (2014) by adding true interaction between mobility and information dissemination to the investigation, by providing quantitative analysis, and by modeling obstacles in the mobile networks simulation.

We computed sensitivity indices to measure the influence of the parameters on the information dissemination quantitatively. We realized that their confidence intervals were too large to draw reliable conclusions on the parameter influence. We suspected that the inherent stochasticity of *CrowNet* overshadows the parameter dependencies.

Thus, we suggested to use a modified version of sensitivity analysis which is based on a surrogate model, namely a universal Kriging model. We proposed to use this model to quantify the effect of stochasticity and to cross-check the results with a multiple surrogate model approach. The surrogates allowed us to compute a coefficient of determination of about 0.3 which confirmed our suspicion regarding the stochasticity of the simulation model. At the same time we observed that confidence intervals for the Kriging model shrank in size compared to the original model, while the order of the indices was preserved. The value of the two influential parameters, number of agents and network load, and the corresponding confidence intervals shifted away from zero. We argue that the surrogate acted as a filter, smoothing the noise caused by stochasticity. We realized that the Kriging model did not capture rare events. The filtering allowed us to draw conclusions: In our scenario, the number of agents has the strongest influence on the dissemination time. The network load plays a role in conjunction with the number of agents. The transmitter power is not influential in our scenario when varied in a range $0.5mW \ldots 2.0mW$. We propose to fix this parameter in further studies to reduce the number of uncertain parameters. Thereby, computational cost is reduced.

In all but very rare cases information dissemination was successful. Thus we think that direct device-to-device communication is indeed suited to disseminate saftey-relevant information in a crowd. However, network and device designers as well as decision makers must keep in mind that it can fail in rare cases for which alternative solutions must be found.

In the course of our investigations we were confronted with the limitations of standard sensitivity analysis when using non-deterministic models, like *Vadere*, *OMNeT++* and their combination *CrowNet*. This led to a second, methodological research questions: Which methods are suitable to quantify the influence of parameters in our stochastic model? We pursued the idea to apply sensitivity analysis not only to the original simulation model but also to a surrogate model, namely a universal Kriging model. For the surrogate one can compute a coefficient of determination that quantifies how much of the variance in the model is caused by parameter variation. We cross-checked the statistic results for the Kriging model with a multiple surrogate model approach. The statistics from the multiple surrogate model approach confirmed the statistics for the single surrogate. This encourages us to propose sensitivity analysis with a Kriging surrogate to handle model stochasticity. We further suggest to cross-check whenever the computational costs allow this.

In our example, the multiple surrogate model approach yields results similar to the single surrogate model approach. We did not observe information being lost, as Hart et al. (2017) feared. This supports the work of Iooss and Ribatet (2009) and Marrel et al. (2012). This may, however, be a coincidence and cannot be naively transferred to arbitrary scenarios. Nevertheless, it demonstrates that the usage of multiple surrogate models, while superior in theory, is not always necessary in practical applications. Moreover, the construction of multiple surrogate models is computationally expensive. We argue that, while cross-checking with multiple models is desirable, one surrogate may suffice in many practical examples. If one wants to be sure, one should cross-check the approach as we do.

6.2. Limitations and open research questions

There are some limitations concerning sensitivity analysis with a surrogate model that we would like to mention.

One should be aware that the multiple surrogate model approach might be sensitive to the method setup. The results of the three multiple surrogate model approaches (25%,37.5%,50% training size) are affected by the training size. In our case, the effect is low. However, this might limit how far the methodology can be transferred to other application use cases.

Also, the results of the sensitivity analysis depend on the choice and setup of the surrogate model. For different model types, the regression surfaces representing the average behavior can differ. 'Fast' but relevant oscillations might be smoothed, while over-estimating the uncertainty with the Gaussian process model. The question which surrogate model is most suitable is still an open question in research.

Other limitations regard the *CrowNet* simulator and the set-up of the scenario.

In our scenario, redirection measures are disseminated successfully through the mobile network except for some rare cases, when the dissemination process takes too long. We see, however, that the information is always received. In the case of a larger topography, the agents might still be informed in time. However, range could become a problem and, thus, the parameter 'transmitter power' could become influential. In scenarios with many obstacles a delay may be even more pronounced. Clearly, the spatial dimensions and the rerouting strategy are influential and no scenario can fit all cases.

Also, in our scenario, all agents immediately follow the instructions which is a very optimistic view. A psychological model is needed that tells how likely people are to react at all and with which delay. This interdisciplinary subject will be part of future research.

Another limitation is the simplicity of the obstacle model that is used in the information dissemination process. When an obstacle is in between agents, the communication fails. This is quite conservative. In reality, communication can still be possible. Hence, the risk of failure might be lower.

We only analyzed the effect of three uncertain parameters that we identified as main model parameters. The effect of other uncertain parameters is not captured. We think that it would be interesting to investigate the effect of the threshold of the 'signal to interference plus noise ratio' (SINR) which is currently fixed to 6 dB.

It is important to mention that our example scenario and our quantity of interest, the dissemination time, may not be fully sufficient to answer safety-related questions in general. Further scenarios and quantities of interest like local densities, pre-movement times and pedestrian flows need to be considered.

Finally, security concepts for direct communication as assumed within this paper are a challenging research topic: While confidentiality is not required for the application investigated, integrity and non-repudiation have to be guaranteed. However, for several systems with similar requirements (such as LTE-A D2D, C-V2X or ITS-G5) security architectures have been proposed[5] or are part of the ongoing research within the field of network security. Therefore, these aspects are considered to be out-of-scope for this article.

7. Conclusion

The goal of this study was to assess how suitable direct communication is to redirect crowds. For that purpose, a simulation model and methodology were proposed. The analysis of the proposed scenario showed that even in the worst-case, assuming that obstacles completely hinder communication, direct communication works except for some rare cases of shadowing. The outcome is affected by the parameters 'number of agents' and the 'network load'. Although the topography and the redirection measure are simple, basic properties of the closed-loop interaction between pedestrian dynamics and mobile networks were captured in the simulation model.

We consider our contribution as a first step in an emerging field of research and application. Many open questions remain. We would like to draw the readers' attention to some that we think are especially important: First, our simulations only demonstrate a worst case of shadowing, that is, complete failure if the line-of-sight is cut. More elaborate obstacle models should be investigated. With respect to the agents' reaction, on the other hand, we consider a best case scenario: all agents follow instructions. The variance in the agents' reaction must be modeled. Moreover we would like to scrutinize more surrogate models to see which is best suited for sensitivity analysis in our field. One should also be aware that a surrogate may not only bring out the main system characteristics but could also filter important non-linearities (oscillations, jumps) in the model behavior.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Universal Kriging

Kriging is an approximation method that predicts unknown values of a random function. This is modelled through a second-order covariance process. The assumption is that "the closer the input data, the more positively correlated the prediction errors" (van Beers and Kleijnen, 2003). In universal Kriging the observations have a polynomial representation: $g^T(q)\beta = \sum_{k=0}^{K}\beta_k g_k(q)$. The covariances of the observations depend only on the "distances" between the corresponding inputs. The behavior of the covariance is represented by a Gaussian process error model $Z(q)$ (Smith, 2014).

In this contribution, the quantity of interest is the dissemination time t_{diss}. The universal Kriging model approximates the dissemination time t as $\widetilde{t}$ (Smith, 2014)

[5] See e.g. ETSI TS 102 731 V1.1.1 (2010-09), https://www.etsi.org/deliver/etsi_ts/102700_102799/102731/01.01.01_60/ts_102731v010101p.pdf (27th April 2021).

$$\widetilde{t}(q,\beta) = g^T(q)\beta + Z(q) \tag{A.1}$$

where q is the vector of the three uncertain parameters (number of agents, transmitter power, network load), $g^T(q)\beta$ is the polynomial trend function and $Z(q)$ represents a Gaussian process error model (Smith, 2014). The coefficients $\beta = [\beta_0, \ldots \beta_k]$ are determined using a least squares regression (Smith, 2014).

The variogram plays a crucial role in the Kriging method. It is the "diagram of the variance of the difference between the measurements at two input locations" (van Beers and Kleijnen, 2003). It is a function of the distance h between two locations (van Beers and Kleijnen, 2003). Such a function is sufficient to describe a second-order covariance process (van Beers and Kleijnen, 2003). In this contribution, a linear variogram model is used. This assumes that the variance increases with the distance between parameter values. We assume that measurement errors are present in the model. This has the effect that the Kriging model is an approximation rather than an excat interpolator. The goodness of fit of the Kriging model can be evaluated with the statistics $Q1$ and $Q2$ (Kitanidis, 1997). $Q1$ measures the bias of $Z(q)$. The model should be rejected, if (Kitanidis, 1997)

$$|Q1| > 2\Big/\sqrt{n-1} \tag{A.2}$$

is true, where n is the number of data points that are used to construct the Kriging model. The statistic $Q2$ measures the variance of the normalized errors of the model $Z(q)$. Ideally, $Q2 = 1$. If $Q2 < 1$, the variance is underestimated. We are interested in the average model behavior but not its variance. This is why look at $Q1$ in this contribution. For background information, we refer to Cressie (1993), Kitanidis (1997), van Beers and Kleijnen (2003), and Smith (2014).

Appendix B. Limitations of standard sensitivity analysis

The system behavior in a deterministic simulation model is completely controlled by the choice of its parameters. The influence of these parameters is quantified through the size of their sensitivity indices. However, random effects in the model we investigate lead to large confidence intervals for the sensitivity indices. With these, drawing reliable conclusions from the index size becomes impossible. We will demonstrate this below for the results of our simulation model.

First we order the parameters according the size of their first-order indices: The parameter 'number of agents' is most influential, followed by 'network load', followed by 'transmitter power', see Table B.4.

The first-order index for the 'number of agents' is 0.27. Its 95% confidence interval has the lower bound 0.02 and the upper bound 0.52. We think that the large size of the confidence interval reflects the parameter's connection to random shadowing. Shadowing is caused when agents happen to take up unfavorable positions in some of the samples. Then the dissemination time is large. In the bootstrapping procedure, we randomly draw sub-sets of samples for which we compute the sensitivity indices. When shadowing occurs for some of these samples the variance of the dissemination time is high, otherwise it is small. The first-order sensitivity index is proportional to the variance which explains the large size of the confidence interval.

In the next step, we analyze the influence of the parameters 'transmitter power' and 'network load'. The first-order indices of both parameters are almost zero. Hence, the parameters, each seen separately, do not contribute anything. The corresponding total-effect indices can be found in Table B.5. The total-effect index for the transmitter power is between 0.07 and 0.72. The corresponding index for the network load is between 0.02 and 0.54. Since the total-effect indices are larger than the first-order indices, there must be interaction effects among the parameters.

This is why we also compute the second-order sensitivity indices: All the confidence intervals of the second-order sensitivity indices include zero. This means that the total variance is not caused by second order interaction effects, but higher-order interaction effects. We find that this is also an indicator for stochasticity in the simulation.

All in all, we find that the confidence intervals of the sensitivity indices are too large to draw conclusions on the importance of the parameters. As result, we cannot fix any parameter. This is indeed a problem for further studies where additional parameters are varied. If the number of parameters is increased, the simulation becomes infeasible. With three parameters only, the evaluation of 2000 simulations took six days.

Table B.4
First-order sensitivity indices of the simulation model. The confidence interval of parameter 2 and 3 are close or even contain the zero. This means, they might not affect the dissemination time t_{diss} directly.

Parameter	First-order sensitivity index	5% Confidence level	95% Confidence level
Number of agents	0.27	0.02	0.52
Transmitter power	0.01	−0.06	0.08
Network load	−0.05	−0.10	0.00

Table B.5
Total-effect sensitivity indices of the simulation model. The confidence interval of parameter 2 and 3 are close to zero. This means, they might not affect the dissemination time t_{diss}. At the same time, the confidence interval is large. This is why we cannot make a clear statement about the influence of the parameters.

Parameter	Total-effect sensitivity index	5% Confidence level	95% Confidence level
Number of agents	0.90	0.48	1.32
Transmitter power	0.40	0.07	0.72
Network load	0.28	0.02	0.54

We think that the size of the confidence intervals is caused by model stochasticity. However, we cannot quantify the effect of the stochasticity using standard sensitivity analysis. This is why we propose to use a modified form of sensitivity analysis that is based on surrogate models.

Appendix C. Number of arrivals at Melbourne central station

The number of arrivals at a train station varies over the day and over the week, see e.g. the publicly available pedestrian counting data in the City of Melbourne.[6] Exceptional situations, such as pandemics, can affect the passenger traffic volume and its distribution. The Melbourne data set contains many distributions. An example distribution for the number of arrivals at a train station is depicted in Fig. C.15. We find that it looks like an exponential distribution because the number of counts decreases over the number of arrivals.

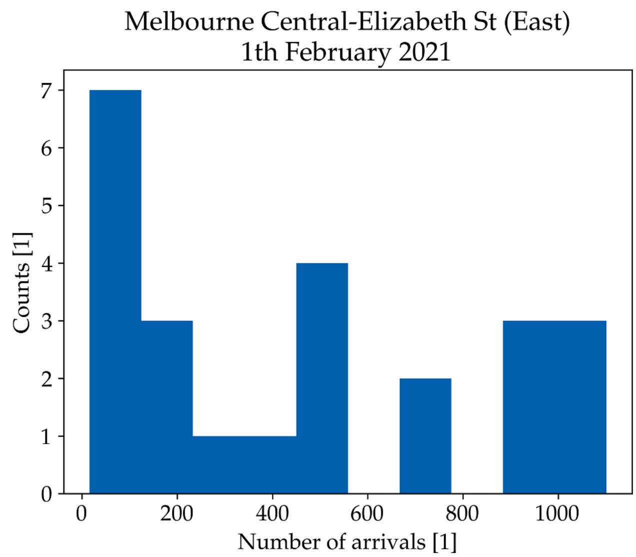

Fig. C.15. Empirical distribution of the number of arrivals at Melbourne Central station. The corresponding sensor in the Melbourne data set is 'Melbourne Central-Elizabeth St (East)'. The distribution looks like an exponential distribution. However, this can differ for other days.

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