Uncertainty and Transparency: Augmenting Modelling and Prediction for Crisis Response

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ABSTRACT

Emergencies are characterised by uncertainty. This motivates the design of information systems that model and predict complex natural, material or human processes to support understanding and reduce uncertainty through prediction. The correspondence between system models and reality, however, is also governed by uncertainties, and designers have developed methods to render 'the world' transparent in ways that can inform, fine-tune and validate models. Additionally, people experience uncertainties in their use of simulation and prediction systems. This is a major obstacle to effective utilisation. We discuss ethically and socially motivated demands for transparency.

Keywords

Uncertainty, transparency, reasoning, modelling prediction, collaboration

INTRODUCTION

When emergencies occur, they are characterised by their 'un-ness' – they are unexpected, unprecedented and unplanned for in their specific unfolding (Crichton 2003, cited in McMaster and Baber, 2008, p. 6). As these authors identify, the 'un-ness' can result in a number of uncertainties particularly when multiple agencies are involved. These include uncertainties about the nature of the crisis (fire or explosion?), details (location? access?), its cause (gas leak or terrorist attack?), available quality of information (source, relevance,accuracy?) and response goals and strategies.

Modelling techniques have been developed to address these issues (Turoff, Hiltz, Bañuls, and Van Den Eede, 2013; Haynes, Jermusyk, and Ritter, 2014). Increasingly, the capability of generating and processing diverse, continuous and even live data feeds can augment situation awareness and decision-making. A recently developed BRIDGE project concept, for example, incorporates sensor data captured by drones, allowing dynamic analysis of environmental and meteorological data in an emergency caused by fire, which can be further interpreted by 3D models to estimate the threat to buildings, the immediate environment, victims and first responders and to recommend response strategies and necessary equipment (Steinhäusler, 2015). Predictive analytics can further augment crisis detection and response by detecting abnormal patterns with trained algorithms.

While it is true that new capability for collecting a wider range of real-time data and feeding analyses to responders can support more detailed and constantly updated situational awareness as well as improved sense- and decision-making, these potentials generate new uncertainties, as well as ethical and legal issues. Whether data, analysis and prediction can be effectively utilised, depends critically on human and social factors.

To chart ELSI in relation to uncertainty, simulation and prediction, this paper starts with discussions on uncertainties emerging from modelling and prediction processes, before elaborating different practices that responders undertake to reason and analyse incidents together with their IT tools. This informs further discussion on design implications for modelling and prediction technologies.

MODELLING AND PREDICTING CROWD EVACUATION: AN EXAMPLE

Modelling and predicting unfolding crisis impacts are complex and difficult tasks. Modelling the damage to architectural structures can draw on generic structural characteristics, e.g. structural similarities between airport and train terminals, but can be complicated by uncertain knowlede about passengers (e.g. gender, age, disabilities, movement patterns) when estimating the impacts of fire or explosions (Steinhäusler, 2015). This section discusses a study of modelling, simulating and predicting crowd movement in the Central Station in Cologne, Germany to unpack some uncertainties emerging during modelling processes.

The VeRSiert project (http://www.versiert.info/) aims to provide tools to understand and predict crowd movement when evacuation is required during major events. The research categorised public events for preparing scenarios of incidents during sport, music and religious events in Cologne as case studies. The main challenges for the design team arose when using data mining, assembling appropriate algorithms and generating data for modelling (Heuer, Roßnagel, Zibuschka, and Maucher, 2012). The team used multiple ways of generating 'empirical data' for modelling and predicting crowd behaviours. They took photos and measured the geometry of important features of the station, as well as performing passenger counts during a large music event and on a normal working day. Passengers were counted going in and leaving the station within specific time frames, at regular intervals. The researchers adapted 'single person pursuit', following randomly selected passengers to record their paths, pauses and activities. The expectation is to provide a 'quick, powerful, flexible and cost-efficient' means to crowd and crisis management, particularly diverting passengers away from exits that are more prone to congestion.

The research team identified a range of issues that could affect the usefulness of their models. There are complex passenger preferences and behaviours in the Cologne area, which are difficult to take into account when drafting the scenarios or when modelling and predicting the crowd. Algorithms themselves can also present difficulties. The selection of appropriate algorithms for particular models, domains and purposes depends on experiences and specialist knowledge. Therefore, previously proven effectiveness, as a concept or tested in experiments, has to be validated again, often requiring parameter adjustment. For the project, the aim was to use simulation footage for engaging with stakeholders and extracting feedback to refine the models and parameters.

While the discussion in this paper focuses on a particular case, the issues discussed are widely relevant to simulation and prediction. Scenario preparation, parameter adjustment and context-fitting of algorithms are commonly shared practices and provide evidence of how uncertainties emerge in modelling and prediction. Particularly important dimensions of these uncertainties are:.

- *Probabilistic and exploratory understandings*: Some aspects of emergency management are more easily quantifiable than others. Physical features and passenger flows can be quantified to a certain extent, but it can be difficult to quantify precisely the values, benefits and costs of tasks, assets and people (even for ordinal orders). Also, when support for decision-making is concerned, uncertainty can arise when breaking down tasks by conditional logic (e.g. If …, then ...) for model and scenario building (Haynes et al., 2014), because responders treat incidents and uncertainties in an exploratory way, evaluating and reacting to unfolding details of their discovery and response to crisis situations.
- *Parameters and negotiation*: Looking into parameters can 'enhance the understanding of the impact of uncertainties and tradeoffs' (Münzberg, Wiens, and Schultmann, 2014, p. 52). Particularly when predictive analyses are used for detecting occurrences of abnormal incidents, e.g., distinguishing bioterrorism from diseases in epidemiological outbreaks, parameters can become sites of uncertainty, ambiguity and tradeoffs. Higher sensitivity encourages earlier response, but also higher chance of costly false alarms. However, increasing specificity of the results (i.e. true positives and negatives) and lowering thresholds for alarm triggers could risk missing signs for early detection (Berndt et al., 2007).

- *Data availability and completeness*: 'There is always incomplete information and uncertainty' because ideal datasets are 'usually too expensive and often simply unattainable' (Berndt et al., 2007, p. 1388). Moreover, there can be multiple constraints dynamically arising for evacuation, and there may be secondary attacks in man-made crises. Decisions made based on the initial crisis can have implications or even create path dependencies for how responses to subsequent events can proceed, and anticipating and imagining cascading consequences can affect how you treat the first one (Arora et al., 2010). However carefully models and algorithms are trained, results are approximations and require trust as well as *in situ* evaluation, and uncertainties are inescapable. These can have serious consequences for use.

More frameworks and techniques have been developed than we can discuss in detail here, not least non-probabilistic uncertainties and sensitivity analyses (Mingers and Rosenhead, 2004; Bertsch, Geldermann and Rentz, 2007; Durbach and Stewart, 2012). They differentiate the nature and episteme of uncertainties and how they can be treated. However, the discussion we present above speaks of uncertainty as persistently emerging as models themselves develop and thus as a site of continued ambiguity and trade-offs. To make effective use of modelling and prediction techniques during crises, it becomes necessary to remain sensitive to the issues of where within the modelling process uncertainties could arise and how reasoning is carried out by modelling and prediction technologies. The importance of supporting this way of understanding uncertainty and modelling is discussed in the next section.

WORKING WITH MODELS

To unpack how practitioners encounter modelling and prediction systems, the discussion below draws on an in-depth study of the difficulties and problems occurring when negotiating with an intelligent dispatch system. Whalen (1995) reviews a costly shift towards an intelligent vehicle dispatch system that measured and predicted unit location, and automated the reasoning process of incident analysis and dispatch decisions. Before the intelligent system, run files were used as a decision support tool, detailing resources, vehicles and their priorities in relation to a given address. Vehicle dispatch decisions were worked out by dispatchers who analysed details of an incident, evaluated vehicles required for it and worked out their availability (by tracking vehicles on an additional note pad). Their reasoning required extensive knowledge and expertise acquired from understanding an area's geography, departmental policy and procedures, different types of incidents, etc. This knowledge, experience and understanding was developed socially and collaboratively, through coordinating tasks, updating and interpreting information, and sharing skills and practices.

However, as the new intelligent system was taken into use, it became clear that the system failed to represent or reproduce the knowledge, intelligence and social practices in the attempt of replacing them with algorithmic reasoning. The new system placed preference on models and algorithms, and had various complications in the design of the system. Only the machine's recommended dispatch choices were shown to dispatchers, and the contextual information for deriving the recommendation, e.g. the location and specificities of other available vehicles, was discarded. The required precision of input data was dramatically increased to an extent that variations of place name abbreviations would not be recognised by the system. This, coupled with its treatment of data 'error' led to vehicles associated with these variations being considered as unavailable for dispatch. However, with information continuously received by dispatchers, it became impossible for them to detect flawed recommendations. Even if they did, they could not correct them because there was no contextual information and no way of understanding how the recommendation was derived in the first place.

The example further illustrates how human decisions are grounded in contextual understanding and communal work practices, and thus almost impossible to operationalise. Recognising the limits of the new system in this case, it became clear that what was missing was a shared frame of reference for dispatchers to contextualise and follow through the process by which the system arrives at a decision. Sufficient 'mutual intelligibility' is needed, and the possibilities for dispatchers to access, review, comprehend and negotiate with the decisions the system comes up with, could better support dispatchers.

DESIGN FOR TRANSPARENCY

The discussion above demonstrates the importance of making it possible for people to understand the frame of reference when analysing and responding to incidents with models and simulation tools, to examine assumptions, anticipate uncertainties, and to creatively disclose instrumental value by tinkering with tools, building confidence through these practices.

To achieve this, the conceptualisation of transparency has to expand from its current emphasis on visibility. Transparency in the context of information systems more broadly is often conceptualised around 'forms of information visibility' (Turilli and Floridi, 2009). In the design and use of ubiquitous computing and data mining, for example, transparency refers to making visible the processes and procedures of data handling, often motivated by privacy concerns (Langheinrich, 2001; Weitzner et al., 2006). In systems of systems approaches for emergency response, the scope, purposes, access points and boundaries of data collection and analysis must be made clear (Büscher, Perng, Liegl 2015), and transparency is also called for as a 'legal-technological infrastructure' needed to move beyond binary opting-in/out mechanisms, towards a more genuine enhancement of understanding for individuals about the practical consequences of governmental and commercial profiling operations (Hildebrandt, 2008). Following this definition of transparency, it is argued that the procedures of modelling and data analytics should be rendered visible and readable, by both machines and humans (Langheinrich, 2001; Zarsky, 2013). Designs for transparency and privacy should support more than a notice-and-consent approach, and proponents argue that what is needed are approaches that can make users more sensitive to contextual flows of information (Nissenbaum, 2011). This argument for transparency as visibility and accessibility is useful, but insufficient.

Visibility is in no small measure defined by the beholder. In other words, people can see what they can understand, which means that it can be impossible to make the inner workings of complex modelling tools 'visible' for the uninitiated. To see how algorithms function, one must understand them. Or otherwise know them enough to be able to trust or probe them. Transparency requires more than disclosure through design. Making a model or simulation system's frame of reference transparent means supporting people in developing trust and capabilities of probing its function, in training and other settings. It means that trust is not given but is worked up gradually through practical engagement with the system and reveal its instrumental value in such ways as accessing, reviewing, negotiating with and drawing upon how machines arrive at interpretations and recommendations to respond to emergencies. Design for the competent and effective use of modelling and prediction systems should support and bring together social, algorithmic and collaborative practices to explore incidents with a sensitivity to all manner of uncertainties inherent in the events themselves, the models and the ways of working with them. Models should enable users to engage with inconsistent analyses, re-examine assumptions and constraints, foreground otherwise ignored knowledge and practices, for replanning or improvising response strategies.

Several design implications to support transparent reasoning are discussed below to indicate some starting possibilities:

- *Human reasoning with machines*: Design should support sense- and decision-making practices that are often social, collaborative, embodied and improvisational. Emergency response should be augmented in ways that incorporate exploratory and dialogical ways of collaborating with colleagues, other agencies and feeds of on-the-fly analysis. Designs should support reviewing, accessing and understanding the assumptions, sources, procedures, interpretations and potential inconsistencies when augmenting sense- and decision-making. Analyses by machines should be considered as one of the tools to sensitise people to particular aspects of incidents, but other practices should hold equal importance.
- *Errors and breakdown*: however well prepared, any sociotechnical system can suffer full or partial breakdown (Graham and Thrift, 2007). It can be sensor failure, less-than-desirable data quality, insufficiently trained algorithms. When this happens, error messages should aim to support human reasoning with machines as argued above. These messages should should not stop at suggesting what the error is, but should further consider required interaction between expert and practical knowledge to diagnose problems and re-draw strategies.
- *Maintenance, tweaking*: Assembling and improving algorithms and parameter adjustment are practices of realising promises (Mackenzie,

2013), of fine-tuning and providing better correspondence between world and model. The instrumental value of such algorithmic practices should be supported more extensively, but this leads to further concerns: Who has the skill to maintain and tweak modelling and prediction systems? What expertise, skills and knowledge are required and how can this be shared more widely or documented in ways that non-experts can grasp?

- *Relational and contextual accountability*: Design for transparency has to explore how different actors – including the non-human agencies of algorithmic logic - become involved in interpreting, acting upon and negotiating with data and the results of modelling and prediction. What kinds of interdependencies arise, and how are they noticed and dealt with? For example, when wearable sensor technologies can be used to feed real-time sense- and decision-making of responders into models, these models can also become performance evaluation tools, capturing data about responders's actions and communications. Who should see such data and should the individuals be identified? When and how to 'forget' such data? And how does the knowledge that real-time collection of performance data is being collected affect how responders perform? Who should be involved in the evaluation of performance on this basis? Responding to these issues should not become a matter of judgement. Rather, it should be a matter of reflection and critical democratic dialogues (Singleton, 2012).

CONCLUSION

This paper explores how modelling and prediction intervene in the un-ness of emergencies, resolving some of uncertainties, but also bringing in new ones in their wake. By discussing an example of modelling crowd behaviour in evacuation situations, and the measures taken to enhance correspondence between an unknown and emergent – not yet and hopefully never to become real – world and a model and prediction tool, we identified a set of three important dimensions of uncertainties inescapably intertwined in modelling: probabilistic and exploratory understandings, parameters and the need to adjust them, data availability and completeness. We then explored uncertainties arising in the use of models and people's difficulties in negotiating these. This led into an exploratory list of issues that design should be more sensitive to and a call to design 'for' transparency or human practices of making things transparent. The discussion shows that it is not possible to 'simply' make the inner workings of modelling 'visible' by design. Visibility is a function of the beholder's position, expertise and capability to probe and make sense of systems. It is the latter – practices of probing and of making sense of complex systems – that design can support. This is what we call for. Further research to enhance transparency is also called for, to follow through and trace back how models are transformed in relation to uncertainties emerging in the process, as well as how responders work out strategies by interrogating the technologies when experiencing uncertainties. These will specify critical situations, unfolding in disasters and in lines of code, where knowing how models reason can be folded into probing and becoming confident in the particular contexts in which the instrumental value of modelling and prediction technologies is revealed for augmenting emergency response.

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