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http://decodingspaces-toolbox.org/

Tools and components developed in the work-stream ‘Cognitive Design Computing’ are published and included in the Decoding Spaces Toolbox, a collection of analytical and generative Grasshopper components for parametric urban planning developed at the Chair of Computer Science in Architecture and the Junior-Professorship in Computational Architecture at the Bauhaus-University Weimar as well as in collaboration with the chair of Information Architecture at the ETH Zurich.

Ian F.C. Smith, Alberto Costa

Cyber Civil Infrastructure

There is a US$1 trillion shortfall each year between demand and supply in civil infrastructure (World Economic Forum 2014). In order to reduce this gap in a sustainable manner, more informed decision making for tasks such as the extension, improvement and repair of ageing infrastructure is needed. This is even more important because conservative design and construction practices usually result in existing infrastructure that has reserve capacity. This reserve can be used to improve exploitation of its embodied energy, lower material use and reduce asset-management costs. The greatest gains are possible when replacement avoidance can be justified. Such measures are not possible without accurate models of behaviour.

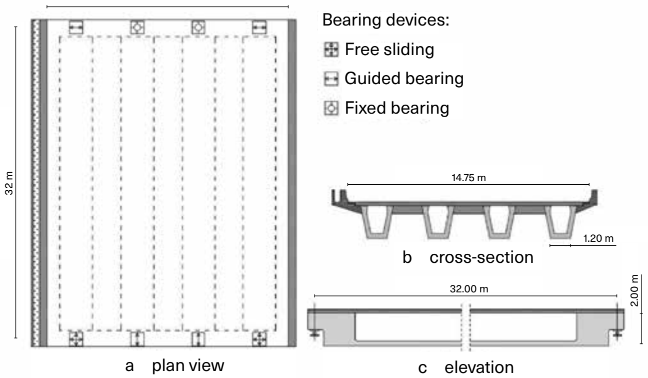
An Internet of Things (IoT) framework can be used to achieve this goal. More precisely, measurements obtained by sensors (such as accelerometers, inclinometers, strain gauges and laser trackers) can be employed to generate accurate models of infrastructure behaviour, thus supporting sustainable and cost-effective decision making by policy makers. At the same time, when IoT is scaled up to the level of a responsive city—a city designed to be measured—‘things’ become more complicated, which means that several important challenges need to be addressed:

- When ‘things’ need to be upgraded due to factors such as a change in demand, they should be improved rather than replaced. Unlike household items, replacing infrastructure is often not cost-effective, nor safe, and sometimes not even possible;
- As a general rule, it is usually effects, rather than causes, that are measured. This leads to ambiguity because there may be many causes that explain the same effects;
- There are multiple sources of uncertainty due to measurements, environmental effects and model simplifications. Moreover, there are systematic uncertainties and their values influence the degree to which uncertainties are correlated (and this violates one of the main assumptions of the Bayesian model—a statistical modelling technique—updating as it is traditionally implemented), thus complicating the analysis;
- Practising engineers dealing with these challenges usually have limited knowledge of advanced statistics—a phenomenon already observed among medical doctors (Wulff et al. 1987).

Interestingly, medical doctors have to deal with similar challenges. Consider, for example, a patient going to the doctor for a consultation. Usually, the patient presents the doctor with a set of symptoms and the doctor’s job is to understand, through examination, the causes that might explain those symptoms. This is an ambiguous task because there can be many illnesses that show the same symptoms and there are many sources of uncertainty—viewers of the TV series *House, M.D.* will be well aware of such situations.

Even though originally proposed to address challenges arising in civil engineering, this stream of research has potential applications across many domains. In addition to large elements found in responsive cities (such as bridges), which can contribute significantly to social and cultural links, the methodologies we are developing are applicable to a wide range of challenges involving sensing. They have been successfully applied not only to bridge diagnosis (Robert-Nicoud et al. 2005; Saitta et al. 2010; Goulet and Smith 2012; Pasquier et al. 2014), but also —just to cite a few examples—to leak detection in water supply networks (Goulet and Smith 2013; Moser et al. 2016), the assessment of earthquake-damaged buildings (Reuland et al. 2017) and simulations of wind flows around buildings (Vernay et al. 2015; Papadopoulou et al. 2016). Hence, our methods have the potential to become part of the data interpretation toolkit of the future inhabitants and custodians of responsive cities. This has been formalised in three research challenges presented below.

2a



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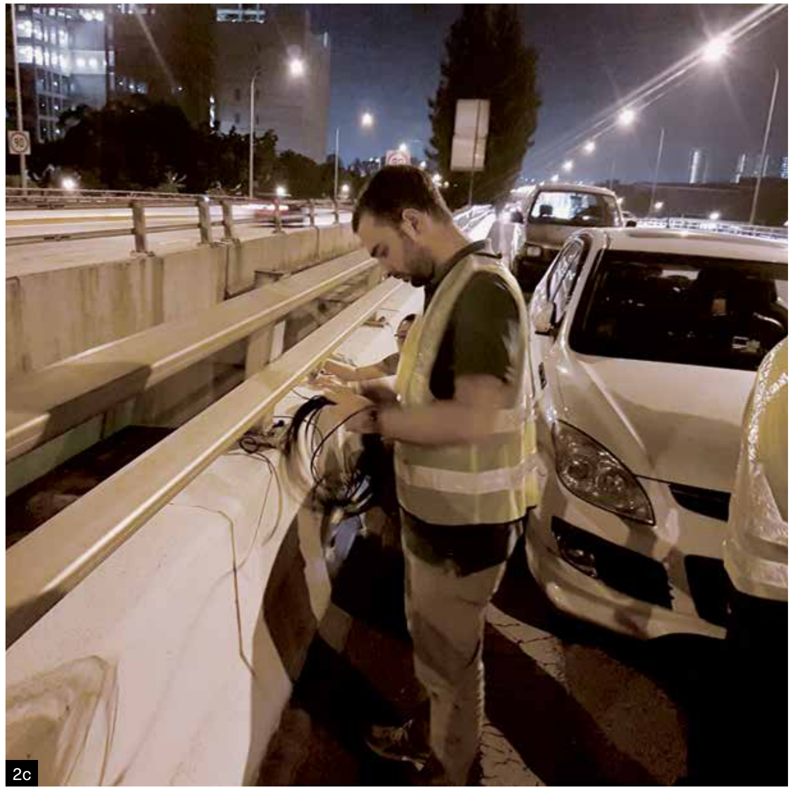

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2d

Fig. 1 Flyover in Singapore. (top)
Fig. 2a–d Sensors on the flyover
Fig. 3 Drawing of the flyover

Fig. 4 Railway bridge in India (bottom view)
Fig. 5 Railway bridge in India (top view)
Fig. 6 Bascule bridge in Exeter, UK

Aims

In *Indicia 01*, we looked at the following research challenges:

Sensor Data Interpretation

Important knowledge related to infrastructure behaviour can be obtained from sensor measurements. Sensors can provide information such as deformations (from strain gauges), rotations (from inclinometers), dynamic movements or vibrations (from accelerometers) and displacements (from laser trackers). The aim here is to identify methodologies that effectively interpret sensor data while providing accurate and robust results for a range of applications in civil infrastructure contexts.

Measurement System Design

When infrastructure is monitored, decisions related to the types and configurations of sensors used are often based on engineering judgement. Suboptimal designs may conceivably result in low effectiveness and unnecessary costs. It is, thus, important to design measurement systems for high efficiency, low costs and accurate results.

Impact of Monitored Structures

Advanced sensor-based methodologies have the potential to provide useful information to policy makers and management, resulting in better decisions related to future design strategies and resilience assessment for civil infrastructure. This is illustrated with case studies that demonstrate how data-interpretation methodologies improve the synergies between science and design within the field of civil infrastructure.

Methodologies

Even though model-free (also called data-driven) methodologies have been studied (Posenato et al. 2010), it is important to combine both behavioural models and data when the aim is to compare alternative scenarios (extrapolation), to support good decision making. Hence, an important step needed to take more informed decisions for civil infrastructure is the identification of sets of model-parameter values that lead to good explanations of measurement data.

Error domain model falsification (EDMF) is a methodology that performs such identification effectively, especially when information on uncertainty sources, including distribution forms, correlations and bias, is not completely known (Goulet and Smith 2013; Smith and Pai 2017). This is often the case in many contexts. According to EDMF, a combination of model and parameter values is considered plausible when predictions are compatible with the sensor measurements within what are called uncertainty bounds.

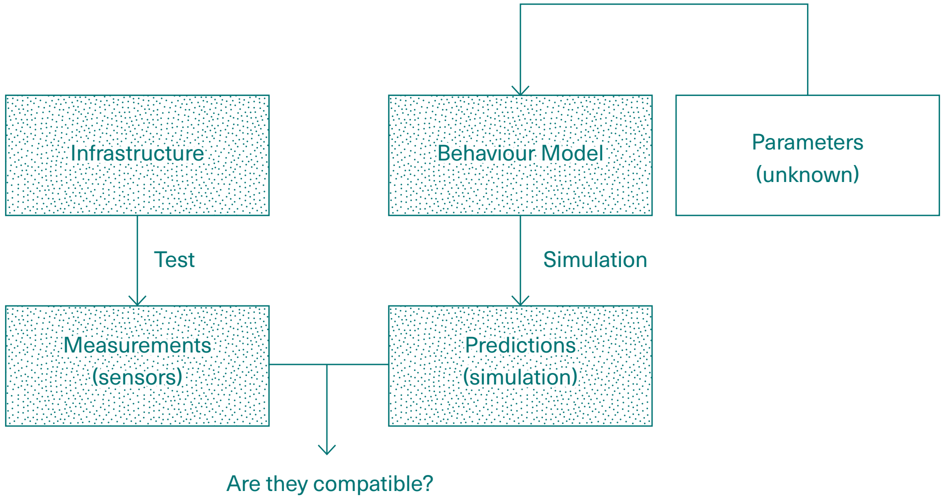
Even though EDMF can be used to meet the research challenges presented in the previous section, its efficacy can be enhanced when combined with optimisation and network analysis techniques. For example, in the *Sensor Data Interpretation* challenge, derivative-free optimisation helps find model parameter values more efficiently, and clustering methodologies provides a better interpretation of results. Moreover, the identification capability of EDMF can be improved when data is obtained from both static and dynamic measurements.

Sensor placement strategies may also be enhanced in the *Measurement System Design* challenge. Finally, EDMF can be used for defining optimal or near-optimal policies in the *Impact on Monitored Structures* challenge, especially in the geotechnical engineering field.

Methods

In many optimisation problems arising in engineering, the mathematical expression of the objective function, which defines the quality of a solution, is not known. However, that unknown function can be evaluated through simulations. This situation is commonly referred to as derivative-free optimisation. There are several derivative-free optimisation methods that can be used together with EDMF to address the challenges presented above. In civil engineering, time-consuming, finite element simulations usually need to be performed. A good method is what we call radial basis function optimisation (Costa and Nannicini 2014), which provides good approximations of the unknown objective function and is specifically designed to tackle derivative-free problems with expensive simulations (Proverbio et al. 2017). When looking for parameter values that explain measurement data, choosing a priori and randomly which ones to test is not the optimal solution. Instead, it is better to decide what to test next based on the results from the parameter values previously tested. In a similar way, a (rational) medical doctor would not randomly prescribe pathology tests to a patient, but rather would start with a small number of tests and then decide what to do next based on the results of these.

An understanding of the methods is essential for their adoption by practising engineers. EDMF results need to be interpreted and presented in an understandable way. This is difficult when the number of the model parameter values that leads to good explanations of measurement data is large. Clustering methodologies can help address this issue. While methods such as principal components analysis are



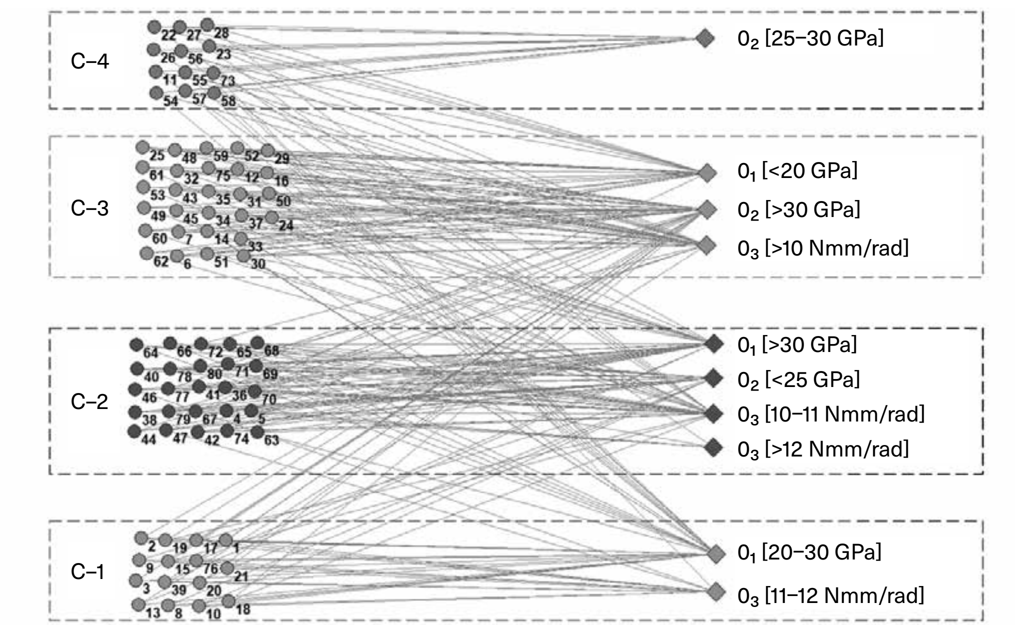


Fig. 7 EDMF methodology to identify good model-parameter values
Fig. 8 Clustering applied on the results of EDMF for the flyover in Singapore, showing identified models (*left*) and corresponding values of the parameters of interest (*right*)

used to reduce dimensions (Smith and Saitta 2008), results are often not intuitive. Bipartite modularity (Barber 2007; Costa and Hansen 2014), a clustering measure which helps group together nodes densely connected in a bipartite graph, can be used to improve understanding, since in this context it provides both good quality results and a clarity of interpretation regardless of the dimension of the problem (Costa et al. 2017).

As mentioned before, another important challenge is related to sensor placement. When collecting measurement data, it is important to assess the value of information. For example, if two sensors of the same type are placed close to each other, it is likely that they will provide similar information. This is not the best configuration for performing identification. As a result, it is important to place the sensors in locations that maximise the amount of information provided by measurements—an idea formalised with the concept of joint entropy, which is useful when considering the combined action of multiple sensors. Once again, optimisation methods can be used to find the sensor configuration that maximises this joint entropy (Bertola et al. 2017).

Another way to employ the results of the EDMF methodology is to derive policies that are more accurate and cost-effective. An interesting application is in the field of geotechnical engineering, where data collected during excavation can increase the knowledge of soil behaviour and thus improve construction safety. More precisely, excavation is a multistage process, where the actions to be taken at each stage depend on the outcome of the previous stages. EDMF can be effectively employed to extrapolate information about soil using the data collected at the current stage of excavation, and that can be used to make better decisions at the next stage (Wang et al. 2018).

EDMF can also be employed with dynamic tests to investigate vibration characteristics of a structural system. In this case, vibration tests, e.g., ambient, forced or free vibration tests, are used to collect data. After obtaining signals from accelerometers, modal analysis methods—i.e., stochastic subspace identification and frequency domain decomposition —are adopted to identify the natural frequencies and detailed mode shape information (Cao et al. 2017).

In addition, the results of EDMF and the input of decision makers can be used to define optimisation tasks where the objective is to find good policies.

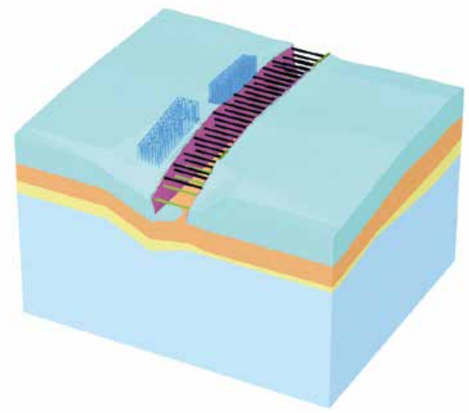


Fig. 9 Excavation test case—Deformation analysis of an earth-retaining structure

Data

Details related to infrastructure and sensor data have been used to test and evaluate the methodologies described above. Currently, data are available for two static and dynamic tests that have been performed on a flyover in Singapore and the Exeter Bascule Bridge in the UK. This data includes specific drawings of infrastructure, which are required to create a computer model for the simulator, and measurements from load tests. Technical details on the sensors, as well as modelling accuracy data, are also needed in order to estimate uncertainties. In addition, data are available for a test performed on a railway bridge in India. For the geotechnical engineering application, measurements have been collected from an excavation in Singapore.

Cases

A flyover in Singapore, a railway bridge in India and the Exeter Bascule Bridge in the UK show aspects of the EDMF methodology. Recently, a new case involving a load test on a bridge in Australia was obtained.

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Transportation Flows in Future Cities

Flows of people, goods, energy, water and waste course through the urban infrastructure and constantly shape urban form. Transportation flows, defined by how people and goods move through the city, determine to a great extent how cities were shaped in the past, and how they will be reshaped in the future (Ascher 2007). This is evident in the compact monocentric city that served pedestrians and horse carts, the polycentric city that emerged with trains and trams and, more recently, highway-based cities that respond to the rise of personal automobiles. Innovations in transportation technology can be linked to how our cities are shaped.

Today, we are faced with many such game-changing innovations. How will the advent of autonomous vehicles (AV) impact the future city? What role will active mobility, such as walking and cycling, play in future? And how can we leverage new opportunities presented by big streams of data to improve transportation flows? Given the rapid and far-reaching transformations occurring in the transportation sector, the study of transport flows, networks and spaces has become increasingly critical.

Traditionally, urban form and placemaking have been the domain of more qualitatively focused disciplines like urban design while transportation planners have focused on how to maximise capacity, minimise obstacles and optimise speed of flows. For a long time, the sole purpose of transport flows was largely seen as being all about getting from one point to another. Gradually, as the destruction wreaked by car-oriented planning on communities and environment became evident, this began to change. There was growing criticism of this idea of movement as the only role of transport infrastructure, but instead began to be seen as a part of life, with social and aesthetic effects (Ascher 2007; Lynch and Hack 1984).

Jane Jacobs describes this concept through the ‘sidewalk ballet’ (Jacobs 1993 [1961]), where she paints a vivid picture of the vibrant life on New York streets—children playing, the barber bringing out his sidewalk folding chair, women in housedresses pausing for quick conversations and so on. Jacobs was one of the first to conceptualise transport as a set of networks stitching together spaces and places, from which locations naturally emerge.

Today, there is a growing body of research concerned with the relationship between travel patterns and urban form (Banister et al. 1997; Breheny 1995; Hansen 1959), notably because it is related to transport, which provides empirical evidence from five case-study cities in the United Kingdom and one in the Netherlands on the links between urban form and energy consumption in transportation. It also links energy-use measures to the physical, economic and social structure of the city to determine whether there are significant relationships. Energy-use measures combine all of the characteristics of travel (mode, distance and frequency) as well as its social effects. It thus becomes necessary for transportation research to broaden its scope from movement flows to include scholarship in infrastructure, urban design, perception and cognition.

The twin challenges of keeping up with rapidly emerging transformative technologies, and effectively engaging with multiple disciplines centred around transport flows, shape the methodological framework that ‘Engaging Mobility’ research operates within.

Four Mobility Questions

We are currently engaged in answering four mobility questions.

Engaging Active Mobility

How can we assess and evaluate different cycling infrastructure designs based on behavioural reactions of cyclists? Despite Singapore’s dense and polycentric urban structure, only about 1 per cent of