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A socio-economic analysis of Smart Infrastructure sensor technology

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ABSTRACT

Smart Infrastructure wireless sensor technology is designed to provide a new way of managing infrastructure. These wireless sensors are able to share information on infrastructure conditions across a range of agencies without human intervention. Thus, false readings can be corrected automatically and further incidents should be avoided. The advantages of using these wireless sensors are their reliability, low-cost, low power and fast deployment characteristics. In this paper, we conduct a socio-economic analysis on the application of Smart Infrastructure sensor technology to the British rail tunnel industry using Monte Carlo simulation. The study would offer insights on the feasibility of the technology. Furthermore, the simulation forecast would bring the deeper understanding of the wider socio-economic implications, which is important for decision makers. Our study shows that the mean value of the cumulative net present value for the application of the Smart Infrastructure sensor to the British tunnel market in the year 2056 is estimated to be US$40 million. According to the sensitivity analysis, the key parameters, which have significant impacts on the net present value, are the maximum target market penetration rate, base year disruption cost due to tunnel closure, total tunnel length, and annual number of tunnel collapses.

1. Introduction

Good quality infrastructure is a key ingredient for sustainable development and human well-being. Adequate supply of infrastructure facilitates both economic growth and social welfare (Aschauer, 1990). Numerous challenges that tunnel infrastructure operators, especially undergrounds, are facing range from impacts of ground water to flooding. Congestion and disruptions caused by delays or cancellations of transport service due to infrastructure failures are serious concerns that could lead to significant economic and social costs. According to Oxford Economic Forecasting (2005), the economic cost of transport delays to employees and businesses in central London is estimated to be US$1870 million a year. There are numerous studies that examine the value of travel time variability (e.g., Jenelius et al., 2011; Fosgerau and Karlstrom, 2010; Fosgerau and Engelson, 2011; Bowman and Ban-Akiba, 2001; Borjesson and Eliasson, 2011; Asensio and Matas, 2008; Carrion-Madera and Levinson, 2011).

Deteriorating ageing infrastructure is a major concern. Houlihan (1994) claims that Europe is facing a difficulty in managing ageing infrastructure. For example, the tunnels of the London Underground are 75–100 years old, with various problems ranging from deterioration of lining to risks from 3rd party construction. London Underground tunnels currently require repairs of approximately 100 locations every year after visual inspection. Thus, accurate monitoring meeting specific needs of repair is urgently required. In the United States, numerous advocates address the necessity of new policies to deal

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with ageing infrastructure (e.g., Connery, 2008). Evidently, the fast growth of Asian countries could also be hampered by ageing infrastructure (Ford, 2008).

Infrastructure is generally under-invested and its operation is often not cost effective (Lortie, 2008). Recent trends on emphasising maintenance rather than new construction is seen in the government (e.g., the United States) favouring in spending more on maintenance (Durango-Cohen and Madanat, 2008). Different studies propose various maintenance approaches for better infrastructure management. These approaches include: risk-based tools for reducing potential risks of equipment failures (e.g., Seyedshohadaie et al., 2010; Ng et al., 2003); an adaptive control approach for optimum infrastructure management under uncertainty (Durango and Madanat, 2002); time series models to estimate infrastructure performance (Chu and Durango-Cohen, 2007); a programming framework to support transport infrastructure maintenance optimisation policies (e.g., Durango-Cohen and Sarytipand, 2010; Kuhn and Madanat, 2005; Madanat, 1993). Advanced inspection technologies such as sensors are identified as increasingly important for collecting infrastructure condition data and their causal factors especially with their capability of simultaneously evaluating and measuring multiple factors and distresses (Chu and Durango-Cohen, 2007). For example, Garcia et al. (2010) have presented an intelligent sensory system for obstacle detection on railways, while Oukhellou et al. (2008) have proposed the combined use of sensor data for a railway infrastructure diagnosis.

At the present time, infrastructure management policy appears to follow reactive rather than proactive monitoring (e.g., McCollum, 2008; Haffejee and Brent, 2008). The tendency of adopting a reactive approach to managing their assets is well explained by limited financial and human resources (McCollum, 2008). Moreover, Haffejee and Brent (2008) claim that a reactive approach to infrastructure management is due to the fact that the exact location and condition of the infrastructure is often not fully known.

Technologies have gained a significant amount of attention recently in the transport sector (Greelings et al., 2009). More specifically, interest in using wireless sensing networks for structural health monitoring to protect infrastructure has increased dramatically (Cheung et al., 2008). The Smart Infrastructure sensor technology enables us to effectively conduct real time monitoring and control of infrastructure. Wireless sensor networks have the potential to be cost-effective tools that can be deployed on all types of civil infrastructure and provide managers with critical real-time data on performance (Hoult et al., 2009). Various infrastructure-related potential applications of Smart Infrastructure sensors exist, ranging from water pipes to bridges. Competitors will be highly likely to develop systems to monitor bridges and buildings, but there is less chance of this happening for tunnels and pipelines (Stajano et al., 2010). There is even less chance that anyone else will develop system with the capability to share across agencies (Stajano et al., 2010).

The contribution of this study can be categorised in three aspects. First, this study demonstrates that a simple probabilistic cost benefit analysis (CBA) can provide a relatively clear picture of the situation to explain 'what if' we introduce a new innovative technology to a market. In addition, the benefit of this emerging technology is presented as a quantified figure, which will be useful for policy makers and managers. The advantage of the model is its flexibility, in which replacing data or modification of parameter specifications can be carried out in a fairly short period. Such easy-to-run feature using a probabilistic analysis is suited to an assessment like this, which includes huge uncertainties. For those parameters having great uncertainties, we will use a large range for their input data to take into account the possible variability. Another great feature of this type of the model is its versatility. We can use multiplier concepts to further expand the model, which is a simple extension from the previous model (Morimoto, 2010). Some data that are difficult to obtain will be estimated by using multipliers to the already existing data in Morimoto (2010) so that date scaling (up/down) can be performed.

Secondly, the study provides justification of developing the Smart Infrastructure wireless sensor technology in response to growing interests in this technology by quantifying its benefit with uncertainty consideration. Thirdly, the application of the proposed approach to the United Kingdom (UK) rail tunnel industry is a timely and useful attempt. The tunnel infrastructure is deteriorating rapidly that requires effective assessments to examine the role of innovative technologies for strategic future infrastructure management policy. This case study will demonstrate the importance of enhancing a strategic and proactive approach towards transport infrastructure management.

In this paper we will examine the socio-economic contributions of Smart Infrastructure sensors if applied to the rail tunnel industry in the UK. With limited financial resources available for infrastructure management, socio-economic justification of implementing emerging technologies would be a useful exercise. Moreover, we could quantitatively demonstrate the role of technology in improving infrastructure management. In order to deal with huge technological and market uncertainties, a probabilistic cost benefit analysis using Monte Carlo simulation technique is applied as the impact assessment tool. The rest of the paper is organised as follows. The next section provides the description of the Smart Infrastructure wireless sensor technology, followed by Section 3 that explains the methodology used in this paper. Section 4 summarises the findings and Section 5 concludes the paper as well as proposes future research directions.

2. Smart Infrastructure sensors

Smart Infrastructure wireless sensor is small in size that communicates over short distances (Fig. 1). The network of wireless sensors is placed along a 100-m stretch of tunnels, measuring small changes in pressure that would indicate movement. As Fig. 2 depicts, the sensors transmit information to receivers located in the access shafts, followed by the receivers sending the information (e.g., cracks), via the mobile phone network, to an online database archive, where the data processing is car-

Fig. 1. Smart Infrastructure sensor. Source: Cambridge University Engineering Department Geotechnical group.

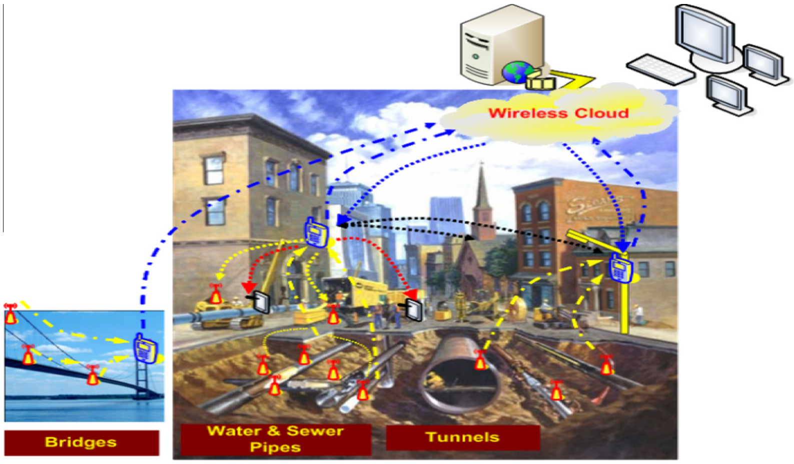

Fig. 2. Operation system of Smart Infrastructure sensor. Source: Cambridge University Engineering Department Geotechnical group.

ried out (Bennett et al., 2010a,b; Stajano et al., 2010). Engineers can observe the real-time situation of the tunnels using the database (Bennett et al., 2010a,b; Stajano et al., 2010).

The Smart Infrastructure sensors can monitor infrastructure systems in real times, as well as increase the capabilities of infrastructure for efficient maintenance (Stajano et al., 2010; Hoult et al., 2009; Bennett et al., 2010a,b). Furthermore, they are able to share information on infrastructure conditions across a range of agencies without human intervention (Stajano et al., 2010; Hoult et al., 2009). Thus, false readings can be corrected automatically and further incidents should be avoided (Stajano et al., 2010; Hoult et al., 2009). Smart Infrastructure technology is expected to allow tunnel collapse to be averted as a result of proactive infrastructure management enabled by real-time monitoring (Stajano et al., 2010). Such technology is promised to greatly advance today's infrastructure management practice (inside story: superstructures Economist 9 December 2010).

Although there are currently a variety of commercially available wireless sensor network systems, each has limitations and none of them seems to provide a complete solution (Stajano et al., 2010). The uniqueness of Smart Infrastructure is its ability to measure changes in geometry (e.g., displacement or inclination). Smart Infrastructure sensor communication is characterised as a tiered structure and adaptive network topology with a scalable protocol design, therefore they are efficient, secure and robust (Stajano et al., 2010). Scalability of the systems is also a key benefit, which allows dynamic system growth and extension (Bennett et al., 2010a,b; Stajano et al., 2010). Smart Infrastructure sensors offer adaptive network configuration and operation in case of failure and unexpected events, leading to improved reliability (Bennett et al., 2010a,b; Stajano et al., 2010). The key advantages of using wireless sensors are low-cost, reliable performance and fast deployment, especially in difficult-to-access areas (Bennett et al., 2010a,b; Stajano et al., 2010; Cheung et al., 2008). Instead of usually more time consuming visual inspection (e.g., Reid, 2008; Spellman, 2008), sensors can communicate by themselves detecting any failures in real-time (Soga and Shureshi, 2010). Thus, the new wireless sensor system is supposed to maximise response speed.

Cost savings can be expected by Smart Infrastructure sensor as radio connections replace wires and associated installation costs. Previously expensive sensors are replaced by inexpensive low-power alternatives as a result of advancement of microelectromechanical systems (Hoult et al., 2009). Moreover, miniaturisation and improved battery life[1] could reduce the individual unit cost of sensors significantly (Stajano et al., 2010). Of course, there will be an upfront cost in order to harmonise the system across the various agencies involved, and this has yet to be established (Hoult et al., 2009). The sensor replacement period should also satisfy specific industry requirements since sensors are battery powered (Bennett et al., 2010b) In addition, the data-transmission bandwidth varies according to the chosen radio frequency and transmission power, which affects the power consumption (Ferri et al., 2010). Occasional failure of the hardware or software could as well happen (e.g., Yu et al., 2007).

Given those innovative features of Smart Infrastructure sensor discussed above, significant socio-economic benefits can be expected through the implementation of this new 'Smart' system. So far, a successful trial on monitoring the condition of the existing London Underground tunnels in real time to test the capability of Smart Infrastructure technology was conducted in March 2003 (Stajano et al., 2010). Furthermore, the technical as well as practical issues involved in deploying a wireless sensor network found from the Prague Metro and the London Underground trials are discussed in Bennett et al. (2010a).

These emerging wireless sensor technologies appear to be promising, though some careful considerations need to be made to deal with the challenges they face. Previously developed sensors have shown several drawbacks: for example, some have only a limited data processing power (Feltrin et al., 2007). Current research in the area of wireless sensor networks largely focuses either on laboratory-based studies (e.g., Paek et al., 2005) or short-term field deployments (e.g., Lynch et al., 2006; Ramanathan et al., 2006; Paek et al., 2005). Although some wireless sensor network systems have been applied to existing infrastructure, normally a trial basis is run for a relatively short period without enough empirical experience (e.g., Lynch et al., 2006; Ramanathan et al., 2006). Trials of wireless sensors on bridges are, especially, frequently carried out. Large-scale and long-term deployments of wireless sensors on bridges often focus on vibration monitoring (Feltrin et al., 2007; Kim et al., 2007). For example, Cheung et al. (2008) have conducted a field test on structural health monitoring of bridge structures using damage detection algorithms based on statistical pattern recognition techniques for ambient vibrations. Their findings indicate the difficulties in field data collection as well as quantification of damage. This is not surprising, as the accuracy of data collected by wireless sensors is often a concern (e.g., Grosse, 2008). The common problem of sensors indicating false signals has also been widely discussed (e.g., Dawsey et al., 2007). The issue here is, there is a significant uncertainty involved in real time monitoring of infrastructure systems both in terms of sensor technology (e.g., data transmission rate and accuracy) and online monitoring (Dawsey et al., 2007, Xu and Goulter, 1998; Bargiela and Hainsworth, 1989). Thus, ensuring the data set provided by Smart Infrastructure is complete and accurate should be a prime goal for the sensor developer.

3. Methodology

3.1. Model concept

Based on the above discussion, we define the following research question: What are the socio-economic benefits of proactively managing tunnel infrastructure with the innovative Smart Infrastructure sensor system? The paper presents a cost benefit analysis (CBA) model that assesses socio-economic impacts of Smart Infrastructure. There are significant presence of uncertainties in measurement and forecasting for transport infrastructure maintenance and rehabilitation planning (Madanat, 1993). Thus, the probabilistic cost benefit analysis that takes into account future uncertainty, is applied to the rail tunnel industry in the UK. This research has used a Monte Carlo simulation; a problem solving technique used to approximate the probability of certain outcomes by running multiple trial runs using random variables. Such technique provides robust outcomes since a range of input is used instead of a single figure, which is often uncertain for this kind of impact assessment with emerging technologies.

When investigating whether a new innovative technology is worthwhile to develop, appropriate decision framework needs to be formed. The CBA is a common method for technology evaluation (e.g., Collopy, 2007). The CBA is a project-based approach focusing on net benefits. In addition to traditional net present value (NPV) analysis, real options approach as an investment decision support system is frequently applied. In this method, option values are used as a justification and prioritisation of portfolio of various potential new technology projects (e.g., Jeffery et al., 2003; Xing, 2009). The main objective of this paper is to examine the impact of a specific innovative technology rather than a portfolio of various projects, therefore real options approach was not considered. Another approach that investigates various alternative options is multi criteria analysis (MCA). The MCA evaluates multiple objectives simultaneously, which can provide decision-makers with additional information to NPV. The MCA enables the decision maker to investigate a number of different alternative projects based on multiple criteria and conflicting priorities (EC, 2000). The MCA provides systematic approach for integrating risk levels, uncertainty and valuation (Linkov et al., 2006). The MCA is especially powerful when quantifying the trade-offs that must be made between conflicting objectives, which are difficult to compare directly. This paper, however, focuses on the contribution of one specific technology rather than many alternatives, therefore the MCA was not considered.

[1] Power harvesting using existing power underground can be considered as an alternative option. Additional to a solar cell or in combination with solar energy, the wireless sensor node can be powered by thermal, vibration (piezoelectric) or radio wave energy harvesting sources (e.g., Mohamed et al., 2011).

There is a study, whose approach is similar but the scope of the model is larger than our proposed model, is presented in Sweeney and Weyant (2003). They have developed an integrated assessment method, computing impact values for the new technologies across a wide range of possible technological and socio-economic futures. Literature reviews, structural models, and expert assessments are used to develop probability distributions about inputs to the technology evaluation models. A set of integrated probabilistic scenarios is then established based on expert assessments with probabilities being assigned.

Another common approach includes one in strategic management context. For example, the contingency-based approach is applied to explain the impact of cost-related technology applications on firm performance while the resource-centered perspective is used to predict technology impacts on firm revenue and profitability (Oh and Pinsonneault, 2007). Other notable approaches, which have a diverse focus from our proposed model, include the following: risk analysis (Webb, 1994; Shishko et al., 2003; GAO, 1999), an integrated decision framework that offers more holistic approach to manage infrastructure (Kleiner et al., 2009), benchmarking and performance monitoring for efficiency gains (Mugisha, 2007).

We have selected the CBA approach since the model best examines the impact of this innovative Smart Infrastructure technology, while dealing with the huge uncertainties the project may face. Furthermore, the subsequent sensitivity analysis can provide us with the key parameters that affect most significantly on NPV. Validation of the model is conducted quantitatively, namely through sensitivity analysis, and qualitatively using interviews with experts. All the parameters as well as the data are verified by the developers. The strength of this type of analysis is that, since we use a range of data instead of a single figure, we can run the simulation readily with other data sets or add/omit some parameters. Moreover, the validity as well as the robustness of this type of statistical models is highly supported by similar impact assessment models that have already been applied to other projects, including water pipe (Morimoto, 2010), hydropower (e.g., Morimoto and Hope (2004a,b)) and aviation (Morimoto and Hope (2005)) projects.

There are two scenarios underlying the model: the baseline scenario and the Smart Infrastructure development scenario. The baseline scenario presents the world without Smart Infrastructure development, but with natural improvement of sensor systems. The Smart Infrastructure scenario represents the world with Smart Infrastructure where the improvement of the sensor system is expected to be much faster than the baseline case as a direct result of this innovative technology. There are three phases to the project – development, harmonisation and market penetration. First, we need to decide whether to fully develop a Smart Infrastructure sensor system. If we decide to develop one and succeed in the commercialisation, possible benefits are expected. If we do not succeed, we lose the development costs, which are already invested. The model can be further extended to consider a broadening of the market to include market areas outside the UK in future research. In such a case, further benefits could be expected without development costs, but some extra modification and harmonisation costs would still be necessary. This last part of global commercialisation is not included in the analysis as it is beyond the scope of this paper. Competitor consideration is also included in the model framework, as competitors might appear in the market after a certain period. The possibility of failing to develop Smart Infrastructure sensors successfully is also considered in the model. Thus the expected impacts are multiplied by the probability of success or failure.

3.2. Model parameters

There are eight categories of costs and benefits used in the model, which are considered to have significant impacts on the NPV. First, the project needs development and harmonisation costs. Then, the direct economic benefits expected by this technology are saved operation and maintenance (O&M) costs, saved repair costs, and saved sensor material costs. The benefits of a reduced rate of tunnel collapse as a result of using Smart Infrastructure technology are saved infrastructure damage costs, saved disruption costs and saved casualties.

A Smart Infrastructure sensor system detects failures of infrastructure at an early stage without any human inspection involved. The sensor also identifies the specific area that needs repairing; therefore unnecessary prospective inspection is avoided. Thus, O&M as well as repair costs are expected to be significantly reduced from the current level. The material costs of Smart Infrastructure sensors are expected to be much lower than the currently existing sensor system, even though sensor installation costs will be needed. In the model, the extra battery changing costs of Smart Infrastructure sensors are deducted from the overall saved O&M costs, and the extra installation costs are deducted from the overall saved material costs. The early damage identification feature of the Smart Infrastructure sensor system could lead, in this model, to early repairing, thus most likely reduced tunnel collapse rates could be expected. This would in turn lower direct damage costs (infrastructure damage), disruption costs (service/traffic, business/school forced to close), and possible casualties.

The model does not include the replacement costs of Smart Infrastructure sensors explicitly, which are instead embedded in the installation costs. This is due to the fact that the exact life period of the Smart Infrastructure sensor system is currently not fully known. The sensors are designed to be durable, therefore the impact of the replacement costs of sensors are supposed to be relatively insignificant (Bennett et al., 2010a,b; Stajano et al., 2010). Additionally, the unusual condition of the installed sensors could be alerted when the network is not able to transmit the data for some periods, which could be either due to radio connectivity or equipment failures.

The following equations are used in the model to calculate the key variables. All the units are in US dollars. First, the total development cost (i.e., DEV_{total}) is estimated as the development cost to date (i.e., DEV) when time $t = 0$. When time t is less than the time when the maximum development cost is required in year ($t_{dmax} + 1$), DEV_{total} equals to the multiplication of the maximum development cost (i.e., DEV_{max}) and the fraction of the time variable $(t + 1) - 1$ to t_{dmax}. When time t is less than and equal to the extra development time in year (t_{dex} + 1), DEV_{total} is estimated as the multiplication of DEV_{max} and the fraction of the time variable $(1-(t-(t_{dmax}-1))$ to $(t_{dex}-t_{dmax})$. All of these can be expressed as follows:

$$\begin{aligned} DEV_{total} &= DEV && \text{if } t=0 \\ &= DEV_{max} \times \tfrac{(t+1)-1}{t_{dmax}} && \text{if } t < t_{dmax}+1 \\ &= DEV_{max} \times \tfrac{1-(t-(t_{dmax}-1))}{t_{dex}-t_{dmax}} && \text{if } t \leqslant t_{dex}+1 \\ &= 0 && \text{otherwise} \end{aligned} \tag{1}$$

The harmonisation cost is calculated in a similar manner. When time t is less than the extra harmonisation time (i.e., t_{hex}) + time at the maxim harmonisation cost is needed (i.e., t_{hmax} + 1), the harmonisation cost is the multiplication of the maximum harmonisation cost HAR_{max} and the fraction of $((t+1)-t_{hmax}-1)$ to t_h, the harmonisation time in year. When time t is less than (t_{hex} + t_h + 1), the harmonisation cost is the multiplication of HAR_{max} and the fraction of $(1-(t-t_{dex}-$ $-\,t_{hmax}-1)$ to $(t_{hex}-t_{hmax})$.

$$\begin{aligned} HAR &= HAR_{max} \times \tfrac{(t+1)-t_{hmax}-1}{th} && \text{if } t < t_{hex}+t_{hmax}+1 \\ &= HAR_{max} \times \tfrac{1-(t-t_{hex}-t_{hmax}-1)}{t_{hex}-t_{dmax}} && \text{if } t \leqslant t_{hex}+t_h+1 \\ &= 0 && \text{otherwise} \end{aligned} \tag{2}$$

The saved annual operation and management cost (i.e., OM_{sav}) is simply estimated as the multiplication of OM (unit O&M cost in US$/km), α (% saved of O&M cost due to Smart sensors), DIS (the total distance of rail tunnel market served by Smart sensors in km), BAT (battery changing cost in US$/sensor, and $SENS$ (number of Smart sensors required).

$$OM_{sav} = (OM \times \alpha \times DIS) - (BAT \times SENS) \tag{3}$$

Similarly, the saved annual repair cost (i.e., REP_{sav}) is the multiplication of REP (unit repair cost in US$/km), β (% saved of repair cost due to Smart sensors), DIS_{rep} (the total tunnel distance needing repair in km).

$$REP_{sav} = REP \times \beta \times DIS_{rep} \tag{4}$$

The saved annual material cost (i.e., MAT_{sav}) is the multiplication of the unit material cost in US$/km ($MAT$), the saved% of material cost due to Smart sensors (γ), the installation cost in US$/sensor ($INST$), and the additional sensors required ($SENS_{add}$).

$$MAT_{sav} = MAT \times \gamma + INST \times SENS_{add} \tag{5}$$

The saved annual casualty cost (CAS_{sav}) is the multiplication of the casualty valuation in US$/person ($CAS$), the number of casualties per collapse ($NOCAS$), and the reduced rate of collapses due to Smart in number of collapses (δ).

$$CAS_{sav} = CAS \times NOCAS \times \delta \tag{6}$$

The saved annual disruption cost (DIS_{sav}) is the multiplication of the disruption damage cost in US$ per collapse (DIS) and reduced rate of collapses due to Smart in number of collapses (ε).

$$DIS_{sav} = DIS \times \varepsilon \tag{7}$$

The saved annual economic damage cost of collapse (i.e., ECO_{sav}), is the multiplication of the direct damage cost of collapse in US$ per collapse (i.e., ECO) and the reduced collapse rate due to Smart sensors in number of collapses (θ).

$$ECO_{sav} = ECO \times \theta \tag{8}$$

The total annual cost (i.e., TC) is estimated as the sum of DEV and HAR which is multiplied by the probability of technical & commercial success of Smart Infrastructure (P).

$$TC = DEV + P \times HAR \tag{9}$$

The total annual benefit (TB) is the sum of OM_{sav}, REP_{sav}, MAT_{sav}, CAS_{sav}, DIS_{sav}, and ECO_{sav}, which is then multiplied by P.

$$TB = P \times (OM_{sav} + REP_{sav} + MAT_{sav} + CAS_{sav} + DIS_{sav} + ECO_{sav}) \tag{10}$$

The net present value at time t (NPV_t) is simply expressed as ($TB_t - TC_t$) multiplied by the discount rate at time t, d_t

$$NPV_t = \sum_{t=0}^{t} (1+d_t)^{-t} \times (TB_t - TC_t) \tag{11}$$

3.3. Key features of the model

3.3.1. Market penetration

Smart Infrastructure is expected to be first introduced in the UK, and then in the EU and US, followed by the rest of the world. Note that the project assessment period is set to be 50 years, which is assumed to be long enough to assess the expected impacts from the market penetration of Smart Infrastructure. According to the experts from Metronet,[2] an approximately 30-year period could cover the life cycle of this technology (design, development, commercialisation and competition).

The market penetration rate of Smart Infrastructure increases gradually, and then reaches the maximum target rate. After a certain period, competitors might start appearing and the market penetration growth rate start decreasing. The model uses one form of a logistic function to portray the market penetration behaviour of Smart Infrastructure. The logistic function exhibits an approximately exponential growth at the initial stage, followed by slow-downs in growth due to competition, and the growth finally stops at maturity. The logistic function is also called '*S*-Curve' as its curve depicts an *S*-shape. The equation to calculate the market penetration rate in the model is presented in Appendix A.1.

We have chosen a logistic function as it is most commonly used to represent technology adoption rates in the transportation sector (Bladucci, 2008). The *S*-Curve depicts that, from initial commercial introduction to 10% market penetration, new technologies evolve, transform, and become viable in the marketplace (Hollinshead et al., 2005). Sceptical investors and manufacturers are initially reluctant to adopt the new technology, which results in a lack of capital investment and resources that are necessary to nurture and refine the new technology (Hollinshead et al., 2005).

3.3.2. Multipliers

The model used in this paper was developed at several stages. First, the UK water pipe assessment model was developed as a core model for the following reasons: (i) Smart Infrastructure is developed in the UK and (ii) water pipe related data is relatively easy to obtain compared to tunnel related data. Then, based on the existing assessment model for the water pipe application (Morimoto, 2010) a new assessment model for the tunnel application of Smart Infrastructure was developed in a straightforward manner. The new model structure has required fairly small additional modifications incorporating the tunnel application specific impacts. Otherwise, multipliers alone were used to scale up/down the impacts since similar behaviours are expected between the water pipe and tunnel applications. In other words, the data used in the UK tunnel model are multipliers to the UK water pipe model (Appendix A).

3.3.3. Discount rate

When conducting a cost benefit analysis, deciding which discount rate should be used is difficult. There is no single rate that satisfies all the requirements for all projects. The appropriate discount rate is project-specific (Lind,et al., 1982). This analysis applies the commonly used values for infrastructure projects as an appropriate range. For example, 3.5% is used for infrastructure project, according to HM Treasury. Vronwenvelder and Krom (2004) argue that the discount rate of 3% is commonly used for tunnel projects.

3.4. Data

3.4.1. Input parameters

Data sets have been collected from various sources including a series of meetings with Smart Infrastructure developers, other experts in the field, the relevant literature, annual reports and Internet resources. All figures used in the data have been agreed upon by the Smart Infrastructure project managers during meetings with the author (see Appendix A.2). A range of values (minimum, most likely and maximum) is used instead of using just a single figure for each input. Thus, a range of outcomes is obtained, which gives more robust results when dealing with great future uncertainty. A large range is used for those data with large uncertainty. All input data are assumed to follow a triangular distribution.

Of course, since the choice of discount rates has significant impacts on the outcome, one must be extra careful in choosing appropriate discount rates. The beauty of this model, however, is the ease of running simulations again with different discount rates. Thus, the variation of the outcome according to different discount rates could be well investigated.

4. Findings

This research has applied the Monte Carlo simulation with 10,000 iterations using Palisade @RISK software. This section presents the expected impacts of Smart Infrastructure when the technology is commercialised in the UK tunnel market. Key findings based on the model results are illustrated below.

4.1. Market penetration

The market penetration rate gradually increases after the year 2023, until the maximum target market penetration of around 27% is reached in the year 2037, as shown in Fig. 3. The market penetration growth rate decreases after competitors might start appearing.

[2] Metronet was one of two companies in a public-private partnership with London underground from 2003 to 2008, which was responsible for the maintenance, renewal and upgrade of the infrastructure on London Underground lines.

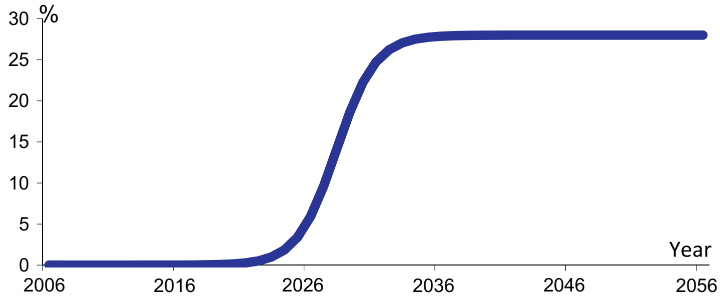

Fig. 3. Market penetration rate. Source: CBA model runs by the author using @Risk.

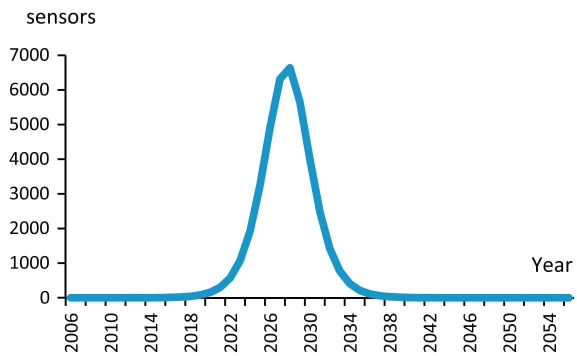

Fig. 4. Additional Smart Infrastructure sensors required by year. Source: CBA model runs by the author using @Risk.

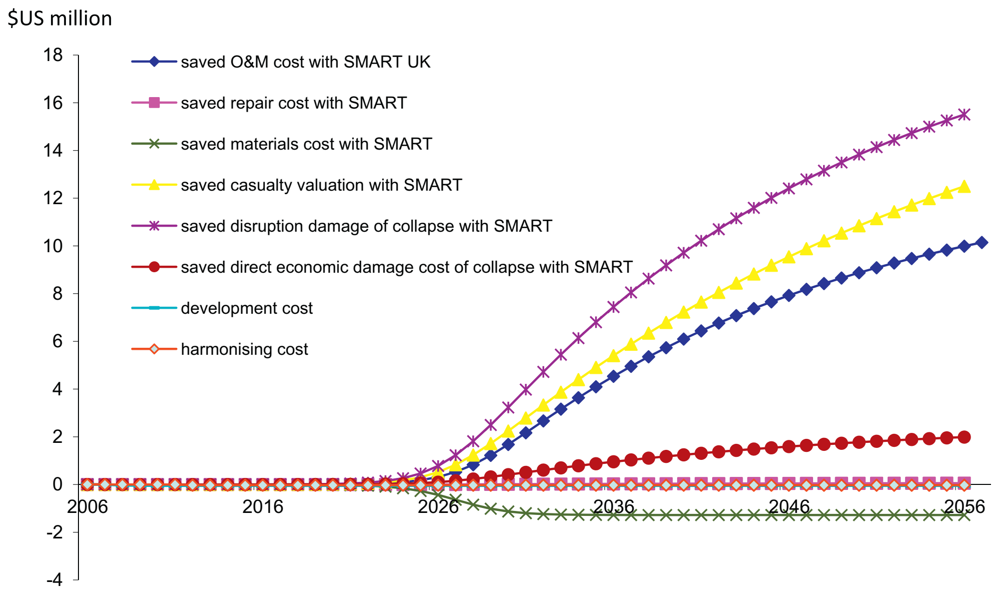

Fig. 5. Present values of the variables used in the model in US $ million (cumulative). Source: CBA model runs by the author using @Risk.

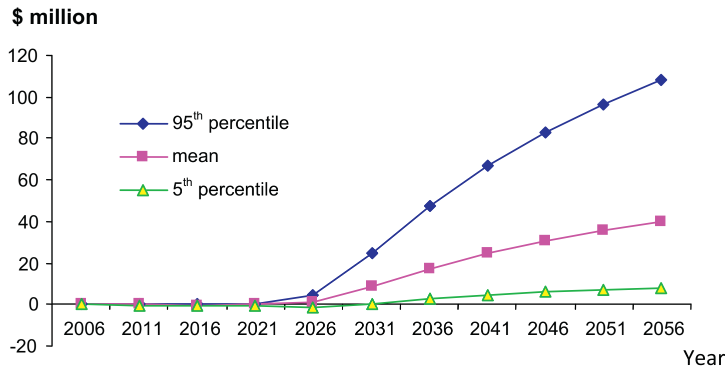

Fig. 6. Cumulative NPV for the UK tunnel model. Source: CBA mode runs by the author using @Risk.

Table 1
Sensitivity analysis for the UK tunnel application model. Source: Sensitivity analysis runs.

Parameters	Unit	Student b coefficient[a]
Max target market penetration rate	%	0.41
Base year disruption damage cost	$/year	0.31
Multiplier of tunnel length		0.31
Annual number of tunnel collapses	collapse/km	0.3
Discount rate	%/year	−0.26

[a] The student *b* coefficient is a coefficient calculated for each input parameter in the regression equation. The input parameter values are regressed against the output (NPV). Source: Sensitivity analysis runs.

4.2. Number of Smart Infrastructure sensors required

The number of additional Smart Infrastructure sensors required start increasing after the development completion and peaks at approximately 6700 sensors in the year 2028. Once the maximum growth of the market penetration is reached, a gradual decrease occurs, as shown in Fig. 4.

4.3. Socio-economic impacts

Fig. 5 shows that, the variables with the most significant impacts to the cumulative NPV would be the saved disruption damage from tunnel collapses followed by saved casualty and saved operation and maintenance costs. This result clearly addresses the key contribution of this type of emerging technology to improve the current infrastructure management not only from an economic perspective but also from much wider social contexts. The other notable finding is that although the material costs of Smart Infrastructure sensors are expected to be much lower than the currently existing sensor system, sensor installation costs seem to be non-negligible, as shown in the negative saved material cost variable.

4.4. Cumulative NPV

The findings of the UK tunnel application model show the following results. The 5th percentile, mean and the 95th percentile of the cumulative NPV for the UK tunnel market in the year 2056 are all positive: $7, 40 and 109 million, respectively, as shown in Fig. 6. For the mean cumulative NPV, the costs start recovering approximately in the year 2021 onwards. The reasons behind this relatively slow cost recovery could be the extra costs of Smart Infrastructure, namely extra installation costs and material costs becoming high, as numerous sensors are required for this new system.

4.5. Sensitivity analysis

Table 1 lists the findings of the sensitivity analysis. The sensitivity analysis shows that the most significant parameter for the cumulative NPV is the maximum target market penetration rate with the factor of 0.41. This result indicates that the pattern of the market penetration rate chosen in this study, i.e., the logistic function, has a significant impact on the outcome. The other notable parameters are base year disruption damage cost, tunnel length, and the annual number of tunnel collapses. The result has therefore clearly indicated the huge benefits of Smart Infrastructure sensors in averting the severe economic damage cost of tunnel collapses. The discount rate has also demonstrated significant impacts on the NPV.

5. Conclusion

This paper has investigated the role of innovative new technologies for improving transport infrastructure management. Our finding shows that the mean value of the cumulative net present value for the UK tunnel market in the year 2056 is estimated to be US$40 million. According to the sensitivity analysis, the key parameters, which have significant impacts on the net present value, are maximum target market penetration rate, base year disruption cost, tunnel length, and annual number of tunnel collapses. The relatively significant impact of the discount rate is also worth mentioning. The previous study (Morimoto, 2010), which has assessed the impacts of applying Smart Infrastructure to the UK water industry, has shown much more significant impacts (cumulative NPV in 2056 was US $13 billion). The possible reasons behind the lower potential impacts for the tunnel industry application in this paper could be due to the fact that there is a much smaller market being served (much shorter total length of tunnels than water pipes), so that lower impacts are expected. The tunnel collapse rate is also likely to be much lower than the water pipe burst rate, therefore, lower benefits of the reduced collapse rates are expected. However, the benefit of managing both industries simultaneously using the Smart Infrastructure sensor could be significant. Thus, this kind of emerging technology is proved to play a major role in improving and integrating the current infrastructure management practice. Moreover, the findings indicate that the potential socio-economic impacts appear to be realised gradually, therefore early implementation could be recommended.

This study has mainly focused on the application of Smart Infrastructure sensor technology to the UK tunnel industry, yet we envision that similar impacts would be expected in the rest of Europe as those nations are facing the same challenges as the UK, such as operating ageing assets, as well as shifting attitudes with budget limitations. The expected impacts could be even larger if applied to developing countries, as malfunction in infrastructure management is often a serious concern and an obstacle for the development process. Therefore, for future research, it would be a useful exercise to assess the socio-economic impacts of diffusing such a technology that was developed in a developed country into the rest of the world. Furthermore, we envisage the importance of examining the impacts of integrating the management system of various infrastructures to improve efficiency. Hence, for future research we propose to conduct an impact assessment not only on a single country basis but also on a global scale if these technologies are diffused to the rest of the world.

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Appendix A.

A.1. Market penetration rate

The market penetration rate (i.e., *PEN*) is zero when time t is less than the sum of the extra development time (i.e., t_{dex}) and the harmonisation time (t_h). When time t is less than and equal to the sum of the extra development time, the harmonisation time and the time when competitors appear (i.e., t_{com}), *PEN* equals to the fraction of the maximum target market penetration rate (i.e., PEN_{max}) to $[(1 + (100) \times (t_{dex} + t_h + t_{pen})^2) \times (e^{-t/1.5})]$. Otherwise, the market penetration rate is the fraction of the $PEN_{max} \times DEC$ (i.e., market penetration rate decrease due to competitors) to $[(1 + (100) \times (t_{dex} + t_h + t_{pen})^2) \times (e^{-t/1.5})]$.

$$
\begin{aligned}
PEN &= 0 && \text{if } t < t_{dex} + t_h \\
&= \frac{PENmax}{(1+100)\times(t_{dex}+th+t_{pen})^2)\times(e^{-t/1.5})} && \text{if } t \leqslant t_{dex} + t_h + t_{com} \\
&= \frac{PENmax\times DEC}{(1+100)\times(t_{dex}+th+t_{pen})^2)\times(e^{-t/1.5})} && \text{otherwise}
\end{aligned}
$$

A.2. Tunnel application input data

Parameter	Unit	Values (min, most likely and max)	Sources of data
Bas year tunnels	km	(350, 1200, 2250)	http://www.tfl.gov.uk
Extra development cost for tunnel application	$US	(5460, 49284, 90000)	CED estimates
Harmonisation cost	$US	(20000, 248888.9, 700000)	CED
Annual no of tunnel collapses	Collapses/km	(0.002, 0.016, 0.04)	CED
Collapse casualties	Casualties/collapse	(0.02, 0.1, 0.24)	CED
Disruption damage cost	$US/collapse	(500, 806000, 6000000)	EIA (2010) and CBI (2009)
Economic damage cost of collapse	$US/collapse	(5000, 103333.3, 375000)	CED
Discount rate	%	(1.8, 3.68, 6)	HM Treasury (2003) and Vronwenvelder and Krom (2004)
O&M cost	$US/km/year	(14000, 21926.67, 29000)	CED
Repair cost	$US/km	(3080, 4450, 5850)	CED
Penetration time	Years	(0.5, 6.67, 18)	CED
Installation cost	$US/km	(4.9, 10.67, 19.5)	CED
% Tunnel requiring repair		(0.25, 2.17, 7.5)	CED

Note: CED: data provided by the Cambridge University Engineering. If input values are the same as the water pipe application, figures are not listed here. The water pipe application data are found in Morimoto (2010).

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