A Resilience Assignment Framework using System Dynamics and Fuzzy Logic

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Abstract

This paper is concerned with the development of a conceptual framework that measures the resilience of the transport network under climate change related events. However, the conceptual framework could be adapted and quantified to suit each disruption's unique impacts. The proposed resilience framework evaluates the changes in transport network performance in multi-stage processes; pre, during and after the disruption. The framework will be of use to decision makers in understanding the dynamic nature of resilience under various events. Furthermore, it could be used as an evaluation tool to gauge transport network performance and highlight weaknesses in the network.

In this paper, the system dynamics approach and fuzzy logic theory are integrated and employed to study three characteristics of network resilience. The proposed methodology has been selected to overcome two dominant problems in transport modelling, namely complexity and uncertainty. The system dynamics approach is intended to overcome the double counting effect of extreme events on various resilience characteristics because of its ability to model the feedback process and time delay. On the other hand, fuzzy logic is used to model the relationships among different variables that are difficult to express in numerical form such as redundancy and mobility.

Key words: Resilience, System dynamics, Fuzzy logic theory, Climate change extremes.

Introduction

The transport sector has a leading role in enhancing economic growth and societal welfare in addition to its influences on various types of human activities. Meanwhile, climate change extremes worldwide and in the UK, such as floods and snowfall, have increased, causing severe impacts on transport networks (e.g. Koetse and Rietveld, 2009). The response of transport networks to weather events is influenced by the event magnitude and network vulnerability. For example, the effect of floods on road networks could vary hugely from minor impacts to a flood-damaged road network (Suarez et al., 2005). Even light weather events, such as fog and high winds, could decrease the road capacity and speed, and increase delay, speed variability and accident risk (Pisano and Goodwin 2004). Nicholson and Du (1997) also referred to the change in travel demand patterns after the disruption arising from the evacuation of affected areas, and also before the disruption because of pre-event warnings.

There are vast numbers of resilience definitions in the context of different disciplines and their associated literature, such as ecosystem, industry, economics, physiology, and infrastructure systems. Hollnagel et al. (2006) defined resilience as the system property, which gives the ability to recoup from system complications including regular events that fall within the design base, and to sustain its functionality under expected or unexpected events. Furthermore, they (Hollnagel et al. 2006) argued that this ability should be judged against its time scale for recovering to measure the system efficiency to spring back quickly after being disturbed. Cimellaro et al. (2010) defined resilience as a function that measures the system ability to maintain a level of functionality over its life span.

In a transport context, a number of investigations (e.g. Murray-Tuite, 2006, Heaslip et al., 2010) have been carried out to define and quantify the resilience concept. Heaslip et al. (2010) defined resilience with respect to a time dimension as the transport network could have four phases: pre-event, during the event, self-annealing and recovery stages. This multi-stage process implies that resilience is a "multi faceted capability" of a system including circumventing, mesmerizing, adjusting to and recuperating from disturbance (Madni and Jackson 2009). Heaslip et al. (2010) used the fuzzy logic approach to develop a sketch level method in order to measure resilience of transport network based on a number of performance indicators. The main advantage of this technique is its simplicity in addition to the ability to express a number of attributers in a linguistic way rather than numerical values. In another study (Mansouri, et al. 2010) resilience is defined as a function of the system vulnerability and its adaptive capacity in recouping to the standard level of service within a limited time. Furthermore, Murray-Tuite (2006) conducted a review of transport network resilience and introduced ten dimensions for resilience, namely redundancy, diversity, resourcefulness, efficiency, autonomous components, strength, collaboration, adaptability, mobility, safety, and the ability to recover quickly. Some of these characteristics are related to network configuration such as redundancy and vulnerability; others could be seen as resilience enablers such as collaboration, while efficiency and safety could be considered as outputs. However, Murray-Tuite (2006) studied only four characteristics, namely adaptability, safety, mobility and recovery, and highlighted the importance of the other six characteristics in determining the resiliency of transport network, though they are difficult to quantify. Cox et al. (2011) studied the resilience of the London transport system during and after the 7/7 London attack. They considered the reduction in passenger journeys that were recorded for each of the targeted modes as an indicator of the disruption direct impact. Consequently, they used the transport model shifts as a measure of resilience. However, Cox et al. (2011) also referred to the importance of other contributors such vulnerability and flexibility. The main drawback of the approach by Cox et al (2011) is using what could be called "lagging indicators" as the impact of the disruption is evaluated based on some measures after the event. Ip and Wang (2009) proposed a quantifiable resilience estimation approach to examine the transport network resilience. They suggested that the resilience of a city node could be estimated as the weighted average of reliable independent paths with all other cities in the network and hence the network resilience is evaluated by the weighted sum of all nodes resilience. Although this technique showed some simplicity, it ignored many other important characteristics of resilience. Li and Murray-Tuite (2008) introduced a measure of resilience as a ratio of the variation in performance measures due to applying a certain strategy relative to the performance measures without the strategy. They evaluated the effectiveness of four strategies on congestion using average travel speed, OD travel time, vehicle travel time and maximum queue length as performance measures.

This paper presents a conceptual framework to quantify the resilience of the transport network. The main advantage of the proposed framework is its ability to take into account attributers such as network configuration represented by redundancy and vulnerability. It also reflects the effect of demand amplification during and after the event by the use of other characteristics such as reliability and mobility. Furthermore, the framework uses collaboration as an indicator for efficiency collaboration between stakeholders and other agencies such as the highway agency. System Dynamics (SD) and Fuzzy logic (FL) approaches are employed to model the proposed resilience framework. The paper first introduces a brief overview of the system dynamics and fuzzy logic, and also discusses the reasons for their integration. The resilience framework is then explained and developed. A study case of the UK M25 motorway (junction 14 to 15) is employed to illustrate the implementation of the methodology on the mobility and reliability of the link.

System Dynamics Overview

System Dynamics (SD) is a well-developed technique introduced by Forrester (1961) in general literature. The SD approach is concerned with studying system characteristics, attributes and the surrounding environment in addition to setting up the relationship between parameters over the time span (Van Gigch 1974). The SD approach in transport modelling has a long history since 1960s as reported by Liu (2007). His review showed that SD is widely used in regional and urban transportation planning, urban road traffic systems, railways, transport energy use and demand, and transport performance. According to Abbas and Bell (1994), SD is one of the most suitable techniques to tackle transport challenges. They concluded that SD modelling could contribute to a better understanding of the relationship between elements of the transport system and its environment, such as multi dimensional and holistic nature of transport networks that require integration of wide varieties of knowledge. Abbas and Bell (1994) also added that the feedback mechanism between supply and demand in SD approach is more realistic than supply/demand equilibrium assumptions that are used in traditional methods.

Dealing with the resilience challenge from a system dynamics point of view will help overcome the double counting effect challenges inherited in different resilience characteristics, for example the feedback mechanism between redundancy and vulnerability. This could be related to the SD ability to model the behaviour of the system by using feedback processes. Another advantage of SD is its ability to model time delay. In general, there are two types of delay; “system delay” which represents the resistance of the system to change and “transport delay” that is the time between implementing policy and its effectiveness (Sterman 2000). The following subsections introduce the main elements of SD and FL, followed by the development of the resilience framework.

Main Elements of System Dynamics

The main principle of the system dynamics approach depends on four main steps summarised as follows. The first step is problem identification, followed by conceptualization and formulation of the model, then model analysis and validation. In the problem Identification stage, a number of questions should be answered in the light of the system context. These questions could include the overall goal of the model, its objectives, users, and beneficiaries (Van Gigch 1974). The responses to these questions are used to outline the boundaries in addition to identifying the limitations imposed on the system. In the model conceptualization stage, the causal loops that are hypothesized to cause observed patterns of system performance are recognised. According to Sterman (2000), model conceptualization is the most important and least understood of all modelling activities. Martinez-Moyano (2002) pointed out that this stage concerns the development of the structure of the dynamic hypothesis using diagrams, for example a causal-loop diagram or stock-and-flow sector diagram and policy structure diagram; that represent the system in context and its associated subsystems. The main elements of the dynamic diagram are variables and causal loops. There are three types of variables, namely levels, rates and auxiliaries. Levels (stocks) represent the current stage or conditions of the system, rates (flow) are used to refer to conditions, actions or any other circumstances that lead to any change in the system, and the auxiliaries (converter) stand for the mathematical representation of the relationships between variables (Abbas and Bell 1994). All variables are constructed together by causal loops. The third step in SD is the model formulation where a number of mathematical relationships are constructed to represent the modelled system in a form of linear and nonlinear functions. The main purpose of this stage is to examine the structure of the system. Model analysis and validation is the final stage of SD. Model validation in SD has two main stages, namely a structural validity test and behaviour validity test (Barlas, 1989). A structural validity test mainly focuses on how the developed model is able to reflect real world system characteristics, while the behaviour validity test is to check the ability of the model to create realistic output behaviour.

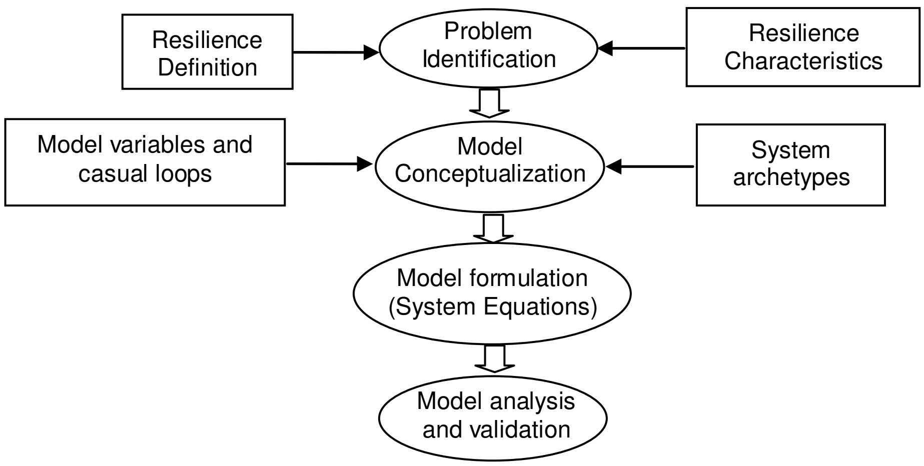

Figure 1 System dynamics stages

Limitations of System Dynamics Approach

SD is well-developed approach in modelling transport challenges, however it has one main shortage as it depends on defining the input parameters in a crisp way. Appendix A gives a description for crisp and fuzzy sets. Uncertainty is dominant in the current research, for example uncertainties related to the demand changes such as traffic patterns during disruption events. Changes in the supply side such as availability of a certain mode or a link in the network are also representing a source of uncertainty. In addition, there is the uncertainty related to the disruption itself, such as severity and its frequency. Furthermore, some characteristics are difficult to express in numerical data such ranking different levels of collaboration between stakeholders, management organisations and users of the transport network. To overcome these shortages, it is important to extend the ability of SD to deal with uncertainty by another approach such as Fuzzy logic.

Fuzzy Logic Approach

The Fuzzy Logic (FL) approach was first introduced by Zadeh (1965) in order to define complex systems using approximate approaches rather than precise methods. It is appropriate to interpolate the inherent vagueness of the human mind and determine the course of action, when the existing circumstances are not clear and the consequence of the course of action is not well identified. In other words, the FL approach deals with the type of uncertainty which arises when boundaries of a class of objects are not sharply defined (Nguyen and Walker 1997). According to Borri et al. (1989), the FL approach offers an effective tool to deal with imprecise and uncertain information associated with system behaviour and human interaction in a precise way.

Zadeh (1965) introduced three main characteristics for FL theory, namely:

- Using “linguistic variables” instead of or along with numerical values; for example free, congested, and very congested flow are values of traffic flow as a linguistic variable.
- Expressing the relation between parameters by fuzzy conditional statements; for instance, using IF-THEN statement to relate fuzzy parameters.
- Using fuzzy algorithms to justify complex relationships, a well-organized series of commands.

Fuzzy Logic Elements

The fuzzy logic approach has four main elements, namely the fuzzy set, the membership function, fuzzy inference system, and basic operations. The fuzzy set is defined as a group of elements having one or more common characteristics. A membership function is used to map elements of fuzzy set A to a real numbered value between 0 and 1. The degree of the membership function could be presented in different forms, logic linear function, the triangular, trapezoid, and Gaussian distribution, or sigmoid function. The choice of membership function is based on expert opinion (Nguyen and Walker 1997). However, membership functions were recently determined by optimization procedures (Jiang et al. 2008). Another important concept in FL is the fuzzy relation between two sets. Fuzzy relation is mapping elements of one set to those of another set through the Cartesian product of two. It represents the strength of correlation between elements of the two sets. Appendix A briefly explains these elements and full detailed coverage are also available in many references for examples, Zadeh (1965) and Nguyen and Walker (1997).

Fuzzy Logic Applications in the Transport Context

The use of the FL approach in transport started with Pappis and Mamdani (1977) and was followed by many applications. These applications could be categorized into two main areas, namely soft and hard applications. Hard applications refer to the use of FL in hardware design such as dynamic traffic signal control, for example, a fuzzy controller for a traffic junction (e.g. Chou and Teng 2002, Zuyuan, et al. 2008) and ramp metering and variable speed limit control (Ghods et al. 2007). The soft applications refer to the use of FL in modelling uncertainty related to various parameters such travel demand. According to Kalic´ and Teodorovic (2003) the FL technique is successfully used in transport modelling including route choice, trip generation, trip distribution, model split and traffic assignment.

However, the FL approach, similar to any other approach, has its own merits and drawbacks. Davarynejad and Vrancken (2009) highlighted a number of these merits and drawbacks based on a comprehensive review. For example, it is a simple method as it uses an easy modelling language, it is also powerful due to its ability to model experience and knowledge of human operator in addition to its ability to deal with imprecise information. The criticism of Davarynejad and Vrancken (2009) to the FL approach focused on its applications in hardware, for example, its limited use in traffic control signal or isolated ramp metering (hardware applications) rather than traffic control. They related this to the difficulty by describing the complexity of large-scale applications such as traffic control by some quantitative information.

Integrating Fuzzy Logic with System Dynamics Modelling

The literature shows that the integration between SD and FL has been recently used across a wide range of disciplines. Each technique complements the other by overcoming the limitations of the independent use of each one. For example, Campuzano et al. (2010) applied Fuzzy estimation and SD for improving supply chains. Liu et al. (2010a) applied both approaches to develop a framework for evaluating the dynamic impacts of a congestion pricing policy for a transport socioeconomic system. Carvalho and Machado (2008) used fuzzy set theory to establish resilient production systems. Liu et al. (2010b) developed a dynamic modelling framework using fuzzy concept to describe model variables and to evaluate the impact of travel demand management policies.

However, to date it appears that no research has been published in the literature that integrates system dynamics and FL to investigate the impact of climate change extremes on transport network systems. Meanwhile, Heaslip et al. (2010) applied FL approach alone to model the resilience of transport network.

Development of a Resilience Framework

In this section, a transport network resilience framework is developed using system dynamics in addition to investigating the cause-effect relations, delays and feedback loops in the system. The SD methodology will follow closely the main four steps of the SD approach explained above. It is to be noted that FL will be introduced at the model formulation step.

Problem Identification

In the context of the current research, the need to develop a resilience assignment framework (RAF) arises from the need to quantify the impacts of climate change extremes on transport network and the ability of the network to mitigate these disturbances. Decision makers and other stakeholders such as the highway agency and local authorities could use this framework as an evaluation tool. Another advantage of the resilience framework is as an alarm to the need for external help based on recovery time and functionality loss during disruption.

The scope of the RAF could be seen to be more related to the regional level in the case of climate change related extremes due to the impacts of natural events. For example, floods in a certain area are more likely to affect the whole network in this area rather than just one link. However, the severity of the effect may vary from one zone to another based on the cause of the flood, heavy rain or overflow of river, in addition to other subsystems efficiency such as the efficiency of drainage system in the case of a flood or efficiency of salt distribution in the case of snowfall.

System Conceptualization

The resilience of transport network influences people's travel patterns, social activity and economic in addition to political systems. Based on the literature (e.g. Murray-Tuite 2006), ten characteristics are identified and used to model the transport network resilience as shown in Figure 2.

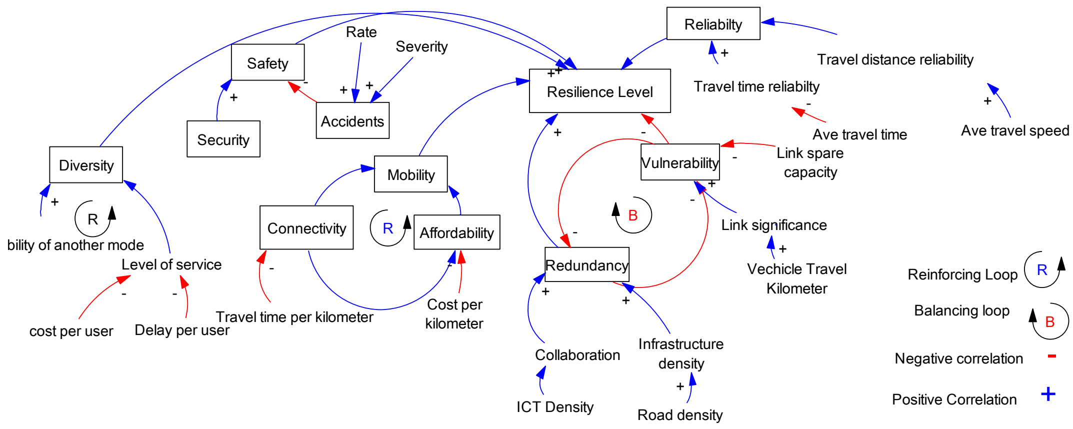

Figure 2 Transport network causal loop diagram

For example, the network mobility is improved by the increase of connectivity and affordability; that consequently increases the network resilience level, where connectivity is measured by travel time per kilometre, meanwhile affordability is measured by cost per kilometre. Figure 2 shows these relationships in terms of feedback loops, for example, to measure the adverse effect of the event on users, delay and cost per user would be combined together as the level of service indicator. The model also shows the link between mobility as a characteristic of the transport network system and travel demand as a subsystem. An increase in mobility for the network would increase the travel demand after some delay.

Furthermore, the increase in vulnerability of the network reduces the resilience level of the network, and at the same time, vulnerability could be decreased by increasing the redundancy of the network. Therefore, an increase in the network redundancy has direct and indirect positive impacts on resilience. The indirect positive impact of redundancy is attributed to its adverse effect on vulnerability which has a negative impact on resilience as depicted in Figure 2. This feedback mechanism between vulnerability and redundancy is represented by the balancing loop in Figure 2.

Model Formulation

A number of indicators are allocated to quantify each characteristic as depicted in Figure 2. For example, travel time per kilometre and cost per kilometre are used to quantify connectivity and affordability, respectively. Instead of introducing these values in crisp way, the values of different characteristics are expressed by fuzzy sets labelled by gradual linguistic terms such as very low, low, medium, etc, using Zadeh's notation (1965). For example; "Very Low" is the label of a fuzzy set defined by:

$$Very\ Low = \left\{\frac{1}{1} + \frac{0.5}{2} + \frac{0}{3} + \frac{0}{4} + \frac{0}{5} + \frac{0}{6}\right\}$$

where "+" denotes union rather than arithmetic sum. Figure 3 shows the representation of six fuzzy sets using triangular and trapezoid membership functions for different resilience characteristics. Other membership functions such as Gaussian distribution may also be used; however, the triangular and trapezoid were chosen for simplicity and convenience. The fuzzy logic toolbox Graphical User Interface (GUI) in MATLAB environment is used to build a Fuzzy Inference System (FIS) to model the correlation among resilience characteristics.

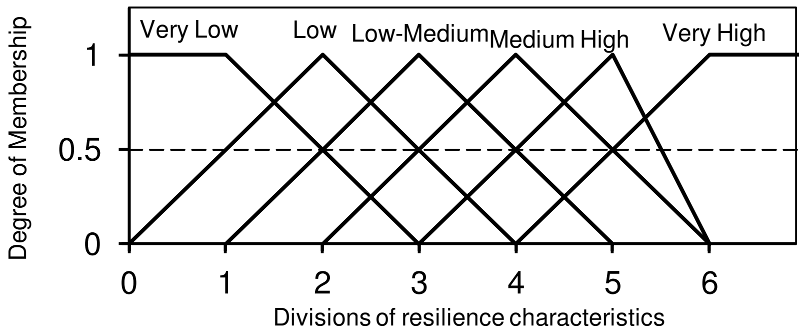

Figure 3 Triangular membership functions for resilience characteristics

As an illustration, redundancy is identified as the ability of the network to offer several paths to a certain O-D route and is measured by mode availability and collaboration. Redundancy is quantified by a fuzzy relationship between mode availability and collaboration level as shown in Figure 4. Mode availability and collaboration as inputs and redundancy as output are introduced to FIS and a number of conditions are developed. A surface plot of redundancy against mode availability and collaboration is presented in Figure 4. This figure reflects the importance of mode availability on network redundancy as high redundancy which could be achieved by only very high mode availability; meanwhile the maximum value of collaboration could only achieve a redundancy less than 4, equivalent to medium redundancy, on its own. However, the combination of high mode availability and collaboration produced high network redundancy. The effect of dynamic variation of mode availability and collaboration on redundancy is also shown in Figure 5. It indicates the validity of FL modelling of redundancy including the successful formulation of different conditions.

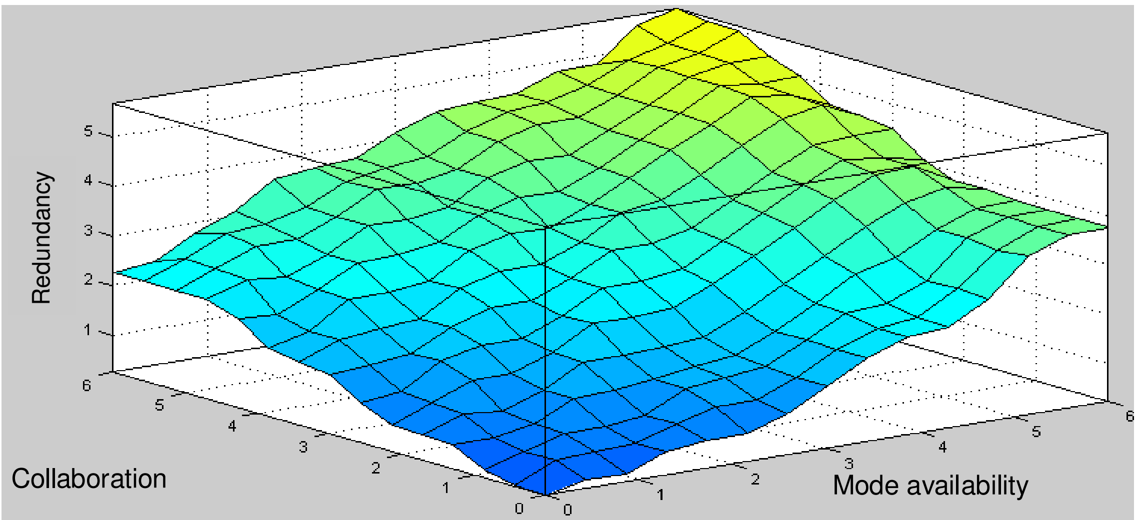

Figure 4 Surface plot of network redundancy

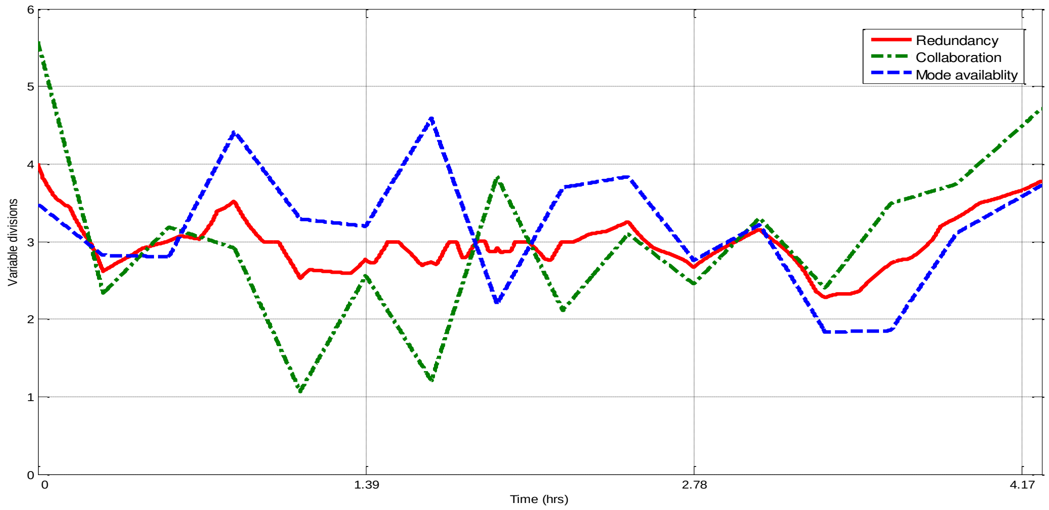

Figure 5 Dynamic variation of redundancy

Study Case from UK

Data from the UK M25 motorway (junction 14 to 15) during the afternoon peak, 2/05/2010 from 15.15 to 19.45, are used to illustrate the implementation of the methodology on two characteristics, namely mobility and reliability. Mobility is defined as the ability of people and goods to move from one place, the origin, to another, the destination, by using an acceptable level of transport service (Litman, 2008). In this paper, connectivity and affordability are used to measure network mobility. Connectivity refers to the ability of the transport to remain connected and could be measured by average travel time per kilometre, whereas affordability indicates the variation in network cost. As time and cost are very important for people movement, both are used to gauge network mobility. Connectivity and affordability (as inputs) and mobility (as output) were introduced to FIS and a number of IF-Then conditions were then formulated.

The compound effect of connectivity and affordability on mobility is depicted in Figure 6. This figure indicated the near equal effect of both characteristics on network mobility in line with the literature conclusions (Litman, 2008).

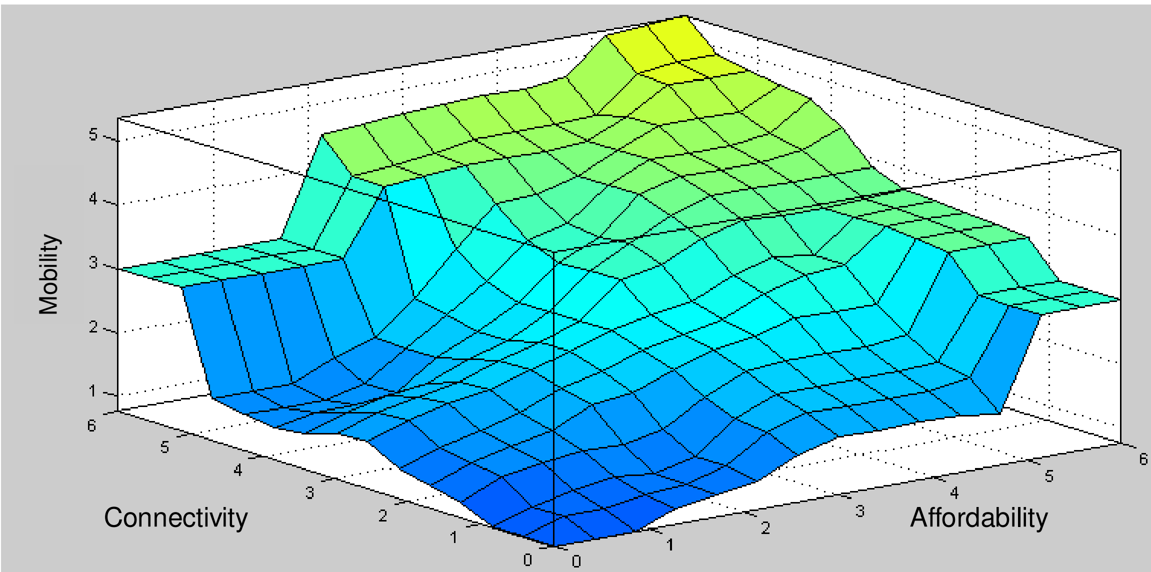

Figure 6 Surface plot of network mobility

To validate these results the Simulink software was used to study the change of link mobility over time for changes in connectivity and affordability. The dynamic variation in mobility closely follows the variation of connectivity and affordability as shown in Figure 7. This demonstrates the successful modeling of the effect of both variables on link mobility using FL approach.

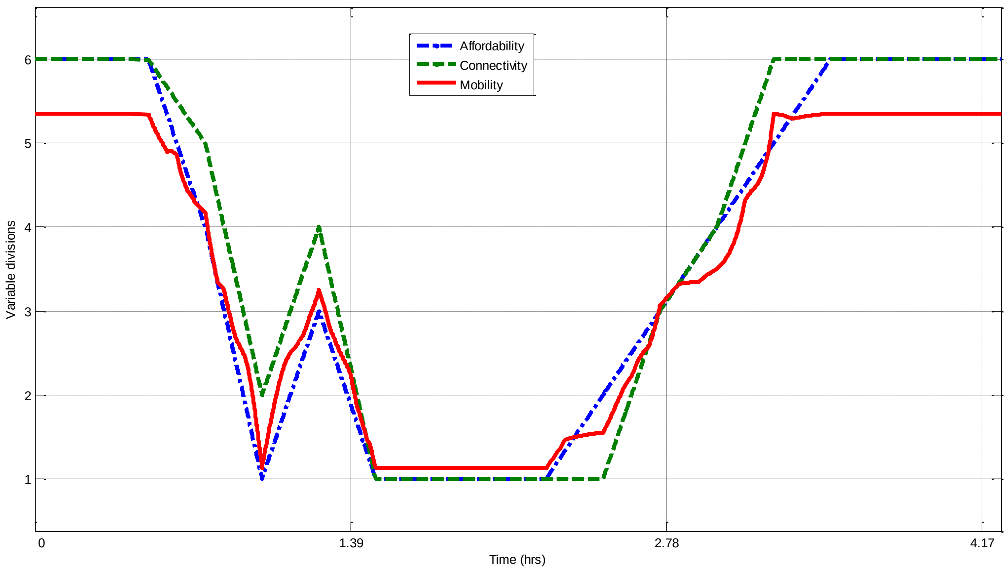

Figure 7 Dynamic variation of mobility

The mathematical calculations of the fuzzy sets for connectivity and affordability based on 15 minutes average data for M25 motorway (junction 14 to 15) during the afternoon peak are explained below.

$$Vey\ high\ Connectivity = \left\{\frac{0.2778}{Very\ low} + \frac{0.0556}{Low} + \frac{0.0556}{Low\ medium} + \frac{0.1111}{Medium} + \frac{0.0556}{High} + \frac{0.4444}{Very\ high}\right\}$$

$$Very\ High\ Affordability = \left\{\frac{0.2778}{Very\ low} + \frac{0.0556}{Low} + \frac{0.1111}{Low\ medium} + \frac{0.1111}{Medium} + \frac{0.0556}{High} + \frac{0.3889}{Very\ high}\right\}$$

The Cartesian product of these two fuzzy sets, based on Equation 4 (Appendix A), is

$$Connectivity\ o\ Affordability = \begin{bmatrix} 0.2778 & 0.0556 & 0.1111 & 0.1111 & 0.0556 & 0.2778 \\ 0.0556 & 0.0556 & 0.0556 & 0.0556 & 0.0556 & 0.0556 \\ 0.0556 & 0.0556 & 0.0556 & 0.0556 & 0.0556 & 0.0556 \\ 0.1111 & 0.0556 & 0.1111 & 0.1111 & 0.0556 & 0.1111 \\ 0.0556 & 0.0556 & 0.0556 & 0.0556 & 0.0556 & 0.0556 \\ 0.2778 & 0.0556 & 0.1111 & 0.1111 & 0.0556 & 0.3889 \end{bmatrix}$$

Then mobility fuzzy set can be derived based on Equations 5, 6 and 7 (Appendix A)

$$Very\ High\ Mobility = \left\{\frac{0.2778}{Very\ low} + \frac{0.0556}{Low} + \frac{0.0556}{Low\ medium} + \frac{0.1111}{Medium} + \frac{0.0556}{High} + \frac{0.3889}{Very\ high}\right\}$$

Therefore, the mobility of the link (M25 J14-J15) is very high with 0.3889 degree of truth.

Average travel time and variation in average travel speed are used to estimate the reliability of the link as presented in Figure 8. Again, this figure indicates the suitability of FL in modelling the effect average travel time and variation in average travel speed on reliability variation with time.

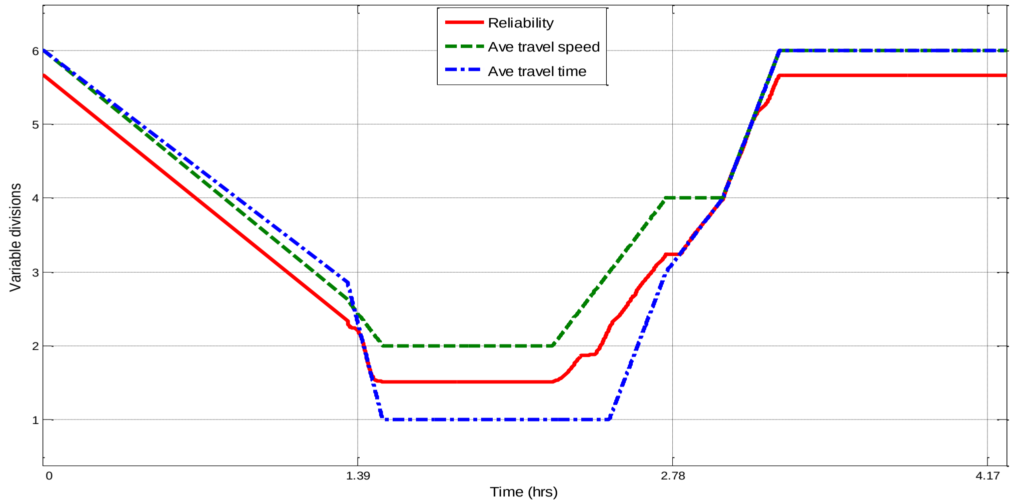

Figure 8 Dynamic varation of reliability

Conclusions

This paper has presented a conceptual resilience framework that measures the resilience of the transport network. SD and FL approaches are integrated to develop the framework. The SD approach was chosen for several reasons. The system dynamics approach is able to overcome the double counting effect of the extreme event on various resilience characteristics because of the feedback process inherited in the system dynamics. It is also able to model time delay. However, system dynamics requires input parameters to be defined in a crisp way and some resilience characteristics are difficult to express in numerical data such as collaboration. Hence, it is proposed to extend the merits of system dynamics with fuzzy logic that can deal with uncertain information associated with system behaviour and human interaction in a precise way. The results show the applicability of using FL to model the compound effect of variables on resilience characteristics modelling.

Future Work

It is proposed that other characteristics will be modelled in a similar way as explained above for mobility, reliability and redundancy. Furthermore, the availability of this framework will also give the chance to investigate the role of Intelligent Transport System in improving resilience of transport network. For instance, the effect of the availability of pre-trip travel information or in route information on the driver decisions during the disruption.

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Appendix A: Basic Elements of Fuzzy Set Theory

A set is defined as a group of elements having one or more common characteristics. For example, green, red and amber are a set of traffic light stages, which have international definitions. In such case, it is called a crisp set, as each light indicates a certain stage. In contrast, hot, cold and good are fuzzy sets representing weather conditions as each could have a wide temperature range as depicted in Figure A-1.

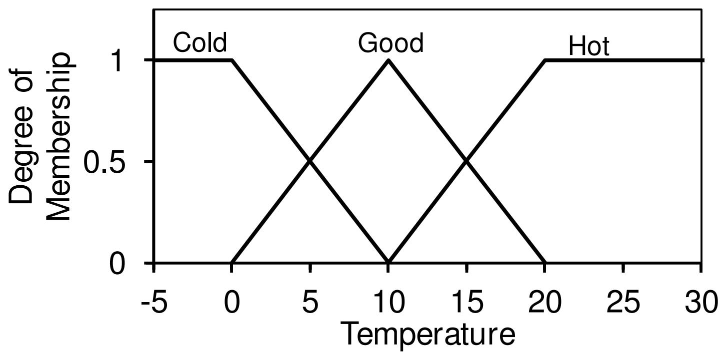

Figure A-1 Representation of fuzzy logic sets using triangular membership functions

The mathematical representation of a fuzzy set is:

$$A = \left\{\frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots + \frac{\mu_A(x_n)}{x_n}\right\} = \sum_{i=1}^{n} \mu_A(x_i)/x_i \quad (1)$$

where A is a fuzzy subset of a universe of discourse U, $\boldsymbol{x_n}$ is an element in the universe of discourse X,

$$\mu_A: X \rightarrow [0,1] \quad (2)$$

$\mu_A(x)$ is the degree of membership associated with element x in a fuzzy set A and has values from 0 to 1. The fuzzy relation between two sets is represented by:

$$R \triangleq \int \frac{\mu_A(x,y)}{(x,y)} \quad (3)$$

$$\mu_R(x,y) = \mu_{X\times Y}(x,y) = \min\left(\mu_X(x) \times \mu_Y(y)\right) \quad (4)$$

where R is a fuzzy subset of the Cartesian product $X \times Y$ representing a fuzzy relation from a set X to a set Y and $\mu_R(x,y)$ is its member function.

If R is a fuzzy relation from a set X to a set Y and S is a fuzzy relation between Y and Z, then the fuzzy relation T from X to Z can be represented by Max-Min composition symbolized by Equation (5) and calculated by Equations (6) and (7) below.

$$T = R\ o\ S \quad (5)$$

$$\mu_T(x,z) = max\_min[\mu_R(x,y), \mu_S(y,z)] \quad (6)$$

$$\mu_T(x,z) = \cup\ [\mu_R(x,y) \cap \mu_S(y,z)] \quad (7)$$