

## Traffic Control and Management

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#### **Overview**

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- Introduction
- Artificial Intelligence and its application in ITS
  - Why AI?
  - Why ITS?
  - Applications
- The role of ITS in sustainable urban mobility planning

# Artificial Intelligence and its application in ITS



## Categories of Al methods



- Al methods can be divided into two broad categories:
  - Symbolic AI: focuses on the development of knowledge-based systems (KBS) <u>https://en.wikipedia.org/wiki/Knowledge-based systems</u>
  - Computational Intelligence (CI): the ability of a computer to learn a specific task from data or experimental observation. Even though it is commonly considered a synonym of soft computing, there is still no commonly accepted definition of computational intelligence
- Al enables computers or machines to think

# What makes Al appropriate for transportation problems



- Transport data:
  - Quantitative
  - Qualitative
- Transport systems behaviour:
  - Interactions among the different components are not fully understood
  - Uncertainties from the human component of the system
- Optimisation problems: challenging to solve using traditional mathematical programming (MP) techniques (e.g. Traffic assignment)
  - Relationships are hard to specify analytically
  - Size of the problem and its computational intractability
- Finally, the complex nature of transportation systems and the fact that their behaviour emerges as a result of interactions among the system components makes agent-based modelling (ABM) techniques quite appropriate for study the behaviour of the system.

# Al functions and applications in ITS



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System identification (ID): a methodology for building mathematical models of dynamic systems using measurements of the input and output signals of the system.



Source: https://commons.wikimedia.org/w/index.php?curid=45608217

In System ID, a black box was described as an unknown system that was to be identified using the techniques of system identification (Wiener 1961)

Wiener, Norbert; Cybernetics: or the Control and Communication in the Animal and the Machine, MIT Press, 1961, ISBN 0-262-73009-X

- Nonlinear prediction focuses on the prediction of the behaviour of systems where the relationship between input and output is not linear. This is often the case with transportation problems including predicting traffic demand and travel time in short-term
- Control: control a system to achieve a desired output. Examples include signal control of traffic at road intersections, ramp metering on motorways, dynamic route guidance, positive train control on railroads, and air traffic control.

# Al functions and applications in ITS



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- Classification (Pattern recognition): classify an object or put it in its right class or category. Examples of classification problems in transportation include automatic incident detection and traffic state estimation
- **Clustering**: group cases with similar characteristics together and identifying the number of groups or classes. For transportation, clustering could be used to identify specific classes of drivers based on driver behaviour.
- Classification vs clustering:
  - Similarity: pattern identification used in machine learning.
  - Difference:
    - classification uses predefined classes (supervised learning)
    - clustering **identifies similarities between objects**, which it **groups** according to those characteristics in common and which differentiate them from other groups of objects (unsupervised learning)

# Al functions and applications in ITS



- Decision making: select a course of action from among multiple alternatives. Transportation officials are continuously faced with challenging situations where a decision needs to be made. Examples of these situations include mitigating traffic congestion during abnormal conditions and whether to divert traffic to an alternative route in an incident situation.
- **Optimisation:** minimise or maximise a function by choosing optimal values for a set of decision variables while satisfying a set of constraints. Examples include developing an optimal timing plan for a group of traffic signals, designing optimal routing to achieve WP2 and optimal scheduling of public transits.

Al Function	Typical use-case
Nonlinear prediction	Short-term traffic flow/travel time prediction, or in modelling the transportation infrastructure health as a function of traffic, construction and weathering.
Control functions	Signal control of traffic at road intersections, ramp metering on motorways, dynamic route guidance, positive train control on railroads
Classification	Automatic incident detection, image processing for traffic data collection and for identifying cracks in pavements or bridge structures and transportation equipment diagnosis.
Clustering	Identifying specific classes of drivers based on driver behaviour, for example.
Decision making	Deciding whether to build a new road, how much money should be allocated to maintenance and rehabilitation activities and which road segments or bridges to maintain, and whether to divert traffic to an alternative route in an incident situation.
Optimisation	Designing an optimal transit network for a given community, developing an optimal work plan for maintaining and rehabilitating a pavement network, and developing an optimal timing plan for a group of traffic signals.

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# **Example of AI in ITS - Traffic Management Solutions**

- Due to its processing, control and optimisation capabilities, AI could be applied to traffic management and decision-making systems in order to enhance and streamline traffic management and make our roads smarter.
- The predictive abilities of AI are also of huge benefit to traffic management systems as they are able to recognise the physical and environmental conditions that can lead to or be the result of heavier traffic flow and congestion.



### **Traffic state estimation**

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#### Vision

- Develop general and transferrable methods to identify traffic state
- Focus on the estimation in a probabilistic manner

#### **Implementation**

- Framework is based on Expectation-Maximisation (EM) algorithm
- ILD data from different sites were used for the evaluation of transferability

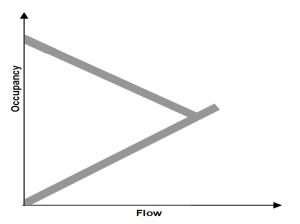
#### **Application**

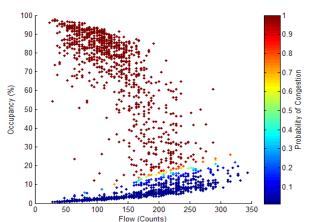
 Case study application in London

#### **Problem Modelling**

**Expectation-Maximization (EM)** 

- Let  $\alpha_i = O_i/q_i$  and assume traffic states are either congested ( $Z_i = 1$ ) or uncongested ( $Z_i = 0$ )
- Assume  $p(\alpha)|_{z=0} \sim N(\mu_0, \sigma_0^2)$  and  $p(\alpha)|_{z=1} \sim N(\mu_1, \sigma_1^2)$
- E step:  $Q(\Theta, \Theta^{(l-1)}) = E[\log L(\Theta \mid \alpha) \mid \alpha, \Theta^{(l-1)}]$
- M step:  $\mathbf{\Theta}^{(l)} = \underset{\mathbf{\Theta}}{\operatorname{arg max}} Q(\mathbf{\Theta}, \mathbf{\Theta}^{(l-1)})$





### Sensor data fusion

#### Vision

- Develop generic framework for multi-sensor traffic data fusion for operational intelligence
- Focus on travel time

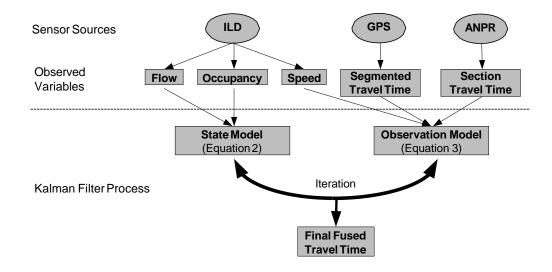
#### Implementation

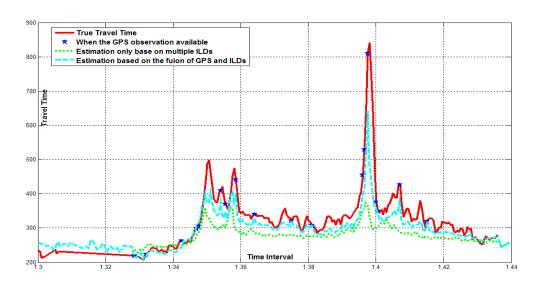
- Framework based on the extended (non-linear) Kalman Filter
- Integrates traffic propagation models
- Accommodates point and linear sensors

#### Application

 Case study application in London and Maidstone

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## Anomaly detection using deep learning techniques

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#### **Background**

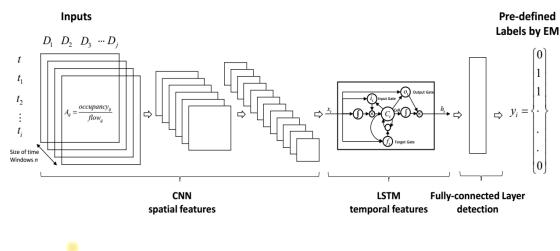
- A road network suffers both recurrent congestion and non-recurrent congestion.
- Can a ML-based model early detect recurrent congestion and detect non-recurrent congestion immediately after its occurrence?

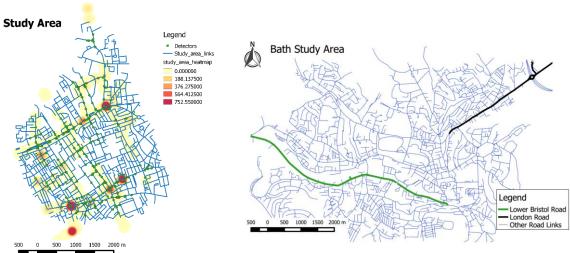
#### **Methods**

- Apply a range of emerging deep learning methods, specifically CNN and LSTM
- Compare new network-centric methods with existing link-by-link methods

#### **Application**

Application to London and Bath data





## Short-term traffic prediction during abnormal conditions



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#### **Background**

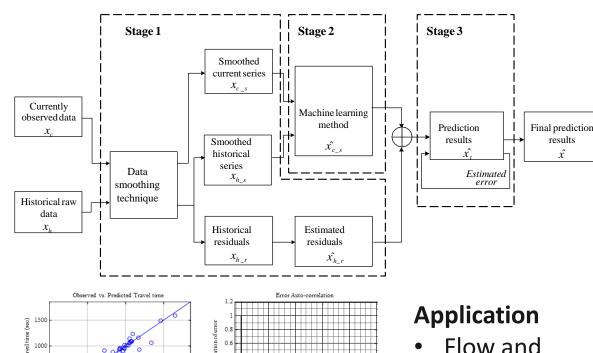
 Existing prediction models are not robust enough to predict traffic variables during abnormal conditions

#### **Objective**

 Develop capability to make short-term (up to 1h) predictions of travel time & flow in abnormal traffic conditions

#### **Implementation**

- Based on fast machine learning techniques
- Novel 3-stage framework including explicit sensor data pre-processing (smoothing), flexible machine learning predictors and error feedback



Predicted

Observed travel time (sec)

 Flow and travel time prediction in London and Maidstone

### **Predictor fusion**

#### Vision

 Develop a novel prediction fusion framework for combining the results of multiple individual predictors in the context of short-term traffic prediction

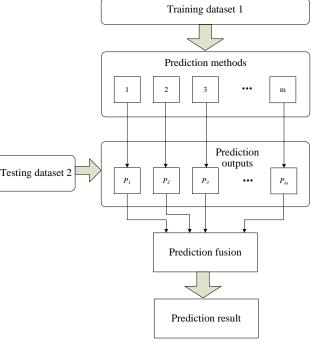
#### Implementation

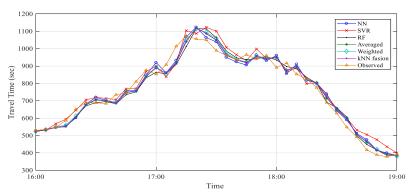
- Based on fast machine learning techniques
- Three different prediction fusion strategies are applied and compared
- The results demonstrate that the proposed prediction fusion framework can improve prediction accuracy, especially during disrupted traffic conditions.

#### Application

 Application to both flow and travel time prediction in London

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## Short-term prediction during incidents at a road network level

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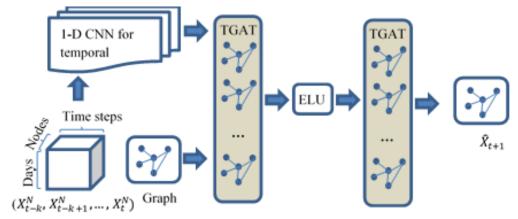
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#### Questions

- In a road network, it is not easy to predict traffic variables link by link
- Can we predict using one model at a road network level rather than hundreds/thousands link level models

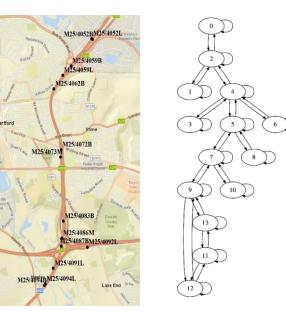
#### **Objectives**

- Transfer a road network to a graph which can be easily understood by deep learning tools
- Apply Temporal Spatial Traffic Graph Attention network (TS-TGAT) to capture temporal-spatial features of a network
- Predict under normal and incident conditions



#### **Case study**

- Traffic variables from the WebTRIS
- Traffic incidents from the DfT STATS
- One-step and multistep ahead



## Short-term traffic prediction with insufficient data



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#### **Background**

- Prediction methods in short-term:
  - from time-series algorithms, machine learning tools, to deep learning methods, or a selective hybrid of these approaches.
- Challenging problem affects the application of such methods in the real world:
  - insufficient data across an entire network.
- Missing data vs insufficient data

  Historical Learning process model f()

  Training

  Traditional ML

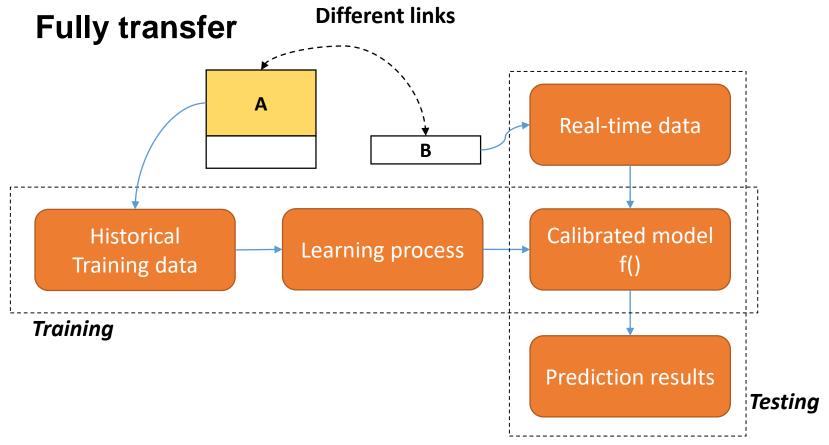
  Real -time data

  Real -time data

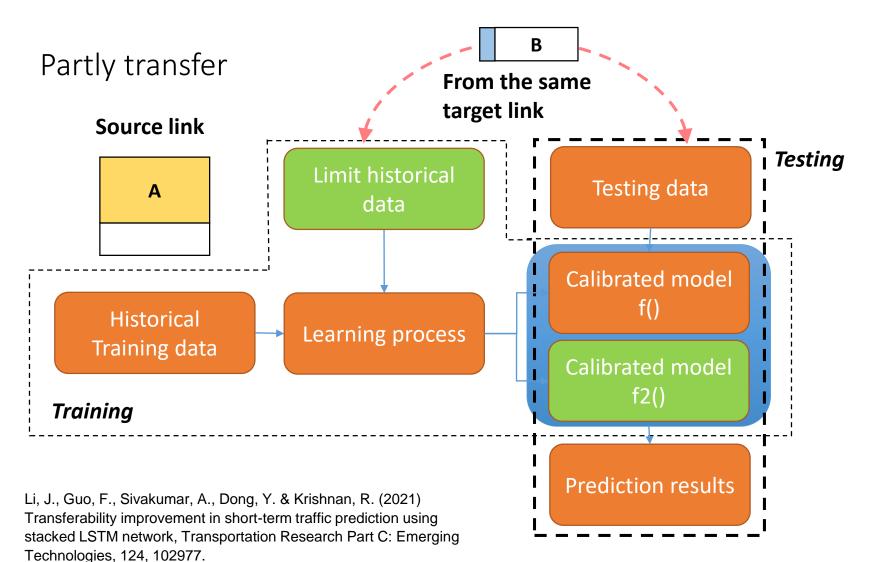
  Prediction results

  Testing





Luan, J., Guo, F., Polak, J. W., Hoose, N. & Krishnan, R., 2018, Investigating the transferability of machine learning methods in short-term travel time prediction, In: Proceedings of the 97th Annual meeting of Transportation Research Board, Washington DC, USA.



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## **Transfer learning**

https://en.wikipedia.org/wiki/Transfer learning

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#### What is transfer learning

• Transfer learning (TL) in machine learning (ML) focuses on storing knowledge gained while solving one problem and applying it to a different but related problem.

Source:

#### Examples:

- Know how to ride a motorbike → Learn how to ride a car
- Know how to play classic piano → Learn how to play jazz piano
- Know math and statistics 

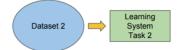
   Learn machine learning

#### **Traditional ML**

- Isolated, single task learning:

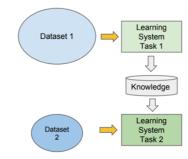
   Knowledge is not retained or
- Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks





#### Transfer Learning

- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data





## Short-term traffic prediction with insufficient data

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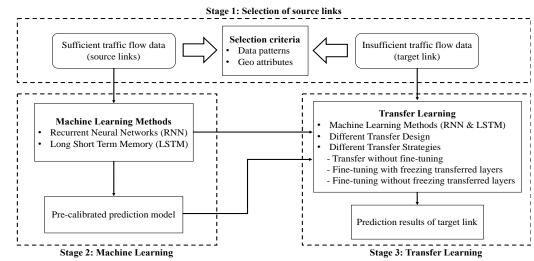
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#### **Background**

Insufficient data to train a ML model

#### **Implementation**

- Based on advanced deep learning
- Apply transfer learning to improve transferability of machine learning
- A novel 3-stage framework for prediction with insufficient data **Findings**
- Transfer learning improves the transferability of machine learning models
- The prediction performance under data deficient scenarios can be improved.
- The performance of the proposed hybrid method is highly dependent upon consistency between datasets but less dependent on geographical attributes of links.



	Scenario 1				Scenario 2				Scenario 3		
		Source links Target link		Source links			Target link	Source links Target lin		Target link	
	M25-5790	M25-4854	M25-5265	M25-4577	M62-1757	M62-1990	M25-5790	M25-4854	M11-6275 M1-2116	M4-2188	M20-6404
Average Cross-correlation Coefficient	0.9723				0.9635				0.8541		
Speed Limit	70 mph				70 mph				70 mph		
Number of Lanes	4	5	4	4	3	4	4	5	4		
Direction	Orbital				Inbound	Outbound	Orbital	Orbital	Inbound		
Emergency Stop Lane	Yes				Yes	No	Yes	Yes	Yes		
Near ramps (<300m)	No				Yes	No	No	No	No		
Location	Location Lo n d on M25/5790 M25/4854 M25/4854			Manchester  Rechalated  Rechal	M62/175	Hudderst	London  2/1990 Wattist  M25/5790	M1/2116	on don	• M11/6275	

## Short-term prediction of traveller's next destination

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#### **Motivation**

 Almost all short-term prediction work has focused on link-level characteristics but short-term demand prediction has many potentially potent applications

#### **Objective**

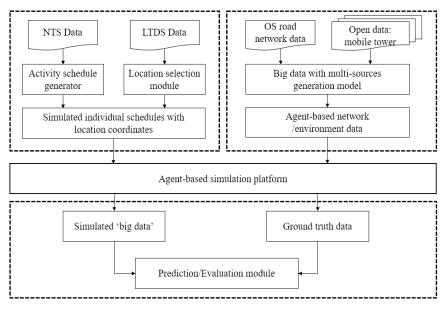
 Develop methods for short-term predictions of the next destination to be visited

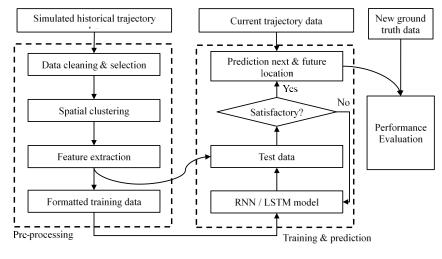
#### **Approach**

- Use deep learning methods, operating on an ensemble of static and real-time data
- An agent-based simulation platform which is capable of producing realistic spatial-temporal trajectory data at individual level

#### **Application**

 Applications to London and Beijing (social media and mobile phone data)





## **Congestion detection using remote** sensing images

#### **Questions:**

- Can we use free remote sensing data as a good substitute for traditional traffic data?
- Can we use free remote sensing to monitor traffic state for links and networks that are not covered by traffic sensors

#### **Objectives:**

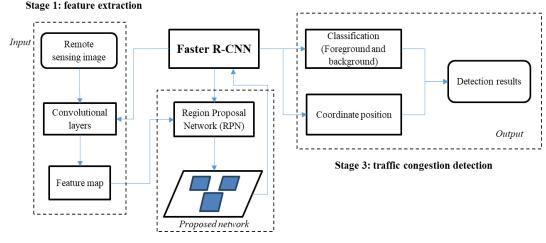
- Fast detect traffic congestion with more flexible and cheaper data sources
- Methodology development for traffic congestion using a Faster Regional Convolutional Neural Network (R-CNN) based deep learning method

#### **Remote sensing data:**

Free QuickBird

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Stage 2: road network localisation

#### **Testing area:** Beijing

#### Finding:

The Faster R-CNN with proposed framework outperforms others in terms of the detection accuracy and computational efficiency



### **Traffic control and management**

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#### Vision

 Develop a platform for traffic intelligence, leveraging military situational awareness technologies

#### **Implementation**

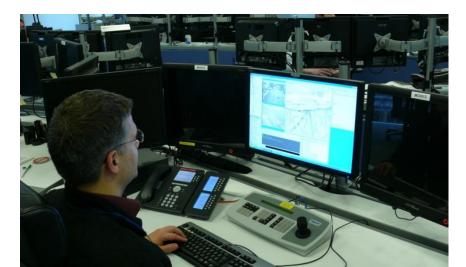
- Traffic sensor processing and data fusion
   + network state estimation and prediction (e.g., where are the queues/incidents, are they growing or clearing, where will the next problem occur?)
- Strategy development and selection (e.g., what should we do, what worked in the past, what does modelling tell us?)
- Tools for integration, visualisation and collaborative decision support (e.g., how do I get at and use all this intelligence?)

#### **Application**

 Case study applications (including London, York and UK motorway network)

### Intelligent decision support of road network management (FREEFLOW)







# The role of ITS in sustainable urban mobility planning

## Sustainable Urban Mobility Planning (SUMP)



Sustainable Urban Mobility Plan (SUMP):

"A Sustainable Urban Mobility Plan is a strategic plan designed to satisfy the mobility needs of people and businesses in cities and their surroundings for a better **quality of life**. It builds on existing planning practices and takes due consideration of **integration**, **participation** and **evaluation** principles."

https://www.eltis.org/mobility-plans/11-what-sustainable-urban-mobility-plan

### Why to integrate ITS in SUMP?



#### Implementation of transport measures to achieve policy goals

• ITS enable measures such as access restrictions, users' behaviour change, environmentally friendly traffic management, parking management, priority schemes for green modes, and safety monitoring all of which feature prominently in the SUMPS.

#### Maximisation of existing infrastructure utilisation

• ITS enable cities to build on existing infrastructure to deliver innovative mobility schemes and leverage measures to accomplish more sustainable and cost effective visions and to tackle urban transport challenges for passengers and freight efficiently and effectively. Depending on the ITS level of readiness and maturity in a city ITS offer tailored support reflecting the city needs and objectives, readiness and implementation plans.

#### Providing historical/real-time data and analytics for SUMPs

• ITS can aggregate the major data sources that support SUMPs development, monitoring and implementation. For example ITS enable collecting and storing, exchanging and elaborating digital information and data, e.g. real-time data on traffic and people flows.

### **Opportunities and challenges**



- ITS applications are tailored to cities as well as to the needs and priorities of the different stakeholders involved the ultimate precise benefits depend on the specific field implementation.
- Each city is unique, so ITS solutions must be adapted to the local context and be in line with the city's vision and ambition to serve wider policy goals.
- Expertise from various fields is required to address the social, economic and environmental challenges that characterise urban mobility as well as the technical expertise to understand the impacts and implications of ITS solutions. Hence, sharing information and cooperating across professions is required.

### **SUMP** principles and the relevance of ITS



**Assure quality** 

Arrange for monitoring and evaluation

Involve citizens and relevant stakeholders

Cooperate across institutional boundaries

Plan for sustainable mobility in the 'functional city'

SUMP Principles Develop a long-term vision and a clear implementation plan

Assess current and future performance

Develop all transport modes in an integrated manner

https://www.eltis.org/mobility-plans/11-what-sustainable-urban-mobility-plan

### **Example: Oxford Park & Ride**



#### **Challenge:**

• With traffic congestion rapidly increasing, there is a huge demand to find innovative solutions to the rise of congestion in the City Centre. Oxford is an old city with numerous protected buildings and landmarks of historical significance. This severely limits the improvement of the city's road network because the street layout and protected infrastructure are not easily modified.

#### **ITS solutions:**

- Using existing Park & Ride facilities, collaboratively sharing real-time data on road congestion, real-time bus locations and real-time parking availability in the city centre, LA was able to develop new app-based information services for travellers that combine information about anticipated car journey times, predicted bus journey times and predicted parking availability for various travel options into the town centre versus the Park & Ride service.
- Such collaborative efforts have enabled the provision of reliable information to promote the benefits of the park and ride service, reducing unnecessary circulation of traffic and resulting pollution and traveller frustration in the city centre.

### **Example: Oxford Park & Ride**



#### **Benefits:**

- Park & Ride usage tends to be promoted by the application as this is often the fastest method of
  accessing the City Centre during peak times. Increased uptake potentially boosts revenues for the
  Local Authority Park & Ride owners and the bus operators.
- Users of the application can avoid driving directly into congestion, so they benefit from improved journey times when accessing the City Centre.
- Reduction of air and noise pollution and the conservation of Oxfordshire's local environment: the ITS-based application represents a new method of shifting people to different modes of transport using existing infrastructure. This makes it relatively cheap to implement and has the potential to shift people away from less sustainable modes of transport. This is particularly useful in cities like Oxford where, due to a high number of historical buildings and landmarks, it is difficult to make

large scale changes to infrastructure.

