Chapter

Advanced Vehicles: Challenges for Transportation Systems Engineering

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Abstract

Automatic vehicles represent one of the most active research fields within engineering. Among transportation systems engineering research topics, we highlight the need to update and/or develop new mathematical models, computer science methods and electronic technologies that contribute to the development of more effective, accurate and robust tools. In order to develop more effective models, it is advisable to consider the opportunity to interact with other specialists from sectors different of the transportation systems engineering to provide solutions to problems that may arise during the modeling and further new points of view. The main goal of this paper is discussing the most likely positive and negative effects of mixed flow expected in the near future, analyzing the main classifying criteria such as ownership, on-board technologies (sensor), and reviewing the most effective tools already available for macroscopic analysis of multi vehicle type transportation systems.

Keywords: advanced vehicles, sensors, classification, transportation systems, macroscopic analysis, mixed flow

1. Introduction

Evolution has always been a fundamental component of life and technology developments have always represented a fundamental step in human civilization evolution. In fact, it is possible to say that technology speeds up everyday life thanks to the continuous introduction of innovative techniques, new devices and new perspectives. This results in turn in huge modifications in human activities perception, due to the time involved, their safety and in general their degree of difficulty.

Among the various cases of the daily life, one of the most discussed and interesting issue of the last years is related to automated or self-driving vehicles (AVs). The introduction of such vehicles resulted in the fact that nowadays car company cannot think of just projecting the mechanical parts or the basic electronic used in the vehicle, but are also involved in the project of sensors, integration issues and in the development of the related software.

In this way the integration of electronic components has become a necessary part in the vehicle development, in order to obtain an increase in safety and in easiness of the driving experience (e.g. Anti-Breaking Systems, Hydraulic Break Assist, Electronic Stability Control, etc.), as well as a reduction of impacts such as air pollution, noise, fuel consumption. This resulted in a major cooperation between companies coming from different backgrounds and in the creation of partnerships and joint ventures among them.

These effects result in a renewed impulse in the research related to the vehicles, due to the growing mingling among the various sectors of the industry. The common goal is to develop new models or update the old ones to simulate real life situations and predict the future developments of the automotive and, in general, of transportation research field. Considering the field of transportation systems engineering, it is possible to state that right now the main focus is to achieve a deeper understanding of the hardware and software involvement in this new kind of vehicles. This, in turn, allows to obtain better models developments and more reliable scenario assessment. These issues are often accentuated by the impossibility of retrieving commercial standards, due to the fact that, in some cases, they are not yet available, or the vehicles are still prototypes.

New technologies for automated vehicles look very appealing, but, it may easily be anticipated that the time needed to turn the existing stock of traditional vehicles (TVs) into the new ones will last several years during which mixed traffic is expected, requiring ad hoc tools for analysis and design [1].

Moreover, the likely effects on congestion, and more generally traffic management and control, are not necessarily positive. Some of them are enlisted below, together with indications of needs of new models:

- increase of max density, since AVs may be shorter on the average,
- increase of capacity, since safety distance may be shorter,
- decrease of speed dispersion, useful for more effective traffic control,
- decrease of the number of vehicles on streets with shared vehicles, since the number of trips per vehicle increases, and a decrease of the number of vehicles parked along the sidewalk might be anticipated, leading to an increase of capacity.
- increase of vehicle x km due to empty movements, if shared vehicles spread, due to longer paths and of change of effective origin and destination,
- discrete space / time access for AVs vs. continuous access for TVs,
- decrease of the number of users per car, if shared vehicles spread, leading to an increase of vehicle (car) demand flows,
- change of modal split leading to an increase of car flows with respect to transit (need of new model split models)
- increase of generated flows, due to increase of mobility index and reference population, likely including mobility-impaired people (need of new trip generation and distribution models)

On the other hand, some positive social impacts may also be anticipated such as

- less pollution and noise (greater effect with electric powered vehicles),
- increase of safety,

- increase of generated flows, due to increase of mobility index and reference population,
- easier integration with medium/long-distance transportation.

The main goals of this paper are:

- discussing the most likely positive and negative effects of mixed flow expected in the near future, as briefly outlined above,
- providing an analysis on sensors used in the automotive field,
- analyzing the main classifying criteria,
- reviewing the most effective tools already available for macroscopic analysis of multi vehicle type transportation systems.

A vehicle classification based on available sensors is surely helpful to support specification and calibration of models for transportation systems analysis, thus a sensor critical analysis is carried out in Section 2, supporting the discussion of classification issues in the same Section 2. Section 3 discusses the main tools for the analysis of transportation systems with mixed flow. Section 4 reports some conclusions.

2. Sensors analysis and vehicle classification

During the last years, electronic systems assumed a growing importance in the development of assisted and automated systems. In particular, the research has been focused around two main topics:

- the development of new algorithms and the improvement of the already existing ones, at the end of obtaining more compact, less consuming and, above all, faster implementations, in order to fit the needs of the automotive industry;
- the development of "ad hoc" sensors capable of operating in the various environments and having performances suitable to detect, intervene and advice the driver in time, making it possible for the human or autonomous driver to take the best decision due to the particular conditions.

This work starts from the sensors evolution to give an insight of the different techniques and sensors families used in nowadays autonomous vehicles, in order to gain insight on the different issues related to their development and provide ideas useful to better integrate them into the traffic models, obtaining more fitting models and better results.

First of all, it is possible to define four types of sensors and related systems used in nowadays smart vehicles:

- Image sensors and processors,
- Radar sensors and systems,
- Lidar sensors and systems,
- Ultrasonic sensors and systems.

Moreover, the data coming in from the different sensors have to be considered as a whole, in order to have a redundant and robust system and to discriminate in the case of contrasting detections from different sensors. This exchange of information between the different systems is done using an internal network, such as a CAN bus, to avoid the instantiation of several sensors of the same type. Ideally, the aim of the data from and to these control units is to describe the status of the car and formulate the actions to be taken at any time. It is interesting to note, that with the new smart vehicles also systems to process and take into account the data coming from other vehicles have to be considered, causing a huge increase in the amount of data to be processed and, thus, an increase in the research for fast computing, stream processing systems and diagnostic protocols [2].

A careful examination of the various techniques used has to be developed, together with evaluation of the differences between the different types of sensors and how and when to use them, in order to achieve both a better understanding of their behavior and develop new models.

2.1 Image sensors and processors

The use of image sensors in automotive field goes back to vision guided auto-parking systems which has been around for the past twenty years [3]. Nevertheless, some of the main techniques are still used nowadays; the main topic has shifted from parking problems to active detection during driving. Several studies have been conducted on these applications, e.g. dedicated to pedestrian crossing and signal recognition. In particular in this type of problems the image sensor has to acquire the images from the environment at resolutions and acquisition rates suitable for the detection problem. Together with the sensor also the image processing methods have to be considered. In particular, to enhance the performances of the sensors in terms of processed frame rate per second (fps) hardware accelerators closely coupled to the image sensor are used. The accelerators are mainly dedicated to filtering operations on the incoming images from the sensors, aiming to send to the processing units only the significant data to be taken into account in the detection. Several systems have been developed, like the ones dedicated to edge detection and recognition, segmentation and object recognition. However, the trend is shifting to the use of Artificial Neural Networks capable of calibrating the various detection parameters according to the incoming stimulus and their previous history. Neural Networks hardware accelerators have been developed in the last years to make the systems capable of operating in real-time. While the training of the Neural Networks to determine the optimal parameters is usually done offline, some parameters could also be varied on-the-fly to achieve a resilience of the system to false detections or to improve the driving performances.

The challenge is nowadays to develop faster Neural Networks systems operating together with the image sensors, in order to process higher amount of data while operating with higher resolution frames; on the other hand, the development of new dedicated algorithms could also allow a complexity reduction of the problem which, in turn, could cause lower latencies in the system and better detection performances, both from a correctness and a speed standpoint.

2.2 Radar sensors

Radar systems are used in automotive to help solve problems like auto-parking, pre-crash sensing and adaptive cruise control, since one of the main characteristics of a radar system is the capability of inferring the velocity of the detected objects in its range. Radar systems used in automotive applications usually operate at 77 GHz frequency. The measurement time could be reduced to 10 ms allowing controlling the scene 100 times per second [4].

Radar systems are used together with other systems and results particularly efficient for detections at distances up to approximately 200 m, with a range resolution of 1 m [4]. These peculiarities make the radar system particularly appealing for mid-range applications in condition of non-optimal visibility, which could cause major problems to systems based on image sensors. However, radar systems have got poor object detection issues in medium ranges (30 m to 60 m) for angles larger than $\pm\pi/6$; for that reason, they need to be supported by other detection systems, based on different technologies [5]. Moreover, it has to be highlighted that a typical radar system shows difficulties in taking into account targets having different azimuth values and, thus, more sophisticated data processing systems are needed, like tracking ones. These systems could show problems in the case of wrong modeling assumptions for the targets, causing detection problems, like target loss.

2.3 Lidar sensors

Lidar systems are capable of good performances in presence of adverse environmental conditions, such as fog, heavy rain or snow, but also in the case of scenes having low illumination levels.

However, also lidar systems show some drawbacks, due to the fact that in some cases the dynamic range of the lidar system could be exceeded. When it happens two extremely severe types of error occur: the loss of targets and the generation of ghost targets, which worsen the detection performances unacceptably in some cases [5].

2.4 Ultrasonic sensors

Ultrasonic systems are mainly used for parking assist systems, where they are capable of insuring low costs and good performances. Several threshold systems are designed to achieve the correct detection of corners and edges, while other systems take care of the steering angle and wheel speed; all is coordinated by a network, like the CAN bus previously mentioned [6]. Moreover, this kind of systems demonstrated to work well in cooperation with laser parking systems or to substitute them [7].

Finally, it has to be highlighted that great importance has to be put on decision algorithms, which could be usually implemented in software and which could represent the bottleneck in some systems. In what follows we concentrate on the effect related to the sensors, assuming that the performances of the software are the same for all the considered systems in order to do not undermine the comparison results.

2.5 Classification issues

The schemes that is internationally used as standard for the classification of “Automated Vehicles” is the “SAE Levels” [8], written by “SAE INTERNATIONAL” (U.S.-based, globally active professional association and standards developing organization for engineering professionals in various industries) (**Figure 1**).

As shown in **Figure 1**, a six levels taxonomy proposed; these six levels are collected in a meta-classification based on two macro categories (Human Driver e Automated Driving System) that identify the technology inside the vehicle and the type of driver.

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 1.
SAE levels.

To understand the differences between each SAE level, guidelines written by AdaptIVe (a project co-founded by European Commission) [9] have been taken into account. In the following a brief explanation for each SAE level is reported:

- Level 0: no electronic device and human driver,
- Level 1: some electronic devices but the driver is still human,
- Level 2: more electronic devices for security, the driver is helped in some maneuvers, but it still has the main control of the vehicle,
- Level 3: in a smart road, the vehicle is supervised by human driver that takes control of the vehicle in case of emergency,
- Level 4: in a smart road, the vehicle is still supervised by the human driver, but the driver can make other actions,
- Level 5: completed automated vehicle.

In current research and practice SAE levels are grouped into 2 classes: 012 and 345 as it can be seen within the **Figure 1**.

Still, several considerations about the relationships between kinds of sensors available on a vehicle and SAE Levels support a 3-class meta-classification useful to effectively support specification and calibration of models for transportation systems analysis.

Table 1 shows the relationship between SAE Levels and types of sensors, supporting the 2-class meta-classification in **Figure 1**: Human driving vs. Automated driving. It could be noticed indeed that there is a huge difference between the type

	Human driving			Automated driving		
	SAE 0	SAE 1	SAE 2	SAE 3	SAE 4	SAE 5
Image sensors and processors	N	N	Y	Y	Y	Y
Radar sensors and systems	N	Y	Y	Y	Y	Y
Lidar sensors and systems	N	N	N	Y	Y	Y
Ultrasonic sensors and systems	N	Y	Y	Y	Y	Y

Table 1.
Relationship between SAE levels and types of sensors.

of sensors installed in vehicles of each level. Note that the ultrasonic sensors are used only for parking maneuvers and not for drive assistance, thus they will not be further considered within the following.

From these considerations, it is possible to see why many authors choose to use two macro classes, to group SAE Levels [10]:

- Human Driver: as shown in **Figure 1**, the vehicle certified within SAE Level 0 to Level 2 is in this macro class. Even if they show some technological differences between each level, in this type of vehicles the driving function is still human related. Hence, the currently available models for transport systems analysis [11] can almost straightforwardly be applied to these vehicles;

- Automated Driving System: the other levels are defined this class; the types of vehicles in this class are still at a prototypal stage, but it can easily be anticipated that new models need to be studied and developed.

This meta-classification is probably over-simplified: at a closer look, vehicles in the "Automated Driving System" class cannot be conceived as homogeneous, as shown below.

First, looking at the relationship between Automated Driving SAE Levels (3 to 5) and ranges of sensors, as shown in **Table 2**, it can easily find out that application ranges of sensors for SAE levels 3 and SAE Level 4 and quite different from those for SAE level 5.

In addition to sensors application range, by studying the SAE Levels definitions [10], it's possible to see that SAE Level 3 and SAE Level 4 vehicles still need a human driver compare to SAE Level 5. The human driver function within this level represents only a safeguard measure in emergency conditions or both SAE Levels: both presents different reaction times for the takeover, but the description used for the possible action that can be made by the driver during the travel are too permissive for the human driver and their reaction time. On the other hand, SAE Level 5 vehicles do not need a human driver at all, not even a steering wheel (as show in some prototype vehicle that have the possibility to hidden it), leaving all the control function to the vehicle. Starting from those considerations about the control of

	SAE 3	SAE 4	SAE 5
Radar sensors and systems	200 [m]	200 [m]	200 [m]
Image sensors and processors	250 [m]	250 [m]	200 [m]
Lidar sensors and systems	150 [m]	150 [m]	100 [m]

Table 2.
Relationship between automated driving SAE levels (3 to 5) and ranges of sensors.

the vehicle, it's possible to see that "Automated Driving System" class present a non-homogeneous control, but these criteria it's not the only one.

Another criterion is represented by the "type of ownership". Different from SAE Levels 0 to SAE Levels 2 that present a huge percentage of private owned vehicle; it's possible to notice that:

- SAE Level 3 and SAE Level 4 can be considered a technological evolution of traditional vehicles aiming at reducing effort of human drivers and will likely be mostly privately owned,

- SAE Level 5 vehicles should be considered an evolution of taxi, other vehicles available on demand and public transport system and will likely be mostly not privately owned such as the so-called robotaxi).

Therefore different "user definitions" [11] must be considered in the two cases. Moreover, the new models needed to be studied and developed should be differentiated, at least with respect to parameters.

For all these reasons, a new approach to vehicle meta-classification should be formulated. Assuming that:

- the sensors related software and involved algorithms are the same for each vehicle and level,

- the sensors have their functional range as described in **Table 2**,

- the sensors functional range as line of vision for the user,

- the SAE Level Certification remains as fundamental definition for the type of vehicles,

- the SAE Level can be used for an "ownership" definition by the user (Starting for SAE Level 0 to be private to arrive at SAE Level 5 as Shared Vehicle)

The new meta-classification proposed is the following including three classes:

- Human Driver: the same definition as the previous 2-class meta-classification,

- Advanced Driving System: this class includes the SAE Level 3 and SAE Level 4 vehicles; these vehicles can be modeled as the same type of vehicle for the "user definition", since a human driver is needed to control the vehicle and the considered sensors have the same application range,

- Automated Driver: this class includes the SAE Level 5 vehicles only.

This meta-classification allows the analysis of the following future scenarios:

- short-term scenarios with both Human Driver and Advanced Driving System vehicle classes only,

- medium-term scenarios as above with low percentage of Automated Driver class vehicles,

- long-term scenarios with Advanced Driving Systems and Automated Driver classes only and no Human Driver class.

3. Analysis of transportation systems with mixed flow

A change so great may be not technology-driven only, but also requires a carefully analysis of its several impact through well designed enhancements of tools of Traffic and Transportation Theory (TTT) already available to the transportation systems modelers and planners (see the comprehensive book by Cascetta [11]).

The analysis of transportation systems with several types of vehicles require a generalization of existing models and algorithms for travel demand assignment to transportation networks, as described in Cantarella and Di Febbraro [12], Cantarella et al. [13, 14]; the proposed approach can be applied to real size networks. It is briefly reviewed in the following.

Users are partitioned into o-d pairs they are traveling from/to, user categories (with common socio-economic and behavioral features) and types of used vehicle, such as traditional, connected, automated, autonomous, ...; fossil fuel vs. electrical powered; privately owned vs. shared; .... Demand flows are assumed constant and known.

Transportation supply is modeled through a flow network, say a graph with a transportation cost and a flow associated to each arc. All costs are assumed measured by a common unit, usually travel time or money, through duly homogenization of different attributes, if the case. A route connecting an Origin Destination pairs is described by a path. (Presented results still hold if more general definitions of routes are used, such as hyperpaths).

3.1 Assignment to uncongested networks

In uncongested networks the arc flows depend on the arc costs, through the arc-flow function obtained as described below; its structure is shown in **Figure 2**.

The arc costs (**c**) may be different among the vehicle types to reflect different performances, and we assume that the arc cost per vehicle type are given by an affine transformation of the arc generic costs.

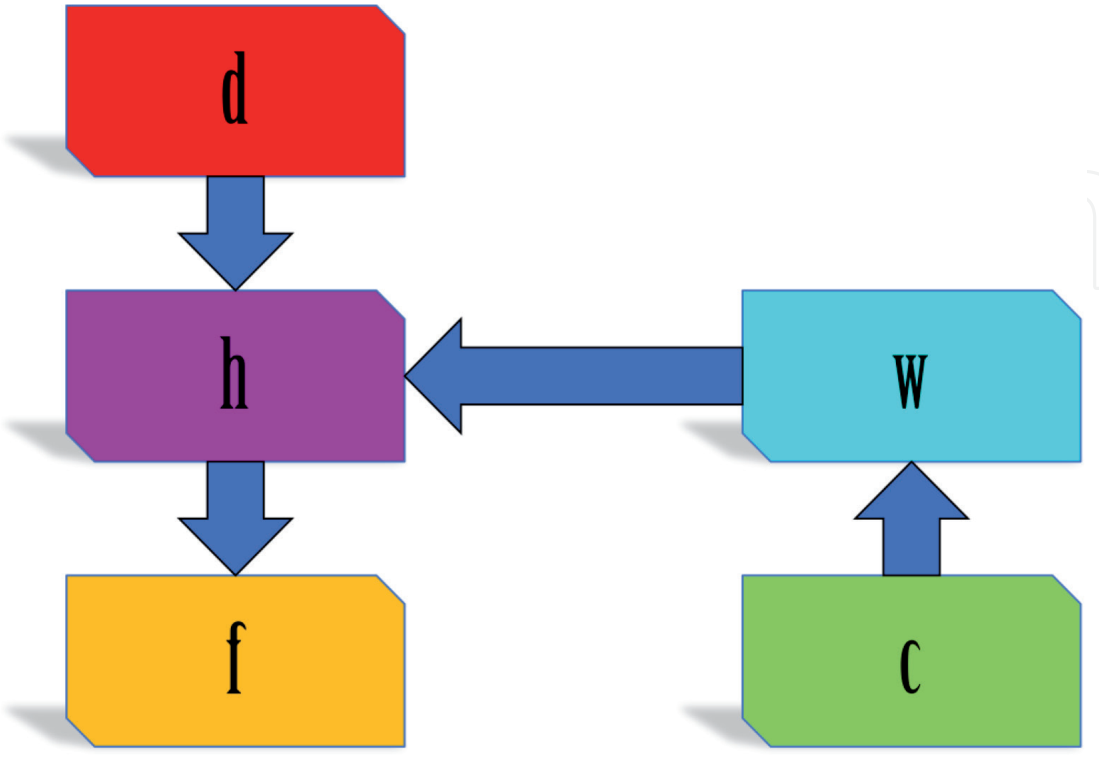

Figure 2.
The arc-flow function for assignment to uncongested networks.

Then, the route costs (**w**) for each o-d pair, user category and vehicle type can be obtained from the corresponding arc total costs through an affine transformation from the arc space to the route space defined by the transpose of arc-route incidence matrix.

The utility function for each o-d pair, user category and vehicle type is almost always specified through an affine transformation of costs both in research analysis and in practical applications.

Route choice behavior for users of each o-d pair, user category and vehicle type m can be modeled by applying any discrete choice modeling theory, such the well-established Random Utility Theory. In this case the choice proportion of an alternative is given by the probability that its perceived utility is equal to maximum among all alternatives. When the perceived utility co-variance matrix is non-singular, probabilistic route choice functions are obtained.

Demand conservation flow relation for each o-d pair, user category, vehicle type assures that flows of all connecting routes (**h**) sum up to demand flow (**d**).

The arc flows (**f**) due to each o-d pair, user category and vehicle type can be obtained from the route flows through a linear transformation from the route space to the arc space defined by the arc-route incidence matrix. Having assumed that all arc flows are measured in TVs per time unit, the arc total flows are given by the sum over all o-d pairs, user categories and vehicle types.

Main input data of the arc flow function are arc costs, and demand flows. Vehicle types may be distinguished with respect to:

- flow equivalence
- mean number of users on board
- cost equivalence
- specific arc, cost, e.g. monetary cost (and VoT), access cost, …
- route utility parameter and route choice function parameters
- route choice function

The arc flow function is monotone non-increasing with respect to arc costs under mild assumptions. It can be computed for large scale applications through algorithms derived from network theory, avoiding explicitly path enumeration.

3.2 Equilibrium assignment to congested networks

In congested transportation networks arc flows depend on arc costs, and user equilibrium assignment searches for mutually consistent arc flows and costs. Arc generic costs depend on the arc total flows through the arc cost function, which models user driving behavior at macroscopic level.

Equilibrium assignment can effectively be described through fixed-point (FP) models obtained combining the arc-flow function and the arc cost function. These models can be solved for large scale applications through algorithms based on the Method of Successive Averages, which avoid the use of matrix algebra and computation of derivatives. Their structure is shown in **Figure 3**.

Existence is guaranteed if both the arc flow function and the arc cost function are continuous (and the network is connected), applying Brouwer theorem. For a monotone decreasing arc flow function, if the arc cost function is monotone strictly increasing uniqueness is guaranteed. Uniqueness of arc flows also guarantees

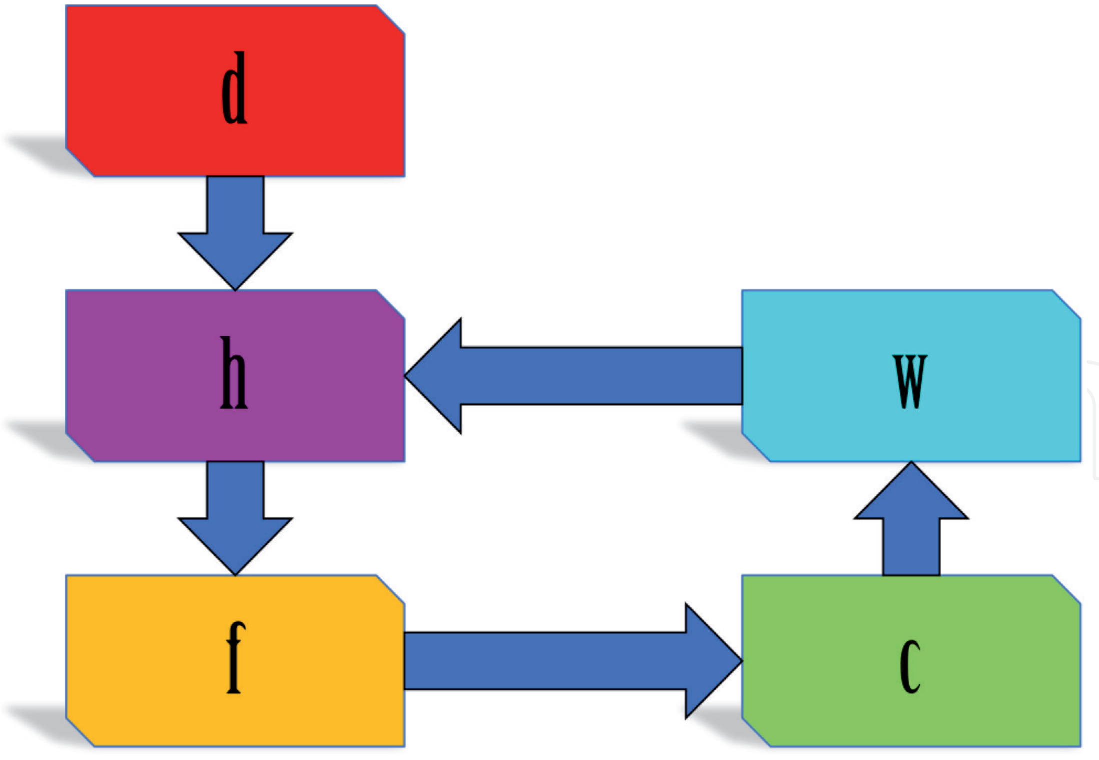

Figure 3.
Fixed point models for equilibrium assignment to congested networks.

uniqueness of arc costs as well as route flows and costs, and of flows and cost per o-d pair, user category, vehicle type.

3.3 Day-to-day dynamic assignment to congested networks

The evolution over time of arc flows and costs can effectively be described through day-to-day dynamic assignment models. The specification of these models requires an extension of models for the equilibrium assignment by including sub-models of

- User memory and learning: how users forecast the level of service that they will experience today, from experience and other sources of information, such as informative systems, about previous days;

- User habit and inertia to change: how users make a choice today, possibly repeating yesterday choice to avoid the effort needed to take a decision, or reconsidering it according to the forecasted level of service.

The arc cost updating relation, modeling user memory and learning, gives the today forecasted route costs with respect to previous day costs. It extends the arc cost function. In the simplest instance, this relation can be specified by an exponential smoothing (ES) filter, say a convex combination of yesterday route forecasted costs and yesterday actual route costs, given by an affine transformation of the yesterday arc costs.

The arc flow updating relation, modeling user habit and inertia to change, gives the today arc flow with respect to forecasted costs and previous day flows. It extends the above arc flow function. In the simplest instance, this relation too can be specified by an exponential smoothing (ES) filter, say a convex combination of yesterday arc flows due to users who do not reconsider their yesterday choice and today arc flows due to users who reconsider their yesterday choice.

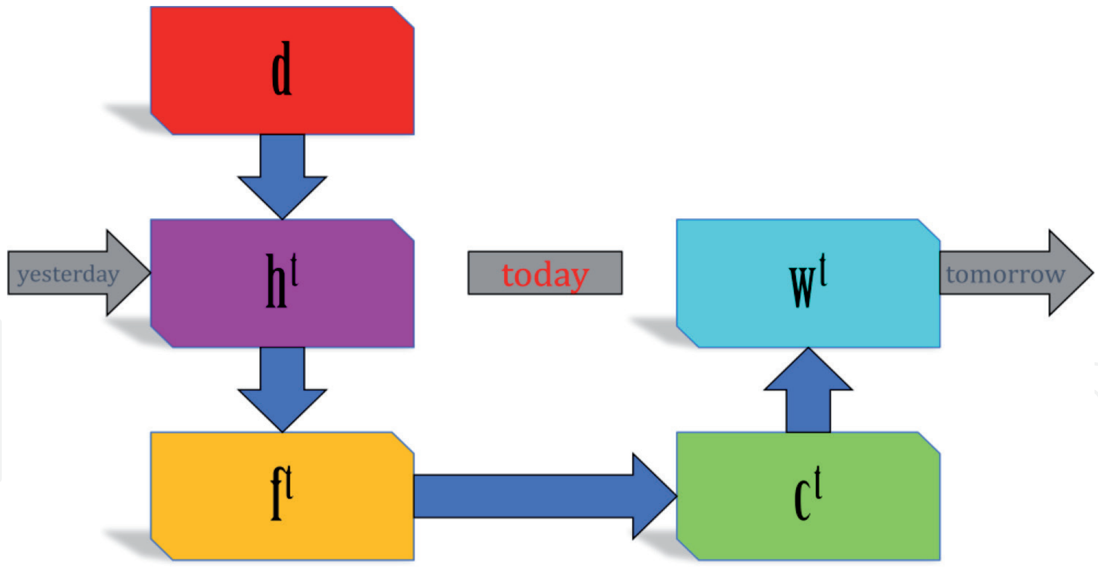

Figure 4.
Dynamic process models for day to day dynamic assignment to congested networks.

The arc flow updating relation can be combined with the arc cost updating relation to specify Deterministic Process (DP) models for day-to-day dynamic assignment. Their structure is shown in **Figure 4**.

The fixed-point states of the DP model specified by the ES filters are equivalent to the equilibrium states as defined by FP model mentioned above). Applying techniques from the theory of discrete-time non-linear dynamic systems, the above DP models can be used to study the local stability of each fixed-point state, say whether it is an attractor. Moreover, a bifurcation analysis can be carried to single out which attractor is reached by the evolution over time when an input data and or a parameter is changed.

The DP model specification can be used as a base to specify time discrete Stochastic Process models, which may provide full statistical characterization.

3.4 Within-day dynamic assignment to congested network

All the above models can be extended to cope with Within-day Dynamics requiring highly non-linear specification. This kind of models are useful to describe while-trip re-routing due to interaction with information and/or control system as well as queuing phenomena.

4. Conclusions

At first this paper has reviewed the analysis of the most likely effects of the introduction of new type of vehicles including vehicles with different level of automation, differently powered, privately owned or shared, ... Then, this paper has discussed the main technological and modeling issues for the analysis of transportation systems with mixed flow.

Some issues are worth of further research work, such as:

- specification of new models of Traffic Flow Theory to deal with congestion in mixed traffic,

- new path choice models for travel demand assignment within the general framework of Transportation System Analysis,

- parameter calibration from real data, or laboratory studies (survey, driving simulator, etc.).

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