6 CONCLUSION

6.1 RESEARCH CONTRIBUTION

The two main contributions of this thesis are the implementation and validation of a heuristic for dynamic traffic assignment in AIMSUN and its use in determining short-term traffic prediction based on a set of almost independent neural networks, whose structure corresponds to the OD path structure of the road network, which allows a time- dependent update of the OD matrices.

Another contribution of the research work undertaken in this thesis is the architecture proposed for advanced traffic management and control systems and advanced traffic information systems based on telematic technologies, preliminary versions of which have been evaluated in the European PETRI (PETRI, 1996) and CAPITALS (CAPITALS, 1998) projects. In this architecture, the short-term prediction of traffic flow evolution becomes the key component. To support a sound decision-making process in traffic management and in the dissemination of information to users, the critical point is to achieve a reliable short-term prediction of the network state. The dynamic prediction mechanism of the network state proposed in this thesis is defined in terms of the dynamic prediction of OD matrices.

Neural networks are used for the short-term prediction of the network state in this work, because they appear to be natural candidates for forecasting models, particularly when their easily parallelizable structure is taken into account and high computational speed is required to achieve the system's objectives. Certainly, the quality of the predictions obtained seems to confirm the hypothesis that led us to propose neural networks as a forecasting mechanism and validates the methodology used to predict OD matrices.

The short-term prediction process requires the input of the historical OD matrix and patterns with which to train the neural network that has to produce the forecasts. Time-sliced OD matrices are currently unavailable and their direct production is difficult and costly, although for several telematic applications the possibility of generating such information in real time has been considered. Our proposal in this thesis consists of generating an initial estimate using the information that is available, that is, an initial, old OD and the link flow counts of a subset of network links. The estimation made to adjust the initial matrix to the link volumes observed was based on an ad hoc adaptation of the Spiess heuristic for solving the bi-level formulation of the matrix adjustment problem as a nonlinear optimisation problem.

The dynamic prediction of an OD matrix by means of a neural network has one main drawback: the amount of data required to properly train the neural network. The contribution of this work is a new approach to determining independent OD pairs using a cluster analysis combined with the identification of the *K* shortest path used between each OD pair. This reduces a neural network so large that the training process would be computationally unfeasible to a set of small, almost independent neural networks, each one corresponding to a class of almost independent OD pairs. The resulting network is of a size that makes the process computationally feasible.

The identification of the *K* shortest path used between each OD pair led to the implementation of a heuristic of the dynamic traffic assignment in AIMSUN and its validation. The work proposes methodological patterns for calibrating the parameters of microscopic traffic simulation models based on simple models, with the aim of ensuring the adequacy of the car-following parameters. The method proposed is illustrated with examples built with the AIMSUN microsimulator. The model's validation is discussed, a paradigm based on time series analysis is proposed to explicitly account for the autocorrelation processes of traffic data and the numerical results are presented. A band comparison process is also proposed for cases in which the amount of data available allows one to take the explicit variability of traffic data into account. The method proposed is applied to a real case. Finally, assuming that "dynamic equilibrium" exists, the empirical results show that an appropriate, time-varying *k* shortest paths calculation, in which the link costs are suitably defined; adequate stochastic route choice functions; and the use of a microscopic network loading mechanism achieve a network state that acceptably replicates the flows observed in the simulation horizon and a reasonable set of used paths between OD pairs, as the oscillations within a narrow band of the empirical RGap function indicate.

The contributions of this work can be summarised as follows:

- Feasibility of the architecture of advanced traffic management systems.
- Real-time estimation of OD matrices from traffic counts by neural networks.
- Validity of heuristic dynamic traffic assignment based on microsimulation, which leads to two further contributions: firstly, the validity of heuristic dynamic traffic assignment using microsimulation produces a rational set of OD paths that are likely to be used, which can be used as input in the process of the real-time estimation of OD matrices from traffic counts and also to validate the architecture proposed in this work for ATMS, secondly, a set of guidelines for the validation of route choice parameters, and thirdly the way the cost functions are updated and the way the reactive dynamic assignment is computed.

Further contributions made by this thesis are the following ad hoc developments implemented in AIMSUN, necessary to make the microscopic simulator the software platform to implement the methods and approaches proposed in the research. These new developments, once tested have become standard procedures in a new commercial version of the simulation software, available to AIMSUN customers. The main developments, described in detail in Chapter 3 and in the appendices to this thesis, are the following:

- All the algorithms of the heuristic dynamic traffic assignment procedure are explained in Chapter 3.

- The path analysis tool, which allows to the user to gain insight into what occurs in a heuristic dynamic assignment. For the proper calibration and validation of the simulation model, the user should have access to the analysis of the routes used. The path information that is available is as follows:

    - Shortest path information. The user can view all the shortest path information that is being used by vehicles during the simulation.

    - User-defined path information. The user can view all the user-defined path information.

    - Shortest path display. The user can simultaneously view different shortest paths and their links in the network.

    - Initial path assignment. The user can view all the probabilities considered when a vehicle enters the system.

    - Dynamic path assignment. The user can view all the probabilities considered when a vehicle carries out path reassignment during the trip.

- The simulation output used in the validation of the dynamic traffic assignment is the path information output. The link cost information is generated and all the vehicles are coloured per origin, per destination and both (per origin and destination simultaneously).

- The function editor, which allows the user to define new link cost functions and new route choice models.

6.2 FUTURE RESEARCH

The research presented in this dissertation could be extended in the following directions:

6.2.1 REAL-TIME ESTIMATION OF OD MATRICES

Short-term prediction by means of neural networks could be complemented by other, recently proposed methodologies without invalidating the architecture proposed in this work. These other methodologies use methods such as fuzzy logic or fuzzy neural networks, which combine the complementary capabilities of neural networks and fuzzy logic.

Another possibility would be to explore the method recently proposed by Bierlaire and Crittin (2004), which exploits the path analysis capabilities of the new AIMSUN functions that have been developed.

6.2.2 VALIDATION OF HEURISTIC DYNAMIC TRAFFIC ASSIGNMENT

In the methodology proposed in this work, the estimation of the historical OD matrix becomes a key point, because it is an input requirement in the architecture proposed in this work. Therefore, it will be necessary to implement and test other, alternative heuristics. A proposal that has already been the object of a preliminary exploration is to generate sound estimates of the input target matrix, a process which is based on an iterative, embedded, bi-level optimisation adjustment and is inspired by the adjustment proposed by Spiess (1990).

The planned line of research consists in replacing the lower level static traffic assignment problem, which produces as its result $v(g)_a$ as the flow on link *a*, with a dynamic traffic assignment problem that is implemented using the AIMSUN microscopic simulator.

Preliminary results have been obtained for a medium-sized urban network modelled on the Amara borough of the city of San Sebastian in Spain (see Appendix I). The new approach consists in comparing the matrix adjustment when static traffic assignment in the lower level problem, which was solved using EMME2 (INRO, 1996), is used or dynamic traffic assignment is used. The experiment involves calculating a matrix adjustment from two different OD matrices: the original historical OD matrix from 18:00 to 20:00, "*Matrix 18-20*", and an OD matrix "*Matrix 01*", where the demand of *i*-th OD pair g_i is calculated as

$$g_i = \begin{cases} = 1 & \hat{g}_i > 0 \\ = 0 & \hat{g}_i = 0 \end{cases}, \text{ where } \hat{g}_i \text{ is the original historical demand of } i\text{-th OD pair}$$

The matrix adjustment of "*Matrix 18-20*", using dynamic traffic assignment, uses 3 iterations to reach an R^2 percentage (calculated by comparing the simulated and observed detector counts) of 89.42%, and the adjustment of "*Matrix 01*" uses 8 iterations and results in an R^2 percentage of 92.79%. Table 6.1 depicts the evolution of R^2 according to the number of iterations. If static traffic assignment is used, the same adjustments require 17 iterations with an R^2 percentage of 91.98% for the adjustment of "*Matrix 18-20*" and 20 iterations with an R^2 percentage of 96.84% for the adjustment of "*Matrix 01*".

Matrix 18-20	
Iteration Number	R^2
1	83.06
2	83.46
3	89.42

Matrix 01	
Iteration Number	R^2
1	14.84
2	53.99
3	71.63
4	83.80
5	87.90
6	91.16
7	92.71
8	92.79

Table 6.1. Results of matrix adjustment using dynamic traffic simulation

These preliminary results show the validity of the method and introduce the idea of a framework for a semi-automatic calibration process.

Future research on the semi-automatic calibration process would involve determining a heuristic adaptive algorithm for estimating an origin-destination-dependent scale factor for the route choice models.

The preliminary results were obtained using the logit route choice function and so it will be necessary to extend the experiments to the remaining route choice models.

Taking into account the role of the scale factor in smoothing out the shape of the logit function, the right value of parameter θ should be different for each OD pair, depending on the travel time variability. From a practical point of view, the easy way to define θ is as a global simulation parameter that has the same value for all OD pairs, and this works for road networks in which path travel times are of the same order of magnitude but is probably unrealistic for large networks in which long path travel times coexist with shorter ones. The question is how to input the θ_i values for each OD pair $i \in \mathbf{I}$, the set of all OD pairs, when $|\mathbf{I}|$ is a large number, and how to define the right value for each OD pair. To cope with this problem, the following adaptive heuristics is proposed. Let $\mathbf{tt}^i_1, \ldots, \mathbf{tt}^i_n$ be the ordered set of travel times for the *n* paths of the *r*-th OD pair at time interval *i*, that is, $\mathbf{tt}^i_1 < \ldots < \mathbf{tt}^i_n$. When the variability of the travel times for the *r*-th OD pair between successive time intervals changes beyond a predefined threshold, the estimation by a maximum likelihood procedure of the scale factor θ_r for the route choice function of the *r*-th OD pair is as follows:

1. Estimation of target probabilities: Let $\mathbf{s} = \sum_{\mathbf{j}=1}^{\mathbf{n}} \mathbf{tt}^{\mathbf{i}}_{\mathbf{j}}$ be the sum of the current travel times for the *n* paths between the *r*-th OD pair.

- Compute the set of weights: $w_j = \frac{tt_n^i}{tt_j^i}$, j=1,…,n; Define: $\bar{tt}_j^i = (s - tt_j^i)(w_j)^\beta$

j=1,…,n ;

- Calculate $\bar{s} = \sum_{j=1}^{n} \bar{tt}_j^i$ and compute the estimation of the target probabilities as

$\hat{P}_j = \frac{\bar{tt}_j^i}{\bar{s}}$, j=1,…,n

2. Estimation of the scale factor θ_r: Select $\hat{P}_j$ for some j and define

$$f(\theta_r) = \ln\hat{P}_j + \ln\left(\sum_{k=1}^{n} e^{-\theta_r tt_k^i}\right) + \theta_r tt_j^i \quad \text{and} \quad f'(\theta_r) = \frac{\sum_{k=1}^{n}\left(-tt_k^i\right)e^{-\theta_r tt_k^i}}{\sum_{k=1}^{n} e^{-\theta_r tt_k^i}} + tt_j^i$$

- ***Initialize*** θ_r^0

- ***Iterative step*** k+1 Let $\theta_r^{k+1} = \theta_r^k - \frac{f\left(\theta_r^k\right)}{f'\left(\theta_r^k\right)}$ <u>If</u> $\left|\theta_r^{k+1} - \theta_r^k\right| \le \varepsilon$ then stop

- ***Otherwise*** let k←k+1 and repeat

On the basis of the computational experiments conducted with network models of various sizes, the recommended value for β is $2.5 \le \beta \le 3$, although the determination of the right value in each case will be the outcome of the validation process.

Another line to explore is the possibility of determining the response surface for the dynamic traffic assignment parameters. The objective of this research is to determine the possible relationship between dynamic traffic assignment parameters and a characterisation of the road network, in order to establish guidelines for its validation. The preliminary experiments start by defining the characterisation of the networks using:

- NbSections: The total number of sections in the AIMSUN model.
- NbNodes: The total number of nodes in the AIMSUN model.
- NbCentroids: The total number of centroids or zones in the AIMSUN model.
- Kms: The total number of kilometres in the model, obtained as the sum of the length of all the sections of which the AIMSUN model is that composed.

- Kms x lane: The total number of kilometres of all lanes, obtained as the sum of the length of all lanes that compose the AIMSUN model.
- NbLinks: The total number of links of AIMSUN model. A link is generated since either one section or a polysection (a group of sections that share the same characteristics).
- InternalNodes: The total number of internal nodes. All the nodes (either junctions or joins) that have more that one entrance and/or more than one exit are considered when an internal node is generated. All nodes that represent a direct connection between two different sections are excluded.
- InternalArcs: The total number of internal arcs. An internal arc is a link between two internal nodes.
- ConnectivityIndex: The connectivity index *CI* is calculated as

$$CI = \frac{\sum_{n \in InternalNodes} \frac{ExitArcs_n}{N-1}}{N}$$

  - where *N* is the number of internal nodes,
    $ExitArcs_n$ is the number of exit internal arcs from node *n*, that is, the number of connections to other internal nodes.
- AvgDistance: The average distance in meters between all OD pairs, considering the paths calculated in free flow conditions.
- DevDistance: The distance deviation in meters between all OD pairs, considering the paths calculated in free flow conditions.
- MinDistance: The minimum distance in meters between all OD pairs, considering the paths calculated in free flow conditions.
- MaxDistance: The maximum distance in meters between all OD pairs, considering the paths calculated in free flow conditions.
- AvgTime: The average travel time in seconds between all OD pairs, considering the paths calculated during one simulation.
- DevTime: The distance travel time in seconds between all OD pairs, considering the paths calculated during one simulation.
- MinTime: The minimum travel time in seconds between all OD pairs, considering the paths calculated during one simulation.
- MaxTime: The maximum travel time in seconds between all OD pairs, considering the paths calculated during one simulation.
-

Further research may also do well to explore more sophisticated neural network architectures that can be used for prediction, including ones which may comprise fuzzy neural networks or gating techniques. Other techniques, such as those proposed by Bierlaire and Crittin (2004), should also be taken into account.