5 COMPUTATIONAL RESULTS

The aim of the computational results is to validate the heuristic dynamic traffic assignment based on microsimulation, and therefore to the validity of the heuristic dynamic traffic assignment using microsimulation, which produces a rational set of OD paths that are likely used and proposes a set of guidelines for the validation of the route choice parameters.

The first computational experiment (section 5.1) was conducted to compare the impact on the dynamic traffic assignment results of two different approaches to determining the set of alternative paths K_i that connects the OD pair *i*-th at time interval *t* (section 3.2.2.3 gives the details of these two approaches).

The second set of experiments (section 5.2.1) presents the validation results of dynamic traffic assignment parameters based on GEH index, whose aim is to analyse, the cases studied, which combination of values for dynamic traffic assignment parameters lead to a valid model and to identify the influence of these parameters, and to establish guidelines for the calibration process. This set of experiments presents the validation results of dynamic traffic assignment parameters based on a standard comparison between model and system outputs for an urban network of a medium size that models the Amara borough of the city of San Sebastian in Spain (see Appendix I), only as a show case; complementarily, the same results from Vitoria and Brunnsviken model are presented in Appendix II. The forthcoming conclusions can be applied to all models experimented.

The conclusion from the previous set of experiments has led to an analysis of the influence of each individual parameter and all possible combinations on the global indicator index GEH. Thus, we carried out an analysis of variance of GEH as a response variable and of the dynamic traffic assignment parameters as factors, experiments described in section 5.2.2..

And finally, section 5.3 describes the experiments conducted to validate the heuristic dynamic traffic assignment based on RGap function and section 5.4 presents the validation of the reactive dynamic traffic assignment based on GEH index and RGap, which analysis was carried out using the Amara model.

5.1 DETERMINING THE SET OF PATHS IN THE DECISION-MAKING PROCESS

The path selection process, which is based on discrete route choice models involves estimating the path flow rates of a set of alternative paths K_i that connecting the OD pair *i*-th. This set of alternative paths is updated considering the shortest path trees calculated at every interval in the dynamic traffic assignment.

An aspect that must be studied is the impact on the dynamic traffic assignment results of two different approaches to determining the set of alternative path K_i that connects the OD pair i-th at time interval t (section 3.2.2.3 gives the details of these two approaches).

To illustrate the impact of the different approaches, consider a network, as shown in Figure 5.1, that has one origin centroid and one destination centroid. Between them, there are only two alternative paths: south alternative (path S) and north alternative (path N).

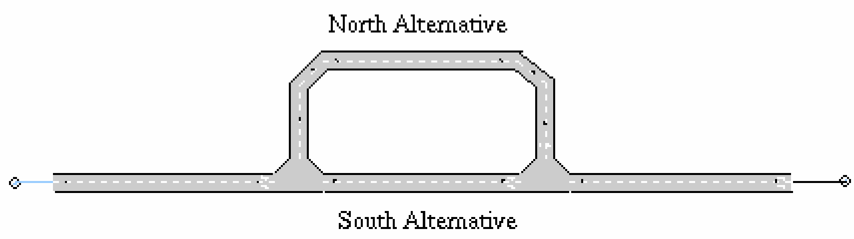


Figure 5.1. Network that has two alternative paths

The traffic demand is 1000 vehicles per hour. The western junction has a pre-timed control plan that has a total cycle of 50 seconds and gives the right of way to path S for 20 seconds (plus 5 seconds as the interphase) and the same time (plus the same 5 seconds of the interphase) to path N.

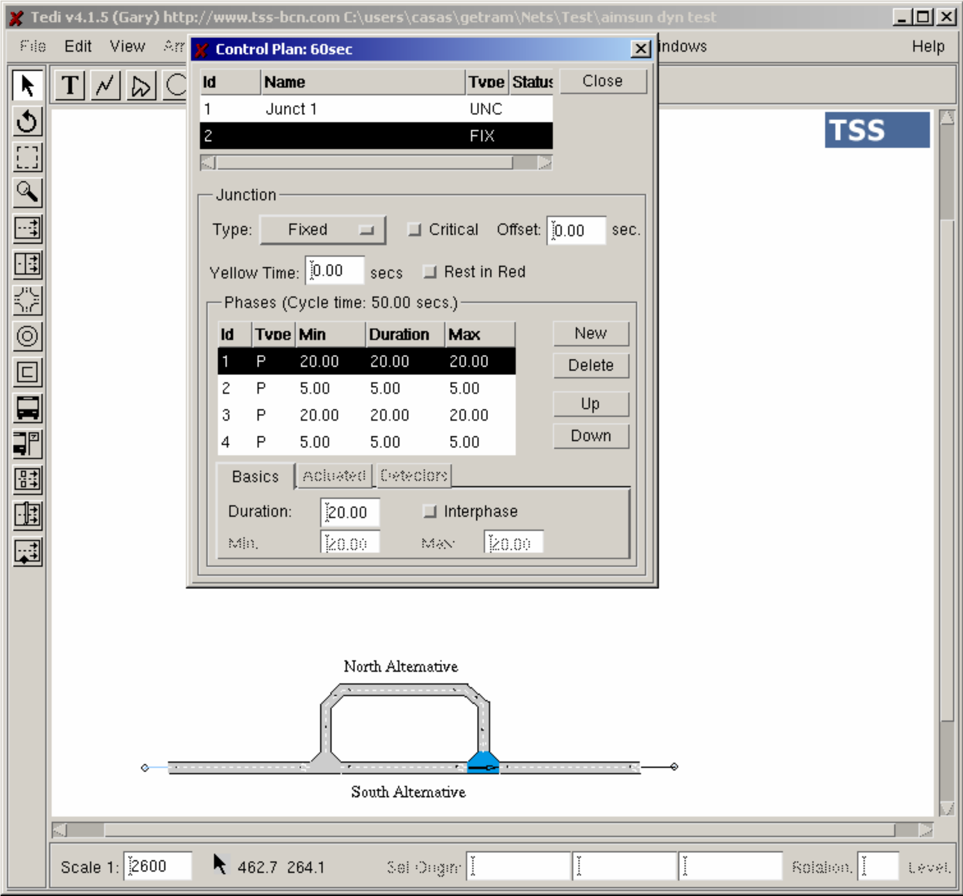


Figure 5.2. Pre-timed control plan definition

If we analyse the path costs in free flow conditions (these costs do not take into account the delay caused by the control plan definition), path S has a total cost of 21.6 seconds and path N a total cost of 28.79. If we consider these costs and take the logit function to be the route choice model and the scale factor θ to have a value of 60 (the same analysis could be applied to other route choice models and parameter values), it follows that, if

$$P_k = \frac{1}{1 + \sum_{l \neq k} e^{(v_l - v_k)\theta}}$$

the expected choice probability of path S and path N will be 0.53 and 0.47 respectively. However, in the first approach, if *MaxNumberSPT* is defined as 2, the simulation is run and the flow for each alternative path is measured, the flip-flop situation shown in Figure 5.3 is observed.

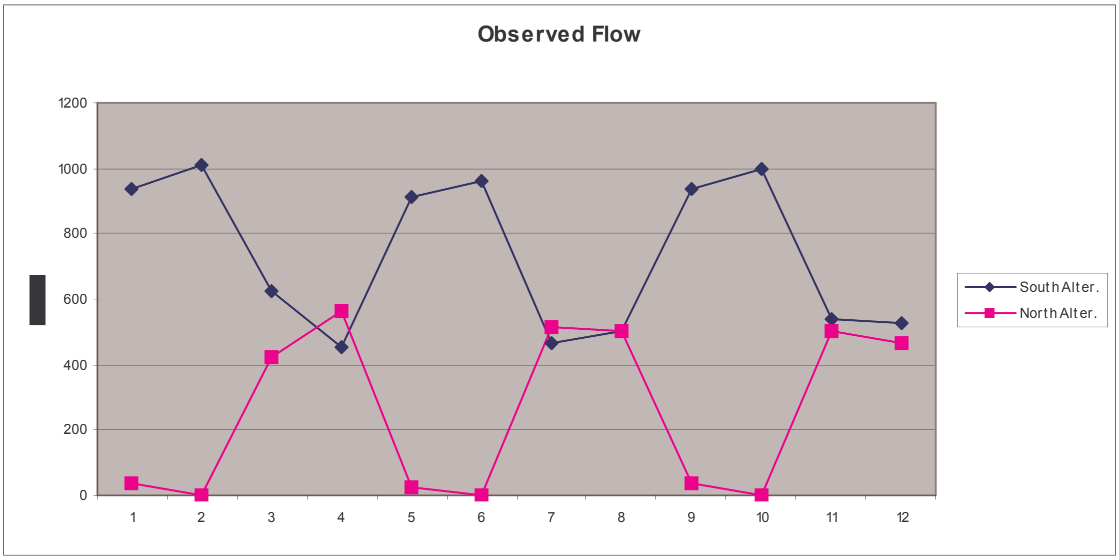


Figure 5.3. Observed flow of paths S and N, where *MaxNumberSPT* = 2

Following the simulation, the shortest paths calculated for each time interval in the first approach are as follows:

Interval	**Shortest Path**
1	Path S
2	Path S
3	Path N
4	Path S
5	Path S
...	...

The evolution of the composition of K_i (set of alternative paths) for each interval in the first approach is as follows:

Interval	**Shortest Path**	K_i
1	Path S	Path S
2	Path S	Path S, Path S
3	Path N	Path N, Path S
4	Path S	Path S, Path N
5	Path S	Path S, Path S
...	...	...

In that case the flip-flop situation is done because, for example, at interval 2 and 5 the path selection considers only path *S*, so all vehicles entered in this interval select path *S* and no one follows path N because is not available in K_i.

To minimize the flip-flop situation in this first approach, the number of shortest paths to be considered is increased by increasing the *MaxNumberSPT* parameter. Figure 5.4 shows the same experiment as Figure 5.3, although in this case the number of shortest paths to consider has been increased to 4.

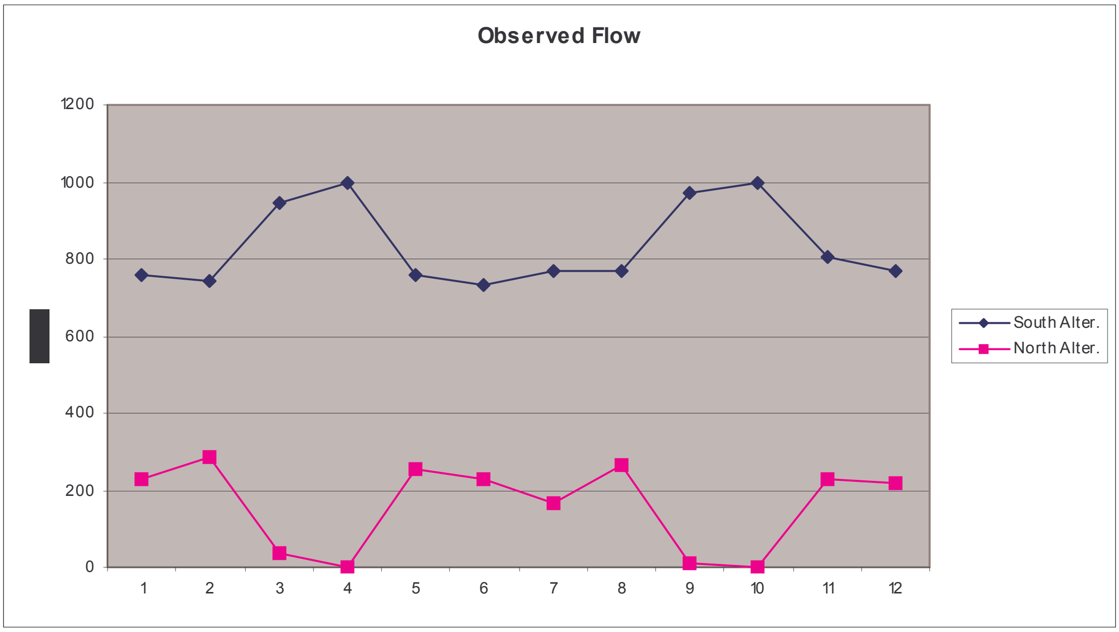


Figure 5.4. Observed flow of path S and N, where *MaxNumberSPT* = 4

Here, the flip-flop situation is smoother than in the experiment in which *MaxNumberSPT* = 2, although on average a probability of 0.84 is given to path S and a probability of 0.16 to path N. The difference is therefore significant with respect to the expected probabilities of each alternative (0.53 for path S and 0.47 for path N), which is because the alternative S is the best alternative in various intervals and thus gives a higher probability than expected.

If the second approach is applied and *MaxNumberRoutes* is defined as 2 and *MaxNumberSPT* is defined as 10, Figure 5.5 depicts the results of running the same simulation experiment. The flip-flop situation does not occur and the average probability assigned is 0.54 for path S and 0.46 for path N, which are acceptable values that are close to the expected theoretical probabilities (0.53 for path S and 0.47 for path N).

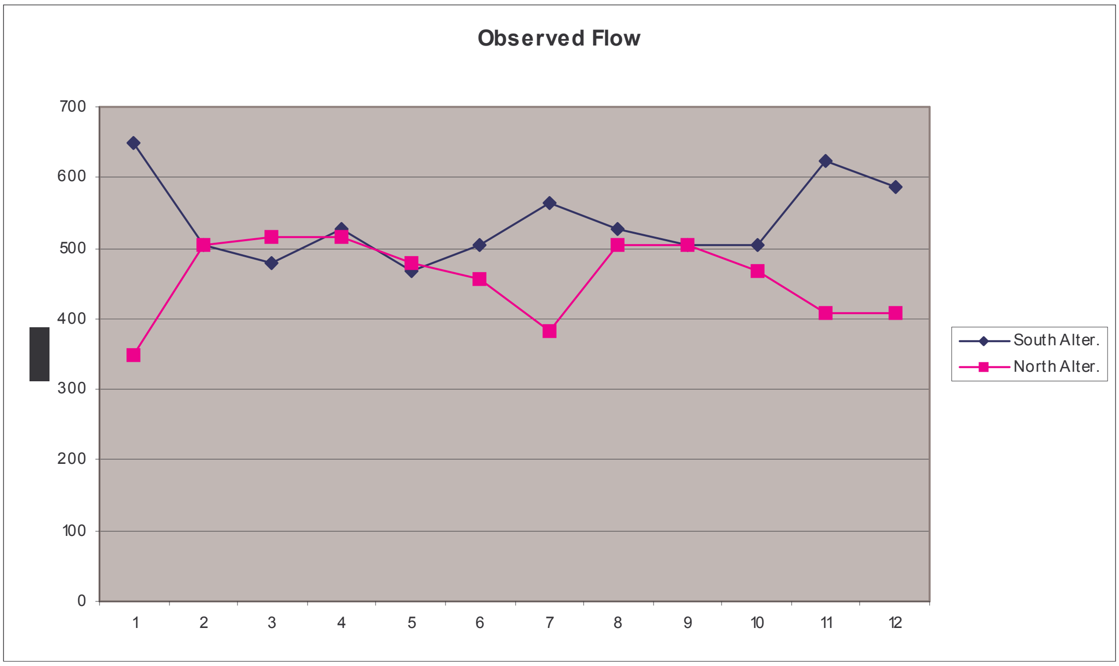
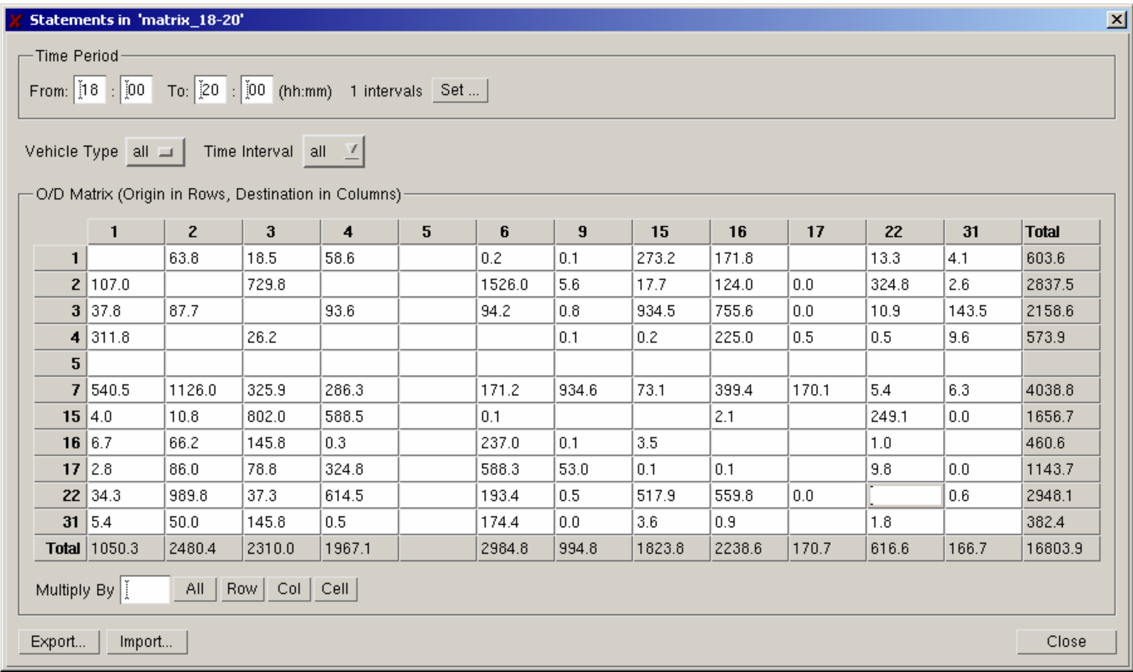


Figure 5.5. Observed flow of path S and N, where *MaxNumberRoutes* = 2 and *MaxNumberSPT* = 2

The second example used to compare the first and second approach is that of an urban network of a medium size modelled on the Amara borough of the city of San Sebastian in Spain. The total traffic demand is 16,803 vehicles during the afternoon peak time from 18:00 to 20:00 and is represented by the OD matrix shown in Figure 5.6.



	1	2	3	4	5	6	9	15	16	17	22	31	Total
1		63.8	18.5	58.6		0.2	0.1	273.2	171.8		13.3	4.1	603.6
2	107.0		729.8			1526.0	5.6	17.7	124.0	0.0	324.8	2.6	2837.5
3	37.8	87.7		93.6		94.2	0.8	934.5	755.6	0.0	10.9	143.5	2158.6
4	311.8		26.2				0.1	0.2	225.0	0.5	0.5	9.6	573.9
5													
7	540.5	1126.0	325.9	286.3		171.2	934.6	73.1	399.4	170.1	5.4	6.3	4038.8
15	4.0	10.8	802.0	588.5		0.1			2.1		249.1	0.0	1656.7
16	6.7	66.2	145.8	0.3		237.0	0.1	3.5			1.0		460.6
17	2.8	86.0	78.8	324.8		588.3	53.0	0.1	0.1		9.8	0.0	1143.7
22	34.3	989.8	37.3	614.5		193.4	0.5	517.9	559.8	0.0		0.6	2948.1
31	5.4	50.0	145.8	0.5		174.4	0.0	3.6	0.9		1.8		382.4
Total	1050.3	2480.4	2310.0	1967.1		2984.8	994.8	1823.8	2238.6	170.7	616.6	166.7	16803.9

Figure 5.6. OD matrix representing traffic demand in the Amara model

The results were analysed using a subset of OD pairs. All the pairs that had a representative number of trips with respect to the total number of trips were considered, such as, for example, the OD pair defined as origin centroid 7 to destination centroid 2, for which the total number of trips was 1126, and the OD pair defined as origin centroid 2 to destination centroid 6, for which the total number of trips was 1526. Figure 5.7 depicts the location in the network model of several of the OD pairs analysed.

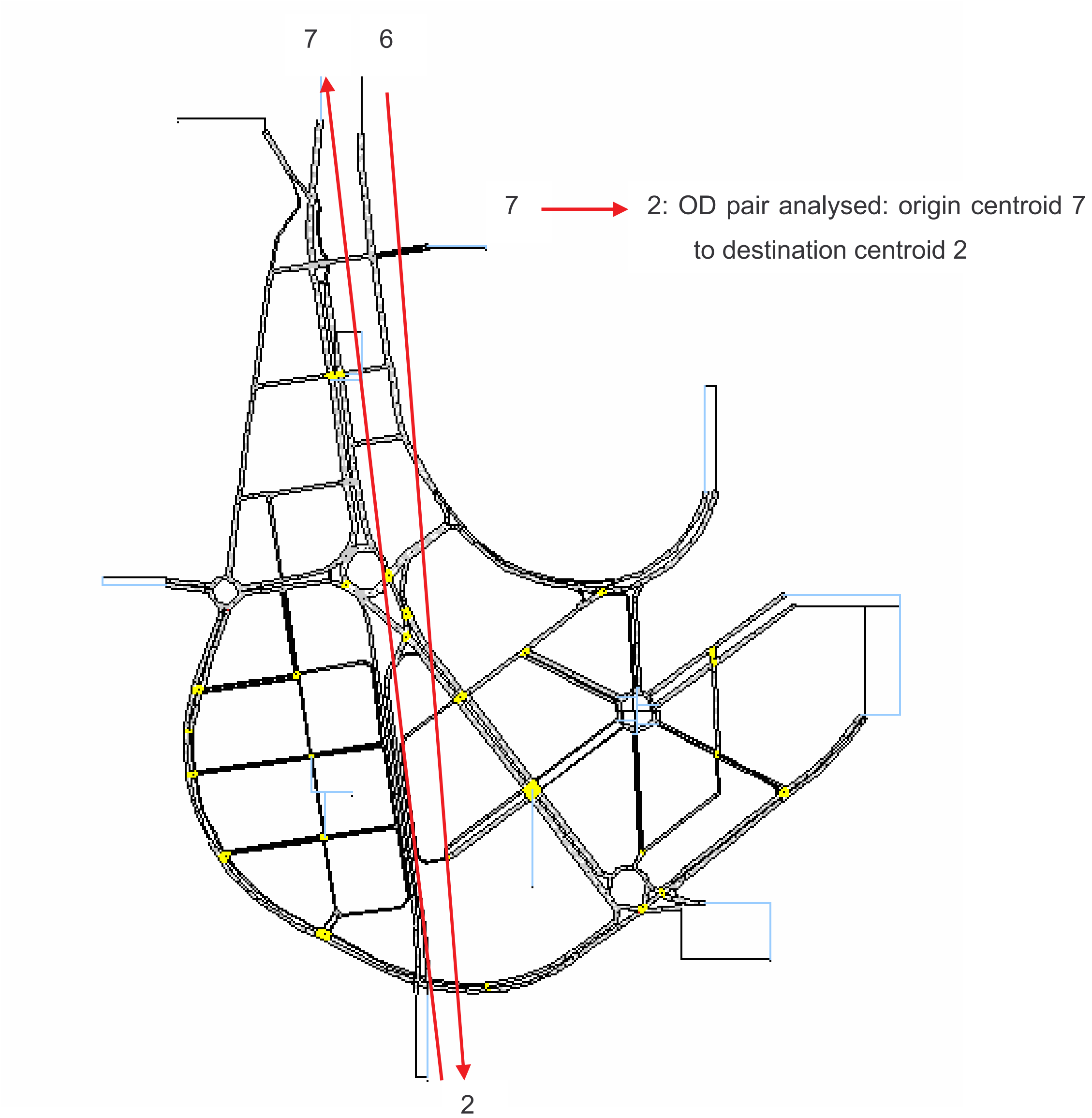


Figure 5.7. OD pairs analysed in the Amara model

During the simulations, two different paths were calculated and used from origin centroid 7 (north) to destination centroid 2 (south): Path A and Path B, as shown in Figure 5.8.

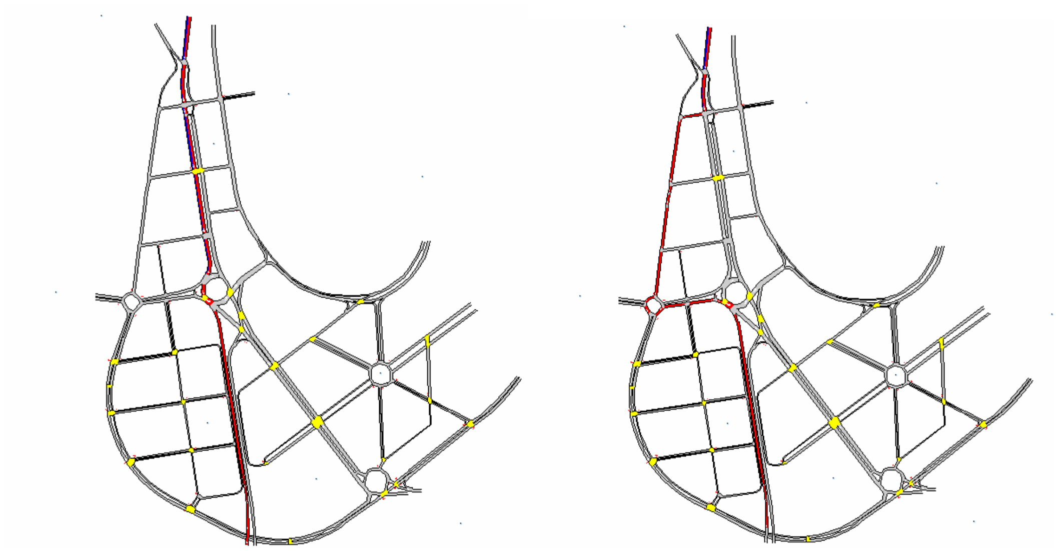


Figure 5.8. Paths A and B from origin 7 (north) to destination 2 (south)

Under free flow conditions, Path A has a cost of 197.1 seconds and Path B has a cost of 264.7 seconds. If these costs were considered and the route choice function (a logit function that takes 60 as the scale factor) were applied, the expected probability of Path A would be 0.75 and the expected probability of Path B would be 0.25. However, these costs change during the simulation according to demand, so the theoretical percentages change. Table 5.1 (below) shows the evolution of the observed cost for each path, in seconds.

Interval		Costs	
From	To	Path A	Path B
18:00	18:06	289.1	318.6
18:06	18:12	319.2	334.7
18:12	18:18	334.1	360.9
18:18	18:24	324.5	366.5
18:24	18:30	375.5	372.0
18:30	18:36	356.7	391.6
18:36	18:42	427.1	489.9
18:42	18:48	407.8	457.4
18:48	18:54	399.9	432.7
18:54	19:00	426.5	451.6
19:00	19:06	426.4	477.4
19:06	19:12	452.4	488.7

Table 5.1. Observed path costs

The theoretical proportion of vehicles assigned to each alternative using a logit function as a route choice model that has a scale factor of 60 should be as follows:

Interval		Theoretical proportion	
From	To	**Path A**	**Path B**
18:00	18:06	62.05%	37.95%
18:06	18:12	56.42%	43.58%
18:12	18:18	60.98%	39.02%
18:18	18:24	66.82%	33.18%
18:24	18:30	48.54%	51.46%
18:30	18:36	64.15%	35.85%
18:36	18:42	74.01%	25.99%
18:42	18:48	69.56%	30.44%
18:48	18:54	63.34%	36.66%
18:54	19:00	60.31%	39.69%
19:00	19:06	70.06%	29.94%
19:06	19:12	64.68%	35.32%

Table 5.2. Theoretical path assignment

The percentage of vehicles assigned during the simulation to each path using the second approach where *MaxNumberRoutes* = 3 and *MaxNumberSPT* = 10 gives the evolution of the traffic assignment.

Interval		Number of vehicles assigned		% of vehicles assigned	
From	To	**Path A**	**Path B**	**Path A**	**Path B**
18:00	18:06	39	0	100.0%	0.0%
18:06	18:12	16	23	41.0%	59.0%
18:12	18:18	21	17	55.3%	44.7%
18:18	18:24	28	8	77.8%	22.2%
18:24	18:30	20	15	57.1%	42.9%
18:30	18:36	28	9	75.7%	24.3%
18:36	18:42	28	8	77.8%	22.2%
18:42	18:48	20	16	55.6%	44.4%
18:48	18:54	26	14	65.0%	35.0%
18:54	19:00	26	11	70.3%	29.7%

19:00	19:06	24	13	64.9%	35.1%
19:06	19:12	25	11	69.4%	30.6%

Table 5.3. Observed path assignment

Figure 5.9 (below) shows the comparison between the theoretical proportion of Path A with respect to the percentage of vehicles assigned during the simulation.

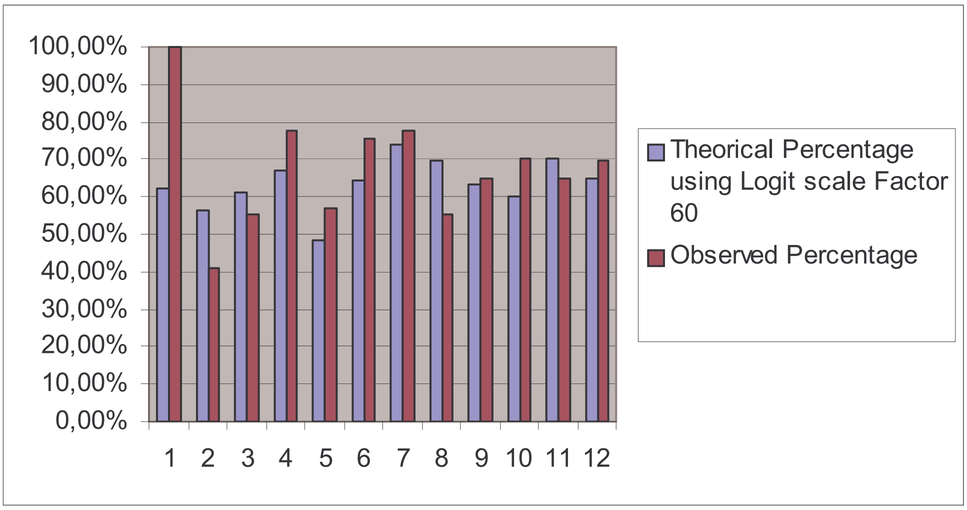
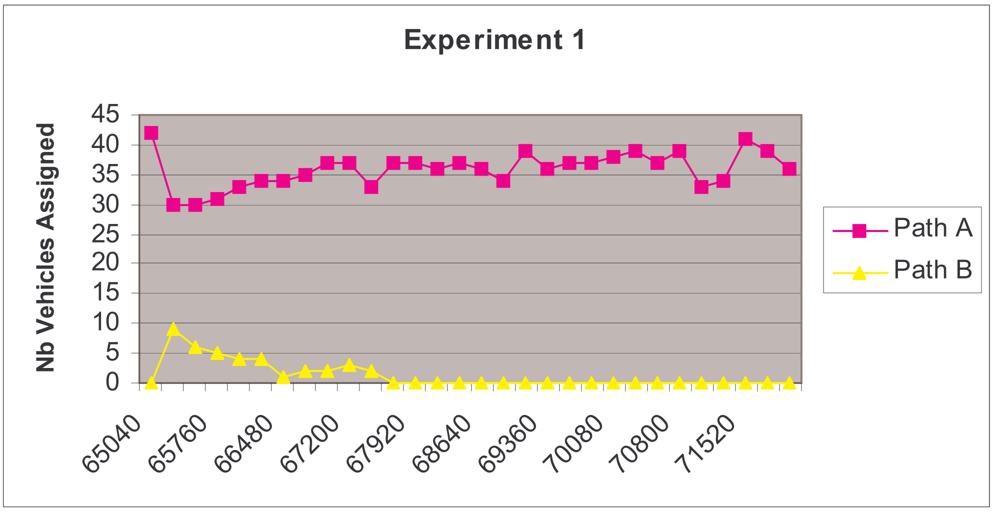


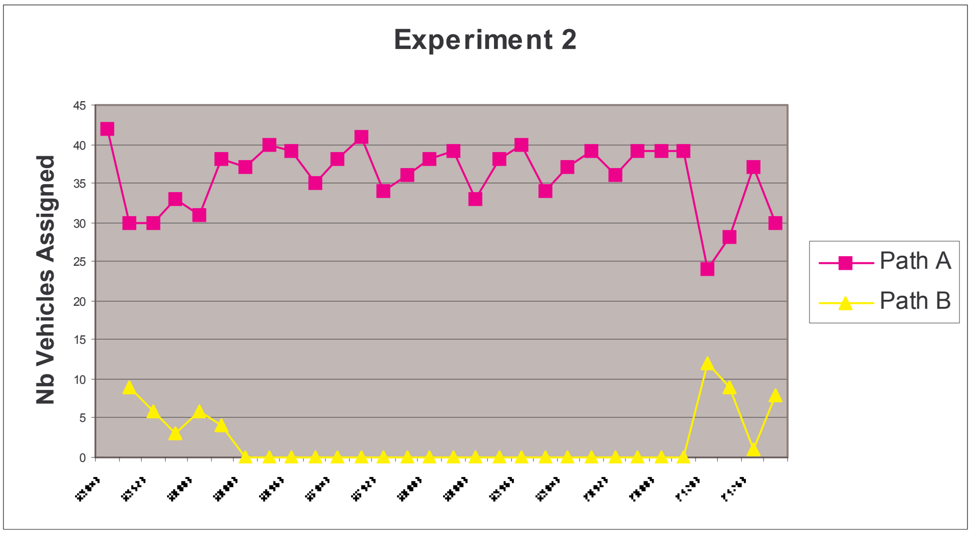
Figure 5.9. Comparison between the theoretical and observed path assignment in Path A

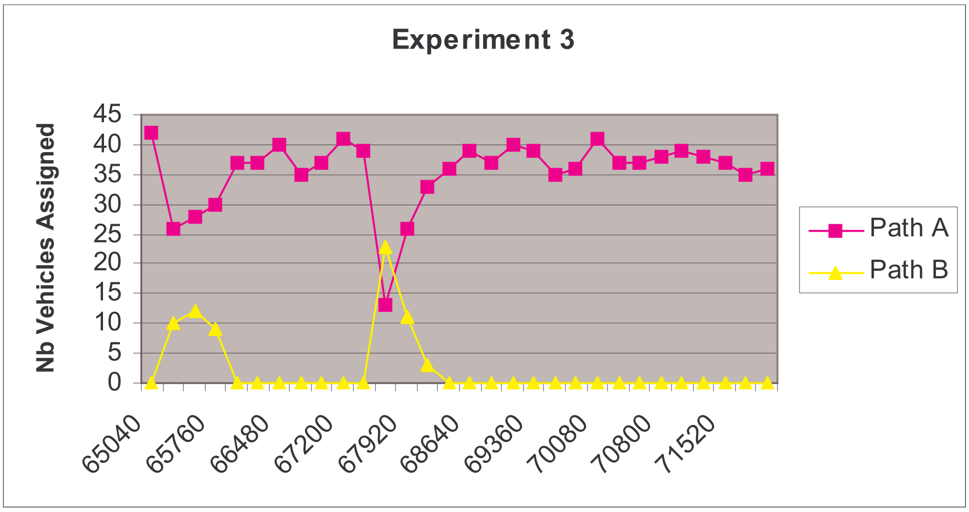
The experiments that were carried out using a logit function as a route choice model, were as follows:

- First approach
    - Experiment 1: *MaxNumberSPT* = 10
    - Experiment 2: *MaxNumberSPT* = 5
    - Experiment 3: *MaxNumberSPT* = 3
- Second approach
    - Experiment 4: *MaxNumberRoutes* = 3 and *MaxNumberSPT* = 10

The time plots below show the number of vehicles assigned to each path during the simulation in each experiment.


Experiment 1
Nb Vehicles Assigned
45
40
35
30
25
20
15
10
5
0
65040
65760
66480
67200
67920
68640
69360
70080
70800
71520
Path A
Path B


Experiment 2
Nb Vehicles Assigned
45
40
35
30
25
20
15
10
5
0
Path A
Path B


Experiment 3
Nb Vehicles Assigned
45
40
35
30
25
20
15
10
5
0
65040
65760
66480
67200
67920
68640
69360
70080
70800
71520
Path A
Path B

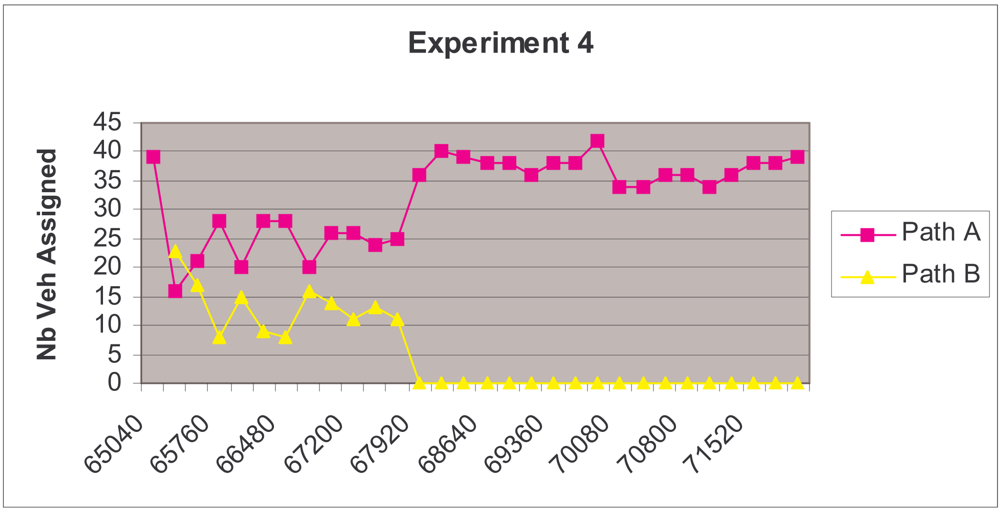


Figure 5.10. Path assignment experiment results

If Experiment 4 is compared to Experiments 1, 2 and 3, which follow the first approach, In experiment 4, can be observed the assignment of vehicles to the two alternative paths, at least the first half of the simulation, but in the second half the path A becomes better in terms of cost. But in Experiments 1, 2 and 3 path B is considered in a very few intervals assigning the greater part of the vehicles to path A, diverging considerably from the expected percentages calculated using the route choice function.

If the first and second approaches are compared, all the experiments carried out show that the second approach gives better results. However, the second approach includes a new element that is not present in the first approach to ensure that the set of alternatives contains different alternatives, and this involves comparing a new alternative with the other paths included in the set. Moreover, although better results are obtained with the second approach, its performance could apparently decrease. The performance analysis was carried out using a Pentium III 1GHz that had 256 Mbytes of RAM. The tables below show the execution times for the simulations carried out with different models.

Performance using the AIMSUN Dyn model

Network Size: 8 sections, 2 nodes and 2 centroids

	Second Approach MaxNumberRoutes = 2 MaxNumberSPT = 3	Second Approach MaxNumberRoutes = 2 MaxNumberSPT = 5	First Approach MaxNumberSPT = 3	First Approach MaxNumberSPT = 10
Execution Time	3.92	3.97	3.79	4.186
Number of Route Choice Applications	1247	1247	1247	1247
Time Applying RC	0.03s	0.03s	0.03s	0.03s
Flow	995	995	996	995
Travel Time	00:01:58	00:01:58	00:02:00	00:02:01
Delay Time	00:00:44	00:00:44	00:00:48	00:00:49

Speed	33.2	33.2	32.5	32.4

Performance using the Amara model

Network Size: 365 sections, 100 nodes and 13 centroids

	Second Approach MaxNumberRoutes = 3 MaxNumberSPT = 4	Second Approach MaxNumberRoutes = 3 MaxNumberSPT = 10	First Approach MaxNumberSPT = 4	First Approach MaxNumberSPT = 10
Execution Time	73,145	77,91	84,181	85,85
Number of Route Choice Applications	17570	17597	17594	17634
Time Applying RC	0,961s	2,123s	0.532s	1.003s
Flow	7640	7480	7663	7751
Travel Time	00:03:34	00:03:53	00:04:41	00:04:25
Delay Time	00:02:30	00:02:49	00:03:37	00:03:31
Speed	25.3	24.2	21.5	22.9

Performance using the DynamoA28 model

Network Size: 5414 sections, 2618 nodes and 81 centroids

	Second Approach MaxNumberRoutes = 3 MaxNumberSPT = 4	Second Approach MaxNumberRoutes = 3 MaxNumberSPT = 6	First Approach MaxNumberSPT = 4	First Approach MaxNumberSPT = 6
Execution Time	529.06	547.71	531.46	629.63
Number of Route Choice Applications	62883	62755	62807	62873
Time Applying RC	12.548s	17.500s	2.523s	6.49s
Flow	41428	38071	41099	41473
Travel Time	00:01:18	00:01:13	00:01:16	00:01:16
Delay Time	00:00:31	00:00:27	00:00:30	00:00:30
Speed	61.1	63.2	61.5	61.5

The tables above show that the execution time for all the experiments in which the second approach was used are equivalent to or better than for the first approach. For instance, with reference to the biggest network, if the second approach is used and MaxNumberSPT = 4, the execution time is 529.06 seconds. If the first approach is used, the execution time is 531.46, which represents an improvement of 0.45%. If MaxNumberSPT = 6, however, the execution time for the second approach is 547.71 seconds, compared with 629.63 seconds for the first approach, which constitutes an improvement in performance of 13.01% in the second approach.

5.2 VALIDATION BASED ON A STANDARD STATISTICAL COMPARISON

This section presents the validation results of dynamic traffic assignment parameters based on a standard comparison of model and system outputs for different networks.

5.2.1 VALIDATION BASED ON GEH

This section presents the validation results of dynamic traffic assignment parameters based on a standard comparison between model and system outputs for an urban network of a medium size that models the Amara borough of the city of San Sebastian in Spain (see Appendix I).

The set of real traffic data available comprises the traffic counts gathered at 15 detector stations from 4 April 1999 to 19 May 1999. The level of aggregation was 1 hour over 24 hours. From the data, we took only the working days and the afternoon peak times (from 18:00 to 20:00) and calculated the average traffic count for each detector. Table 5.4 shows the average traffic count for each detector during the peak hours.

	Average Traffic Counts (vehs)		
Detectors	**18:00-19:00**	**19:00-20:00**	**TOTAL**
A18	1994	2018	3962
A19	531	518	1049
A22	871	782	1653
A23	482	524	1006
A24	1551	1362	2913
A25	1136	1241	2377
A26	897	938	1836
A27	1098	1099	2197
A30	948	958	1906
A42	1838	1731	3569
A51	1469	1556	3025
A52	1446	1443	2889
A53	433	547	979
A54	429	467	896
A55	341	421	602

Table 5.4. Average traffic counts in a working day (Amara model)

Depending on the route choice model employed (proportional, logit or C-logit), the experimental design factors for the simulations were as follows:

- Proportional route choice model:
  - Alpha factor (α), for which values of 0.5, 1, 2 and 3 were considered were considered
  - *Initial K-SP,* for which values of 1, 2 and 3 were considered
  - Maximum number of routes (*MaxNumberRoutes)*, for which values of 3, 4 and 5 were considered

If these three factors are combined, the total number of experiments is 36 (4 * 3 * 3), each of which was simulated 15 times (replications). The following random seeds for the AIMSUN random number generator were used: 9182, 1670, 6534, 8159, 8538, 5768, 1277, 1065, 1846, 8740, 1489, 3334, 6232, 6237 and 1870.

- Logit route choice model:
    - Scale factor (θ), for which values of 10, 60, 100 and 600 were considered
    - *Initial K-SP*, for which values of 1, 2 and 3 were considered
    - Maximum number of routes (*MaxNumberRoutes)*, for which values of 3, 4 and 5 were considered

  If these three factors are combined, the total number of experiments is 36 (4 * 3 * 3), each of which was simulated 15 times (replications). The random seeds were changed as in the proportional route choice model.

- C-logit route choice model with fixed beta and gamma:
    - Scale factor (θ), for which values of 10, 60, 100 and 600 were considered
    - *Initial K-SP*, for which values of 1, 2 and 3 were considered
    - Maximum number of routes (*MaxNumberRoutes)*, for which values of 3, 4 and 5 were considered
    - Beta (β) fixed to 0.15
    - Gamma (γ) fixed to 1
- If these factors are combined, the total number of experiments is 36 (4 * 3 * 3), each of which was simulated 15 times (replications). The random seeds were changed as in the proportional route choice model. C-logit route choice model with varying beta and gamma:
    - Scale factor (θ) fixed to 60
    - *Initial K-SP* fixed to 2
    - Maximum number of routes (*MaxNumberRoutes)* fixed to 3
    - Beta (β), for which values of 0.10, 0.15, 0.50 and 1 were considered
    - Gamma (γ), for which values of 0.5, 1, 1.5 and 2 were considered

If these factors are combined, the total number of experiments is 16 (4 * 4), each of which was simulated 15 times (replications). The random seeds were changed as in the proportional route choice model.

By analysing these experiments, we were able to tackle a critical aspect in the calibration of the dynamic traffic assignment parameters. The results allowed us to determine the effect of each parameter in terms of accepting or rejecting the model.

For each experiment, we analysed the scattergram and a global indicator as the GEH index. Table 5.5 and Table 5.6 show the observed and simulated detector flows from 18:00 to 19:00 and from 19:00 to 20:00, using, as the dynamic traffic assignment parameters, a logit route choice function that had a scale factor θ of 60, an *Initial K-SP* of 1 and *MaxNumberRoutes* fixed to 4. The GEH value was 83.33% and the R^2 value was 94.05. The regression line of observed versus simulated flows, with the 95% prediction interval and the R^2 value of 94.05, is plotted in Figure 5.11.

	Peak Period (18:00-19:00)			
Detector	**Observed**	**Simulated**	**% Diff**	**GEH**
A18	1944	1988	-2.2%	0.98
A19	531	547	-3.1%	0.71
A22	871	842	3.3%	0.98
A23	482	441	8.5%	1.92
A24	1551	1457	6.0%	2.41
A25	1136	1193	-5.0%	1.66
A26	897	528	41.2%	13.85
A27	1098	1064	3.1%	1.03
A30	948	896	5.5%	1.72
A42	1838	1802	2.0%	0.85
A51	1469	1473	-0.3%	0.10
A52	1446	1164	19.5%	7.80
A53	433	489	-13.0%	2.63
A54	429	447	-4.4%	0.90
A55	275	351	-27.8%	4.31

Table 5.5. Simulated vs. observed traffic counts of Amara model from 18:00 to 19:00

	Peak Period (19:00-20:00)			
Detector	**Observed**	**Simulated**	**% Diff**	**GEH**
A18	2018	1986	1..6%	0.70
A19	518	547	-5.7%	1.27
A22	782	804	-2.7%	0.76

A23	524	371	29.1%	7.20
A24	1362	1453	-6.7%	2.42
A25	1241	1206	2.8%	1.01
A26	938	509	45.8%	15.97
A27	1099	1005	8.5%	2.89
A30	958	892	6.9%	2.16
A42	1731	1766	-2.0%	0.83
A51	1556	1524	2.1%	0.82
A52	1443	1188	17.6%	7.02
A53	547	484	11.4%	2.73
A54	467	448	4.1%	0.90
A55	327	390	-19.2%	3.32

Table 5.6. Simulated vs. observed traffic counts of the Amara model from 19:00 to 20:00

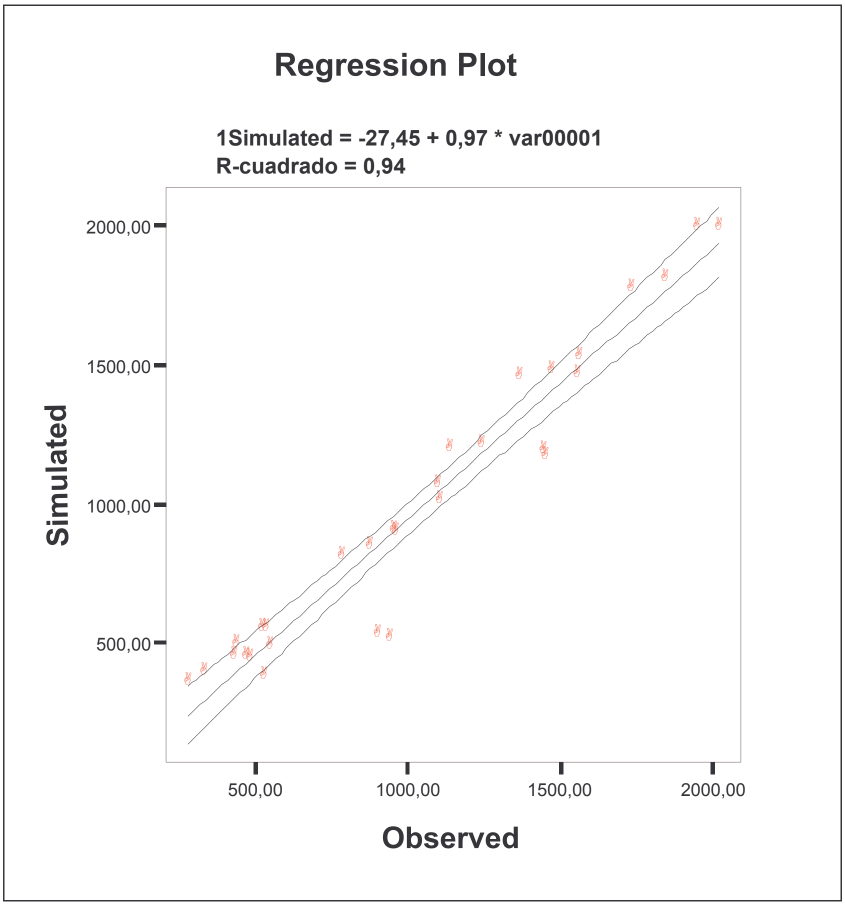


Figure 5.11. Scattergram analysis showing the observed and the simulated flow

The GEH index and the R^2 value enable us to analyse which dynamic traffic assignment parameters reproduce a valid simulation model and which reproduce a simulation model that can be rejected. The analysis is carried out by grouping the experiments that consider the route choice function.

Table 5.7 shows the GEH index and R^2 of the average of all the replications of the experiments for which the proportional route choice function was used.

	Proportional				
Experiment Number	**Alpha Factor**	***Initial K-SP***	***Max number of Routes***	**Global GEH**	**R^2**
1	0,5	1	3	76.7%	91.3%
2	0,5	1	4	80.0%	91.0%
3	0,5	1	5	80.0%	90.9%
4	0,5	2	3	40.0%	76.3%
5	0,5	2	4	43.3%	74.3%
6	0,5	2	5	33.3%	66.5%
7	0,5	3	3	56.7%	76.9%
8	0,5	3	4	33.3%	75.4%
9	0,5	3	5	30.0%	74.2%
10	1	1	3	80.0%	92.4%
11	1	1	4	80.0%	92.5%
12	1	1	5	80.0%	91.9%
13	1	2	3	80.0%	92.8%
14	1	2	4	73.3%	92.2%
15	1	2	5	73.3%	92.5%
16	1	3	3	66.7%	89.9%
17	1	3	4	70.0%	89.6%
18	1	3	5	66.7%	86.2%
19	2	1	3	86.7%	93.4%
20	2	1	4	83.3%	92.9%
21	2	1	5	83.3%	93.1%
22	2	2	3	83.3%	93.9%
23	2	2	4	83.3%	94.0%
24	2	2	5	83.3%	93.8%
25	2	3	3	83.3%	93.5%
26	2	3	4	80.0%	93.4%
27	2	3	5	76.7%	93.6%
28	3	1	3	86.7%	93.9%
29	3	1	4	86.7%	93.5%
30	3	1	5	86.7%	93.8%
31	3	2	3	83.3%	94.4%
32	3	2	4	83.3%	94.2%
33	3	2	5	83.3%	94.4%

34	3	3	3	80.0%	93.8%
35	3	3	4	83.3%	94.4%
36	3	3	5	83.3%	94.3%

Table 5.7. Proportional route choice model

Using the R^2 criteria and accepting an experiment when the R^2 value is greater than or equal to 85% would lead to the conclusion that the models used in all experiments could be accepted as significantly close to the reality, except for Experiments 4 to 9, as Figure 5.12 shows. Using the GEH criteria, however, the conclusion would be to reject all the models except those used in Experiments 19, 28, 29 and 30, as Figure 5.13 shows.

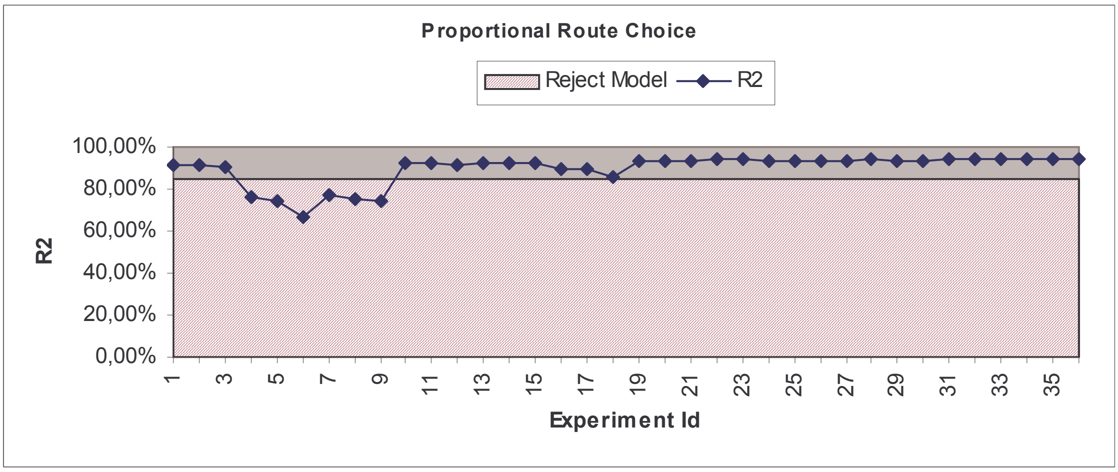


Figure 5.12. Validation of proportional route choice model using R^2 criteria

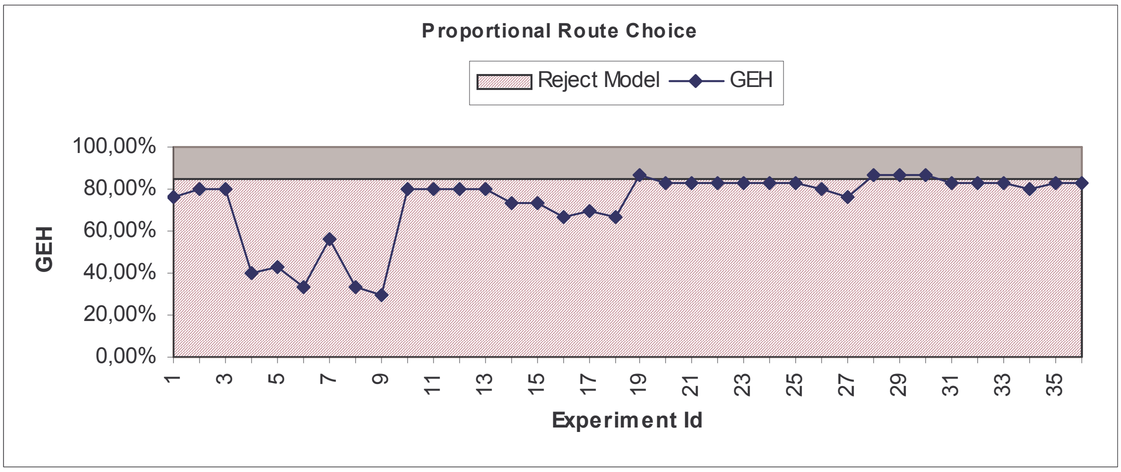


Figure 5.13. Validation of proportional route choice model using GEH criteria

Table 5.8 shows the GEH index and R^2 value for all the experiments in which the logit route choice model was used.

	Logit				
Experiment	**Scale Factor**	***Initial K-SP***	***Max number***	**Global GEH**	**R^2**

Number			***of Routes***		
1	10	1	3	86.7%	93.1%
2	10	1	4	83.3%	93.2%
3	10	1	5	83.3%	92.7%
4	10	2	3	80.0%	93.3%
5	10	2	4	80.0%	93.4%
6	10	2	5	80.0%	93.5%
7	10	3	3	76.7%	92.6%
8	10	3	4	80.0%	92.4%
9	10	3	5	76.7%	93.1%
10	60	1	3	86.7%	93.3%
11	60	1	4	86.7%	93.8%
12	60	1	5	86.7%	93.9%
13	60	2	3	83.3%	94.5%
14	60	2	4	83.3%	94.3%
15	60	2	5	83.3%	94.1%
16	60	3	3	80.0%	93.4%
17	60	3	4	80.0%	93.4%
18	60	3	5	80.0%	93.3%
19	100	1	3	86.7%	92.7%
20	100	1	4	86.7%	92.9%
21	100	1	5	86.7%	92.9%
22	100	2	3	83.3%	93.0%
23	100	2	4	80.0%	93.5%
24	100	2	5	80.0%	94.1%
25	100	3	3	80.0%	93.1%
26	100	3	4	80.0%	92.8%
27	100	3	5	80.0%	93.2%
28	600	1	3	66.7%	89.1%
29	600	1	4	73.3%	89.6%
30	600	1	5	70.0%	89.6%
31	600	2	3	80.0%	92.3%
32	600	2	4	80.0%	91.9%
33	600	2	5	80.0%	91.8%
34	600	3	3	80.0%	92.2%
35	600	3	4	76.7%	91.6%
36	600	3	5	73.3%	91.0%

Table 5.8. Logit route choice model

Using only the GEH criteria, due to the R^2 is less restrictive, the model used in Experiments 10, 11, 12, 19, 20 and 21 could be accepted and the rest rejected, as Figure 5.14 shows.

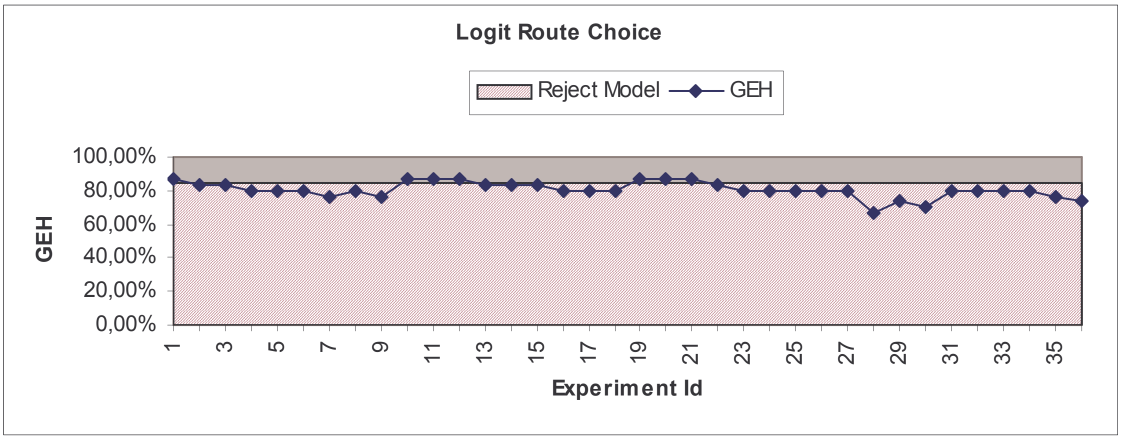


Figure 5.14. Validation of logit route choice model using GEH criteria

Table 5.9 shows the GEH index and R^2 value for all the experiments in which the C-logit route choice model was used and beta and gamma were fixed at 0.15 and 1 respectively.

	C-logit				
Experiment Number	**Scale Factor**	***Initial K-SP***	***Max number of Routes***	**Global GEH**	**R^2**
1	10	1	3	86.7%	93.4%
2	10	1	4	86.7%	93.2%
3	10	1	5	80.0%	92.9%
4	10	2	3	80.0%	93.6%
5	10	2	4	80.0%	93.4%
6	10	2	5	80.0%	93.2%
7	10	3	3	76.7%	93.5%
8	10	3	4	76.7%	92.7%
9	10	3	5	76.7%	92.8%
10	60	1	3	83.3%	92.9%
11	60	1	4	86.7%	93.1%
12	60	1	5	83.3%	92.5%
13	60	2	3	83.3%	93.8%
14	60	2	4	83.3%	93.6%
15	60	2	5	86.7%	93.5%
16	60	3	3	83.3%	93.5%
17	60	3	4	83.3%	93.5%
18	60	3	5	83.3%	92.7%
19	100	1	3	83.3%	91.1%
20	100	1	4	76.7%	91.1%

21	100	1	5	83.3%	91.6%
22	100	2	3	83.3%	93.5%
23	100	2	4	86.7%	93.0%
24	100	2	5	86.7%	92.9%
25	100	3	3	76.7%	91.6%
26	100	3	4	83.3%	93.3%
27	100	3	5	73.3%	92.4%
28	600	1	3	73.3%	88.8%
29	600	1	4	80.0%	91.0%
30	600	1	5	76.7%	89.9%
31	600	2	3	83.3%	92.9%
32	600	2	4	86.7%	92.9%
33	600	2	5	80.0%	92.8%
34	600	3	3	73.3%	91.5%
35	600	3	4	73.3%	91.4%
36	600	3	5	80.0%	92.1%

Table 5.9. C-logit route choice model with fixed beta and gamma

Using the GEH criteria, the model used in Experiments 10, 15, 23, 24 and 32 could be accepted and the rest rejected, as Figure 5.15 shows.

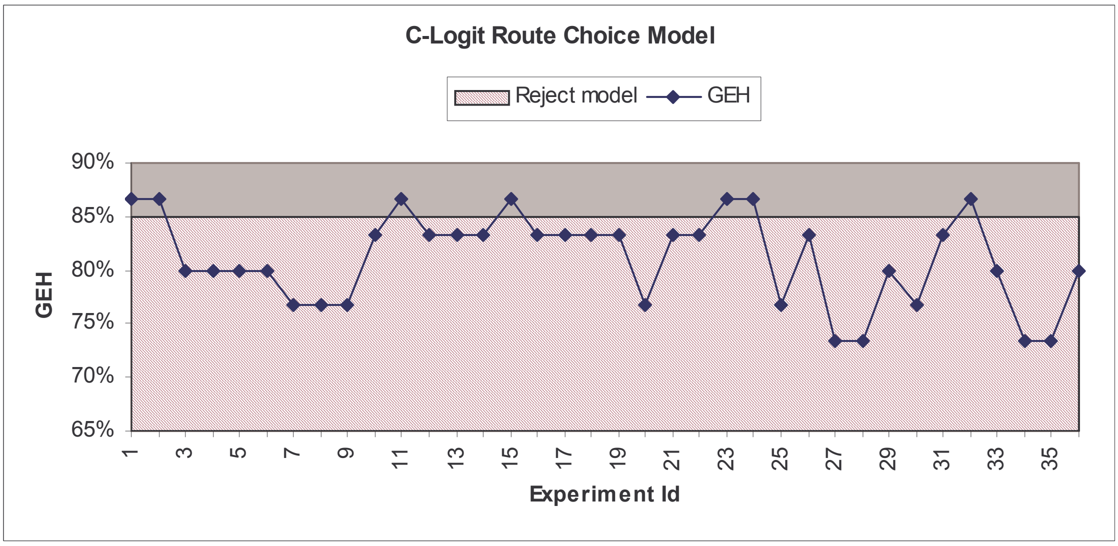


Figure 5.15. Validation of C-logit route choice model using the GEH criteria

Table 5.10 shows the GEH index and R^2 value for all the experiments in which with the C-logit route choice model was used and in which beta and gamma varied, although the scale factor was fixed to 60, *Initial K-SP* was fixed to 2 and the *MaxNumberRoutes* fixed was fixed to 3.

C-logit	

Beta	Gamma	Global GEH	R^2
0.10	0.5	80.0%	93.5%
0.10	1.0	83.3%	93.7%
0.10	1.5	86.7%	93.1%
0.10	2.0	83.3%	93.1%
0.15	0.5	86.7%	93.5%
0.15	1.0	83.3%	93.5%
0.15	1.5	86.7%	93.9%
0.15	2.0	83.3%	93.2%
0.50	0.5	86.7%	94.1%
0.50	1.0	86.7%	93.5%
0.50	1.5	86.7%	93.7%
0.50	2.0	86.7%	93.5%
1.00	0.5	86.7%	93.7%
1.00	1.0	86.7%	93.6%
1.00	1.5	86.7%	93.1%
1.00	2.0	86.7%	93.6%

Table 5.10. C-logit route choice model varying beta and gamma

Using the GEH criteria, the model used in Experiments 3, 5 and 7 and Experiments 9 to 16 could be accepted and the rest rejected, as Figure 5.16 shows.

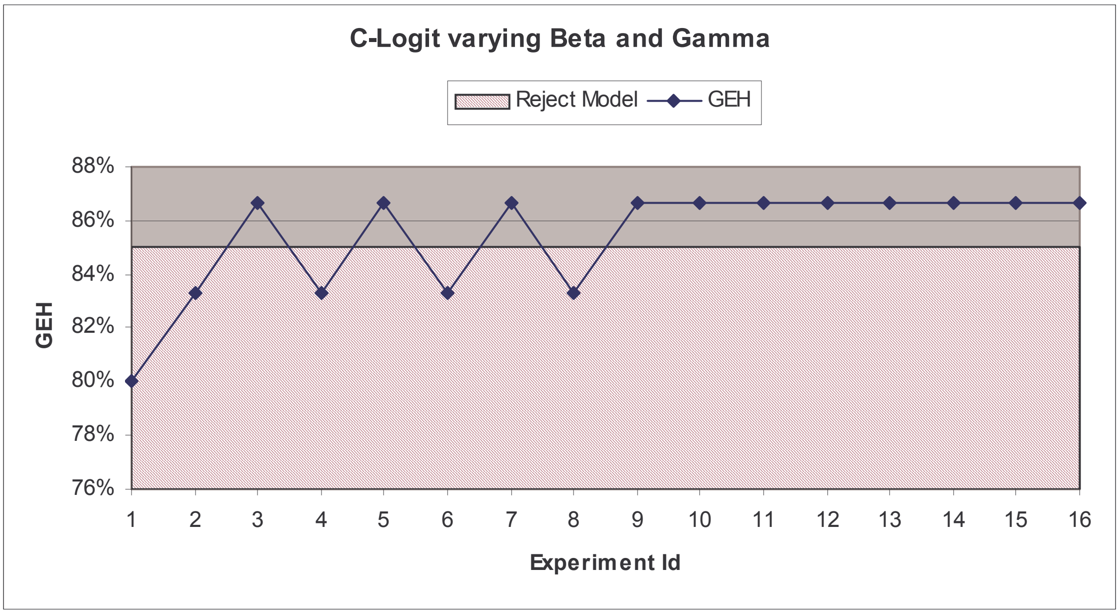


Figure 5.16. Validation of C-logit route choice model, for which beta and gamma vary, using the GEH criteria

The research undertaken, the results of which are reported in these sections, pursue two main objectives: to analyse, the cases studied, which combination of values for the parameters lead to a valid model and to identify these parameters' influence, and to establish guidelines for the calibration process.

Such a systematic analysis is certainly computationally heavy, due to the combinatorial nature of the process that makes computationally inaccessible any variant of factorial design to proceed to an analysis which could determine the influence of the parameters. Even if the influence of these parameters were to be identified, the question of whether the results could be transferred or generalised would still remain open.

For the specific values of the parameters to be transferable from one case to another is obviously not to be expected, since the parameters represent behavioural aspects and consequently their values should be context-dependent. This fact seems to be confirmed by the computational results obtained in the experiments. Nevertheless, the computational results also seem to confirm (within the limit of the number of cases studied) that the roles of these parameters and their interactions tend to exhibit a degree of similarity that might induce patterns that would provide the expected guidelines. The main results found from the computational experiments show that

- For the proportional route choice model, the most relevant parameter, which has a direct influence on the level of goodness of the model, is alpha. Figure 5.17 shows how, depending on the series characterised by the alpha value, the GEH index is distributed in layers and the best results are given when alpha is set to 2 or 3. This layered distribution might lead one to conclude that, in the calibration process, alpha could be calibrated independently of the other parameters and, when a certain value produces acceptable results, the calibration could be focused on the other parameters.

- The same effect can be observed when the logit route choice model considers the scale factor (Figure 5.18) and the C-logit route choice model considers the scale factor (Figure 5.19).

The results shown in the subsequent section confirm this preliminary analysis.

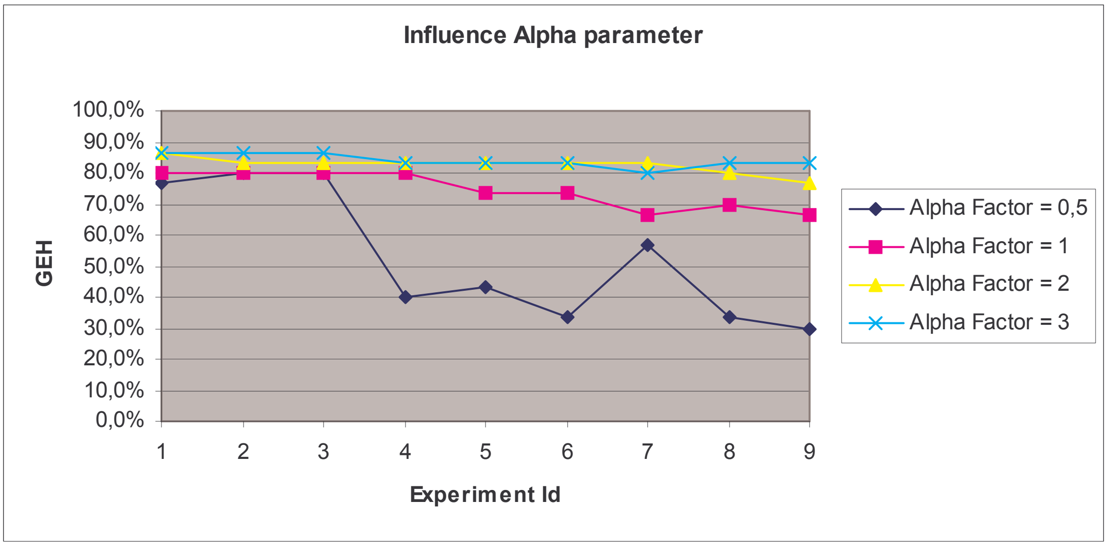


Figure 5.17. Influence of the alpha factor in the proportional route choice model

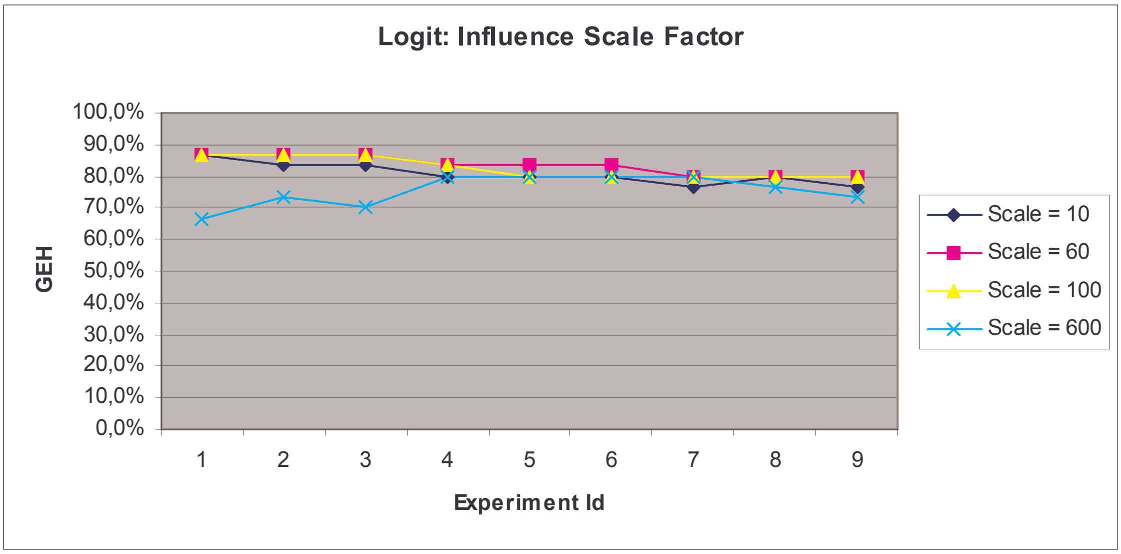


Figure 5.18. Influence of the scale factor in the logit route choice model

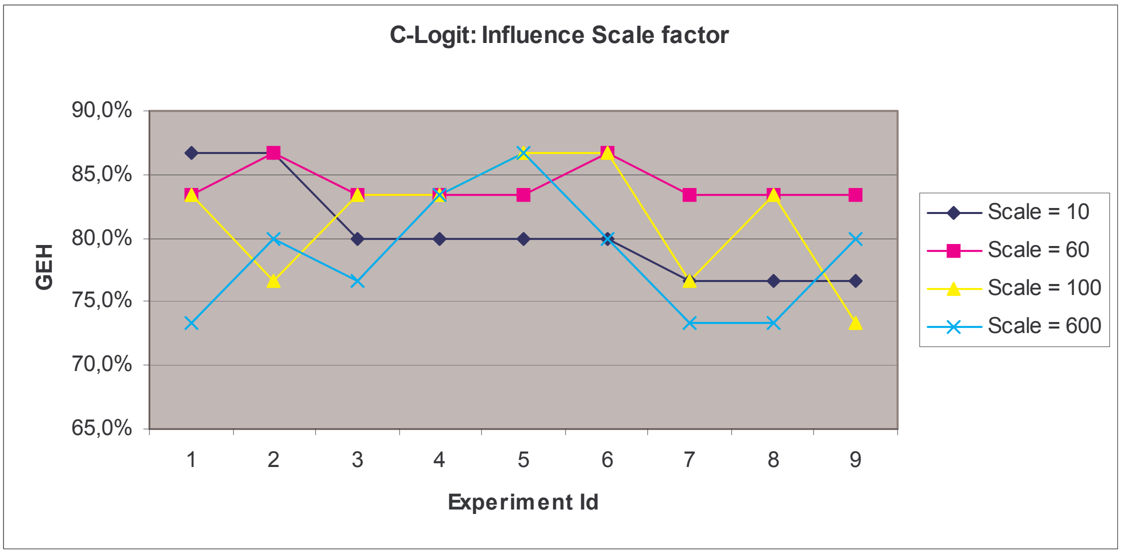


Figure 5.19. Influence of the scale factor in the C-logit route choice model

The conclusions from this set of experiments has led to an analysis of the influence of each individual parameter and all possible combinations on the global indicator GEH index, which determines an index with which to compare the model and system outputs. Thus, we carried out an analysis of variance of GEH as a response variable and of the dynamic traffic assignment parameters as factors.

Appendix II contains a complete description of the results of the experiments, in addition to tables and graphics for all the network models and route choice models.

5.2.2 Analysis of Variance of GEH

This section presents the analysis of variance in which the GEH index was used as a response variable and the dynamic traffic assignment parameters as factors. Initially, this analysis followed the same experiment design as that discussed in Section 5.2.1.

The first step is to analyse the GEH response variable as a function of each dynamic traffic assignment parameter. Figure 5.20, Figure 5.21, Figure 5.22 and Figure 5.23 depict the descriptive statistics for GEH as a function of the different values of the scale factor θ using the logit function as the route choice model in the Amara model. The Anderson-Darling test's *p*-value, used in this test, identifies whether there is evidence that the data follow or not a normal distribution. This information is complemented by the values of the quartiles, the skewness as a measure of asymmetries and the kurtosis as a measure of how different the empirical distribution is from the normal. The descriptive analysis provides insight on the compliance of the hypothesis for the variance analysis.

Figure 5.24 depicts the test for equal variances for GEH as a function of the scale factor θ using the logit function as the route choice model, and Figure 5.25 shows the output of the analysis of the variance. When the scale factor is 600 and logit is used as the route choice model, the GEH generates atypical observations, and its behaviour is very different to what it is when the scale factor takes other values. As a consequence of the results in this preliminary exploratory analysis, the value of 600 for the scale factor of the Amara model was discarded and the computational results were restricted to the other values in the range of possible values for the scale factor of the Amara model.

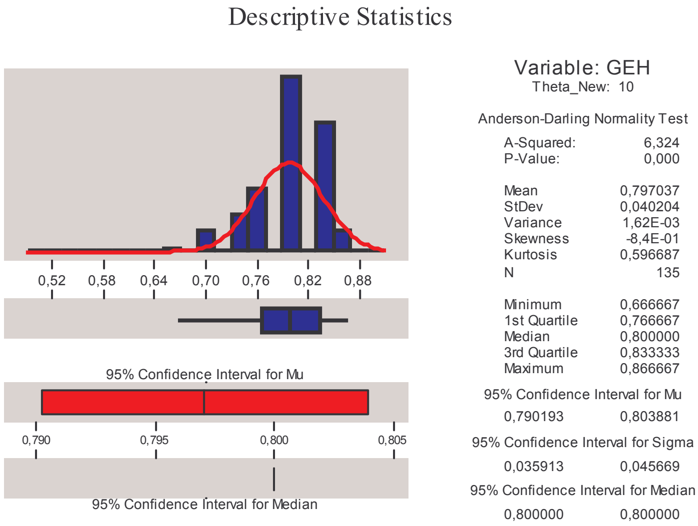


Figure 5.20. Description of GEH as a function of $\theta = 10$, using logit as the route choice model

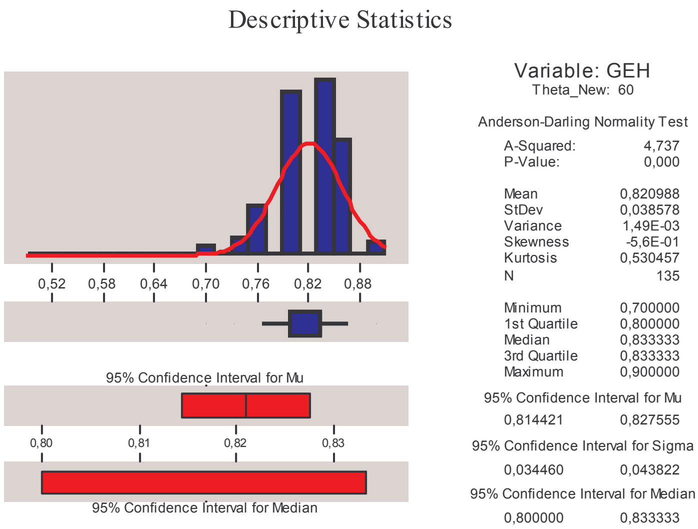


Figure 5.21. Description of GEH as a function of $\theta = 60$, using logit as the route choice model

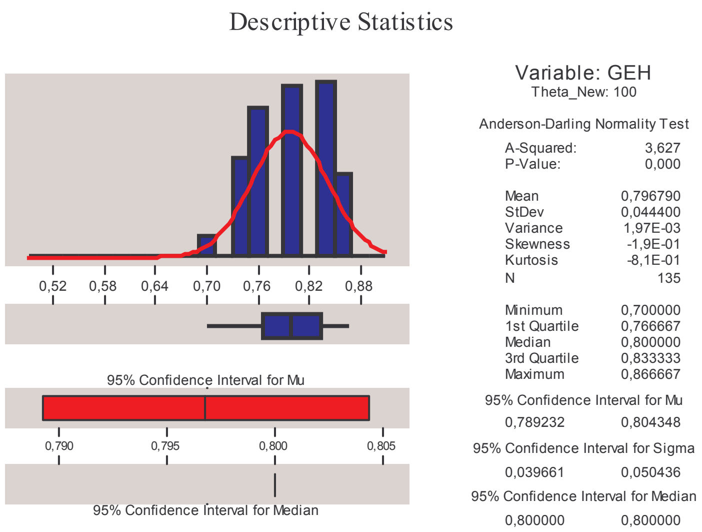


Figure 5.22. Description of GEH as a function of θ = 100, using logit as the route choice model

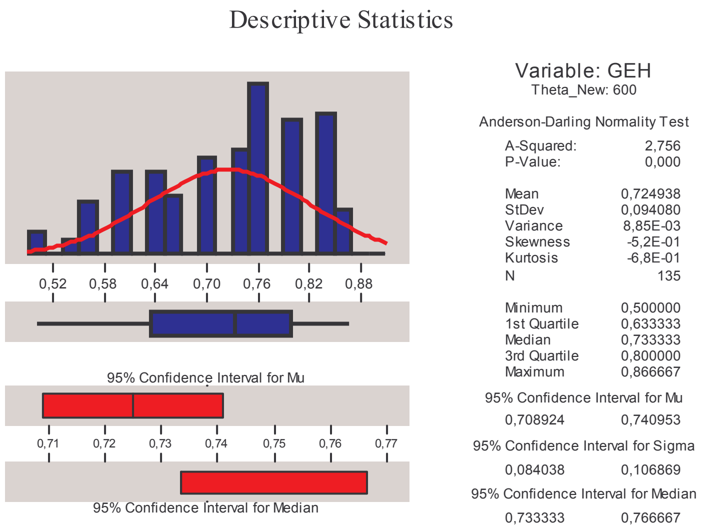


Figure 5.23. Description of GEH as a function of θ = 600, using logit as the route choice model

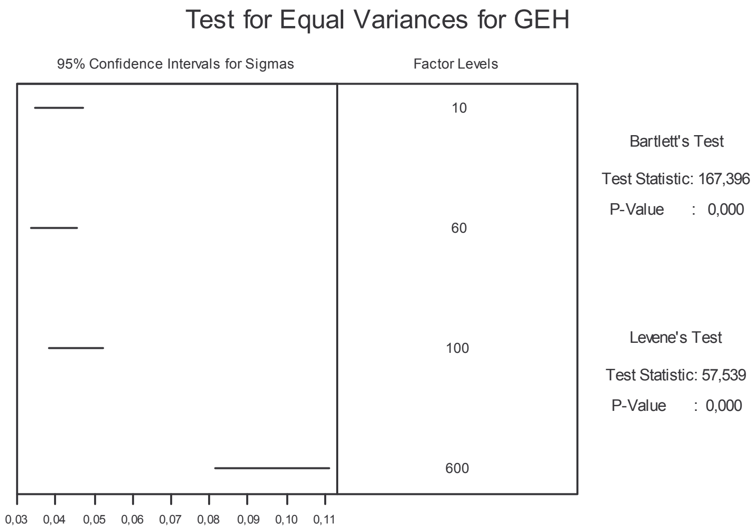


Figure 5.24. Test for equal variances for GEH as a function of θ, using logit as the route choice model

```
Analysis of Variance for GEH
Source     DF        SS        MS        F        P
Theta_Ne    3   0,70016   0,23339    67,03    0,000
Error     536   1,86622   0,00348
Total     539   2,56639
                                   Individual 95% CIs For Mean
                                   Based on Pooled StDev
Level       N      Mean     StDev  ------+---------+---------+---------+
 10       135   0,79704   0,04020                     (--*--)
 60       135   0,82099   0,03858                            (--*-)
100       135   0,79679   0,04440                     (--*--)
600       135   0,72494   0,09408  (--*--)
                                   ------+---------+---------+---------+
Pooled StDev =  0,05901                0,735     0,770     0,805     0,840
```

Figure 5.25. Output of analysis of variance for GEH as a function of θ, using logit as the route choice model in Amara

Table 5.11, Table 5.12 and Table 5.13 contain the summary of the analysis of variance results for each network model grouped by route choice model (Appendix **III** contains the results and figures of the analysis of the variance of each particular network model). The analysis has been conducted on basis to a General Linear Model to determine the influence of each individual factor as well as the crossed effects. The significance level is established in terms of the regression coefficient R^2.

Vitoria Model

LOGIT	**Design Factors**	**Levels**
	θ	10, 60, 100, 600
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	2, 3, 4
	Significance Level	
	R^2 = 0, 465	
	Parameters with an Influence	
	θ Initial K-SP MaxNumberRoutes θ * Initial K-SP θ * MaxNumberRoutes Initial K-SP * MaxNumberRoutes	
C-LOGIT	**Fixed Parameters**	**Value**
	β	0.15
	γ	1
	Design Factors	**Levels**
	θ	10, 60, 100, 600
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	2, 3, 4
	Significance Level	
	R^2 = 0, 465	
	Parameters with Influence	
	θ Initial K-SP MaxNumberRoutes θ * Initial K-SP θ * MaxNumberRoutes	
L O G	**Fixed Parameters**	**Value**
	θ	60
	Initial K-SP	2

	MaxNumberRoutes	4
	Design Factors	**Levels**
	β	0.1, 0.15, 0.5, 1
	γ	0.5, 1, 1.5, 2
	Significance Level	
	$R^2 = 0.452$	
	Parameters with Influence	
	β	
	$\beta * \gamma$	
C-LOGIT	**Fixed Parameters**	**Value**
	MaxNumberRoutes	4
	Design Factors	**Levels**
	θ	10, 60, 100
	Initial K-SP	**2, 3**
	β	0.1, 0.15, 0.5, 1
	γ	0.5, 1, 1.5, 2
	Significance Level	
	$R^2 = 0.5875$	
	Parameters with Influence	
	θ	
	Initial K-SP	
	β	
PROPORTIONAL	**Design Factors**	**Levels**
	α	0.5, 1, 2, 3
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	2, 3, 4
	Significance Level	
	$R^2 = 0{,}574$	
	Parameters with an Influence	
	α Initial K-SP MaxNumberRoutes	

	α * Initial K-SP Initial K-SP * MaxNumberRoutes

Table 5.11. Analysis of variance results of the Vitoria Model

AMARA Model		
LOGIT	**Design Factors**	**Levels**
	θ	10, 60, 100
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	3, 4, 5
	Significance Level	
	R^2 = 0,28	
	Parameters with an Influence	
	θ Initial K-SP	
C-LOGIT	**Fixed Parameters**	**Value**
	β	0.15
	γ	1
	Design Factors	**Levels**
	θ	10, 60, 100
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	3, 4, 5
	Significance Level	
	R^2 = 0,14	
	Parameters with Influence	
	θ Initial K-SP θ * Initial K-SP	
C-LOGIT	**Fixed Parameters**	**Value**
	θ	60

	Initial K-SP	2
	MaxNumberRoutes	3
	Design Factors	**Levels**
	β	0.1, 0.15, 0.5, 1
	γ	0.5, 1, 1.5, 2
	Significance Level	
	R^2 = 0,19	
	Parameters with Influence	
	β	
C-LOGIT	**Fixed Parameters**	**Value**
	MaxNumberRoutes	4
	Design Factors	**Levels**
	θ	10, 60, 100
	Initial K-SP	**2, 3**
	β	0.1, 0.15, 0.5, 1
	γ	0.5, 1, 1.5, 2
	Significance Level	
	R^2 = 0,206	
	Parameters with Influence	
	θ	
	Initial K-SP	
	β	
PROPORTIONAL	**Design Factors**	**Levels**
	α	0.5, 1, 2, 3
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	3, 4, 5
	Significance Level	
	R^2 = 0,14	
	Parameters with an Influence	
	α Initial K-SP MaxNumberRoutes	

	α * Initial K-SP α * MaxNumberRoutes

Table 5.12. Analysis of variance results of the Amara Model

Brunnsviken Model		
LOGIT	**Design Factors**	**Levels**
	θ	1,10, 60, 100
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	3, 4, 5
	Significance Level	
	R^2 = 0, 966	
	Parameters with an Influence	
	θ Initial K-SP MaxNumberRoutes	
	Significance Level without θ=1	
	R^2 = 0, 837	
	Parameters with an Influence without θ=1	
	θ Initial K-SP θ * Initial K-SP	
C-LOGIT	**Fixed Parameters**	**Value**
	β	0.15
	γ	1
	Design Factors	**Levels**
	θ	10, 60, 100,
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	3, 4, 5
	Significance Level	

	R^2 = 0, 799	
	Parameters with Influence	
	θ Initial K-SP MaxNumberRoutes θ * Initial K-SP	
C-LOGIT	**Fixed Parameters**	**Value**
	θ	60
	Initial K-SP	2
	MaxNumberRoutes	3
	Design Factors	**Levels**
	β	0.1, 0.15, 0.5, 1
	γ	0.5, 1, 1.5, 2
	Significance Level	
	R^2 = 0,036	
	Parameters with Influence	
	β	
C-LOGIT	**Fixed Parameters**	**Value**
	MaxNumberRoutes	4
	Design Factors	**Levels**
	θ	10, 60, 100
	Initial K-SP	**2, 3**
	β	0.1, 0.15, 0.5, 1
	γ	0.5, 1, 1.5, 2
	Significance Level	
	R^2 = 0,7381	
	Parameters with Influence	
	θ	
	Initial K-SP	
	β	
	γ	
O R TI	**Design Factors**	**Levels**

	α	2, 2.5, 3
	Initial K-SP	1, 2, 3
	MaxNumberRoutes	3, 4, 5
	Significance Level	
	R^2 = 0,454	
	Parameters with an Influence	
	α Initial K-SP MaxNumberRoutes α * Initial K-SP α * MaxNumberRoutes	

Table 5.13. Analysis of variance results of the Brunnsviken model

Table 5.14 depicts the summary of the most significant parameters for each route choice model and network model and the results of the method explored in this work enable guidelines to be established for the calibration process of each route choice model. In all experiments in which the shape factor (θ in the logit and the C-logit models and α in the proportional model) is a design factor, this factor becomes significant. Therefore, this parameter plays a relevant role during the calibration process. Focussing on each route choice model, the logit and C-logit function have more relevant parameters the aforementioned θ and the Initial K-SP, but in C-logit β must be added because it plays the same role as the scale factor.

	AMARA	VITORIA	BRUNNSVIKEN
LOGIT	θ Initial K-SP	θ Initial K-SP MaxNumberRoutes θ * Initial K-SP θ * MaxNumberRoutes Initial K-SP * MaxNumberRoutes	θ Initial K-SP θ * Initial K-SP
C-LOGIT with fixed β and γ	θ Initial K-SP θ* Initial K-SP	θ Initial K-SP MaxNumberRoutes θ * Initial K-SP θ * MaxNumberRoutes	θ Initial K-SP MaxNumberRoutes θ * Initial K-SP
C-LOGIT with θ, fixed KInitialSP and MaxNumberRoutes	β	β β * γ	β

C-LOGIT with fixed MaxNumberRoutes	θ Initial K-SP β	θ Initial K-SP β	θ Initial K-SP β
PROPORTIONAL	α Initial K-SP MaxNumberRoutes α* Initial K-SP α * MaxNumberRoutes	α Initial K-SP MaxNumberRoutes α* Initial K-SP KInitialSP * MaxNumberRoutes	α Initial K-SP MaxNumberRoutes α* Initial K-SP α * MaxNumberRoutes

Table 5.14. Significant parameters

5.3 VALIDATION BASED ON RGAP

No formal convergence proof can be given for the proposed heuristic dynamic assignment algorithm, since the heuristic network loading process based on microscopic simulation does not have an analytical form. In the case of the analytical user equilibrium approaches, static as well as dynamic, an assignment's progress towards equilibrium, and therefore the quality of the solution, may be measured using the relative gap function, RGap. Janson (1991) proposes a generalisation for the dynamic assignment, which was adapted by Florian et al. (2001) to the heuristic case in which network loading is based on simulation. The *RGap(t)* function proposed by Florian et al. is defined as

$$RGap(t) = \frac{\sum_{i \in I} \sum_{k \in K_i} h_k(t)\left[s_k(t) - u_i(t)\right]}{\sum_{i \in I} g_i(t) u_i(t)}$$

The function estimates, at time t, the relative difference between the total travel time actually experienced and the total travel time that would have been experienced if the travel times of all vehicles were equal to the current shortest path. In this function, $u_i(t)$ are the travel times on the shortest paths for the i-th OD pair at time interval t, $s_k(t)$ is the travel time on path k that connects the i-th OD pair at time interval t, $h_k(t)$ is the flow on path k at time t, $g_i(t)$ is the demand for the i-th OD pair at time interval t, K_i, is the set of paths for the i-th OD pair, and I is the set of all OD pairs.

In the heuristic network loading approach based on microscopic simulation that we propose, paths are selected on the basis of logit or C-logit route choice models and discrete choice theory, when the discrete choice set is defined at each time step in terms of K shortest paths. The resulting network loading can then be interpreted in terms of heuristic stochastic user equilibrium (Sheffi, 1985), namely in the case of congested networks in which the difference between user equilibrium and stochastic user equilibrium tends to disappear (Sheffi and Powell, 1982), and therefore we propose using Florian's *RGap(t)* function to measure whether the *K* shortest paths that constitute the discrete choice set for each OD pair at each time step tend to be equivalent, and therefore in equilibrium, or otherwise.

This section presents an analysis of the RGap function for the various route choice models and dynamic traffic assignment parameters. Initially, this analysis was carried out following the same experiment design as in Section 5.2.1, for a medium-sized urban network that models the Amara borough of the city of San Sebastian in Spain (see Appendix I).

Figure 5.26 depicts the time evolution of the *RGap(t)* function using the proportional route choice model and varying the dynamic traffic assignment parameters. The nomenclature used to identify the experiment with the parameters used is as follows: the first digit (3) is the proportional route choice model, the second and third digits divided by 10 denote the alpha factor, the fourth digit is the number of Initial K-SP and the fifth denotes the maximum number of routes. For example, Experiment 32023 is an experiment in which the proportional route choice was used, 2.0 is the alpha factor, the Initial K-SP is 2 and the maximum number of routes is 3.

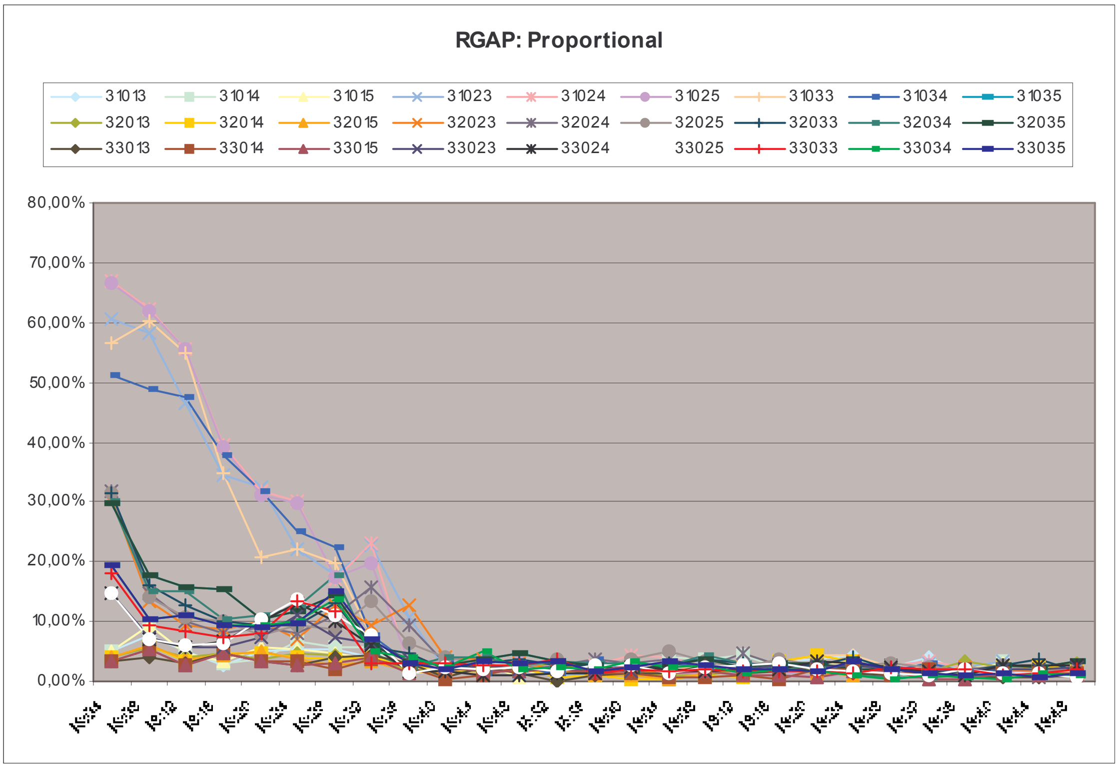


Figure 5.26. RGap function evolution using a proportional route choice model

In the figure above, the expected role of the alpha factor in terms of the RGap function becomes evident in the combination of the proportional route choice model with the assignment procedure. Improper choices of the parameter values (α = 1,0) tend to produce a bang-bang effect, which is a consequence of the tendency to move most of the flow to the current shortest path, as the oscillations of the RGap function show, while a more appropriate α not only smoothes the RGap oscillations out significantly but also shows that a path selection has acceptable path cost differences (10% in this model).

Figure 5.27 depicts the time evolution of the *RGap(t)* function using the logit route choice model and varying the dynamic traffic assignment parameters. The nomenclature used to identify the experiment with the parameters used is as follows: the first digit (4) is the logit route choice model, the second digit denotes the scale factor, where 0 is $\theta = 10$, 1 is $\theta = 60$, 2 is $\theta = 100$ and 3 is $\theta = 600$, the third digit is the number of initial K-SP and the fourth denotes the maximum number of routes. For example, Experiment 4123 uses the logit route choice, 60.0 as the scale factor, 2 is the Initial K-SP and 3 is the maximum number of routes.

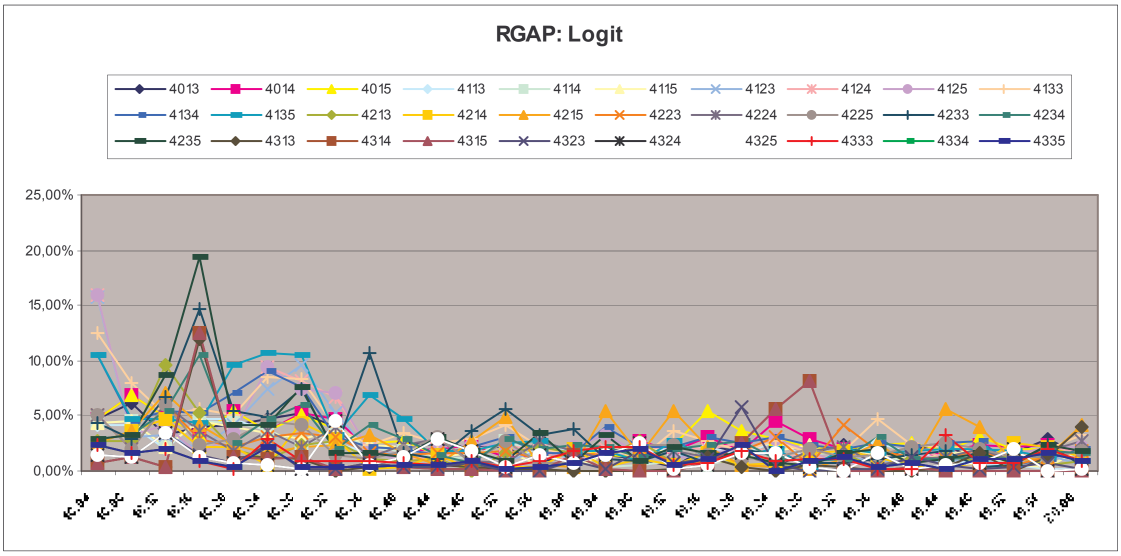


Figure 5.27. RGap function evolution using a logit route choice

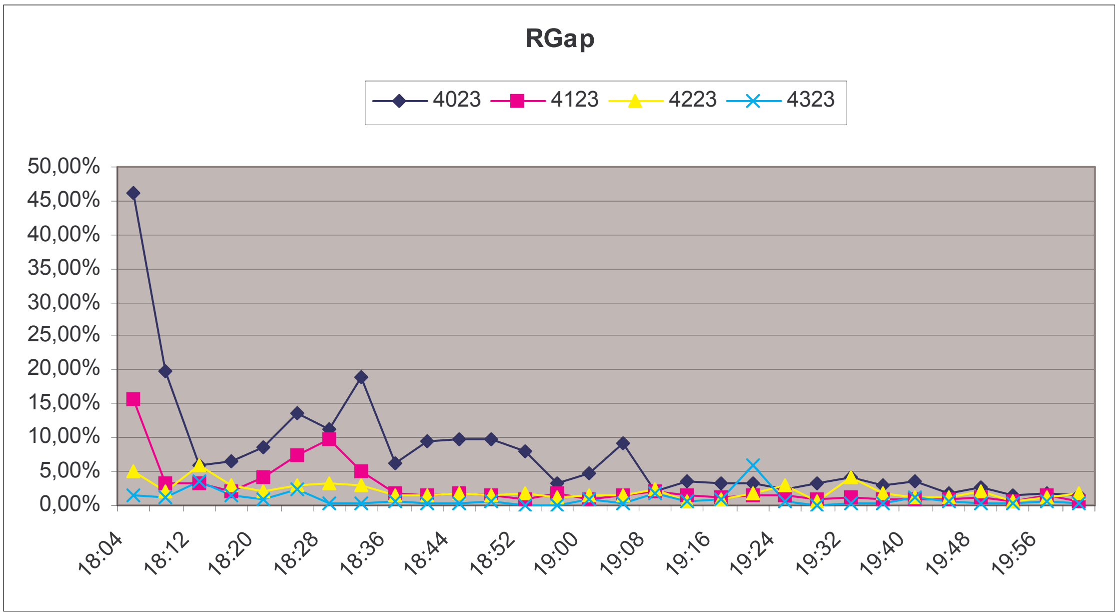


Figure 5.28. RGap function using a logit route choice model with the Initial K-SP fixed to 2 and the maximum number of routes fixed to 3

Figure 5.29 depicts the time evolution of the RGap(t) function using the C-logit route choice model and varying the dynamic traffic assignment parameters. The nomenclature used to identify the experiment with the parameters used is as follows: the first digit (5) is the C-logit route choice model, the second digit denotes the scale factor, where 0 is θ = 10, 1 is θ = 60, 2 is θ = 100 and 3 is θ = 600, the third digit is the number of Initial K-SP and the fourth denotes the maximum number of routes. For example, Experiment 5123 uses the C-logit route choice, 60.0 as the scale factor, 2 is the Initial K-SP and 3 is the maximum number of routes.

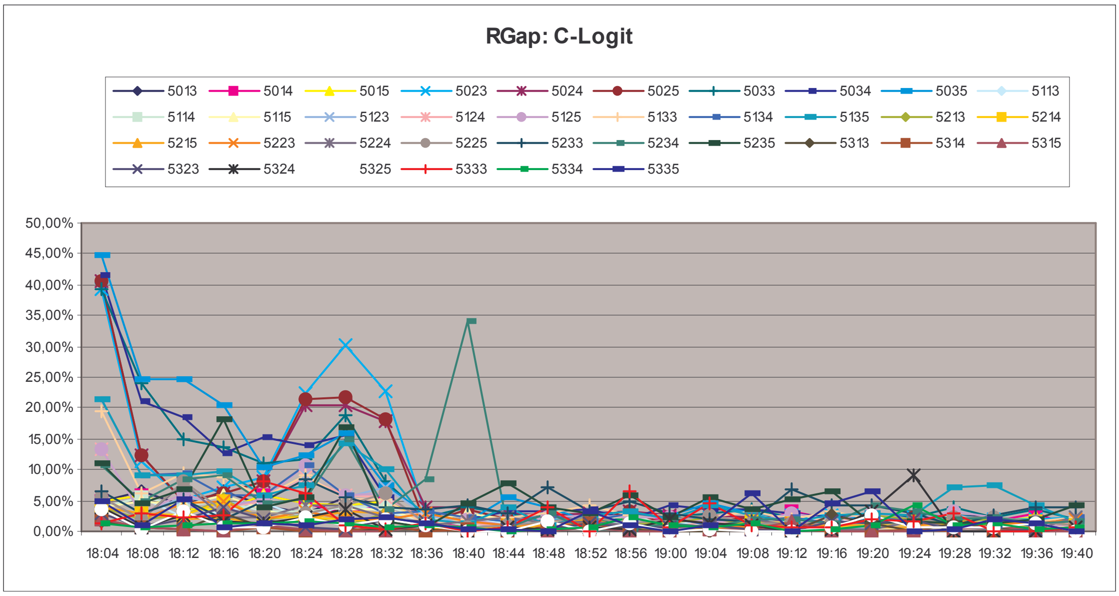


Figure 5.29. RGap function evolution using a C-logit route choice with fixed beta and gamma

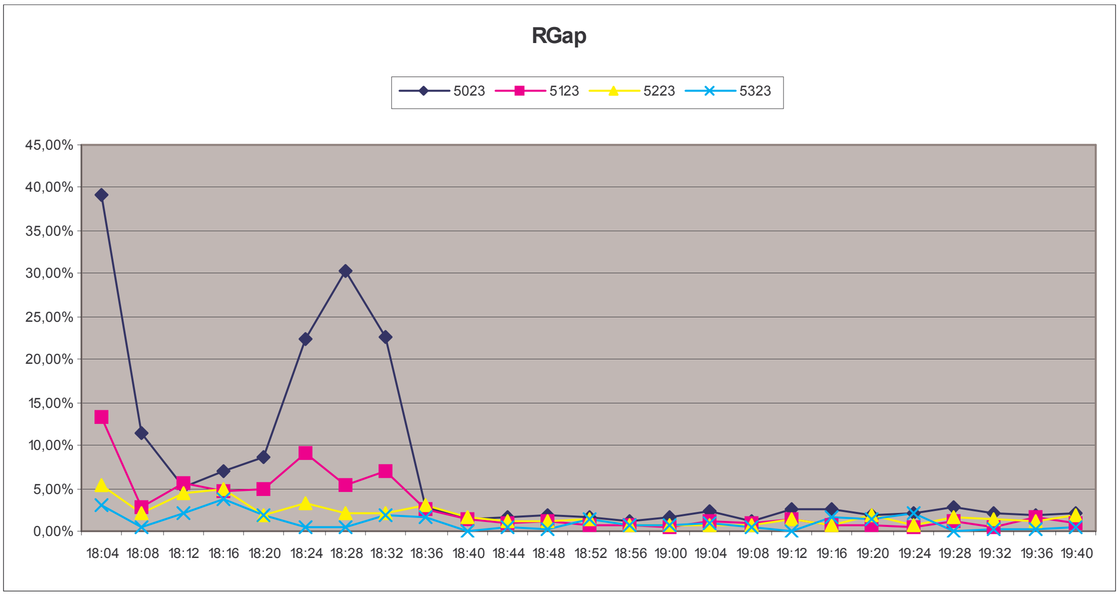


Figure 5.30. RGap function using a C-logit route choice model with the Initial K-SP fixed to 2 and the Max number of routes fixed to 3

In Figure 5.27, 3-54, 3-55 and 3-56, the expected role of the scale factor in terms of the RGap function becomes evident in the combination of the logit and C-logit route choice models with the assignment procedure. Inappropriate choices of the parameter values (θ = 10) tend to produce a bang-bang effect, which is a consequence of the tendency to move most of the flow to the current shortest path, as the oscillations of the RGap function show, while a more appropriate θ not only smoothes the RGap oscillations out significantly but also shows an acceptable path has been selected.

Figure 5.31 depicts the time evolution of the *RGap(t)* function using the C-logit route choice model, where the θ is fixed to 60, the Initial K-SP is fixed to 2, the maximum number of routes is fixed to 3 and the beta and gamma factors vary. The nomenclature used to identify the experiment with the parameters used is as follows: the first digit (6) is the C-logit route choice model, the second digit denotes the beta factor, where 0 is β = 0.10, 1 is β = 0.15, 2 is β = 0.50 and 3 is β = 1, the third digit denotes the beta factor. where 0 is γ = 0.5, 1 is γ = 1, 2 is γ = 1.5 and 3 is γ = 2. For example, Experiment 612 is an experiment that uses the C-logit route choice model, θ is fixed to 60, the Initial K-SP is fixed to 2, the maximum number of routes is fixed to 3 and β = 0.15 and γ = 1.5.

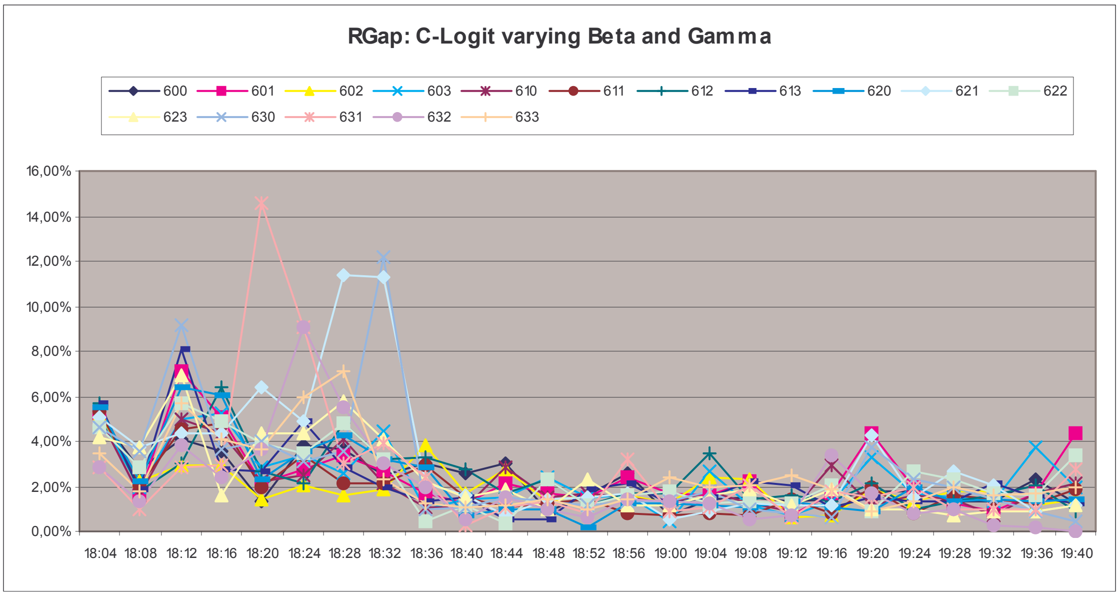


Figure 5.31. RGap function evolution using a C-logit route choice varying beta and gamma

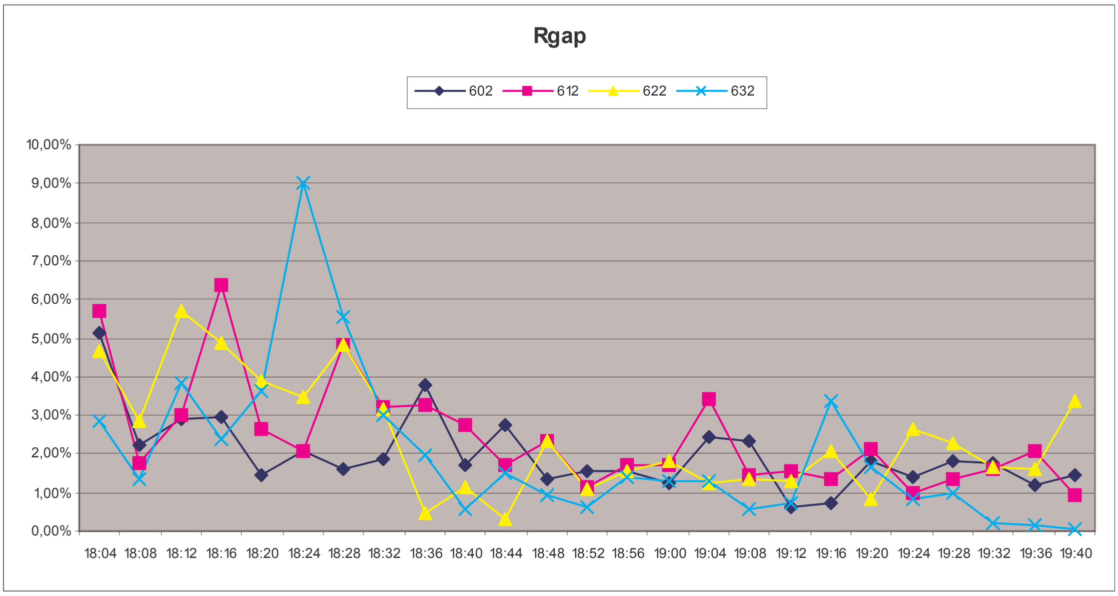


Figure 5.32. RGap function using a C-logit route choice model where θ = 60, the Initial K-SP is fixed to 2, the maximum number of routes is fixed to 3 and γ is fixed to 1.

Figure 5.32 depicts the effect of the beta factor when the other parameters considered are fixed. In this case, all the values of the beta factor produce an acceptable evolution of the RGap function but if the beta factor is fixed to 1, there is an increase of the RGap and a bang-bang effect during the interval from 18:24 to 18:28.

5.4 Validation of the Reactive Version Based on RGAP and GEH

The reactive version of the assignment procedure that uses the cost function (see Section 3.3.2.1 for details) $C_i^{k+1}(t) = \lambda\, C_i^k(t) + (1-\lambda)\, \hat{C}_i^k(t)$, where $0 \le \lambda \le 1$ and $C_i^k(t)$ is the input cost of link *i* at iteration *k* at time interval *t* and $\hat{C}_i^k(t)$ is the output cost of link *i* at iteration *k* at time interval *t*. The input cost $C_i^k(t)$ could be interpreted as the expected cost considered at interval *t*, while the output cost $\hat{C}_i^k(t)$ could be interpreted as the experimented or experienced link cost at the end of interval *t*.

This section presents the validation results of the reactive dynamic traffic assignment parameters based on a standard comparison between model and system outputs, using the GEH index and the validation based on the *RGap(t)* function for Amara model, (Appendix IV contains all the results of these experiments). In order to limit the number of experiments, due to the exponential growing of the number of combinations, we have fixed some parameters and taken into account only those values that fit better in the previous experiments.

Depending on the route choice model employed (proportional, logit or C-logit), the experimental design factors for the simulations were as follows:

- Proportional route choice model:

    - Alpha factor (α), for which values of 0.5, 1, 2, 2.5 and 3 were considered
    - *Initial K-SP*, for which values of 1, 2 and 3
    - Maximum number of routes (*MaxNumberRoutes)* fixed to 3
    - Lambda factor of the cost function (λ), for which values of 0.25, 0.50 and 0.75 were considered

  If these three factors are combined, the total number of experiments is 45 (5 * 3 * 3), each of which was simulated 15 times (replications). The following random seeds were changed: 9182, 1670, 6534, 8159, 8538, 5768, 1277, 1065, 1846, 8740, 1489, 3334, 6232, 6237 and 1870.

- Logit route choice model:

    - Scale factor (θ), for which values of 10, 60 and 100 were considered
    - *Initial K-SP*, for which values of 1, 2 and 3 were considered
    - Maximum number of routes (*MaxNumberRoutes)* fixed to 3
    - Lambda factor of the cost function (λ), for which values of 0.25, 0.50 and 0.75 were considered

  If these three factors are combined, the total number of experiments is 27 (3 * 3 * 3), each of which was simulated 15 times (replications). The same random seeds were changed as in the proportional route choice model.

- C-logit route choice model:

    - Scale factor (θ), for which values of 10, 60 and 100 were considered
    - *Initial K-SP*, for which values of 1, 2 and 3 were considered
    - Maximum number of routes (*MaxNumberRoutes)* fixed to 3 were considered
    - Beta (β), for which values of 0.10, 0.15, 0.50 and 1 were considered
    - Gamma (γ) fixed to 1
    - Lambda factor of the cost function (λ), for which values 0.25, 0.50 and 0.75 were considered

If these three factors are combined, the total number of experiments is 108 (3 * 3 * 4 * 3), each of which was simulated 15 times (replications). The same random seeds were changed as in the proportional route choice model.

Figure 5.33 plots the *RGap(t)* function and the GEH for all the experiments in which the proportional route choice model was used. In this plot, the experiments can be considered valid when the RGap function is less than or equal to 10% and the GEH is greater than or equal to 80% or 85% (values based on purely empirical grounds as a rule of thumb). Therefore, the experiments accepted are located in the top, left-hand corner. If we consider this criterion in order to accept or reject the experiments, we can distinguish two separate clouds of points: one that shows an acceptable GEH and RGap (to different degrees) and another that shows an unacceptable GEH and acceptable RGap. Acceptable GEH and RGap are observed in the experiments represented below.

Alpha factor	Initial K-SP	Lambda
0,5	1	0.25
1	1	0.25
2	1	0.25
2.5	1	0.25
3	1	0.25
2	1	0.50
2.5	1	0.50
3	1	0.50
3	3	0.50
2.5	1	0.75
3	1	0.75
3	3	0.75

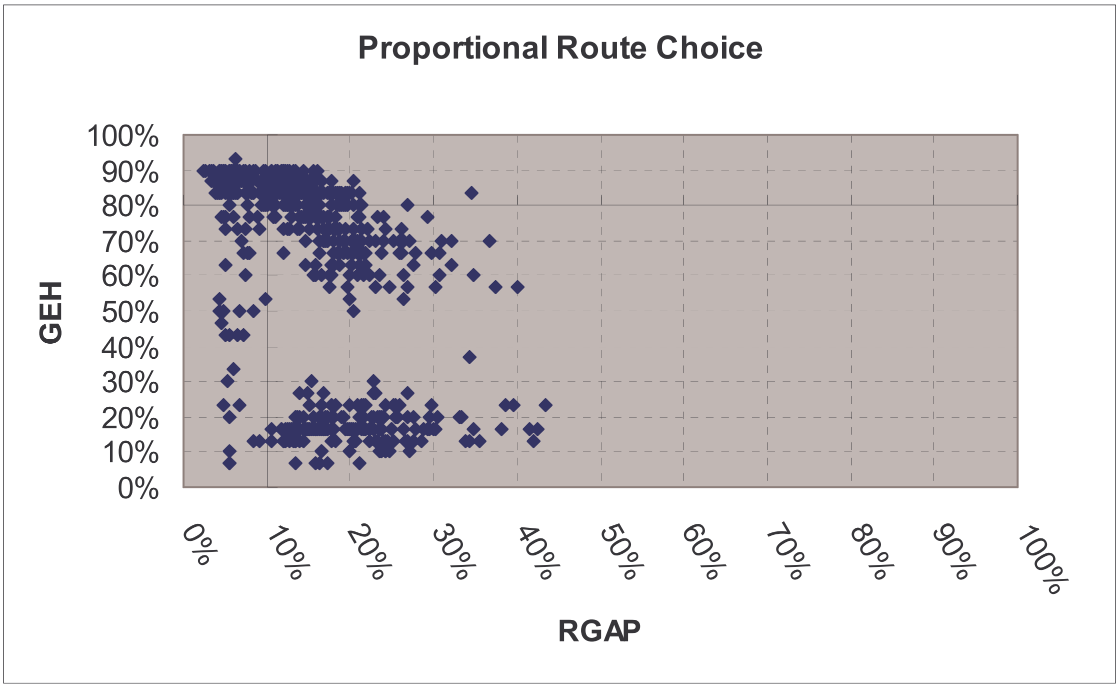


Figure 5.33. RGap and GEH of all replications using the reactive assignment procedure and the proportional route choice model

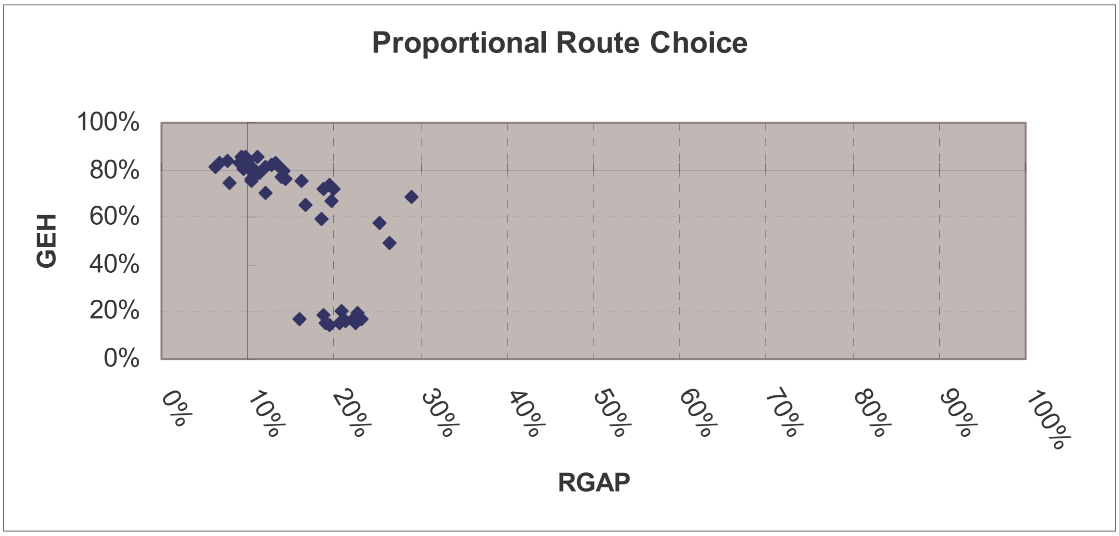


Figure 5.34. RGap and GEH of the average of each experiment using the reactive assignment procedure and the proportional route choice model

Figure 5.34 depicts the plot of the RGap and GEH average from all replications of the same experiment and it allows us to identify the set of experiments that produces acceptable RGap and GEH using the proportional route choice model. Table 5.15 identifies the experiments that show an acceptable average of RGap and GEH. It is important to highlight the fact that a combination of the alpha Factor fixed to 3 and the Initial K-SP fixed to 1 generates an acceptable RGap and GEH, regardless of the lambda value.

Alpha Factor	Initial K-SP	Lambda
2	1	0.25
2.5	1	0.25
3	1	0.25
2	1	0.50
3	1	0.50
2.5	1	0.75
3	1	0.25
3	3	0.75

Table 5.15. Acceptable RGap and GEH using a proportional route choice model

Figure 5.35 depicts the plot of the RGap versus GEH index of all replications using the logit route choice model. The cloud of points that are in the area of the acceptable RGap and GEH index represent 70% of the experiments in which the logit route choice was used.

Figure 5.36 depicts the plot of the RGap and GEH average from all replications of the same experiment and it allows us to identify the set of experiments that produces acceptable RGap and GEH using the logit route choice model (see Appendix IV for numerical data).

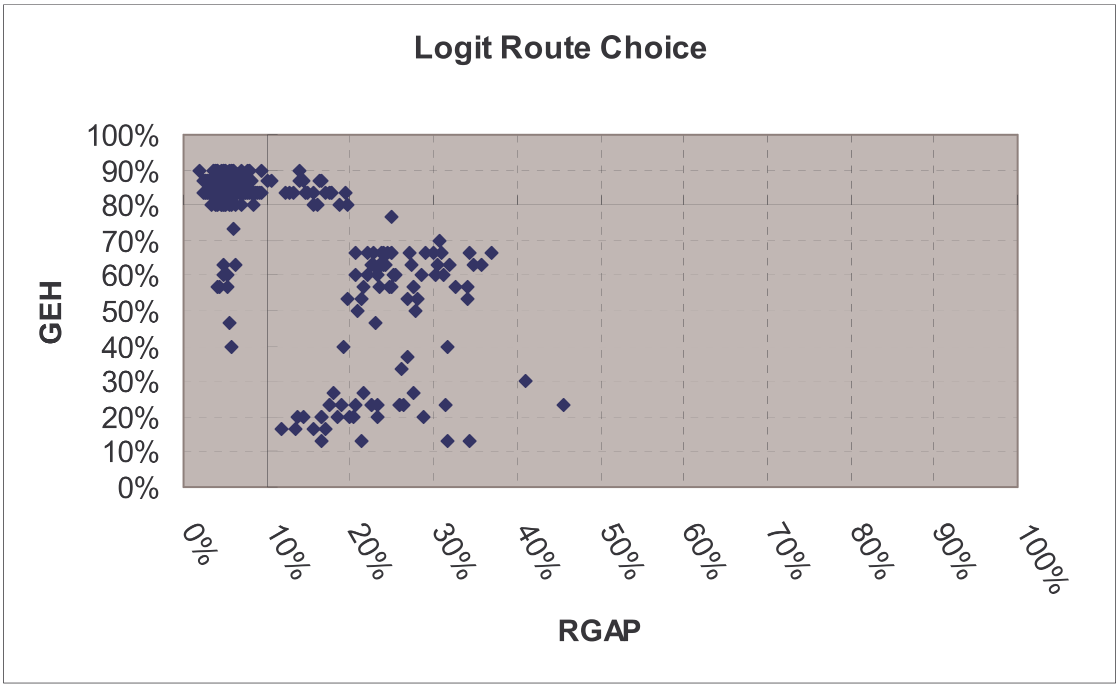


Figure 5.35. RGap and GEH of all replications using reactive assignment procedure and the logit route choice model

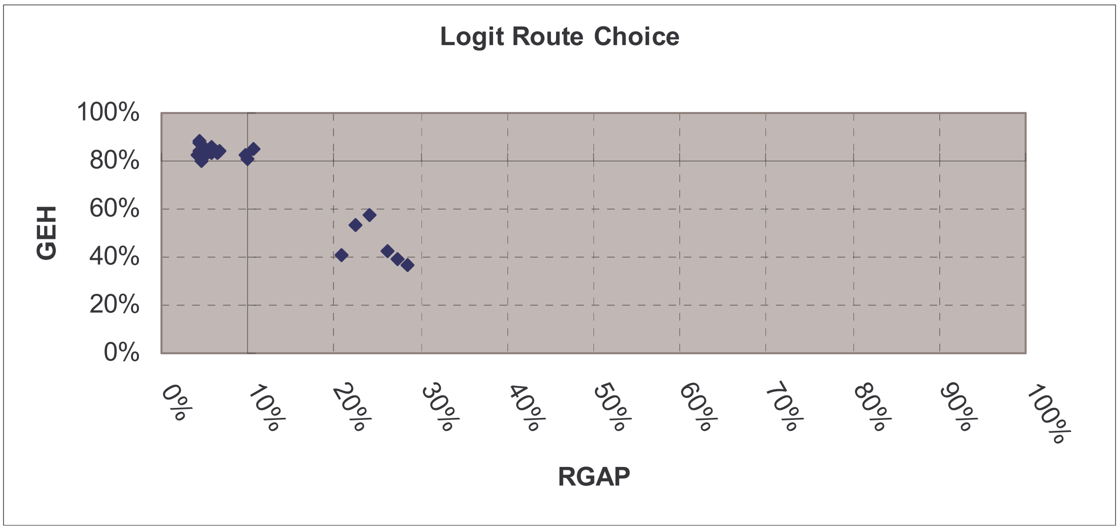


Figure 5.36. RGap and GEH of the average of each experiment using reactive assignment procedure and the logit route choice model

Table 5.16 identifies the experiments that have an acceptable average of RGap and GEH. It is important to highlight the fact that the scale factor fixed to 60 or 100 generates acceptable RGap and GEH, regardless of the lambda value and the initial K-SP parameter.

Scale Factor	Initial K-SP	Lambda
10	1	0.25
60	1	0.25
60	2	0.25
60	3	0.25
100	1	0.25
100	2	0.25
100	3	0.25
10	1	0.50
60	1	0.50
60	2	0.50
60	3	0.50
100	1	0.50
100	2	0.50
100	3	0.50
60	1	0.75
60	2	0.75
60	3	0.75
100	1	0.75
100	2	0.75
100	3	0.75

Table 5.16. Acceptable RGap and GEH using a logit route choice model

Figure 5.37 depicts the plot of the RGap versus GEH index of all replications using the C-logit route choice. The cloud of points that are in the area of the acceptable RGap and GEH index represents 56% of the experiments in which C-logit is the route choice model used.

Figure 5.38 depicts the plot of the average RGap versus the GEH index of all replications of the same experiment.

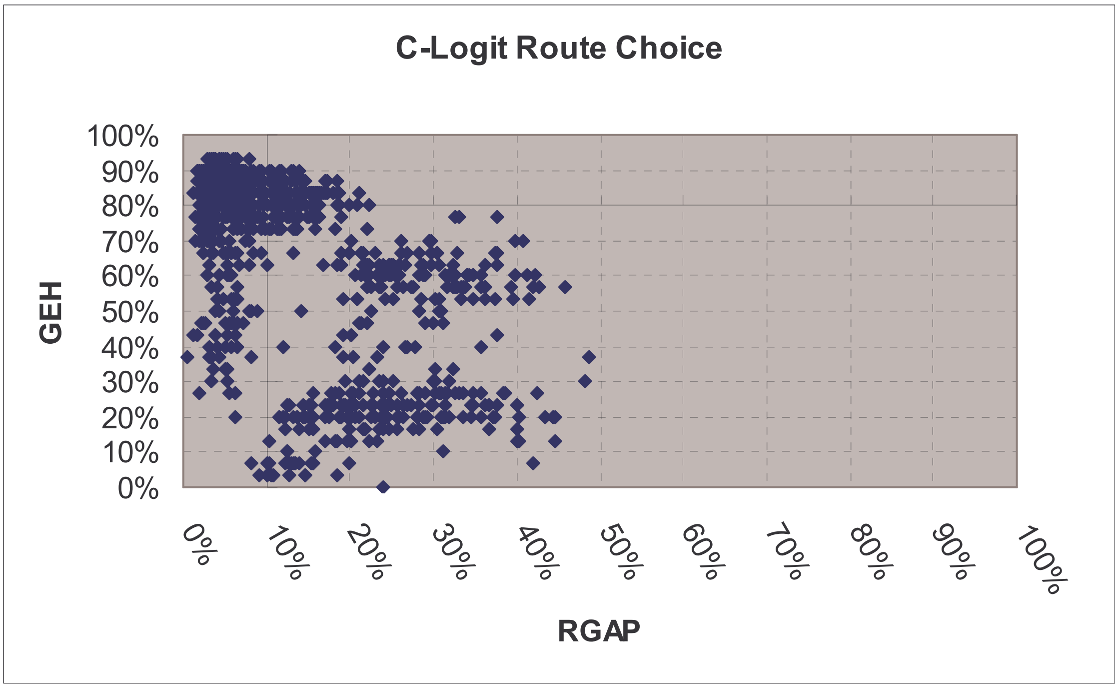


Figure 5.37. RGap and GEH of all replications using reactive assignment procedure and the logit route choice model

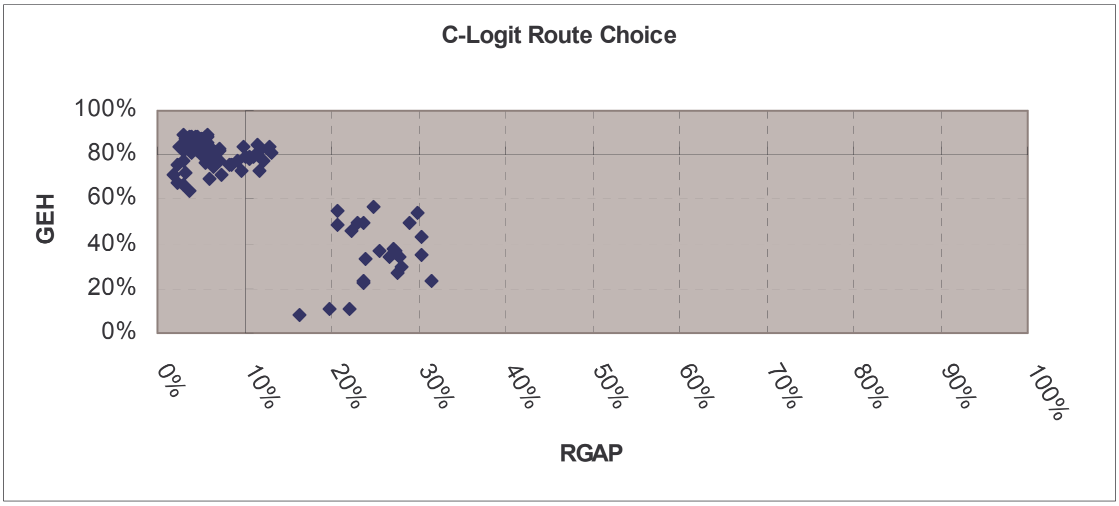


Figure 5.38. RGap and GEH of the average of each experiment using reactive assignment procedure and the C-logit route choice model

Table 5.17 identifies the experiments that have an acceptable average of RGap and GEH using a C-logit route choice model. It is important to highlight the fact that a scale factor fixed to 10 generates unacceptable RGap and GEH, regardless of the values of the other parameters (the only combination that produces an acceptable RGap and GEH is a scale factor fixed to 10, an initial K-SP of 1, a beta factor of 0.50 and a lambda value of 0.5). Another fact to highlight is the scale factor fixed to 60 and the Initial K-SP fixed to 1 and 2 generates an acceptable situation, regardless of the values of the beta and lambda parameters (except the combination of a scale factor of 60, an Initial K-SP of 2, a beta factor of 0.50 and a lambda value of 0.25). The same effect would be observed if the scale factor took 100 as its value, the beta factor was irrelevant, the initial K-SP was either 1 or 2 and the lambda was either 0.50 or 0.75.

Scale Factor	Initial K-SP	Beta Factor	Lambda
60	1	0.10	0.25
60	1	0.15	0.25
60	1	0.50	0.25
60	1	1.00	0.25
60	2	0.10	0.25
60	2	0.15	0.25
60	2	1.00	0.25
60	3	0.15	0.25
100	1	0.10	0.25
100	1	0.50	0.25
100	1	1.00	0.25
100	2	0.50	0.25
100	3	0.10	0.25
100	3	0.50	0.25
10	1	0.50	0.50
60	1	0.10	0.50
60	1	0.15	0.50
60	1	0.50	0.50
60	1	1.00	0.50
60	2	0.10	0.50
60	2	0.15	0.50
60	2	0.50	0.50
60	2	1.00	0.50
60	3	0.10	0.50
60	3	0.15	0.50
100	1	0.10	0.50
100	1	0.15	0.50
100	1	0.50	0.50

100	1	1.00	0.50
100	2	0.10	0.50
100	2	0.15	0.50
100	2	0.50	0.50
100	2	1.00	0.50
100	3	0.10	0.50
100	3	0.15	0.50
60	1	0.10	0.75
60	1	0.15	0.75
60	1	0.50	0.75
60	1	1.00	0.75
60	2	0.10	0.75
60	2	0.15	0.75
60	2	0.50	0.75
60	2	1.00	0.75
60	3	0.10	0.75
60	3	0.15	0.75
100	1	0.10	0.75
100	1	0.15	0.75
100	1	0.50	0.75
100	1	1.00	0.75
100	2	0.10	0.75
100	2	0.15	0.75
100	2	0.50	0.75
100	2	1.00	0.75
100	3	0.10	0.75
100	3	0.15	0.75

Table 5.17. Acceptable RGap and GEH using a C-logit route choice model

An additional result of the method explored in this section is the guidance that the computational results provide for the calibration of the dynamic traffic assignment parameters, depending on the route choice function selected. This is based on the assumption that, as far as the assignment process described is concerned, and depending on how it is implemented, it can be associated with a heuristic carrying out of a preventive or reactive dynamic assignment. A proper route selection should lead to some degree of equilibrium, and the progress towards such equilibrium is measured in terms of the RGap function.

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.