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February 2009

CIRRELT-2009-04

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Some Enhancements of the Gradient Method for O-D Matrix Adjustment

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Abstract. In this paper, the gradient method for adjusting a single class origin-destination matrix by using observed flows is extended to consider a reference matrix and to adjust simultaneously the O-D matrices for several classes of traffic. The importance of using a reference matrix is demonstrated with computational results that are carried out with two networks originating from practice. The conclusion reached is that, in order to maintain the structure of the O-D matrices that are adjusted, it is highly desirable to include a demand term in the objective function of the adjustment model.

Keywords. Multi-class equilibrium assignment, demand adjustment, gradient method.

Acknowledgements. This research was supported in part by an individual operating grant from the Natural Sciences and Engineering Research Council of Canada (NSERC). We would like to thank the "Service de la modélisation des systèmes de transport" of the Ministry of Transportation of Quebec for permission to use the Montreal region model (MOTREM) for this research.

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Dépôt légal – Bibliothèque nationale du Québec,
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Introduction

The purpose of this paper is to point out some relevant facts related to the use of recent current observed flows to update (or adjust, estimate) origin-destination (O-D) demand matrices which are "out-of-date". The updating of such matrices by using counts is a common practice for achieving short term forecasts without the use of a full scale update of a demand forecasting model in the absence of new survey data. The practice is quite common and several O-D adjustment methods are available in some commercial packages used in practice. A short survey of the methods that have been developed for matrix adjustment follows.

Due to its practical importance, the adjustment of an origin-destination (O-D) matrix by using observed flows (counts) on the links and turns of a transportation planning network has attracted the attention of many researchers. The methods proposed may be subdivided into two categories, depending whether the network considered is assigned constant travel times (uncongested) or flow-dependent (congested) travel times.

Some of the contributions made for O-D matrix adjustment on uncongested networks include those of Van Zuylen and Willumsen (1980), Maher (1983), Cascetta (1984), Bell (1984), Spiess (1987), Tamin and Willumsen (1989), Willumsen (1984), Bell (1991) and Bierlaire and Toint (1994).

When the network considered for the O-D matrix adjustment is subject to congestion the underlying route choice method is an equilibrium assignment. Some of the numerous contributions made for this version of the problem are those of LeBlanc and Farhangian (1982), Nguyen (1984), Fisk (1988, 1989), Spiess (1990), Kawakami et al (1992), Florian and Chen (1995), Yang et al (1992) and Yang et al (1994). In this case the O-D matrix adjustment method may be formulated as a bi-level optimization problem or, as others denote such problems, a mathematical programming problem with equilibrium constraints (MPEC).

Several of these methods have been implemented in practice (see for instance Van Vliet, 1982, and Spiess, 1990, INRO, 2007), and are used on a regular basis for the adjustment of an out-of-date O-D matrix for the evaluation of contemplated network changes for a *short term* planning horizon.

In the following a multi-class O-D adjustment model is formulated, a solution algorithm is developed and numerical results are reported. The inclusion of the demand term into the simultaneous class formulation and the resulting gradient based algorithm are new developments.

The paper is organized as follows. The next section states the formulation of the model that includes a demand term and considers multiple classes of traffic. Section 3 presents the development of the solution algorithm and Section 4 presents computational results obtained on two networks with single and multi-class adjustments. A short conclusion ends this article.

1. The multi-class O-D adjustment model formulation

In this section, the notation used in order to state the mathematical formulation for the multi-class O-D adjustment problem is introduced. The nodes of the road network are denoted n, $n \in N$ and the links are denoted a, $a \in A$ where N is the set of nodes and A is the set of links. The set of O-D pairs is denoted by I and it is convenient to refer to the O-D pair with index $i = (p, q)$, $i \in I$, where p (*origin*), q (*destination*) $\in N$. There are several classes of traffic which are denoted m, $m \in M$. The demand for travel by user class $m \in M$ for the O-D pair i is denoted g_i^m. $\hat{A}^m \in A$ is the set of links where counts are available for class m. The O-D demands may use paths $K_i^m \in K$ where K is the set of all routes $K = \bigcup_{(i)m} K_i^m$ and k is a path index. The path flow of class m on the route k is denoted h_k^m and gives rise to link flows v_a^m of classes m, $m = 1,..,|M|$ on link a, $a \in A$; the total link flow v_a on link a is the sum of the class flows $v_a = \sum_m v_a^m$, for $m = 1,...,\ |M|$. The counts by class are denoted as $\hat{v}_a^m$, $a \in \hat{A}^m$. And finally, $s_a(v_a)$ is the travel time (cost) function of link a for a total link flow v_a. The adjusted demand by class should yield assigned flows which are close to the observed link flows and remain close of the original values $\hat{g}_i^m$ for all the O-D pairs $\hat{I}^m \in I$.

A compact formulation of the bi-level (or Mathematical Programming with Equilibrium Constraints) multi-class O-D adjustment problem is given by

$$Min\ Z(v,g) = \frac{\alpha}{2} \sum_{m \in M} \sum_{a \in \hat{A}^m} (v_a^m(g) - \hat{v}_a^m)^2 + \frac{(1-\alpha)}{2} \sum_{m \in M} \sum_{i \in \hat{I}^m} (g_i^m - \hat{g}_i^m)^2 \qquad (1)$$

Subject to

$$v(g) = assign(g). \qquad (2)$$

Where α is the weight associated to the link flows term and $assign(g)$ is the notation used to indicate that the vector of flows v is the result of the multi-class equilibrium assignment of demand g. This assignment problem is:

$$Min\ F(v) = \sum_{a \in A} \int_0^{v_a} s_a(v)dv \qquad (3)$$

Subject to

$$v_a = \sum_{m \in M} v_a^m \qquad a \in A \qquad (4)$$

$$v_a^m = \sum_{i \in I} \sum_{k \in K_i^m} \delta_{ak}^m h_k^m \qquad a \in A,\quad m \in M \qquad (5)$$

$$\sum_{k \in K_i^m} h_k^m = g_i^m \qquad i \in I, \quad m \in M \tag{6}$$

$$h_k^m \geq 0 \qquad k \in K_i^m, \quad m \in M \tag{7}$$

$$\delta_{ak}^m = \begin{cases} 1 \text{ if } a \in k \text{ for mode } m \\ 0 \text{ otherwise} \end{cases} \tag{8}$$

The formulation of the model allows the consideration of both the matrix to be adjusted $\hat{g}_i^m$ and the observed counts $\hat{v}_a^m$. By varying the weight α between 1 and values less than 1 one can obtain an adjustment that reduces the importance of the link flow term and increases the importance of the demand term. This would ensure that the adjusted (estimated) O-D matrix is not "too different" than the matrix that is being adjusted. In the adjustment process judgment is usually exercised to determine if an adjusted matrix is "reasonable" so there is quite a bit of art that complements the use of a rigorous model in order to judge the results. The aim of this paper is to test the sensitivity of the results to various values of the parameter α.

2. The solution algorithm

The solution algorithm is based on an adaptation of the gradient approach developed by Spiess (1990). The main difference, apart the multi-class generalization, is the addition of the demand term in the objective function. Since the details are not trivial the derivation of the gradient and the solution algorithm are presented in detail.

In order to develop a solution algorithm of this bi-level optimization problem, based on a descent approach, it is necessary to derive the local gradient of the objective function. This is approximated by assuming that the path proportions p_k^m, resulting from the equilibrium assignment of demand g^m, are locally constant and can be used to derive an analytical relation between $v(g^m)$ and g^m. This would facilitate the derivation of an analytical expression for the gradient.

Using the path proportions p_k^m, $p_k^m = \dfrac{h_k^m}{g_i^m}$, $k \in K_i^m$, $m \in M$, v_a^m can be rewritten as:

$$v_a^m = \sum_{i \in I} \sum_{k \in K_i^m} \delta_{ak}^m p_k^m g_i^m \tag{9}$$

$$= \sum_{i \in I} g_i^m \sum_{k \in K_i^m} \delta_{ak}^m p_k^m \qquad a \in A, \quad m \in M \tag{10}$$

As a consequence:

$$\frac{\partial v_a^m}{\partial g_i^m} = \sum_{k \in K_i^m} \delta_{ak}^m p_k^m \qquad a \in A, \quad i \in I, \quad m \in M \tag{11}$$

The gradient of (1) consists of two parts: the term that corresponds to the flows, $Z_1(v^m) = \frac{\alpha}{2} \sum_{m \in M} \sum_{a \in \hat{A}^m} (v_a^m - \hat{v}_a^m)^2$, and the term that corresponds to the demand, $Z_2(g^m) = \frac{(1-\alpha)}{2} \sum_{i \in \hat{I}^m} (g_i^m - \hat{g}_i^m)^2$. The derivative of the first term is obtained by applying the chain rule:

$$\begin{aligned} \frac{dZ_1(v^m)}{dg_i^m} &= \frac{\partial Z_1(v^m)}{\partial v_a^m} * \frac{\partial v_a^m}{\partial g_i^m} \\ &= \alpha \sum_{a \in \hat{A}^m} (v_a^m - \hat{v}_a^m) \sum_{k \in K_i^m} \delta_{ak}^m p_k^m \\ &= \alpha \sum_{k \in K_i^m} p_k^m \sum_{a \in \hat{A}^m} \delta_{ak}^m (v_a^m - \hat{v}_a^m) \end{aligned} \tag{12}$$

The derivative of the second term is simply:

$$\frac{dZ_2(g^m)}{dg_i^m} = (1-\alpha) * (g_i^m - \hat{g}_i^m) \, .$$

Hence,

$$\nabla Z(v,g) = \frac{dZ(v^m, g^m)}{dg_i^m} = \alpha \sum_{k \in K_i^m} p_k^m \sum_{a \in \hat{A}^m} \delta_{ak}^m (v_a^m - \hat{v}_a^m) + (1-\alpha) * (g_i^m - \hat{g}_i^m), \; i \in I, \quad m \in M \tag{13}$$

The descent direction is usually obtained as the negative of the gradient $-\nabla Z(v,g)$. In order to ensure that the cells with a zero demand remain unchanged, it is convenient to multiply $-\nabla Z(v,g)$ by the demand g in order to obtain the descent direction (this assumes that there are no major land sue changes in the *short term*).

$$d = -g \nabla Z(v,g) = -g * \frac{dZ(v^m, g^m)}{dg_i^m}, \; i \in I, \quad m \in M, \text{ hence}$$

$$d_i^m = -g_i^m \Big(\alpha \sum_{k \in K_i^m} p_k^m \sum_{a \in \hat{A}^m} \delta_{ak}^m (v_a^m - \hat{v}_a^m) + (1-\alpha) * (g_i^m - \hat{g}_i^m)\Big), \; i \in I, \quad m \in M \tag{14}$$

The descent direction applies directly to the demands g and indirectly to the flows v. By using the path proportions p_k^m one can determine the rate of change of the flows as a consequence of a change in the O-D matrix given by (14). The assignment of the gradient matrix to the paths of the network by using the path proportions produces the rate of change of the link flows that yields the direction (15) for changing the link flows.

$$y_a^m(d_i^m) = \sum_{i \in I} d_i^m \frac{\partial v_a^m}{\partial g_i^m} = -\sum_{i \in I} g_i^m (\alpha \sum_{k \in K_i^m} p_k^m \sum_{a \in \hat{A}^m} \delta_{ak}^m (v_a^m - \hat{v}_a^m) + (1-\alpha) * (g_i^m - \hat{g}_i^m))(\sum_{k \in K_i^m} \delta_{ak}^m p_k^m)$$
$$a \in A, \quad i \in I, \quad m \in M \qquad (15)$$

The optimal step length by class, λ^{m*}, is obtained by solving:

$$\underset{\lambda^m}{Min} \; Z(v^m, g^m, \lambda^m) = Z(v^m + \lambda^m y^m, g^m + \lambda^m d^m) \qquad (16)$$

where y^m is the vector with components given by (15) and d^m is a vector with components given by (14).

The derivative of (16) with respect to λ^m is computed by the chain rule as:

$$\frac{dZ(\lambda^m)}{d\lambda^m} = \sum_{a \in \hat{A}^m} \frac{dv_a^m}{d\lambda^m} * \frac{\partial Z(\lambda^m)}{\partial v_a^m} + \sum_{i \in \hat{I}^m} \frac{\partial Z(\lambda^m)}{\partial g_i^m}. \qquad (17)$$

Since the objective function (1) is quadratic the optimal step sizes λ^{m*} may be computed by annulling the derivatives (17). Some algebraic manipulation yields

$$\lambda^{m*} = \frac{\alpha \sum_{a \in \hat{A}^m} (\hat{v}_a^m - v_a^m) y_a^m + (1-\alpha) * \sum_{i \in \hat{I}^m} (\hat{g}_i^m - g_i^m) d_i^m}{\alpha \sum_{a \in \hat{A}^m} (y_a^m)^2 + (1-\alpha) * \sum_{i \in \hat{I}^m} (d_i^m)^2}, \; m \in M. \qquad (18)$$

It is important to note that the optimal step size is different for each class of traffic.

The statement of the algorithm is given next.

The Multi-Class O-D Adjustment Algorithm

Step 0. *Initialization.* Iteration $l = 0$

Step 1. *Multi-class assignment.* Multi-class assignment of demand $g^{m,l}$ ($\forall m \in M$) to obtain link volumes $v_a^{m,l}$ for $a \in A, \quad m \in M$

Step 2. *Link derivatives and objective function*. Computation of the link derivatives $(v_a^{m,l} - \hat{v}_a^{m,l})$ for $a \in \hat{A}^m$, $m \in M$ and the objective function:

$$\frac{\alpha}{2} \sum_{m \in M} \sum_{a \in \hat{A}^m} (v_a^{m,l} - \hat{v}_a^{m})^2 + \frac{(1-\alpha)}{2} \sum_{m \in M} \sum_{i \in \hat{I}^m} (g_i^{m,l} - \hat{g}_i^{m})^2$$

If the maximum number of iterations L is reached go to Step 7.

Step 3. *Assignment to compute the gradient matrix*. Carry out a multi-class assignment with path analysis to compute the gradient matrices; then add the demand term.

$$\nabla Z(v,g)^{m,l} = \frac{dZ(v^m, g^m)^l}{dg_i^{m,l}} = \alpha \sum_{k \in K_i^{m,l}} p_k^{m,l} \sum_{a \in \hat{A}^m} \delta_{ak}^{m,l} (v_a^{m,l} - \hat{v}_a^m) + (1-\alpha) * (g_i^{m,l} - \hat{g}_i^m)$$

Step 4. *Assignment to obtain the derivatives*. Carry out a multi-class assignment with path analysis to obtain the descent direction:

$$y_a^{m,l}(d_i^{m,l}) = -\sum_{i \in I} g_i^{m,l} \ \nabla Z(v,g)^{m,l} (\sum_{k \in K_i^{m,l}} \delta_{ak}^{m,l} p_k^{m,l})$$

Step 5. *Update of the demand matrices*. For each class $m \in M$:

Computation of the optimal step length as:

$$\lambda^{m,l*} = \frac{\alpha \sum_{a \in \hat{A}^m} (\hat{v}_a^m - v_a^{m,l}) y_a^{m,l} + (1-\alpha) * \sum_{i \in \hat{I}^m} (\hat{g}_i^m - g_i^{m,l}) d_i^{m,l}}{\alpha \sum_{a \in \hat{A}^m} (y_a^{m,l})^2 + (1-\alpha) * \sum_{i \in \hat{I}^m} (d_i^{m,l})^2}$$

Update of the demand matrix:

$$g_i^{m,l+1} = g_i^{m,l} + \min(\lambda^{m,l\,*}, 1) * \nabla Z(v,g)^{m,l}$$

Step 6. *Iteration counter*. Update the iteration counter $l = l + 1$ and return to Step 1.

Step 7. *End*.

The implementation of the algorithm was done by using the Emme 3 (INRO, 2007) transportation planning software. The assignment algorithm used is the linear approximation method of Frank and Wolfe (1956), which is still the most common method for computing equilibrium flows. The critical part of the algorithm, which is the computation of the path proportions p_k^m, $k \in K_i^m$, $m \in M$, is achieved by using implicitly the step sizes generated at each iteration of the linear approximation algorithm.

4. Numerical results: the effect of the parameter α

The O-D adjustment algorithm was used in several experiments to test the effect of the values of the parameter α on the resulting flows and changes in the O-D matrix.

The first test was carried out with a network originating from the city of Winnipeg, Canada. This is a relatively modest size network of 154 zones, 903 nodes, 752 turns and 2975 links. The network is displayed in Figure 1; the 70 available counts on the links are shown in blue. The total assigned demand consists of 56,219 vehicles; it corresponds to the AM peak. The volume-delay functions used are of the BPR type and there is only one class of traffic.

The parameter α was varied to be 1, 0.95, 0.90 and 0.80 (appropriate values of α depend on the relative magnitude of the demand term and the network term of the objective function (1)). Tables 1 and 2 below give the fit of the flows and the deviations from the original O-D matrix for 5 iterations of the demand adjustment algorithm. It is easy to note that as the demand term is given more weight the deviations from the original O-D matrix are smaller. When the demand term is not considered the deviations from the original O-D matrix are rather large.

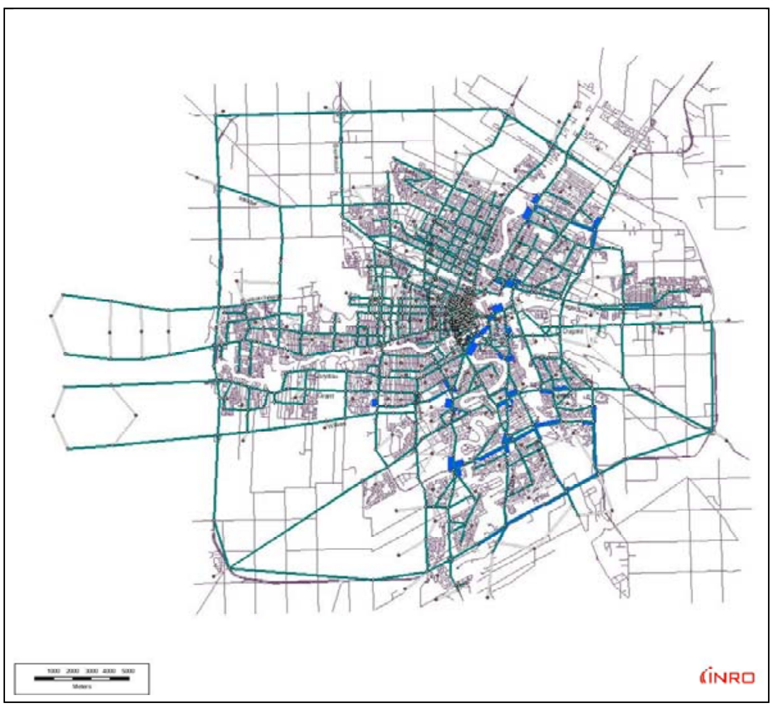

Figure 1. The Winnipeg road network

		Regression coefficients				
Iterations	α	A	B	R2	RSTD	Obj. Function
0		- 84.47	1.02	0.82	248.7	
5	**1.00**	- 15.39	1.01	0.96	111.1	847
	0.95	- 60.30	1.00	0.92	156.3	1 801
	0.90	- 68.28	1.00	0.90	173.8	2 126
	0.80	- 74.15	1.01	0.88	195.4	2 355

Table 1. Winnipeg flows comparison regression coefficients

		Regression coefficients					
Iterations	α	A	B	R2	RSTD	To adjust	Adj. demand
5	**1.00**	0.05	1.00	0.81	3.89	56 219	57 611
	0.95	0.01	1.00	0.95	1.77	56 219	56 118
	0.90	0.00	0.99	0.97	1.34	56 219	55 863
	0.80	- 0.00	0.99	0.99	0.90	56 219	55 797

Table 2. Winnipeg demand deviations regression coefficients

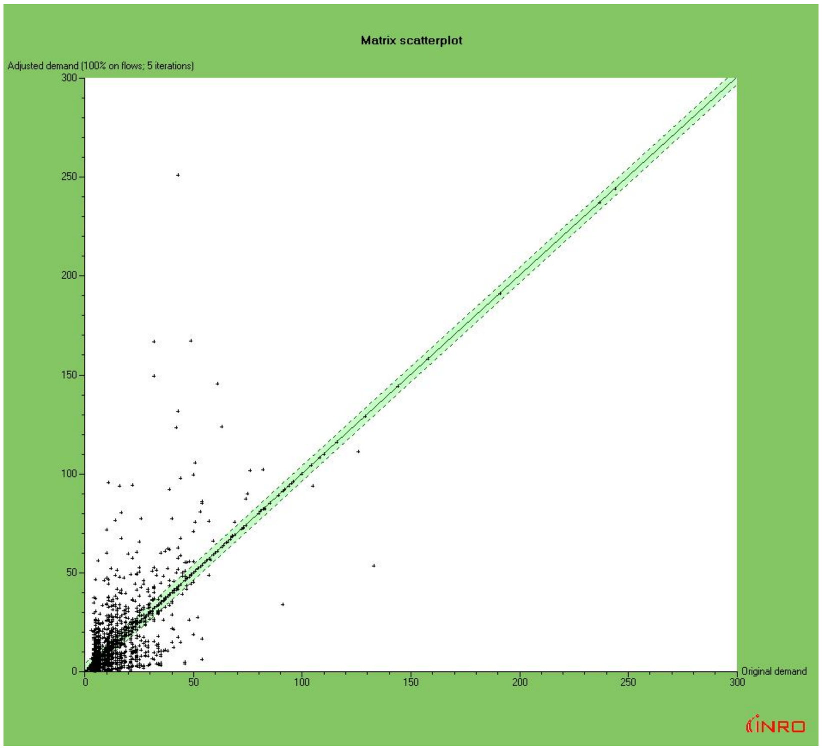

Figure 2. Winnipeg demand deviations for $\alpha = 1.00$, 5 iterations

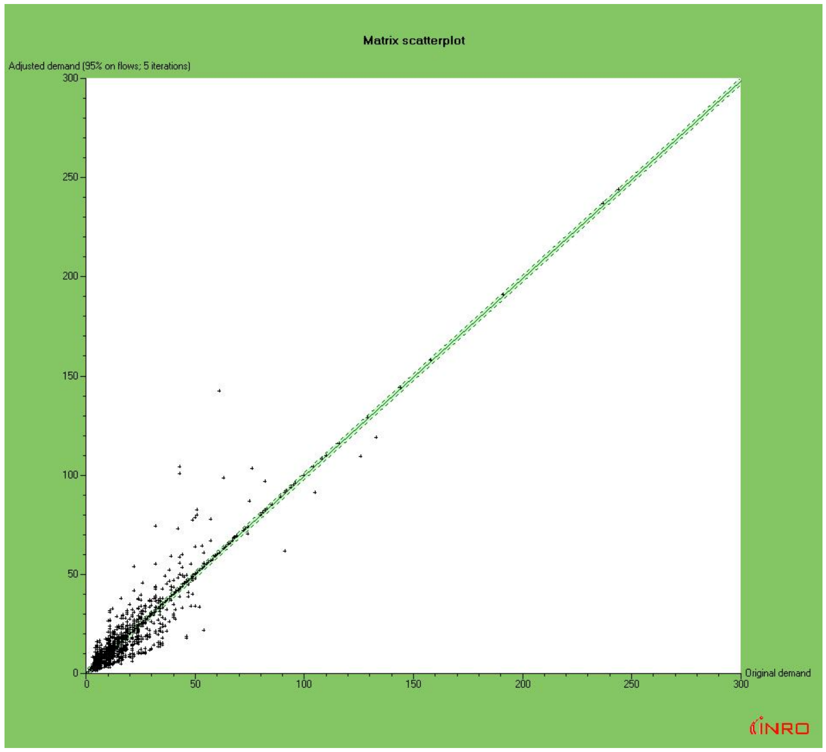

Figure 3. Winnipeg demand deviations for $\alpha = 0.95$, 5 iterations

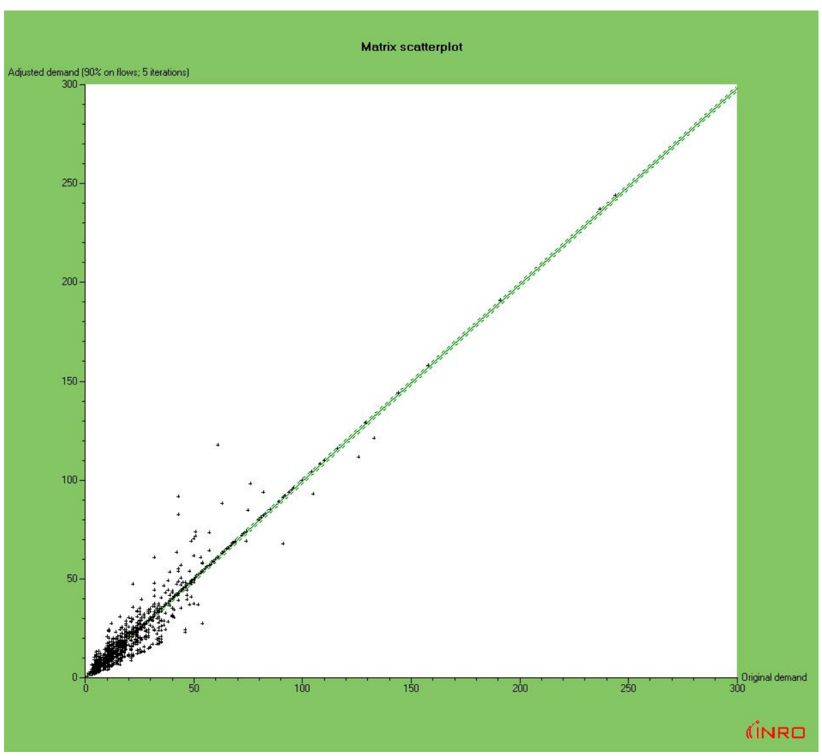

Figure 4. Winnipeg demand deviations for $\alpha = 0.90$, 5 iterations

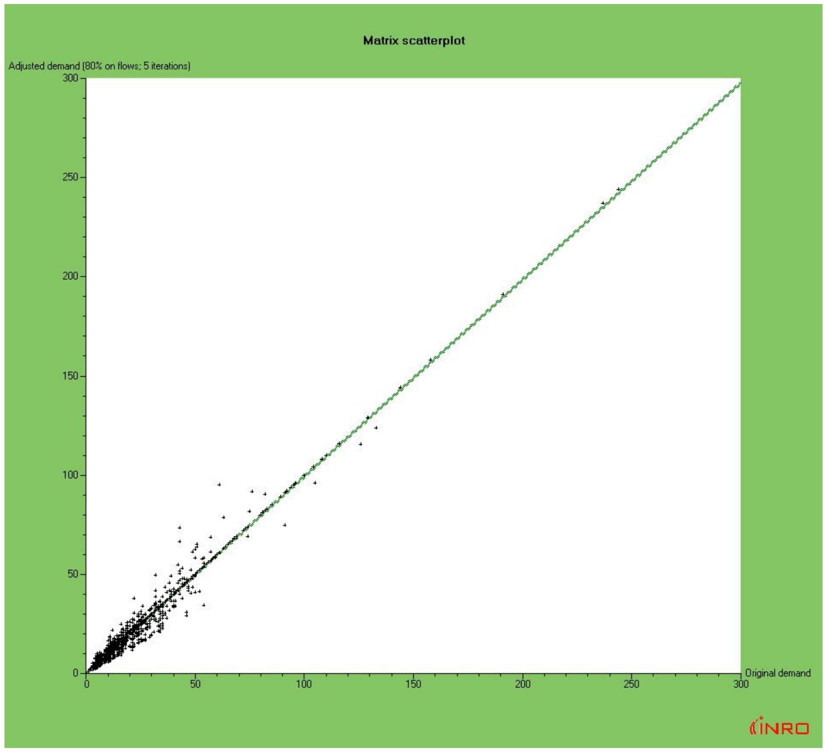

Figure 5. Winnipeg demand deviations for $\alpha = 0.80$, 5 iterations

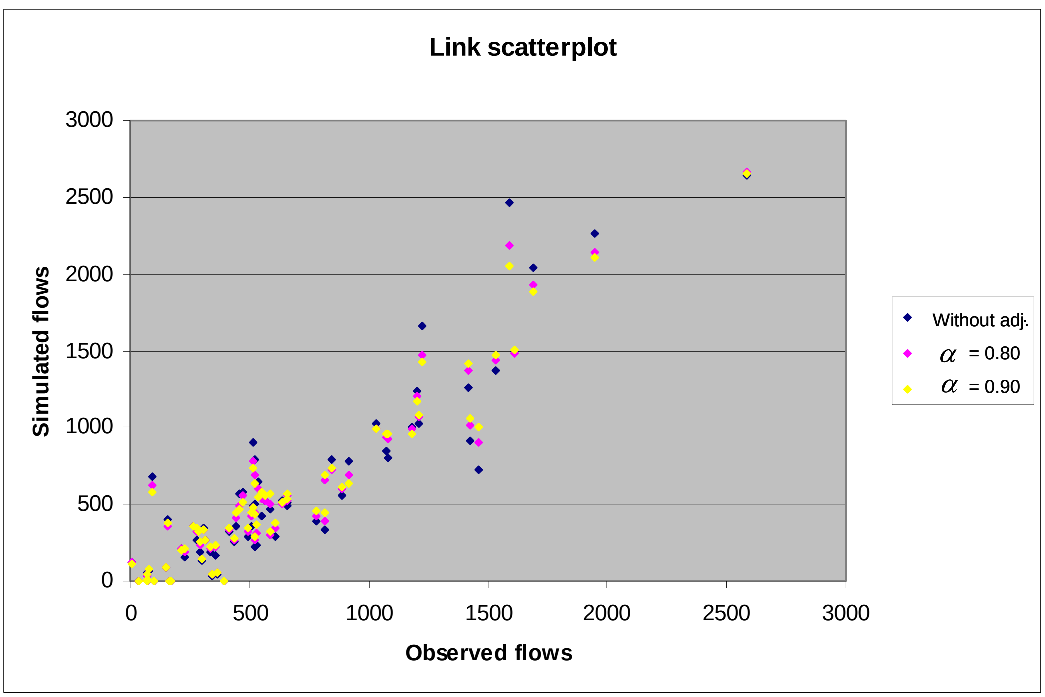

Figure 6. Winnipeg flows comparison (a), 5 iterations adjustment

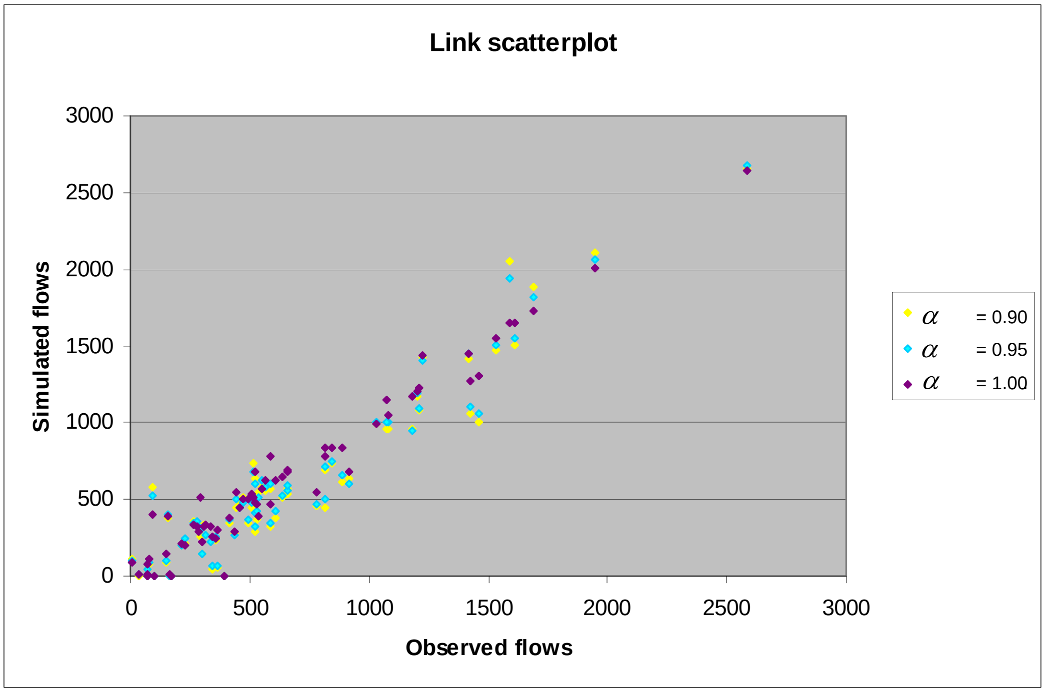

Figure 7. Winnipeg flows comparison (b), 5 iterations adjustment

The computation time was approximately 1 min. for each of the 5 iterations of adjustment. The tests were carried out on a desk top PC with 2 Intel ® Core (TM) CPU 6400 @ 2.13GHz, 3.25 Gb of RAM.

Another set of computational tests was carried out by using a network data set originating from the Metropolitan Region of Montreal. The corresponding network is displayed in Figure 8 (536 link counts in bleu). The network has 1,425 zones, 13,019 nodes and 32,284 links. The considered Montreal network uses 3 classes of traffic: private car, regular trucks (one unit, 2 or 3 axles) and heavy trucks (one unit, 4 axles or more than one unit). The day is divided in 5 periods: Night, AM peak, Off day peak, PM peak and Off night peak. Presented results correspond to the Off day peak period.

A set of logistic volume delay functions were calibrated for all the links of the network by the “Service de la modélisation des systèmes de transport” of the Ministry of Transportation of Quebec. The logistic functions are continuous positive non decreasing functions of the flow.

The results presented in the following correspond to three different values of the parameter α; 0.9997, 0.9999 and 1.00; the same α value was used for all the classes. In each case 5 adjustment iterations were carried out. Table 3 lists the regression coefficients that result from the comparison of the observed vs. the simulated flows before and after the adjustments. The coefficients of the adjusted demand deviations are shown in Table 4. Figures 9 to 12 show the scattergrams comparing the observed versus the simulated flows obtained before and after the adjustments for the Auto class. The demand variations after the adjustment for the three values of α and the three classes of vehicles are presented in Figures 13 to 22.

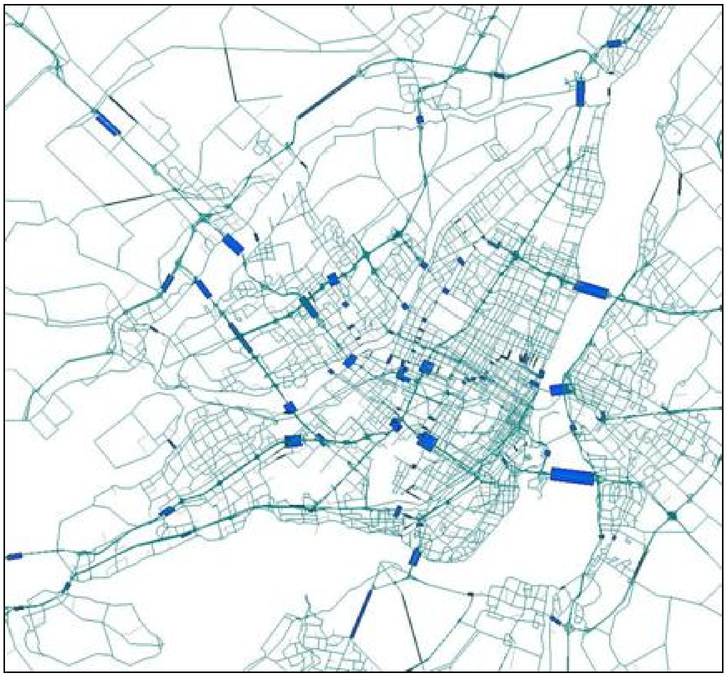

Figure 8. The Off day peak Montreal Network

Iterations	α	Class	Regression coefficients				Objective function
			A	B	R2	RSTD	
0		Auto	35.56	0.93	0.94	1 232.27	
		Regular truck	- 69.65	0.94	0.94	151.52	
		Heavy truck	- 7.23	0.96	0.96	80.81	
5	1.00	Auto	- 28.96	1.00	0.99	543.46	266 101
		Regular truck	- 55.41	0.98	0.96	131.71	
		Heavy truck	- 8.31	0.96	0.97	69.54	
5	0.9999	Auto	- 4.45	0.98	0.98	674.31	368 812
		Regular truck	- 67.88	1.01	0.95	144.21	
		Heavy truck	- 9.84	0.98	0.97	70.27	
5	0.9997	Auto	28.77	0.95	0.96	940.46	647 024
		Regular truck	- 78.69	1.01	0.95	145.74	
		Heavy truck	- 10.47	0.99	0.97	71.54	

Table 3. Montreal Off day peak; flows comparison regression coefficients

Iterations		Class	Regression Coefficients				Original	Adjusted
			A	B	R2	RSTD		
0		**Auto**					1 905 037	
		Regular truck					84 091	
		Heavy truck					42 157	
5	1.00	**Auto**	- 0.01	1.06	0.97	2.29		1 994 162
		Regular truck	- 0.00	1.16	0.93	0.51		95 252
		Heavy truck	- 0.00	1.04	0.95	0.20		42 860
5	0.9999	**Auto**	- 0.00	1.04	0.99	1.41		1 968 722
		Regular truck	- 0.00	1.13	0.97	0.32		93 144
		Heavy truck	- 0.00	1.05	0.96	0.17		43 050
5	0.9997	**Auto**	0.00	1.01	1.00	0.53		1 932 420
		Regular truck	- 0.00	1.08	0.99	0.18		89 904
		Heavy truck	- 0.00	1.03	0.99	0.10		42 702

Table 4. Montreal Off day peak; demand deviations regression coefficients

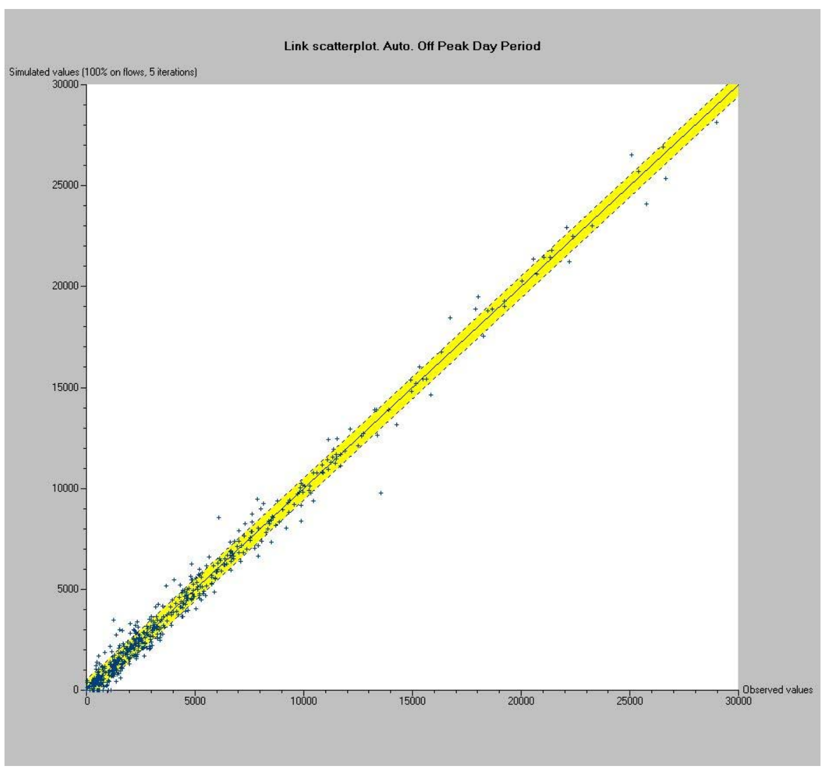

Figure 9. Montreal flows comparison; Auto; $\alpha = 1.00$

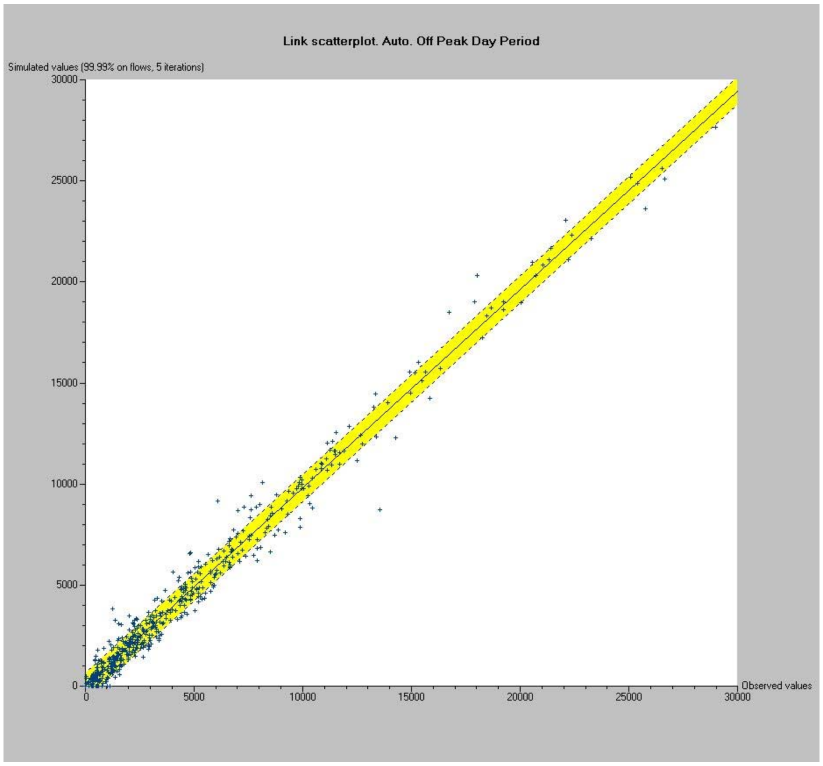

Figure 10. Montreal flows comparison; Auto; $\alpha = 0.9999$

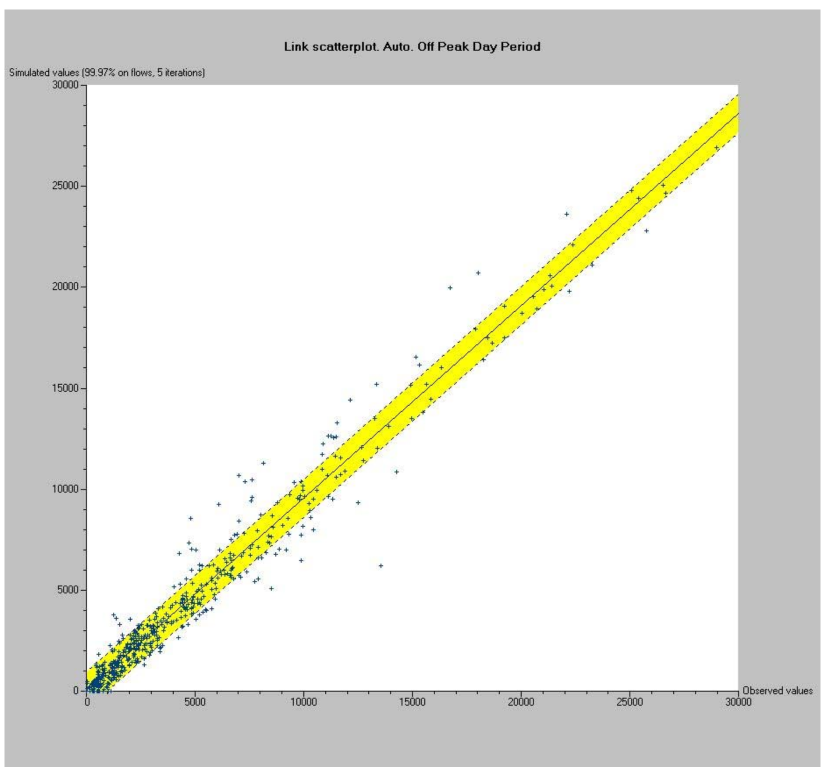

Figure 11. Montreal flows comparison; Auto; $\alpha = 0.9997$

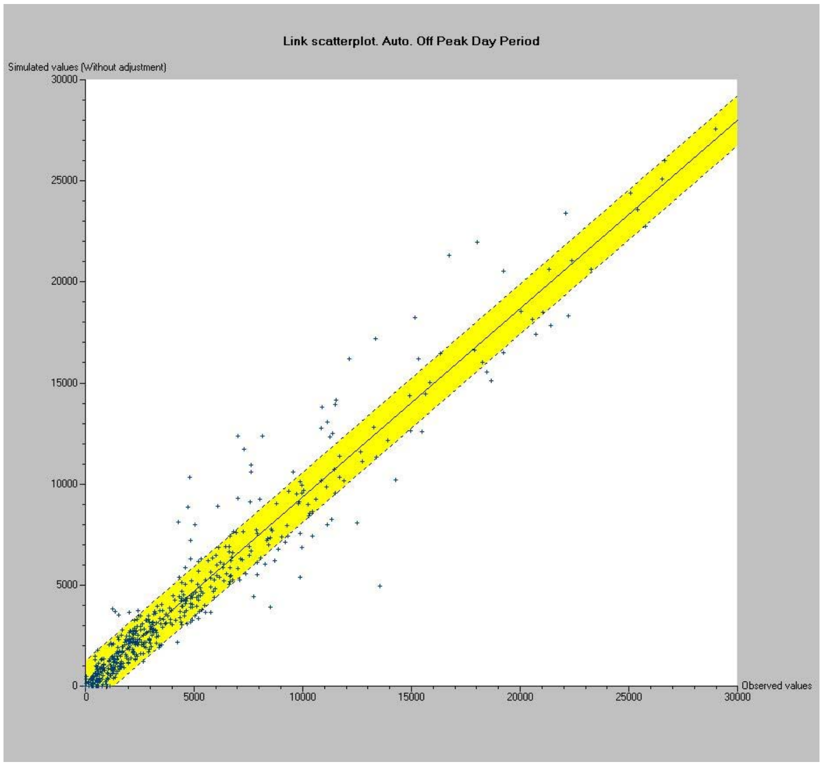

Figure 12. Montreal flows comparison; Auto; without adjustment

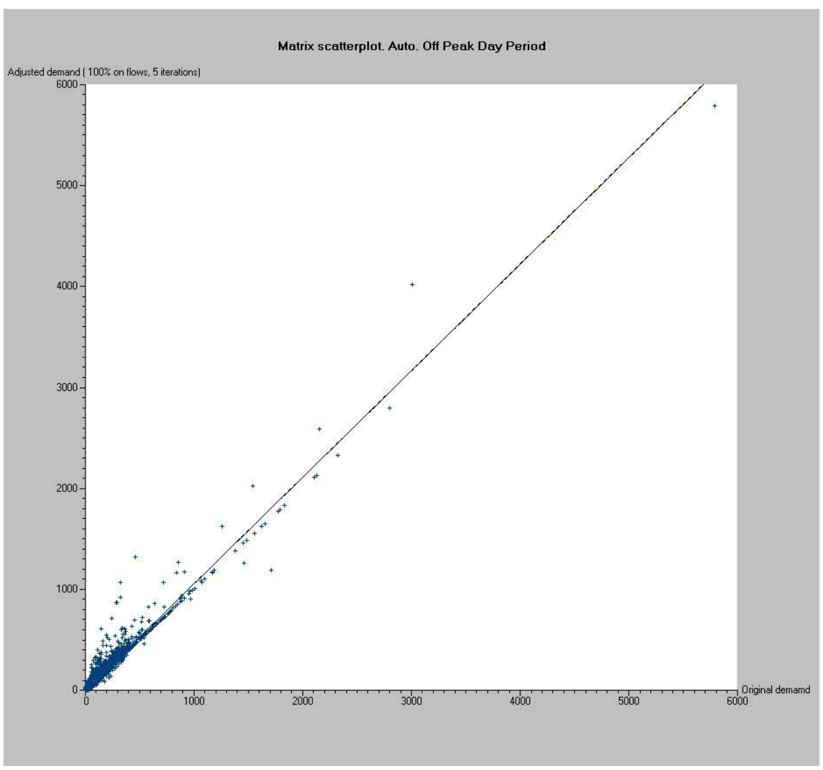

Figure 13. Montreal demand deviations; Auto; Off day peak; $\alpha = 1.00$

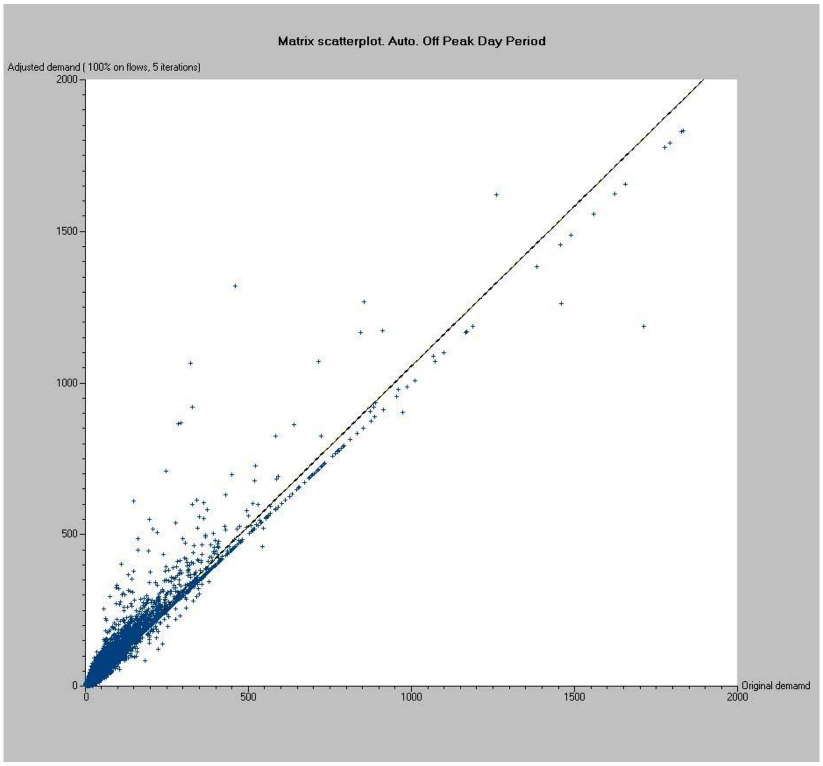

Figure 14. Montreal demand deviations; Auto; Off day peak; $\alpha = 1.00$**;**

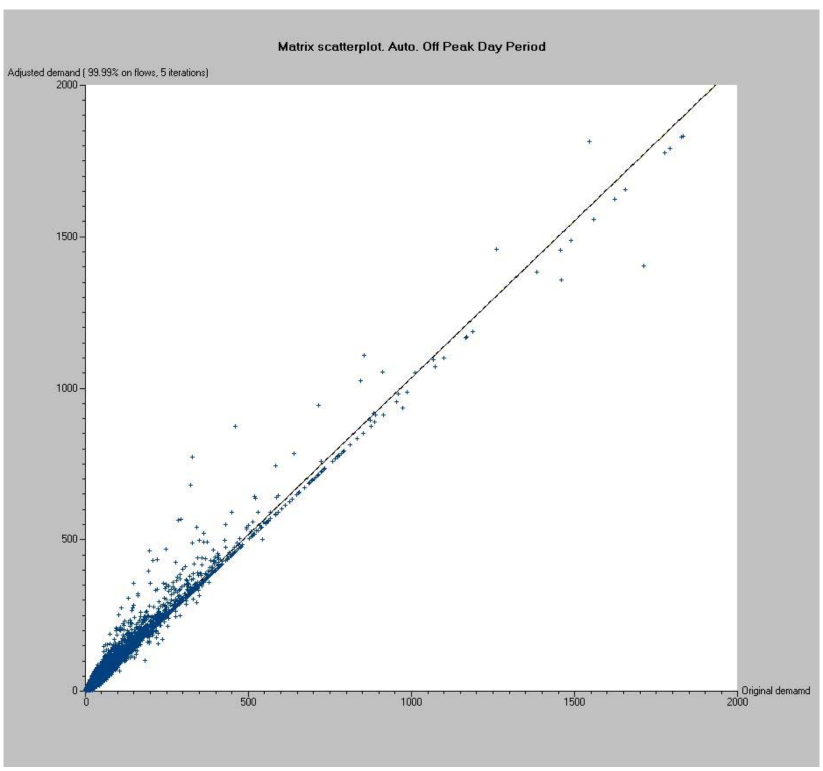

Figure 15. Montreal demand deviations; Auto; Off day peak; $\alpha = 0.9999$**;**

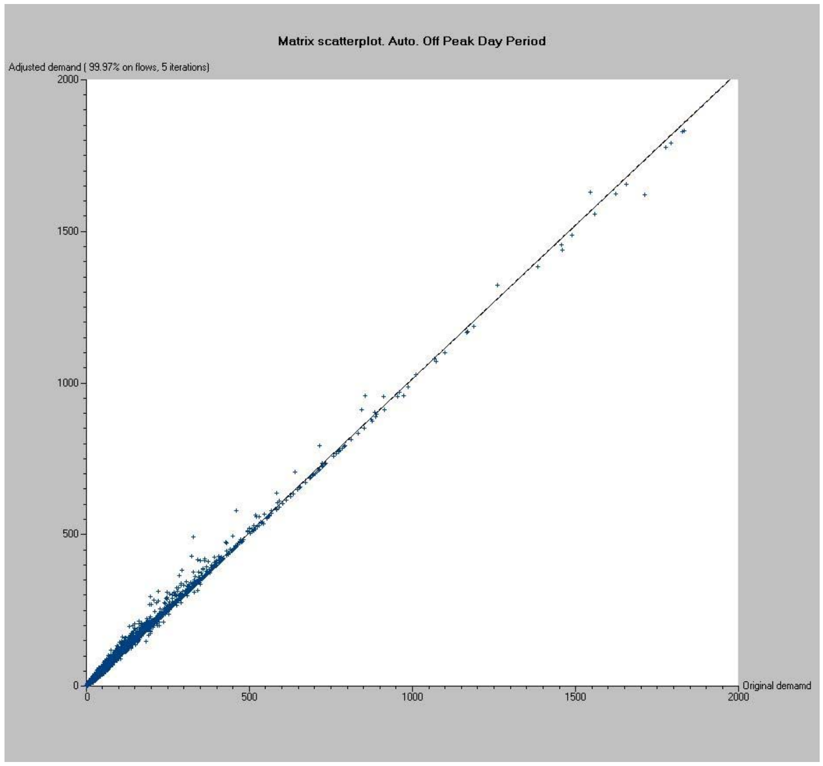

Figure 16. Montreal demand deviations; Auto; Off day peak; $\alpha = 0.9997$ **;**

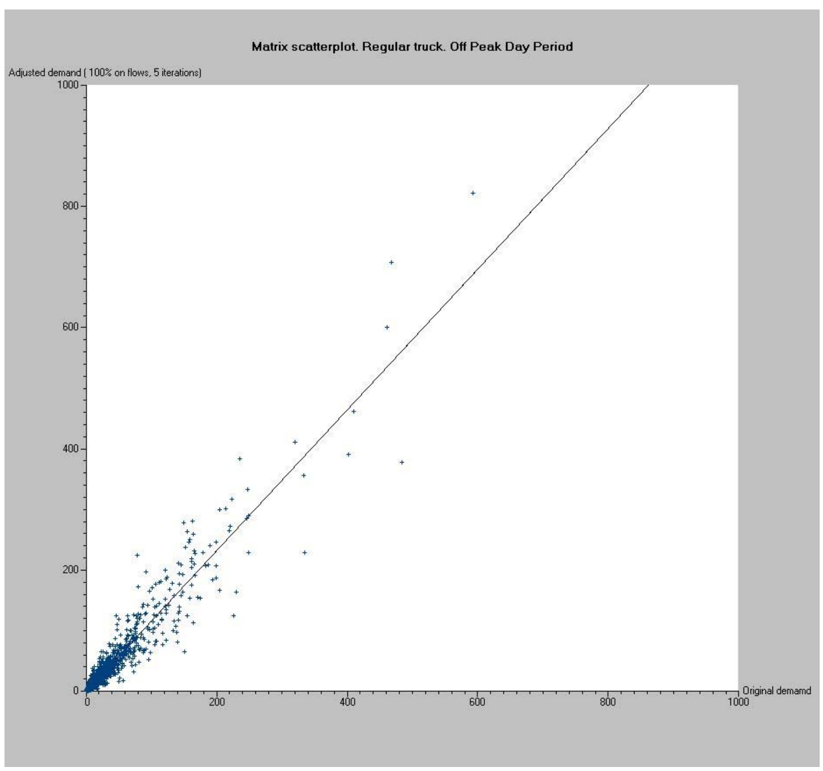

Figure 17. Montreal demand deviations; Regular truck; Off day peak; $\alpha = 1.00$

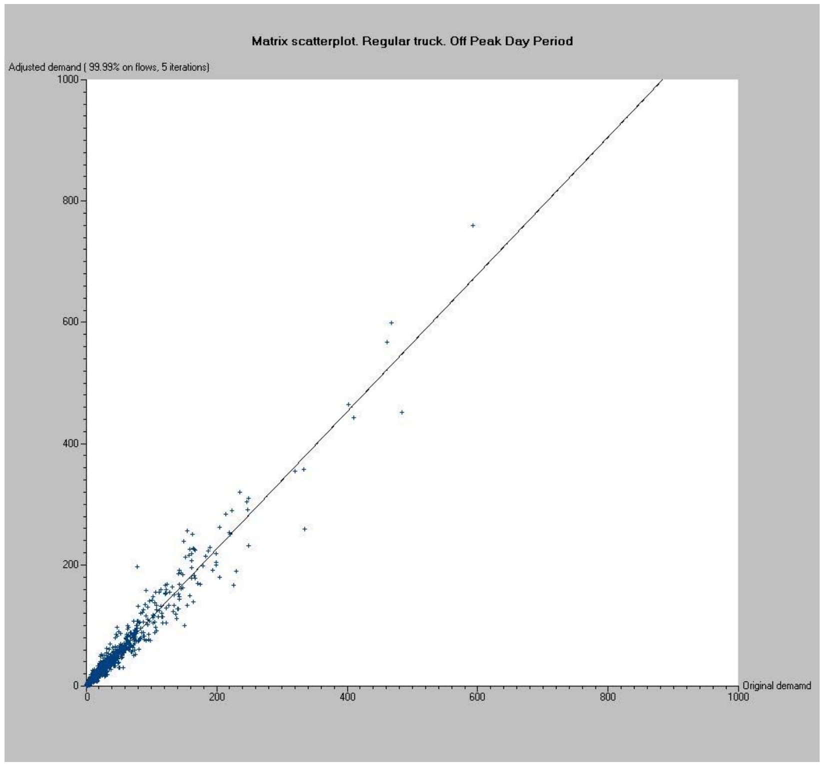

Figure 18. Montreal demand deviations; Regular truck; Off day peak; $\alpha = 0.9999$

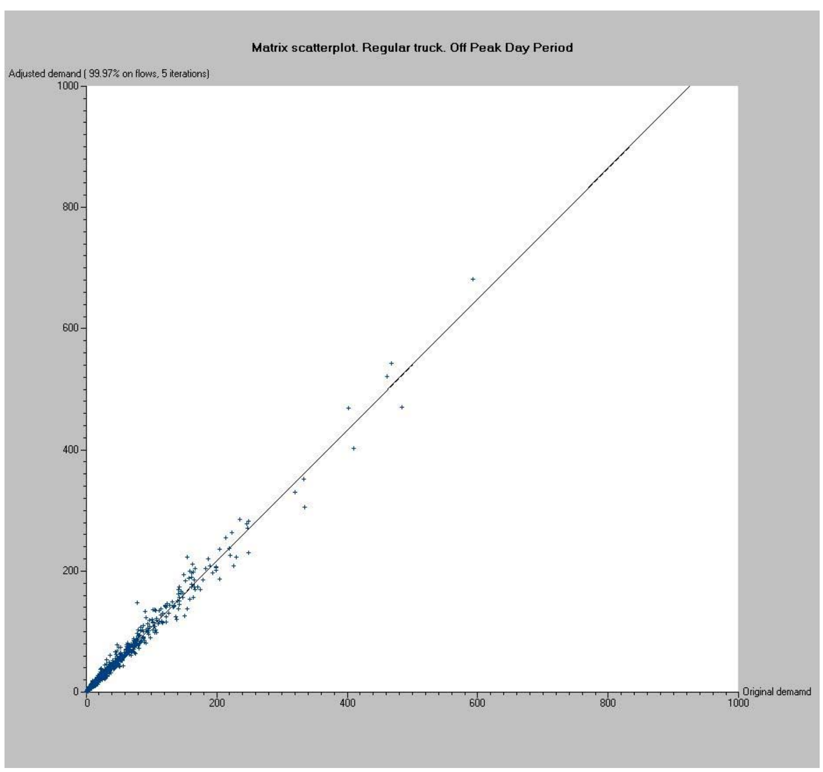

Figure 19. Montreal demand deviations; Regular truck; Off day peak; $\alpha = 0.9997$

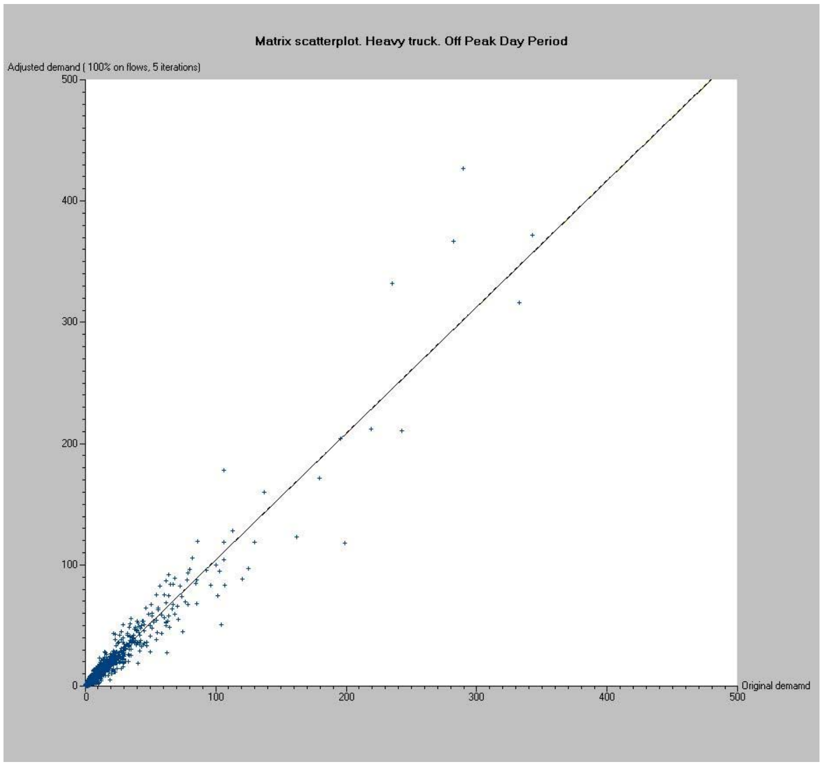

Figure 20. Montreal demand deviations; Heavy truck; Off day peak; $\alpha = 1.00$

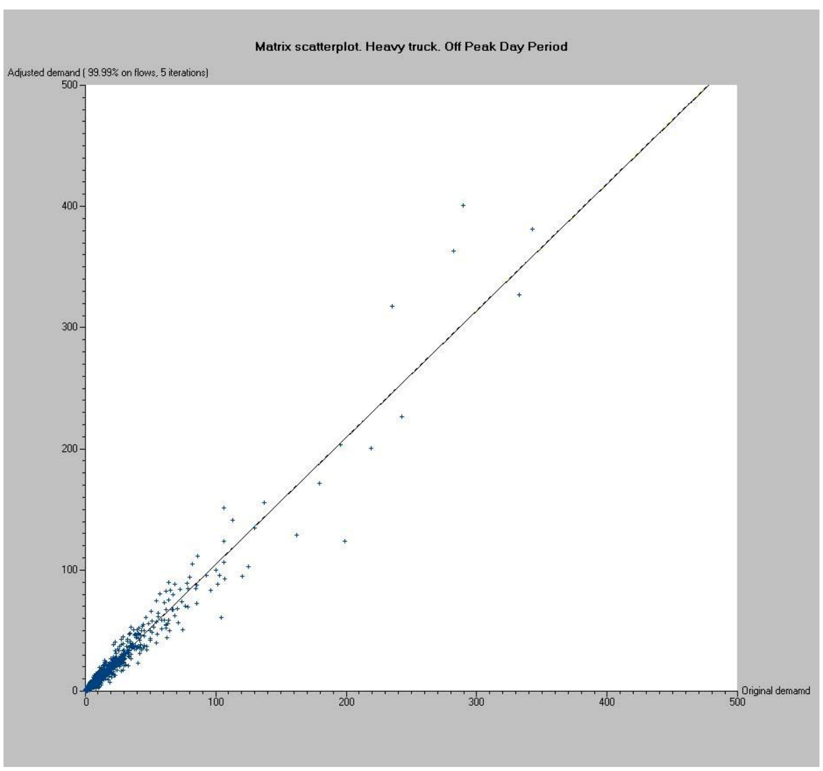

Figure 21. Montreal demand deviations; Heavy truck; Off day peak; $\alpha = 0.9999$

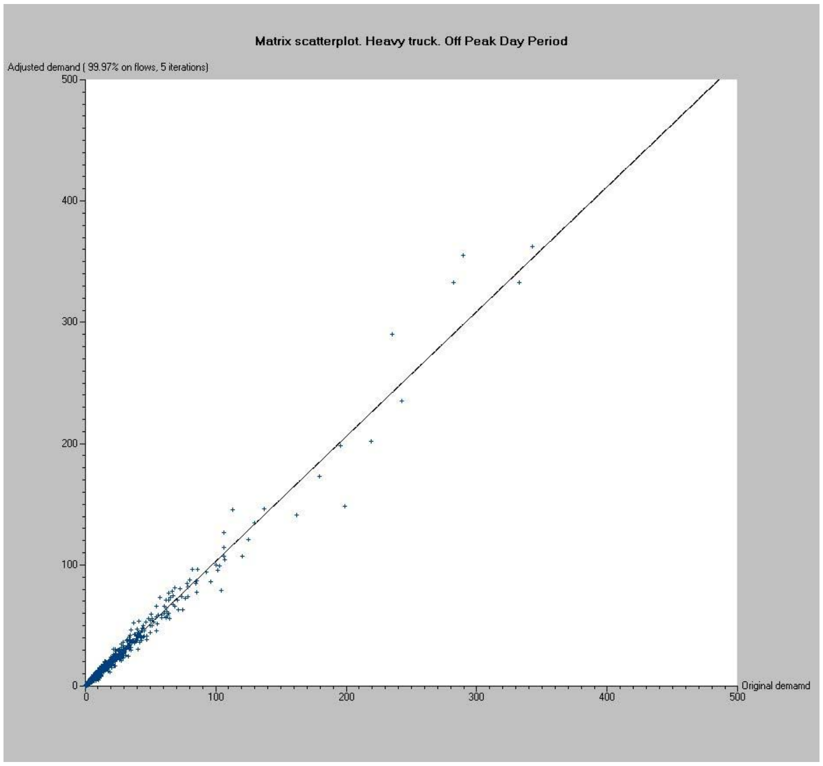

Figure 22. Montreal demand deviations; Heavy truck; Off day peak; $\alpha = 0.9997$

The choice of the α values, in the multi-class case, should be done carefully because all the classes share the facilities and variations in the demand of one class could affect the demand of the other classes. In this particular test main improvements were obtained for the classes Auto and Heavy truck.

Figures 14 to 22 show visibly the effect of including the demand term in the objective function for the multi-class case.

The computation time was near 2.25 hours for every 5 iterations adjustment. The tests were carried out on a laptop with 2 Intel ® Core (TM) CPU T7400 @ 2.16GHz, 2.00 Gb of RAM.

5. Conclusions

The development of a more general O-D adjustment model that considers both demand term differences and simultaneous multi-class adjustment is a new tool that is available for analyzing short term changes in demand based on current link flow counts. The numerical results obtained with the method show that it is both computationally feasible and useful.

Acknowledgements

This research was supported in part by an individual Operating Grant from NSERC. We would like to thank the "Service de la modélisation des systèmes de transport" of the Ministry of Transportation of Quebec for permission to use the Montreal region model (MOTREM) for this research.

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