15th Triennial World Congress, Barcelona, Spain

PERFORMANCE EVALUATION OF PREDICTIVE FEEDBACK ROUTING FOR FREEWAY NETWORKS

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Abstract: Available routing strategies for traffic networks may be classified as feedback and iterative strategies. Recently, a new predictive feedback strategy has been developed incorporating the advantages of both kinds of strategies and attenuating their disadvantages. The new strategy runs a mathematical model once at each time step and bases its feedback routing decisions on the predicted traffic conditions. Preliminary investigation indicated that very satisfactory routing results could be achieved by use of this strategy. In this paper, the performance of the new strategy is evaluated in more detail by comparison with the feedback and iterative strategies. *Copyright © 2002 IFAC*

Keywords: Transportation, network, routing algorithms, predictive feedback control.

1. INTRODUCTION

Traffic networks typically include various couples of network nodes each connected with multiple routes. Under **user equilibrium** conditions, all alternative routes for any node couple that are actually utilized should have **equal** travel times that are not greater than the travel times on non-utilized routes. User-equilibrium traffic conditions usually improve the network performance (although they are not explicitly aiming at system-optimum conditions) without disadvantaging a part of the driver population. For this reason, most modern route guidance systems aim at establishing user-equilibrium conditions within traffic networks (Papageorgiou, 1990).

Routing strategies may be distinguished into two classes:

- **Feedback strategies** may be employed to **approximate** dynamic user equilibrium in traffic networks. This is achieved via simple reaction to real-time traffic measurements with the aim of equalizing **instantaneous** (**reactive**) travel times along alternative utilized routes despite the impact of various disturbances including incidents, weather conditions, demands, OD rates, compliance rate, etc.
- **Iterative strategies** may be applied to establish **exact** dynamic user equilibrium in traffic network models. This is achieved by running the traffic network model repeatedly over a future time horizon, based on real-time measurements and disturbance prediction, in order to equalize **experienced** (**predictive**) travel times along alternative utilized routes.

Wang, *et al*., (2002) have recently developed a new **predictive feedback** routing strategy. The simulation results indicated that the new strategy incorporates the advantages and attenuates the disadvantages of both classes of routing strategies above. The new strategy is further investigated in this paper, and its performance is evaluated in more detail by comparison with feedback and iterative strategies.

2. THE ROUTE GUIDANCE PROBLEM

Route guidance here aims at establishing **dynamic user equilibrium** (**DUE**) in a traffic network by guiding vehicles among alternative routes over a given time horizon. The attribute *dynamic* emphasizes the fact that traffic demands, OD rates, traffic states, and travel times vary over time and space. This chapter briefly introduces the DUE condition, routing strategies, and corresponding notions. For more details, see Wang *et al*., (2001a, b).

Splitting rates play a crucial role in route guidance. With the aid of virtual nodes and dummy links (Papageorgiou, 1990), any bifurcation node in a network may be decomposed into several nodes so that each resulting bifurcation node has only one entering link and two leaving links (a primary and a secondary). Consider such a bifurcation node n and a destination j that may be reached via both leaving links of node n. There is exactly one splitting rate $\beta_{n,j}$ for such a **(n,j)-couple**, which determines the portion of j-bound traffic that leaves node n via its primary leaving link. For a couple (n, j), the directions to j via both leaving links of n are referred to as the primary and secondary directions.

The **compliance rate** $\varepsilon \in [0,1]$ reflects the conformity degree of drivers to route recommendations. The impact of partial compliance on route guidance may be modeled as

$$B_{n,j}(k) = \varepsilon\beta_{n,j}(k) + (1-\varepsilon)\beta^{N}_{n,j} \qquad (1)$$

where $k = 1, 2,...$ denotes the time instants, $\beta_{n,j}$ is the splitting rate ordered by the routing strategy, $\beta^{N}_{n,j}$ is the nominal splitting rate (in the absence of guidance), and $B_{n,j}$ is the real splitting rate. All these variables are real numbers within [0, 1].

Instantaneous (**reactive**) travel time along a route (including several links) is an ideal travel time spent by an ideal vehicle traveling along that route under the currently prevailing traffic conditions. **Experienced** (**predictive**) travel time along a route is the real travel time that vehicles will actually experience along the route. Let $\tau^{p}_{n,j}(k)$ and $\tau^{s}_{n,j}(k)$ be (instantaneous or experienced) **shortest** travel times along the primary and secondary directions of a couple (n, j), respectively. **Travel time difference** of a couple (n, j) is defined as $\Delta\tau_{n,j}(k) = \tau^{s}_{n,j}(k) - \tau^{p}_{n,j}(k)$.

The **dynamic user equilibrium condition** may be formulated as

$$\begin{aligned} \Delta\tau_{n,j}(k) &\geq 0 \quad \text{if} \quad \beta_{n,j}(k) = 1 \\ \Delta\tau_{n,j}(k) &= 0 \quad \text{if} \quad 0 < \beta_{n,j}(k) < 1 \\ \Delta\tau_{n,j}(k) &\leq 0 \quad \text{if} \quad \beta_{n,j}(k) = 0 \end{aligned} \qquad (2)$$

for all considered (n, j)-couples. When eq. (2) holds, travel times along both directions are equal if both directions are utilized, i.e. if $0 < \beta_{n,j}(k) < 1$. Thus the objective of routing strategies is to keep $\Delta\tau_{n,j}(k)$ close to zero so long as the splitting rate does not hit the bounds.

Splitting rates may be calculated by a variety of routing strategies. **Feedback** strategies attempt to keep the **instantaneous** travel time differences close to zero, while **iterative** strategies aim at equalizing the **experienced** (**predicted**) travel times along both directions of each considered (n, j)-couple. A **PI-controller** may be employed as a feedback strategy

$$\begin{aligned} \beta_{n,j}(k) = \beta_{n,j}(k-1) + K_p[\Delta\tau_{n,j}(k) - \Delta\tau_{n,j}(k-1)] \\ + K_i\Delta\tau_{n,j}(k) \end{aligned} \qquad (3)$$

where K_p and K_i are the proportional and integral gains, respectively; $\Delta\tau_{n,j}$ is the reactive travel time difference. **Iterative strategies** run a traffic network model over a future time horizon repeatedly. At each iteration, the splitting rate trajectory calculated in the last iteration is updated in a suitable way and then applied to the model to produce the experienced travel times of the current iteration, and so forth, until the DUE condition (2) is satisfied with sufficient accuracy. The $\beta_{n,j}(k)$ resulting from both strategies are truncated if they exceed the admissible region [0, 1]. A disbenefit criterion is used to assess the degree of approximation to the exact DUE over the whole time horizon. It reflects the total vehicle-hours wasted on time-longer directions due to non-DUE routing. If the total disbenefit value is zero, the DUE condition (2) is fully established.

3. PREDICTIVE FEEDBACK ROUTING CONTROL STRATEGY

The predictive feedback routing control structure is shown in Figure 1. The whole structure mainly includes the process under control (freeway network), two feedback controllers, and a predicting model (predictor). Without model mismatch (the predicting model matches exactly the freeway network dynamics and disturbance prediction is accurate), it is sufficient to employ only feedback controller 1 to achieve nearly perfect routing performance while feedback controller 2 is introduced in order to obtain more satisfactory routing performance in the case of model mismatch.

Modeling: The predictor may be based on a macroscopic freeway network traffic simulator such as METANET (Technical University of Crete and Messmer, 2000). In our simulation-based investigations, both the predictor and the freeway network are using the same simulation tool independently of each other. The input configuration of METANET comprises network characteristics, demands, OD rates, compliance rate, incidents, etc. Thus, the differences in the input configurations of both simulators may be used to emulate modeling and prediction inaccuracies.

Input and output of the predictor: The predictor is used for predicting the experienced travel times of vehicles leaving a bifurcation node n for a reachable destination j at each **predicting time step** (when the predictor is activated). To this end, the splitting rates calculated by feedback controller 1 at the last predicting time step are used as constant **inputs** to the predictor for a specified **prediction horizon**, which should be long enough for all vehicles mentioned above to reach their respective destinations. The resulting predictive travel time differences of all considered (n, j)-couples are the (only) **outputs** of the predictor.

Initialization of the predictor: When the predictor is activated, the (measured or estimated) density and space mean speed of each freeway segment are transferred to the predictor and used as initial state for the predictor-run of the current time step.

Disturbance prediction for the predictor: The disturbance prediction (demands, OD rates, compliance rate, etc) is updated each time the predictor is activated, and is used over the prediction horizon. In this sense, the predictive feedback controller works similarly to a rolling-horizon procedure with a single forward model-run replacing the multiple iterations of iterative methods.

Feedback controller 1: A static relationship is actually obtained by running the predictor in the way described above. With respect to such a static block, an I-regulator is sufficient and guarantees zero-offset in the output of the predictor, i.e.

$$\beta_{n,j}(k+1) = \beta_{n,j}(k) + K_i \Delta\hat{\tau}_{n,j}(k) \tag{4}$$

where $\Delta\hat{\tau}_{n,j}(k)$ are the predictive travel time differences from the predictor. If the model-match is perfect, $\beta_{n,j}(k)$ will quickly shift so as to equalize the predictive travel times along alternative routes or hit a bound.

Model mismatch and countermeasures: In the presence of model mismatch, the pursued system performance of the predictive feedback routing controller may not be guaranteed. Model mismatch may take place for the following reasons:

- Inaccurate model or parameter estimation
- Inaccurate disturbance predictions
- Inaccurate initial state
- Unpredictable traffic incidents.

In order to tackle the negative impact of model mismatch, an outer feedback loop (feedback controller 2) may be introduced. Then the splitting rates for the freeway network resulting from the overall feedback routing strategies are calculated as

$$\begin{aligned}\beta'_{n,j}(k+1) &= \beta_{n,j}(k+1) + \\ &K_p(\Delta\tau_{n,j}(k) - \Delta\tau_{n,j}(k-1)) + K'_i \Delta\tau_{n,j}(k)\end{aligned} \tag{5}$$

where $\beta'_{n,j}$ denotes the ordered input to the freeway network which differs from $\beta_{n,j}$, the ordered input to the predictor; $\Delta\tau_{n,j}$ represents the reactive travel time difference from the network; K_p and K'_i are the proportional and integral parameters of the PI feedback controller 2, respectively. In this paper, a PI-controller is considered in the outer feedback loop; but other types of controllers may also be employed. For more details on the predictive feedback routing strategy, see Wang, *et al*., (2002).

4. SIMULATION INVESTIGATIONS

4.1 Simulation setup

The test network is shown in Figure 2, where "N", "L", "O", and "D" represent nodes, links, origins, and destinations, respectively; the digit next to each link name is its length (in km). Two routes (directions) lead to destination D1 from bifurcation node N1. The primary route consists of the links L2, L4, and L6, while the secondary route consists of the links L3, L5, and L7. Only the route guidance for (N1, D1) is considered for this network.

A number of simulations have been conducted for this network by use of the PI, iterative, and predictive feedback (**PF**) strategies. For iterative and PF strategies, each simulation run has a total duration of 3 hours (7:00~10:00 AM) with traffic demands displayed in Figure 3, while for the PI-strategy each simulation run has a total duration of 7 hours (7:00 AM~2:00 PM) with the same traffic demands for the first three hours and with constant demands (same as the values at 10:00 AM) for the remaining time horizon. Two groups of traffic demand are considered for the simulations. "Demand 1" is utilized for all simulations except for the robustness test of the various strategies, where "demand 2" is considered (note that the demand at O3 is the same for both cases). Similarly, two groups of OD rates for (O1, D1), (O1, D2), and (O1, D3) are utilized. The first group ("OD 1") is (0.92, 0.04, 0.04), while the second group ("OD 2") is (0.6, 0.1, 0.3). The control interval is set equal to the simulation time step (10 s) and the compliance rate is set equal to 1, unless specifically mentioned. Note that the predicting time step for the PF-strategy always equals the control interval.

Five simulation scenarios are considered for the test network. (Demand 1, OD 1), (demand 2, OD 1), and (demand 1, OD 2) constitute **normal scenarios 1, 2, and 3**, respectively. Under normal scenario 1, the strategies are tested with respect to various control intervals and compliance rates, while under normal scenarios 2 and 3, the robustness of the strategies is tested with respect to demand and OD variations, respectively. An **incident scenario** is the same as normal scenario 1 except that an incident occurs at 7:50 AM in the middle of L6, and lasts 10 minutes. During the incident, the freeway capacity of L6 is reduced by 50%. A **hybrid scenario** is the same as the incident scenario except that the control interval is set equal to 150 s and 30% drivers are assumed to disregard the route guidance. Note that the predictor **always** runs under normal scenario 1, i.e. it has no direct information about the variation of OD rates or demands or compliance rate nor about the occurrence of incident.

All simulation results are shown in Figures 4~14, where predictive travel time differences are relative travel time differences $\Delta\tau_{n,j}(k)/\tau^{p}_{n,j}(k)$ of the freeway network. The corresponding disbenefit values (calculated from 7:00 to 10:00 AM for each strategy) are presented in Table 1. Note that the iterative strategy is applied in an open-loop manner (no rolling-horizon procedure is employed).

4.2 Simulation results

Unless specifically mentioned, the simulation results for the PF-strategy are obtained without outer feedback loop. Figure 4 shows that under the normal scenario 1 the trajectories of splitting rates and predictive travel time differences resulting from the PF-strategy nearly **coincide with** those of the open-loop iterative strategy. They both **nearly perfectly** establish the DUE condition over the simulation horizon. Comparatively, the PI-controller **approximately** establishes the DUE condition over the same time horizon. The simulation results under the incident scenario are displayed in Figure 5. The iterative strategy exactly establishes the DUE condition in this case (assuming anticipated knowledge of the incident occurrence to obtain perfect reference routing), while the performance of PF-strategy degrades only slightly during the incident. On the other hand, the routing performance of the PI-controller deteriorates as compared to normal scenario 1. Figures 6 and 7 compare the routing performance of the PI and PF strategies with respect to various control intervals. Note that longer control intervals may even slightly improve the performance of the PI-strategy while the PF-strategy is little sensitive to the control intervals so long as a perfect predicting model is employed. Some simulations are also conducted to investigate the impact of partial compliance on the routing results. It is demonstrated that the PI-strategy is not sensitive to the partial compliance (Figure 8), while the open-loop iterative strategy fails due to the model-mismatch (Figure 9). For the PF strategy, three cases are considered to test the impact of partial compliance. The real compliance rate in the network is set 0.5, while the predictor assumes; first, full compliance ($\hat{\varepsilon}=1$); second, an inaccurate compliance prediction ($\hat{\varepsilon}=0.7$); third, full compliance but an outer feedback loop is added to the control structure according to Figure 1. As shown in Figure 10, a rough compliance prediction greatly improves the routing performance as compared to the no-prediction case ($\hat{\varepsilon}=1$), but an additional outer feedback loop can further reduce the influence of the partial compliance even without prediction. The robustness of the various strategies is also investigated under scenarios 2 and 3. Figure 11 shows that the PI-strategy is little sensitive to the OD and demand variations, while the open-loop iterative strategy is strongly sensitive to the same disturbances (Figure 12). It is illustrated in Figure 13 that the PF-strategy is hardly sensitive to the same disturbances. Finally, figure 14 compares the performances of the PI and PF strategies under the hybrid scenario.

The disbenefit values in Table 1 are consistent with the simulation results shown in the above figures. For example, the three disbenefit values (up to down) for the PF-strategy under scenario 1 with $\varepsilon=0.5$ correspond to the three cases mentioned above. Note that with rough compliance predictions, the routing performance is worse than that of PI-strategy. Similarly, the introduction of the outer feedback loop improves the routing performance with respect to the OD variation. These results indicate that the outer feedback loop is valuable for the PF strategy to deal with unpredicted external disturbances effectively.

5. CONCLUSIONS

A predictive feedback routing strategy for freeway networks is compared with the feedback and iterative routing strategies. The simulation investigations provide evidence for the following statements:

- The predictive feedback strategy works nearly as perfectly as the iterative strategy in establishing the predictive DUE condition in the case of perfect model match.
- The predictive feedback strategy considers the real-time information (transfer of the network state to the predictor) and works efficiently with moderate computational effort even for a network with long links.
- Hence, the predictive feedback strategy works in a rolling-horizon-like manner, but no optimization problem needs to be solved in real-time.
- With the aid of an additional outer-feedback loop, the negative impact of the model mismatch can be efficiently rejected.

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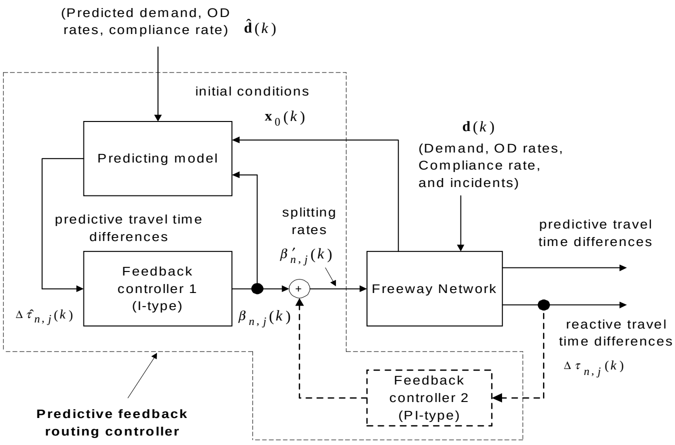

Figure 1 Predictive feedback routing control structure.

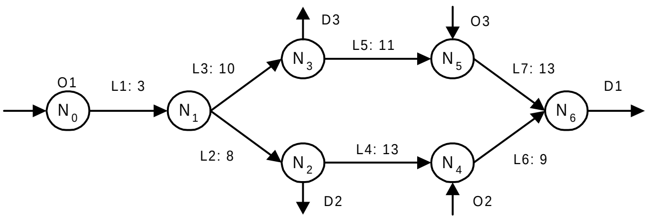

Figure 2 Test network.

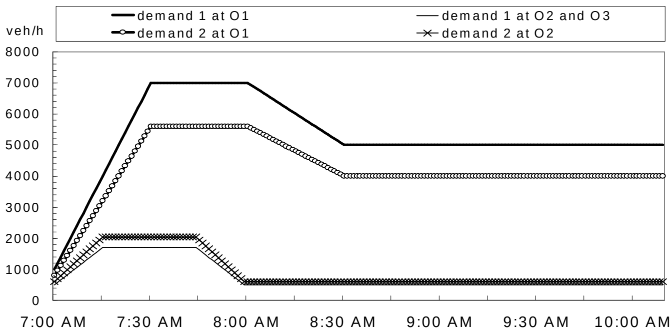

Figure 3 Demands for test network.

Table 1 Disbenefit values for various strategies.

<table>
<tr><th colspan="3"></th><th>PI</th><th>PF</th><th>Iterative</th></tr>
<tr><td rowspan="10">Normal scenarios</td><td colspan="2">normal case</td><td>72.6</td><td>1.1</td><td>0.1</td></tr>
<tr><td rowspan="3">control intervals</td><td>60 s</td><td>56.8</td><td>3.4</td><td rowspan="3">⁄</td></tr>
<tr><td>150 s</td><td>56.5</td><td>4.6</td></tr>
<tr><td>300 s</td><td>66.5</td><td>15.9</td></tr>
<tr><td colspan="2" rowspan="3">half compliance</td><td rowspan="3">58.6</td><td>311.2</td><td rowspan="3">2999</td></tr>
<tr><td>85.9</td></tr>
<tr><td>25.9</td></tr>
<tr><td colspan="2" rowspan="2">OD variation</td><td rowspan="2">24.4</td><td>38.41</td><td rowspan="2">171.6</td></tr>
<tr><td>16.7</td></tr>
<tr><td colspan="2">demand variation</td><td>121.1</td><td>9.1</td><td>60.2</td></tr>
<tr><td colspan="3">Incident scenario</td><td>258.5</td><td>105</td><td>0.6</td></tr>
<tr><td colspan="3">Hybrid scenario</td><td>373.5</td><td>61.9</td><td>⁄</td></tr>
</table>

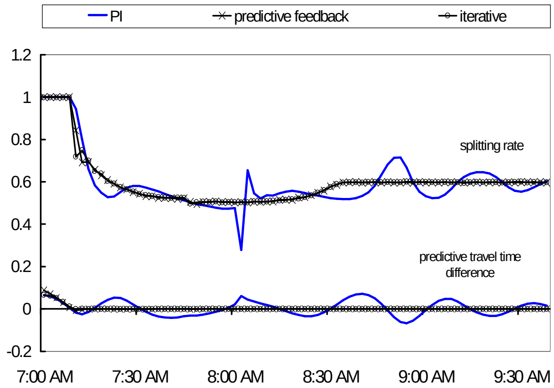

Figure 4 Routing results under normal scenario.

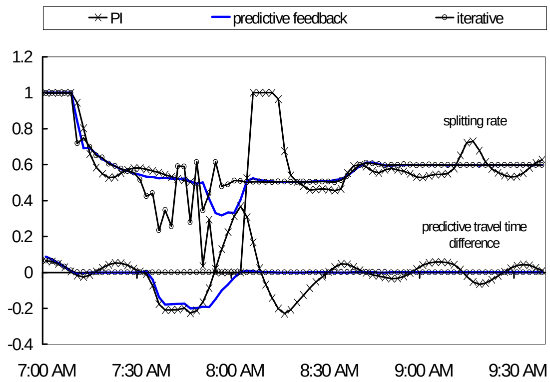

Figure 5 Routing results under incident scenario.

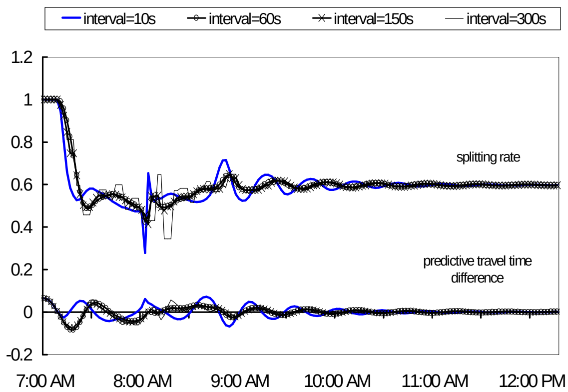

Figure 6 PI-controller under normal scenario: control intervals.

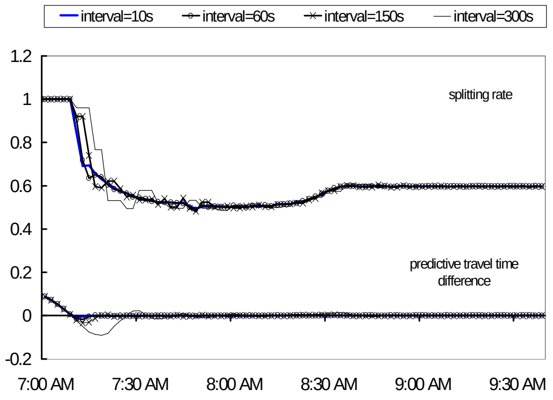

Figure 7 PF-controller under normal scenario: control intervals.

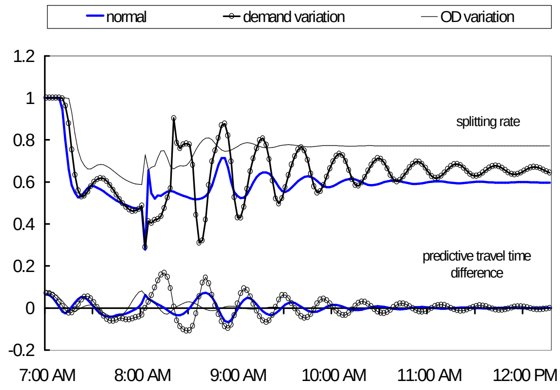

Figure 11 PI-strategy under normal scenario: robustness.

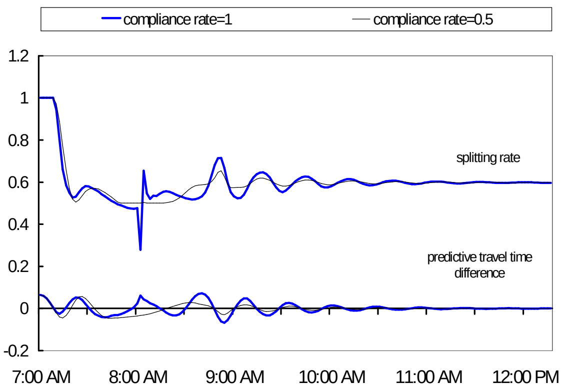

Figure 8 PI-strategy under normal scenario: compliance rates.

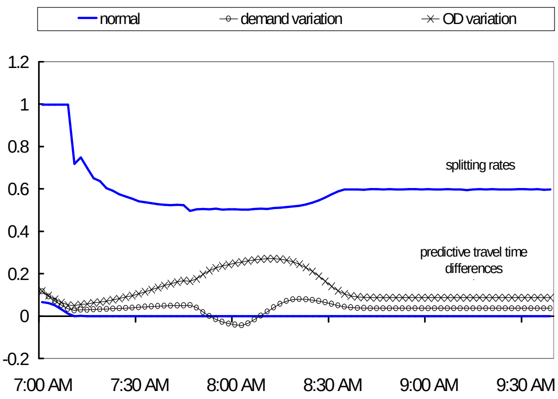

Figure 12 Iterative strategy under normal scenario: robustness.

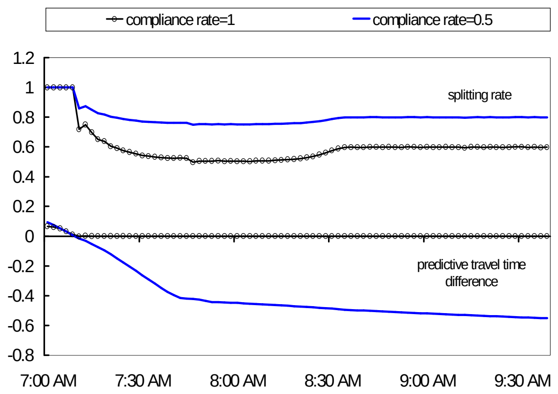

Figure 9 Iterative strategy under normal scenario: compliance rates.

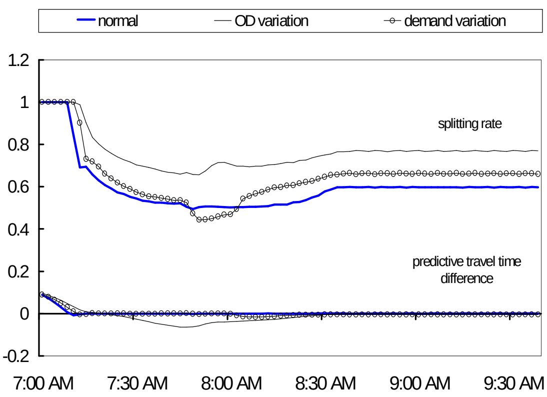

Figure 13 PF-strategy under normal scenario: robustness.

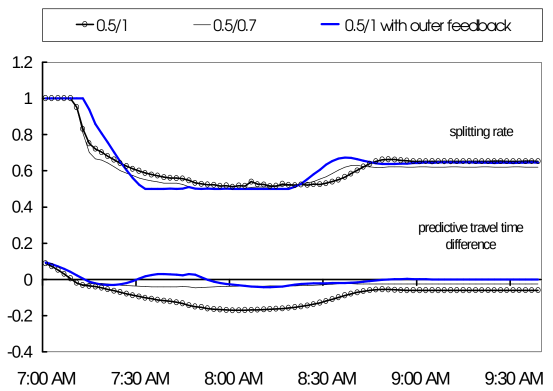

Figure 10 PF-strategy under normal scenario: compliance rates.

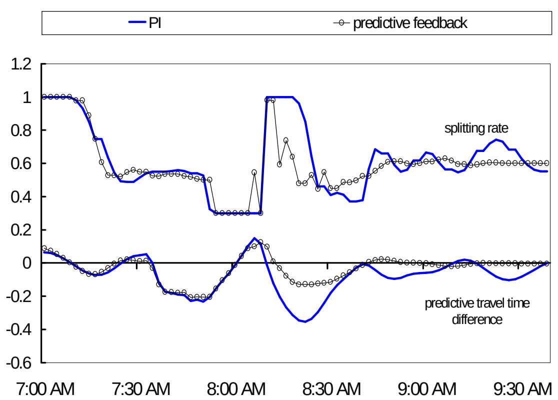

Figure 14 Routing results under hybrid scenario.