tion of the task, together with the appropriate schedule and cost status.

VII. Freedom Within a System

No one can deny the evil of tyranny, and people will not easily cede their identity to true self at the threat of a dictatorship. "I'll have no part in it" is a valid response when 'it' is manifestly unwholesome. On the other hand, the belongingness of man to mankind could not have been more powerfully or eloquently expressed than by the words of John Donne:

> "No man is an island, entire of itself; every man is a piece of the Continent, a part of the main; if a clod be washed away by the sea, Europe is the less, as well as if a promontory were, as well as if a manor of thy friends or of thine own were; any man's death diminishes me, because I am involved in Mankind; And therefore never send to know for whom the bell tolls; it tolls for thee."

The responsibility of designers (technological or social) must be to ensure a *wholeness of design* to the extent that the objects they wish assembled (human or otherwise) will yield a compliance born of an affinity for the whole to be created; attracted to the whole's emergence, and confident of the essential nature of component contribution to that emergence. The part can then be free—to be a part in the whole; it is then that the part is a whole itself.

The Christian message defines a freedom, that is rich in mystery, yet must be accepted by childlike faith. Among the words of Jesus Christ are these:

> *"If you hold to my teaching, you are really my disciples. Then you will know the truth and the truth will set you free. So if the Son sets you free, you will be free indeed".*
>
> The Bible, John 8.32, 36.

It seems then, to be free we have to hold on—to something worthwhile; to belong—to a whole. For each one of us, whose very hairs on our head are numbered, our aim should be to search out that whole to which we can rightly belong, play the part, and find our freedom.

> *"Our little systems have their day;*
> *They have their day and cease to be:*
> *They are but broken lights of thee,*
> *And thou, O Lord, art more than they"*
> Alfred, Lord Tennyson

References

[1] I. M. Beeton (né), *The Book of Household Management*, 1861.
[2] J. T. Boardman and A. J. Cole, "Developing a framework for concurrency by capturing systems engineering rationale using a process modeling methodology," *Proc. AIAA Conf.* 'Aerospace 9', San Diego, CA, 1993.
[3] P. B. Checkland, *Systems Thinking, Systems Practice*. New York: John Wiley, 1981.
[4] C. W. Churchman, *The Systems Approach*. New York: Dell, 1968.
[5] J. Donne, *Devotions upon Emergent Occasions 'Meditation XVII'*, 1624.
[6] F. Jacob, *The Logic of Living Systems*. London: Allen Lane, 1974.
[7] J. R. Galbraith, *Organization Design*. New York: Addison-Wesley, 1977.
[8] A. Pope, *An Essay on Man*, Epistle 1, 1733.
[9] A. Tennyson, *In Memoriam A.H.H.*, 1850.

Optimization of Traffic Dynamic Route Guidance With Drivers' Reactions in a Queue-Based Model

Jacques Weymann, Jean-Loup Farges, and Jean-Jacques Henry

***Abstract*—This correspondence presents an optimal guidance algorithm which takes into account the driver's compliance to route advice. The optimal control consists of minimizing the travel time of guided vehicles using a queue-based model. The optimization is based on the use of Forward Dynamic Programming and decomposition-coordination methods. Driver's compliance is modeled by a linear function of the guidance advice (control). An assessment of the criteria degradation induced by nonperfect compliance is performed. Results show that this degradation of the criteria is low in fluid traffic conditions but high in congested situations. Thus human factors cannot be neglected in route guidance systems.**

I. Introduction

In industrial guidance systems, route guidance for urban traffic is performed by computing quickest paths on a graph whose link weights are the forecast travel times. These times are updated at each sampling period, see Catling *et al.* [1], Henry *et al.* [2], Hoffman [3], and Von Tomkewitsch [4]. During a sampling time which is typically five minutes, this guidance strategy consists of sending all vehicles equipped with a guidance system and going to the same destination on the same route. Hounsell has shown, with simulation results, that this approach is efficient for few equipped vehicles, but not with a large number of equipped vehicles [5]. Indeed, when the proportion of equipped vehicles increases, this method leads to negative journey time savings for guided vehicles. Consequently, if a large proportion of vehicles is guided, in order to maintain the benefits of route guidance, the relation between guidance advice and future travel times should not be neglected in the route computation algorithms. In addition, during a sampling period, the guidance system should be able to split the demand of a given origin-destination couple into various paths.

The beneficial effects of route guidance can be obtained by solving an optimal control problem. For example, Papageorgiou [6] proposed a state model based on a flow concentration relationship and on composition and splitting rates for each traffic subflow with a specific destination. The optimal control problem is solved by a numerical method, based on the discrete maximum principle. Another optimal control approach integrating those features in a queue-based model was proposed by Charbonnier, [7] and [8]. Those algorithms make the assumption that drivers obey route guidance perfectly. However, precise studies on drivers' disobedience are available and show that drivers do not always follow route advice.

This contribution presents an optimization procedure for a given urban network when drivers disobey route advice. Compliance relationships are consequently integrated in the algorithm proposed by Charbonnier. In the next section, the modified traffic model

Manuscript received July 14, 1993; revised April 1, 1994, and August 20, 1994.

The authors are with the CERT-ONERA Institute Centre d'Etude et de Recherche de Toulouse, Départment d'Etudes et de Recherche en Automatique, Office des Etudes et Recherches Aérospatiales, 31055 Toulouse Cédex, France.

IEEE Log Number 9410818.

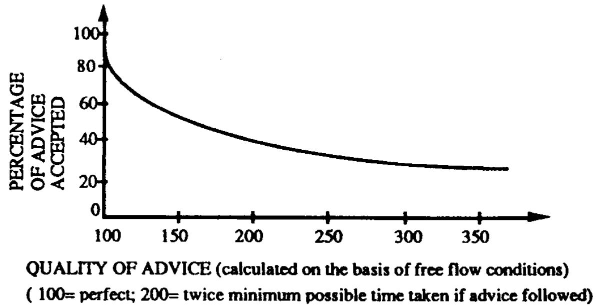

Fig. 1. Acceptance of advice as a function of the quality of advice, from Bonsall *et al.* [9].

is presented. The second section is devoted to the optimization algorithm. The last section presents some numerical results obtained with the new algorithm.

II. Traffic Model

A. Modeling of the Driver's Compliance

The traffic network is modeled by an oriented graph composed of N nodes and L links. The guided vehicles are controlled at each choice node, a choice node being composed of two downstream links, the first choice link $I(n)$ and the second choice link $J(n)$. Without loss of generality, the quickest route at free speed from node n to the destination passes through the link $I(n)$. The control u^d_{nk} is defined as the ratio of guided vehicles sent on the second choice link at sampling time k, node n, and for a destination d. Consequently controls follow the two constraints

$$0 \leq u^d_{nk} \leq 1. \tag{1}$$

The controls u^d_{nk} will differ from the actual proportions e^d_{nk} of drivers which go to the second choice link due to disobedience of drivers. Indeed, previous work has gathered quantitative evidence on compliance with different types and qualities of guidance using route choice simulator [9]–[11]. Bonsall, Pickup and Stathopoulos, [9], have found quantitative results on drivers' disobedience. In this survey, participants play the role of drivers and make journeys through hypothetical networks given by the computer by progressing from one junction to the next. The guidance is given by the computer and the participant is free to accept or reject the guidance advice. For a driver who is at a given node n of a urban network, results show that the driver's obedience depends on free speed travel times of the paths from node n to the driver's desired destination. Precisely, the compliance decreases when the difference between the proposed and the optimal route in terms of free speed travel time increases (see Fig. 1).

The actual proportions of drivers on the second choice link are obtained by adding proportions of drivers who obey to go to the second choice link plus drivers who disobey to go to the first choice link

$$e^d_{nk} = \left(\eta^d_{I(n)} + \eta^d_{J(n)} - 1\right) u^d_{nk} + 1 - \eta^d_{I(n)} \tag{2}$$

where $\eta^d_{I(n)}$(resp. $\eta^d_{J(n)}$) is the compliance read on the graph of Fig. 1, corresponding to the abscissa which is the ratio of the shortest route to the destination d including $I(n)$ (resp. $J(n)$) on the shortest route to the destination d.

B. Queue-Based Model

The traffic behavior is modeled using a discrete state representation: (1) the state variables are the average numbers of vehicles guided to each destination d (x^d_{lk}) and of non guided vehicles (y_{lk}) present on each link l at each sampling time k; (2) the uncontrolled inputs are, for each link, the generation of unguided vehicles (E_{lk}) and the generation of vehicles guided to each destination d (D^d_{lk}); (3) the time varying parameters are, for each link, the throughput capacity (c_{lk}) and the percentages of non guided vehicles going to the first choice (p_{lk}) and to the second choice (q_{lk}) links. The sum of the variables q_{lk} and p_{lk} is less or equal to one.

The model requires a sampling time superior to the greatest free speed travel time of the network links in such a way that, when the network is not congested, each link is travelled in less than a sampling time. We note τ_l the ratio of the free speed travel time on the sampling time for each link l. The progression of vehicles in the network is based on a vertical queues model: a vehicle travels each link at free speed and packs into a vertical queue. The state equations are obtained by integrating the difference between arrivals and outputs for each kind of vehicle.

$$x^d_{lk+1} = x^d_{lk} + a^d_{lk} - b^d_{lk} \tag{3}$$

$$y_{lk+1} = y_{lk} + \alpha_{lk} - \beta_{lk} \tag{4}$$

where a^d_{lk} (respectively α_{lk}) is the number of vehicles guided to the destination d (respectively non guided) entering the link l during the period k. In the same way, b^d_{lk} (respectively β_{lk}) is the number of vehicles guided to d (respectively non guided) leaving the link l during the period k. a^d_{lk} and α_{lk} can be expressed as a function of: (1) the vehicles leaving the upstream links of the link l during the period k multiplied by the percentage of vehicles taking the link l, and (2) the vehicles generated on the link l during the period k.

Then, if l is the second choice link

$$a^d_{lk} = \left(\sum_{j \in \mathrm{Up}(l)} b^d_{jk}\right) e^d_{nk} + D^d_{lk} \tag{5}$$

$$\alpha_{lk} = \left(\sum_{j \in \mathrm{Up}(l)} \beta_{jk} q_{jk}\right) + E_{lk} \tag{6}$$

and if l is the first choice link

$$a^d_{lk} = \left(\sum_{j \in \mathrm{Up}(l)} b^d_{jk}\right) (1 - e^d_{nk}) + D^d_{lk} \tag{7}$$

$$\alpha_{lk} = \left(\sum_{j \in \mathrm{Up}(l)} \beta_{jk} p_{jk}\right) + E_{lk}. \tag{8}$$

$\mathrm{Up}(l)$ is the set of upstream links of the link l and n is the upstream node of link l.

The relation giving the arrivals of guided vehicles is valid only when link l is not the destination link d. Otherwise, a^d_{lk} variables are equal to zero. On the other hand, if B_{lk} is the total number of vehicles (guided and unguided) leaving the link l at the period k, this number must be lower than the throughput capacity of the link l, and lower than the total number of vehicles present in the queue of the link l during the period k

$$B_{lk} = \mathrm{Min}\left(c_{lk}, \sum_d x_{lk}^d + y_{lk} + (1-\tau_l)\left(\sum_d a_{lk}^d + \alpha_{lk}\right)\right). \quad (9)$$

Then assuming that the distribution of guided and unguided vehicles in a link is homogeneous, the two following expressions can be written:

$$b_{lk}^d = \frac{x_{lk}^d + (1-\tau_l)a_{lk}^d}{\sum_d x_{lk}^d + y_{lk} + (1-\tau_l)(\sum_d a_{lk}^d + \alpha_{lk})} B_{lk} \quad (10)$$

$$\beta_{lk} = \frac{y_{lk} + (1-\tau_l)\alpha_{lk}}{\sum_d x_{lk}^d + y_{lk} + (1-\tau_l)(\sum_d a_{lk}^d + \alpha_{lk})} B_{lk}. \quad (11)$$

It is important to note that in the general case, because of the expression of a_{lk} and b_{lk}^d (respectively α_{lk} and β_{lk}), the state equations obtained are implicit and a method like the "fixed point method" is necessary to integrate the state equations. In the case discussed in this paper, the network is an acyclic directed graph and does not require fixed-point iterations.

The objective is to optimize the total presence time of guided vehicles in the network for a given horizon H. It can be written as

$$R = \sum_{k=1}^{k=H} \sum_{l=1}^{L} \sum_d x_{lk+1}^d. \quad (12)$$

The optimization problem is formulated as an optimal control problem whose criterion is to minimize (12) and whose state equations are (2)–(11). Constraints on controls are defined by (1).

III. Optimization

For perfect compliance, the optimal control has already been determined for a network which have one origin-destination and two paths to reach the destination and no unguided vehicles. It has been shown that the optimal control can take only four values, see Charbonnier [8], which lead to four strategies

- Sending all vehicles on the first choice link
- Sending all vehicles on the second choice link
- Spliting the demand in order to lead the first choice link to the limit of saturation
- Spliting the demand in order to lead the second choice link to the limit of saturation.

Those four values were analytically determined by propagating properties of the optimal cost-to-go of backward dynamic programming. It has also been demonstrated that, in presence of unguided vehicles, those four values were optimal for the one sampling time horizon. Furthermore, numerical experiments on a set of problems, with a twelve sampling period horizon and presence of unguided vehicles, have shown that the resolution of the optimization problem with only those four optimal values gives better results than an optimization which uses 10 values equidistant from each other between 0 and 1.

The optimization is performed by a Forward Dynamic Programming algorithm, see Larson [12] and [13], and using those four optimal values. Taking into account the compliance of drivers, the optimal controls take also only four values. The two values corresponding to send all vehicles on one link are the same as with perfect compliance. The two other values are calculated in order to lead the limit of the saturation of the first choice link and the second choice link. The optimal values are known without driver's disobedience, consequently, with driver's disobedience, the optimal values are determined through the inverse of (2).

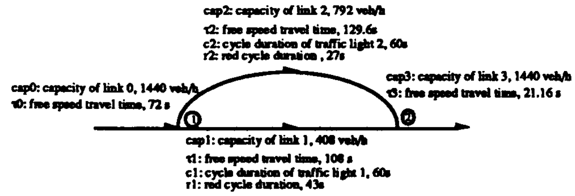

Fig. 2. Network.

As for the model with perfect compliance, the optimization is performed by Forward Dynamic Programming. The method is based on the principle of optimality which may be conceptualized as follows: in the state space, any portion of the optimal trajectory is optimal. So, starting from the initial state and building the tree of decisions, when a state is reached by two different trajectories, only the trajectory associated with the minimum cost has to be stored. This trajectory elimination can be performed by computing the optimal cost $R_i(X_i)$ at a given state X_i at a time step i. Denoting by $U(X_i)$ the set of admissible controls, and F the state equations, the forward optimal cost equation is given by

$$R_{i+1}(X_{i+1}) = \underset{\substack{U_i, X_i \mid F_i(U_i, X_i) = X_{i+1} \\ U_i \in U(X_i)}}{\mathrm{Min}} \{r_i(X_i, U_i) + R_i(X_i)\} \quad (13)$$

with $R_1(X_1) = 0$. Note that the optimal cost $R(.)$ is only defined for reachable states. Usually the equation is solved numerically by computing the cost on state grid points, using the "inverse" of state equation and extrapolating cost between grid points. Here, the approach involves partitioning the state space into non overlapping subsets and assuming that the minimization can be performed over all the states of the subset. If S_i is the subset associated with the state $X_i(S_i)$, the optimal cost equation is

$$R_{i+1}(S_{i+1}) = \underset{\substack{U_i, S_i \mid F_i(U_i, X_i(S_i)) \in S_{i+1} \\ U_i \in U(X_i(S_i))}}{\mathrm{Min}} \{r_i(X_i(S_i), U_i) + R_i(S_i)\}. \quad (14)$$

The control $u_i(S_{i+1})$ and the subset $S_i(S_{i+1})$ which perform the minimization are associated with each subset S_{i+1}. At the end of the horizon, the subset corresponding to the lowest cost is selected and the optimal control over the horizon is recovered using the backward links $S_i(S_{i+1})$.

For complex network and perfect compliance, a heuristic decomposition-coordination is used with the Forward Dynamic Programming algorithm for the subsystem optimization [8]. The introduction of compliance depending on free flow travel time does not change the decomposition-coordination method because the control is not used as a coordination variable.

IV. Numerical Experiments

A. Scenarios, Obedience Models and Strategies

The network shown on Fig. 2 is used: For this network, there is only one origin, the link 0, and one destination, the link 3. This network presents two controllable states (x_{1k}^3, x_{2k}^3) and one control for the node 1, u_{1k}^3. This control can take the value 0, 1,

$$\frac{\frac{c_{1k} - x_{1k}^3 - y_{1k} - (1-\tau_1)(b_{0k}^3 + B_{0k} p_{0k})}{(1-\tau_1) b_{0k}^3} + \eta_2^3 - 1}{\eta_1^3 + \eta_2^3 - 1}$$

and

$$\frac{\frac{c_{2k} - x_{2k}^3 - y_{2k} - (1-\tau_2) B_{0k} q_{0k}}{(1-\tau_2) b_{0k}^3} + \eta_2^3 - 1}{\eta_1^3 + \eta_2^3 - 1}.$$

TABLE I
SCENARIOS

sc.	demand veh/h	%	sc.	demand veh/h	%
S1	300	20	S8	900	20
S2	300	50	S9	900	50
S3	600	20	S10	1200	0.1
S4	600	50	S11	1200	1
S5	900	0.1	S12	1200	10
S6	900	1	S13	1200	20
S7	900	10	S14	1200	50

TABLE II
TOTAL TRAVEL TIME OF GUIDED VEHICLES (VEH.H/H)

strategies–scenarios	C1	C2	C3	C4	C5
S1	3.50	3.34	3.41	3.34	3.41
S2	8.75	8.36	8.53	8.36	8.53
S3	7.00	6.69	6.83	6.69	6.83
S4	17.50	17.58	17.07	16.85	17.07
S5	0.053	0.050	0.051	0.050	0.051
S6	0.531	0.501	0.512	0.501	0.512
S7	5.310	5.309	5.272	5.242	5.236
S8	10.63	10.78	10.70	10.53	10.54
S9	26.57	27.56	26.82	26.42	26.49
S10	0.191	0.078	0.143	0.078	0.143
S11	1.914	0.779	1.427	0.779	1.427
S12	19.14	7.40	13.55	7.40	13.55
S13	32.28	14.80	26.03	14.80	26.03
S14	95.70	48.55	55.62	36.66	55.62

Those two last values are authorized only if they are between 0 and 1. They are calculated with the two equalized terms of the minimum function of (9), and (2)–(8). The network is used with the scenarios S1 through S14 defined in the Table I with percentage of equipped vehicles.

Five guidance strategies are tested

- The routed vehicles act as the unguided vehicles (C1)
- Perfect compliance and use of only the two first values for the control (0 or 1) in the optimization process (monorouting) (C2)
- Compliance depending on free speed travel time and monorouting (C3)
- Perfect compliance and optimization with the four values (multirouting) (C4)
- Compliance depending on free speed travel time and multirouting (C5).

The monorouting concept consists of advising the same route for all guided vehicles for a same destination. It is known that this strategy is not efficient for high penetration rate. However, the purpose of the experiments made here is to assess the performance of monorouting strategies, when drivers disobey route advice.

Unguided vehicles are split into the network with controls of 0.5.

B. Results and Comments

Table II presents the results:

- For low demand, or average demand with low percentage of equipped vehicles (scenarios S1 to S3), monorouting and multirouting give the same results. In those case, the degradation due to the nonperfect compliance is low (2%). The benefit of guidance taking into account nonperfect compliance with respect to no routing is 4%.

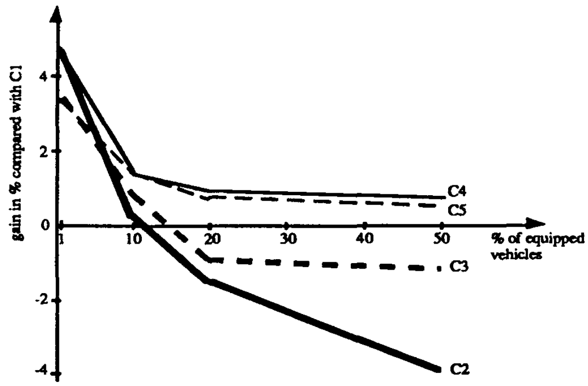

Fig. 3. Gains in percentage of C2, C3, C4, and C5 compared with C1, for scenarios S5 to S9.

- For average demand and high percentage of equipped vehicles (scenario S4), monorouting is improved (3%) by the introduction of nonperfect compliance while multirouting is degraded (1%) leading to the same performance. In that case, the benefit of guidance taking into account nonperfect compliance with respect to no routing is 4%.
- For high demand and high percentage of equipped vehicles (scenario S8 and S9), monorouting is improved by about 2% with the introduction of nonperfect compliance while multirouting is insignificantly degraded. In that case, the monorouting taking into account nonperfect compliance gives worse results (1%) than no routing. However, multirouting improves the criterion of about 1% with respect to no routing.
- Scenarios S5 to S9 allow one to compare gains as a function of the rate of equipped vehicles for monorouting and multirouting with respect to the case without routing (constant demand of 900 veh/h). Gains in percentage induced by the routing strategy are represented in Fig. 3.

For the multirouting strategies (C4 and C5), gains compared with the case without guidance (C1) are always positive. The multirouting strategy (C4) with perfect obedience has always a gain above the gain for the multirouting strategy with free flow travel time obedience (C5).

These remarks are true for the monorouting when percentage of equipped vehicles are low (until 8% maximum). Above 8%, the perfect monorouting strategy (C2) has an inferior gain compared with the monorouting strategy (C3) depending on obedience, because in that case, the effect of all-or-nothing command is smaller because of the obedience which bounds the controls. Above 15% of equipped vehicles, monorouting strategies (C2 and C3) deteriorate the criterion compared with the case without guidance, whatever the compliance is.

With a given obedience and for low percentages of equipped vehicles, gains of monorouting and multirouting strategies are equal because in that case, the optimal control consists of advising the same shortest path to all vehicles.

Lines are decreasing. In this case of a demand of 900 veh/h, the more the equipped vehicles increase, the less these vehicles win times. This is explained by the fact that the assignment of 100% of unguided vehicles is very close to the optimal guidance for 100% of guided vehicles.

- For very high demands, scenarios S10 to S14, gains are very high because the model is used in congested situations (see Fig. 4). In

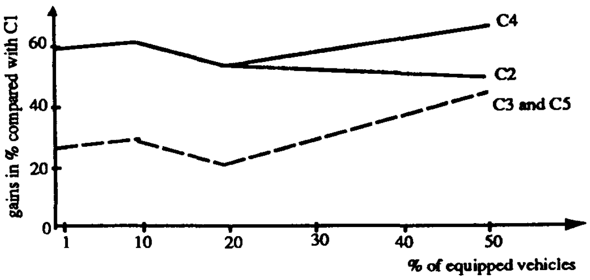

Fig. 4. Gains in percentage of C2, C3, C4, and C5 compared with C1, for scenarios S10 to S14.

these scenarios, the guidance avoids the congestion. For perfect compliance, gains reach 60%. Monorouting and multirouting (C2 and C4) show differences in gains for percentages of equipped vehicles higher than 20%. For compliance depending on free speed travel time, gains compared with the case without routing reach 40%, and monorouting and multirouting (C3 and C5) are identical.

- The results obtained for more complex networks are not significant because the decomposition-coordination method is not optimal. For some scenarios, the total travel time with perfect compliance is higher than the total travel time with compliance depending on free speed travel time.

V. Conclusion

For the queue-based model, static acceptance based on the quality of advice (shortest route at free speed) is introduced. At a given node of the network, when drivers disobey route advice, the actual proportions on downstream links of the considered node following the guidance advice is a linear function of the control. For a simple network where a Forward Dynamic Programming algorithm is used, we note that the effect of nonperfect compliance depends on three main factors: level of the demand, type of routing and proportion of equipped vehicles. High differences for the guidance benefits are only obtained in saturated conditions. In those cases, multirouting and monorouting lead to similar performances when disobedience is modeled, although for a high proportion of equipped vehicles and a perfect compliance, multirouting is clearly more efficient. For low and average demands, nonperfect compliance induces a moderate degradation of the criterion (2% maximum). For complex networks, a full assessment needs optimal algorithms instead of heuristics. New efficient algorithms will be developed taking into account the driver acceptance.

This correspondence emphasizes then, the importance of the consideration of drivers' reaction in future Dynamic Route Guidance systems. Only the short term acceptance was considered. Further research should integrate long term considerations: the modeling of the evolution of acceptance over a month could be very relevant for assessing the future of route guidance.

Acknowledgment

This work is based on research conducted in the European DRIVE LLAMD project. Thanks to the EEC DGXIII and to the Partners involved in this project.

References

[1] I. F. Catling, O. De Beek, C. Casimir, R. Mannings, F. Zijderhand, W. Zechnall, and J. Hellaker "SOCRATES: System of cellular radio for traffic efficiency and safety," in *Advanced Telematics in Road Transport, Proc. of the DRIVE Conf. Brussels*, Elsevier, vol. I, pp. 28–43, 1991.

[2] J.-J. Henry, C. Charbonnier, and J.-L. Farges, "Route Guidance, Individual," in *Concise Encyclopedia of Traffic and Transportation Systems*, M. Papageorgiou, Ed. New York: Pergamon Press, 1991, pp. 417–422.

[3] G. Hoffman, "LISB—An individual route guidance and information in Berlin," *Computers, Communications in Transportation, Control*, J. P. Perrin, Ed., IFAC Symposia series 12, 1990 New York: Pergamon Press, 1989, pp. 265–268.

[4] R. Von Tomkewitsch, "ALI-SCOUT—A universal guidance and information system for road traffic," *Second International Conf. on Road Traffic Control, Conference Publication Number 260*, IEE, 1986, pp. 22–29.

[5] N. B. Hounsell, S. R. Njoze, and M. McDonald, "Modeling the dynamics of route guidance," *The 3rd Int. Conf. on Vehicle Navigation & Information Systems*, RTI/IVHS, Conference record of papers, Oslo, 1992, pp. 127–134.

[6] M. Papageorgiou, "Dynamic modeling, assignment and route guidance in traffic network," *Transportation Research*, vol. 24B, pp. 471–495, 1990.

[7] C. Charbonnier, "Le routage dynamique des véhicules," *ENSAE Thesis*, no. 74, 1991.

[8] C. Charbonnier, J.-L. Farges, and J.-J. Henry, "Le routage dynamique des véhicules," in *Proc. of the First European Control Conf.*, Hermes, vol. 3, 1991, pp. 2391–2396.

[9] P. Bonsall, L. Pickup, and A. Stathopoulos, "Measuring behavioral responses to road transport informatics," *Advanced Telematics in Road Transport, Proc. of the DRIVE Conf. Brussels*, Elsevier, vol. II, 1991, pp. 1457–1487.

[10] H. N. Koutsopoulos, T. Loten, and Q. Yang, "A driving simulator and its application for modeling route choice in the presence of information," presented at *The TRB Meeting*, Washington DC, 1993.

[11] J. L. Adler, W. W. Recker, and M. G. McNally, "In-laboratory experiments to analyze enroute driver behavior under ATIS," presented at *The TRB Meeting*, Washington DC, 1993.

[12] R. E. Larson and J. L. Casti, "Principles of dynamic programming," in *Basic Analytic and Computational Methods*, Part I, ch. 4, Decker, pp. 210–291, 1978.

[13] ——, "Principles of dynamic programming," in *Advanced Theory and Applications*, Part II, ch. 4, Decker, pp. 223–345, 1982.