2001 IEEE Intelligent Transportation Systems Conference Proceedings - Oakland (CA), USA - August 25-29, 2001

A Methodological Framework for Integrated Control in Corridor Networks

Yannis Pavlis[a] and Will Recker[b]

Abstract-- This paper presents a framework for an integrated control system, with an embedded travel demand model that reflects drivers' response to the control strategy. The integrated control problem is formulated as an optimal control problem of determining such control variables as the on-ramp metering rates, the minimum green duration, the maximum green duration (or force off), background cycle length (if coordinated) and the critical time gap for vehicle actuated urban signals, subject to the control constrains, so as to optimize a performance index. The approach takes into consideration the interaction between the control strategy and drivers' response to it recognizing the later as a critical parameter to the performance of the system. Finally, a numerical method is proposed for the solution of the formulated optimal control problem.

Index Terms--Integrated control systems, multinomial probit models, optimal feedback control problem .

I. INTRODUCTION

Transportation operations/management agencies have relied on two widely-used control strategies to increase system performance in corridor networks[1]: 1) the coordination of identical control strategies (e.g., coordinated ramp-metering or coordinated urban traffic signals) and 2) the simultaneous activation (without coordination) of distinct control strategies (e.g. simultaneous activation of ramp metering and route guidance). These approaches either optimize the operation of a subnetwork (e.g., a subnetwork of traffic signals), or their control objective relies on the cumulative effects from the simultaneous activation of the control strategies.

However, as the spatial extent of recurrent or non-recurrent traffic congestion increases, control strategies by which each subnetwork operates in virtual isolation become increasingly ineffective. Situations often arise in which optimal solutions to a traffic congestion problem in one subnetwork indirectly generate an even larger problem in an adjacent subnetwork, since the operation of most signalized networks and highways is interdependent [16]. Moreover, the simultaneous activation (without coordination) of distinct control strategies does not guarantee a solution with common objective [4]. As a result, control strategies that operate in virtual or real isolation often result in antagonistic, rather than synergetic, effects.

To some extent, the ability of multiple agencies to integrate their decision-making toward a common goal of system (e.g., a network of freeways and arterials that provide urban connectivity) rather than component (e.g., freeway ramp meters or arterial traffic signals) management has been hampered by technical issues related to real-time data sharing and fusion. With recent advances in information technology these technical issues have largely been overcome; what remains are the institutional barriers to joint management and the requisite analytical tools for determining sound integrated management strategies. Before we can expect that corridor agencies adopt system-optimal management practices, it must first be investigated that integrated management strategies can provide benefit beyond that achievable under current policy and practice.

The geographical integration and coordination (or hereafter integrated control system) of control measures (different or identical) in corridor networks aims at eliminating traffic congestion taking advantage of the spare capacity that probably exists in some parts of the network. The underlying idea of the integrated control system is to coordinate the activated control measures (e.g. ramp meters, urban traffic signals, Changeable Message Signs (CMS), etc.) so as to achieve a pre-specified goal that is common for all of these measures. In other words, the integrated control system seeks a global (joint) control objective in contrast to the isolated control strategies described above.

However, the geographical integration and coordination of some control measures is only one aspect that should be considered when trying to design efficient management strategies. The other aspect reads for the integration between the control strategy and drivers' response to it. As a matter of fact, it has been documented that the driver's response to the proposed control actions can be crucial to the performance and effectiveness of any control strategy [5], [7], [13]. This resulting from drivers making their own decisions with regard to route choice depending on their knowledge on current traffic conditions, while the prevailing traffic conditions are merely a result of

[a,b] Institute of Transportation Studies and Department of Civil and Environmental Engineering, University of California, Irvine, CA 92697.

[1] For the purposes of this paper, a corridor network is defined as a road network consisting of a highway component and a parallel surface street, that are connected through a number of on- and off-ramps as well as possibly with minor urban roads.

the ordered control actions. Thus, in case of integrated control an efficient strategy should take into account the complex interaction between the desired control actions that satisfy a common objective and drivers' collective response to these actions.

This paper attempts to lay the foundation for an integrated control strategy with an embedded travel demand model that reflects drivers' response to this strategy. In the problem formulation, it is assumed that drivers make decisions with regard to route choice based on their knowledge of traffic conditions. This knowledge either can be obtained as a cumulative drivers' experience (drivers based on their daily experience have found one or more alternatives to their shortest travel time route) or can be provided through the radio (many radio stations provide travelers with information on traffic conditions), or in some limited cases through CMS, or in greatly limited cases through individual communication with suitably equipped vehicles. In the proposed research, drivers' route choice behavior will be characterized as a response to a Dynamic Traffic Management System (DTMS) and modeled by discrete choice modeling techniques, e.g., drivers traveling between an O-D pair of nodes choose the paths that maximize their utility. The integrated control strategy in this context is formulated as an optimal control problem that could be roughly described as that of finding the on-ramp metering rates and the urban vehicle-actuated signal timing settings given the information on traffic conditions, which is provided by the routing model, so as to optimize a common control objective.

The developed strategy is designed for real-time applications and is further traffic-responsive in the sense that it considers the interaction between the control actions and drivers route choice behavior in response to these actions assuming that information is provided on current traffic conditions. The methodological framework is described in a rather abstract level due to space limitations.

II. The Route Choice Model

Before proceeding in the development of the route choice model, we provide a brief overview of route choice models used in integrated control strategies. Three cases regarding route choice can be distinguished:

1. Routes are assumed to be fixed (but time dependent), determined using, for example, historical data [3], [11], [14].
2. The routes that optimally match the proposed control actions are additionally determined by the control strategy [8], [9].
3. Routes are selected by drivers based on estimations (according to their knowledge) or real-time information on current traffic conditions. For example, these routes could be determined so as to satisfy the user-optimum condition or by using behavioral route choice models [2], [4], [5], [13], [15].

We now briefly describe the travel demand model employed to reflect drivers' route choice behavior in response to the ordered control actions that are determined by the integrated control strategy.

Consider a traffic corridor and a number of drivers on its surface streets traveling toward a common destination. Its freeway component consists of links F_i, i=1,..., N, while the parallel surface (urban) street consists of links S_i, i=1,..., N–1. These two components are connected by N on-ramps with R_i, i=1,..., N denoting the i-th on-ramp connecting urban link S_{i-1} to freeway link F_i. For the sake of simplicity and without loss of generality, we will assume that drivers on the surface streets of the corridor are traveling towards the destination being at the end of link F_N. Such drivers are faced with two options at bifurcation nodes on the surface streets: either to enter the highway through the corresponding on-ramp or to keep traveling on the surface street until the next bifurcation node where a new decision is taken. These bifurcation nodes are designated as decision nodes c, c=1,...,N–1 in terms of the route choice model. In addition, an origin node o, o=1,...,N–1 is a decision node connected to a production zone and a destination node d, d=1,...,N–1 is a network node connected to an attraction zone. Furthermore, the sets of all origin and destination nodes are designated as O, and D, respectively.

Let $U_{i,c}^{d}$ denote the utility, that is a random variable, of the route that contains the i-th on-ramp from decision node c to destination node d. Then,

$$U_{i,c}^{d} = \sum_{q=1}^{i-1} U_{S_q} + \sum_{l=1}^{d+1} U_{F_l} + U_{R_i}, \forall o \in O, \forall d \in D, d \geq o,$$

$$c = o,\ldots,d,\ i = c,\ldots,d+1,\ d \geq c,$$

with U_{S_q}, U_{F_l}, and U_{R_i} denoting the utilities of a driver who travels on the q-th urban link, l-th freeway link and i-th on-ramp, respectively. In vector notation, $\mathbf{U}_c^d = \mathbf{X}\mathbf{S}_c^d + \mathbf{Y}\mathbf{F}_c^d + \mathbf{Z}\mathbf{R}_c^d$, where $\mathbf{U}_c^d$ is the (d–c+2)×1 vector of the utilities of all the alternative routes between a decision node c and a destination node d, $\mathbf{X}$ is a square (d–c+2)×(d–c+2) lower triangular matrix with the elements of the principal diagonal being zero and the rest of the elements being equal to 1, $\mathbf{Y}$ is a square (d–c+2)×(d–c+2) upper triangular matrix with the non-zero elements being equal to 1, $\mathbf{Z}$ is a square (d–c+2)×(d–c+2) unit matrix, while the rest (d–c+2)×1 vectors are defined as $\mathbf{S}_c^d = \left[U_{S_c} \ldots U_{S_{d+1}}\right]'$, $\mathbf{F}_c^d = \left[U_{F_c} \ldots U_{F_{d+1}}\right]'$, and $\mathbf{R}_c^d = \left[U_{R_c} \ldots U_{R_{d+1}}\right]'$, where the prime denotes matrix transposition. Then, vector $\mathbf{U}_c^d$ contains the utilities of all routes that contain ramp i, i=c,..., d+1, between decision node c and destination node d.

Assuming that $\mathbf{U}_c^d$ is multivariate normally distributed with mean vector $\mathbf{V}$ and variance-covariance matrix $\boldsymbol{\Sigma}$, and that the covariance between any two alternative routes is only in the links they share, it can be shown that the variance-covariance square matrix $\boldsymbol{\Sigma}$ can be written as $\boldsymbol{\Sigma} = \mathbf{G} + \mathbf{H}$, where the ($d$–$c$+2)×($d$–$c$+2) variance-covariance square matrices $\mathbf{G}$ and $\mathbf{H}$ are of a particular form that renders the covariance matrix $\Sigma^* = \mathbf{M}\,\Sigma\,\mathbf{M}'$ of the transformation $\Delta\mathbf{U} = \mathbf{M}\,\mathbf{U}$, where the transformation matrix $\mathbf{M}$ is given by

$$\mathbf{M} = \lfloor \mu_{ij} \rfloor \text{ with } \mu_{ij} = \begin{cases} 1 & \text{if} \quad i = j \\ -1 & \text{if} \quad i - j = 1 \\ 0 & \text{otherwise} \end{cases}.$$

Based on this result, we end up after some algebra with the probabilities of choosing any alternative route between a decision and a destination node. We can state that the probability of selecting a route between a decision and a destination node on a corridor network equals the probability the corresponding route utility be greater than or equal to the utilities of all upstream routes and the immediate downstream one. These probabilities are calculated for every route between all pair of decision-destination nodes in the corridor network, whenever driver(s) are in decision nodes. It is a trivial task to calculate at a final stage the route choice probabilities of the *a priori* known demand between a single Origin-Destination (O-D) pair of nodes from the overlapping probabilities of all decision-destination pair of nodes that lie in between. Obviously, the route choice probabilities can be determined for any O-D pair of nodes which means the behavioral model has a multi-origin, multi-destination structure. The behavioral model is a function of system attributes that correspond to aggregated traffic variables (e.g. link travel times, off-ramp outflow, links queues, etc.), and drivers' attributes.

III. Description of the Integrated Control System

In the following, a description of the various components of the integrated control system is provided. The ***plant***, or the controlled physical object, corresponds to the traffic flow in the corridor network. The traffic flow can be defined either as individual vehicle movements on network links or as the number of vehicles passing through a specific network location over a period of time divided by this period. The dynamical behavior of the plant is described by a mathematical model. Depending on the definition of traffic flow a number of different mathematical models could describe the same plant. Such models could be a microscopic car-following and lane-changing model, such as PARAMICS or MITSIM. Other models are based on relationships between aggregated traffic variables[2] such as the mesoscopic model DYNASMART, or the macroscopic model METACOR. External quantities to the process are: (i) the ***inputs*** (or controls) and (ii) the ***disturbances***. The inputs are selected from an admissible region and their task is to force the plant to behave according to a pre-assigned pattern or according to the operator's wishes. They are the solution of a mathematical problem. In the case under consideration here, the inputs are the ramp metering rates (veh/h) and the green per cycle time ratios for each phase of a signalized intersection,[3] assuming that under moderate to heavy traffic conditions the behavior of vehicle actuated signals closely resembles signals with fixed phase sequence and only moderately varying green splits and corresponding cycle length. There are 3 independent such ratios per cycle. As an example, in a corridor network with 2 on-ramps and 2 signalized intersections there are 8 inputs to the plant.

The disturbances represent external forces that can not be manipulated, and/or modeling inaccuracies. Examples of such disturbances include accident/incidents that occur at various locations in the corridor network, possible adverse weather conditions, or drivers route choice when traveling between an O-D pair of nodes.

The three cases regarding route choice in integrated control systems, mentioned in section II above, are revisited for a further explanation in control theory terms. We thus have:

1. Fixed routes. Since the routes are fixed or known *a priori*, drivers' route choice in this case is not a disturbance that affects the dynamical behavior of the plant. Even if it is assumed that, at equilibrium, drivers' routes are fixed this assumption fails in the case of unpredictable disturbances (e.g., accidents). Obviously, in this case the implemented control actions will fail to force the plant to behave according to a pre-specified behavior.
2. Optimal routes. Even in this case driver's route choice is assumed not to be a disturbance to the plant under consideration. Instead, the variables that express mathematically these routes[4] are assumed to be an additional input to the plant. Therefore, the control strategy determines routes that match suitably (or even optimally) the other plant inputs (i.e., the ramp metering rates and the green per cycle time ratios). Although this approach is highly acceptable from a systems point of view, it is difficult to implement the corresponding solution in practice. In addition, the number of inputs is increased with a subsequent increase in the CPU-solution time of the mathematical problem.
3. Behavioral route choice models. In this case driver's route choice is considered as a disturbance. For example, modeling route choice using discrete choice theory produces a disturbance that is predictable. The advantage of this approach is that it represents a realistic route choice behavior: drivers make their own pre- and en-route choice decisions based on real-time information on current traffic conditions. Conversely, the integrated control system takes into account the interaction between the proposed control actions and driver's response to these actions. The disadvantage of this approach is the possible limited accuracy of the behavioral model.

---

[2] e.g. flow expressed in veh/h, density expressed in veh/mi/lane, and mean speed expressed in mi/h.

[3] For the sake of simplicity it is assumed that the cycle time is fixed and equal for all signalized intersections and that phases with non-conflicting right of way are grouped together.

[4] The routes connecting an O-D pair of nodes are expressed mathematically as turning (or splitting) rates at urban intersections, and diversion rates at on- and off-ramp locations.

Continuing on the description of the integrated control system, the ***outputs*** are quantities that represent the response of the plant to the various inputs. They are observed by a suitable collection of sensors called the measurement system. In our case, the measurements could be individual vehicle positions, speeds, etc., or aggregated parameters of traffic such as speed, flow measurements, etc., at various network locations. Finally, the ***control strategy*** determines the inputs by solving a mathematical problem with a suitable scheme (e.g., a theorem, a numerical procedure, etc.), given that the plant is accurately represented by a dynamical system (a mathematical model). If the inputs are determined so as to optimize a measure of the cost or the effectiveness of control actions (e.g., minimization of total travel time, maximization of system throughput, etc.) then, the corresponding mathematical problem is called an optimal control problem.

In the case of an optimal control problem the task of the control strategy is to determine the inputs based on available real-time measurements on current traffic conditions and on any available disturbance predictions, so as to force the dynamical behavior of the plant to be such as to optimize a performance index. In our integrated control system the task of the control strategy is to calculate the ramp metering rates and the green per cycle time ratios based on available real-time information on current traffic conditions and predictions of drivers' route choice (provided by the corresponding behavioral model), and which in so doing minimizes the system total travel time (or any suitable performance index).

In [16] the performance of a number of integrated control systems (which are described by different mathematical models) is examined, by testing these under various simulation scenarios. The authors conclude, among others, that an efficient integrated control system should be simulated using a microscopic model, and that the system should consider drivers' route choice behavior.

Despite the apparent usefulness of microscopic models in integrated control systems, could such models be used in the control strategy? We know that microscopic models require significantly higher CPU time to simulate traffic conditions in a road network as compared to the macroscopic models. In addition, microscopic models are governed by ordinary differential equations (e.g., equations representing individual vehicle positions and velocities) and logical rules that reflect driving behaviors in road networks. When considering even relatively small road networks the number of differential equations (and the corresponding number of state variables) that describe the car-following behavior of traffic would be enormously large. As a final remark, the microscopic models can not be solely described by a system of differential equations (see section IV below) due to the existence of logical rules.

Therefore, according to optimal control theory, this means that if a solution of the mathematical problem which explicitly includes a microscopic traffic flow model exists, its derivation would be so time consuming (in CPU time terms), that would be impractical to implement the integrated system even in case of off-line applications.

The solution to this problem arises in a quite natural way. On one hand, the mathematical accuracy of macroscopic traffic flow models is within the tolerances allowable by control strategies [10]. On the other hand, a microscopic model is necessary for the modeling of individual driver's route choice behavior, while at the same time describes with high accuracy traffic dynamics in transportation networks.

Therefore, in the integrated control system proposed in this paper the ***plant*** will be a microscopic simulator (e.g. PARAMICS, MITISIM, etc.). This will allow: (i) the simulation of individual drivers' route choice behavior in response to the provided real-time information on current traffic conditions (ii) a detailed description of the traffic flow phenomena in corridor networks (e.g., platoon progression between signals, merging and weaving phenomena, oversaturation, queue splillback, etc.) and, (iii) acquisition of accurate network-wide instantaneous traffic measurements as traffic flow (veh/h), mean speed (mi/h), traffic density (veh/mi/lane), occupancy (%), queue length, etc.

The mathematical model explicitly considered in the ***control strategy*** will be a macroscopic corridor traffic flow model (e.g., METACOR, etc.). This will allow: (i) a state representation of the dynamical system (under suitable assumptions), and, (ii) a consequent employment of powerful solution methods that enable a quick (in CPU time terms) determination of a solution (if any exists[5]). Drivers' route choice will also be considered (collectively though) using the same behavioral model and nodal traffic flows [11]. Even drivers' attributes can be represented in a macroscopic context as follows: drivers with different socioeconomic characteristics travelling between an O-D pair of nodes can be considered as percentages of the corresponding demand (partial flows in [11]). The operational scheme of the integrated control strategy is demonstrated in Fig. 1.

The benefits of this approach are outlined in the following: (i) compatibility with the modeling needs of integrated control systems by using the state-of-the-art in microscopic models (ii) modeling of the complex drivers' behavior in response to the control strategy (iii) application of mathematical methods in contrast to questionable heuristic techniques in the solution of the formulated control problem (iv) real-time implementation of the integrated control system by utilization of macroscopic models in the control strategy and of microscopic models that run faster than real-time (e.g., PARAMICS) (v) investigation of various scenarios (e.g., different O-D demand levels, etc.) in a simulation environment rather than a real-life corridor network.

[5] At this point it should be noted that that the macroscopic model (resp. microscopic) should be validated using traffic data provided from the microscopic model (resp. real traffic data measurements).

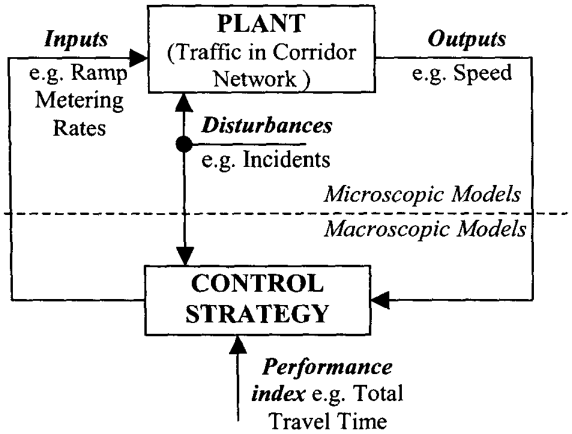

Fig. 1. Schematic representation of the Integrated Control System.

IV. Optimal Control Problem Formulation

We proceed with the mathematical formulation of the optimal control problem. The formulation will be given in an abstract level following the underlying idea of this paper. However, the reader is referred to [1], [6] for a concrete mathematical description of optimal control theory. We start with the following definitions adopted from [6]. Consider a plant represented by a dynamical system (a set of equations that are described below). Let U denote the set of admissible inputs and Y denote the set of output values of a plant (these sets can be assumed to correspond to vector spaces). Furthermore, let X represent the state space. Let $\mathbf{u}(t)\in U$, $\mathbf{x}(t)\in X$ be vector-valued functions of the continuous time index t denoting the plant input, and state, respectively, while $\mathbf{w}(t)$ is a vector-valued function of time denoting the predictable disturbances. We further assume that the dynamical system is represented by a set of equations of the form $d\mathbf{x}/dt=\mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{w}(t), t)$, satisfying the initial condition $\mathbf{x}(t_0)=\mathbf{x}_0$, where $\mathbf{f}(.)$ is a vector-valued function. The pair $(t, \mathbf{x})$ is called an event, while the space containing all events is called an event space. Let S denote a target set which is contained in the event space, see [6].

Generally speaking (a rigorous mathematical definition which can be found in [1], and [6] is based on numerous mathematical assumptions and properties regarding the dynamical system) the optimal control problem is that of finding an admissible control $\mathbf{u}(*)$ (if any exists) which transfers any initial event $(t_0, \mathbf{x}_0)$ to the target set S so as to minimize a cost-of-control functional $J(t_0, \mathbf{x}_0, \mathbf{u}(*))$, given the disturbance trajectories $\mathbf{w}(*)$. Note that $\mathbf{u}(*)$ (and similarly $\mathbf{w}(*)$ and $\mathbf{x}(*)$) denotes a function of time while $\mathbf{u}(t)$ (and similarly $\mathbf{w}(t)$ and $\mathbf{x}(t)$) denotes the value of this function at time t.

Based on this definition, let us now re-examine some parts of the integrated control system. Consider the control action (input) that represents the ramp metering rates. There are two constraints involved with this variable that define a corresponding region of admissible values (or admissible control region). First, it is assumed that there is a minimum allowable metering rate; CALTRANS do not allow a metering rate less that 3 veh/min (the idea being that drivers may think that the signal is broken and violate the indication). Second, when the on-ramp queue exceeds its maximum value (i.e. just before queue starts to spill back on to the surface street), then the ramp signal indication either turns to green or to a pre-specified high rate to discharge the queue even if the mainline capacity do not allow such a rate.

The disturbance function $\mathbf{w}(*)$ contains the traffic flows for each network link and for each O-D pair of nodes over the whole simulation horizon. These flows are provided by the behavioral route choice model. Consider, now, the system state. It is known that states are abstract quantities which represent inaccessible variables inside the plant. There are only few cases where state variables have a physical meaning. Such a case is when the dynamical system is a macroscopic traffic flow model where the state variables usually have a physical meaning since they are representing, for example, link densities at all network links. This means that, in this case, the state variables can be read out as outputs from the dynamical system utilized by the control strategy, which in turn means that there is no need to employ a numerical scheme to determine states from the outputs[6]. This is another reason for using macroscopic models in the control strategy module.

Finally, the cost-of-control functional (or as it is mentioned above the performance index) could also represent such quantities as the total travel time, total waiting time, total time spent, etc., according to the needs of the system operator. If the dynamical system is not a linear function of the state variables and the control inputs it can be linearized around some nominal state [8]. Linear dynamical systems have been extensively examined in optimal control theory, providing a great number of mathematical tools (theorems or numerical schemes) that can be used for the solution of the corresponding optimal control problems.

V. Proposed Solution Method

When the optimal control actions are applied to the plant the actual state trajectory may be displaced from the optimal state trajectory due to the following reasons:

i. Limited accuracy of the model used in the control strategy (i.e. the macroscopic traffic flow model).

ii. Limited accuracy of the predicted disturbances (e.g. due to possible unobserved attributes).

iii. Occurrence of unpredictable disturbances (e.g. accidents/ incidents, lane closures, etc.).

It is known, however, that, in case of disturbances (instantaneous), the dynamics of a plant may be altered so as to achieve some desirable behavior by means of feedback[7] subject to the requirement that the plant is

[6] The reader should also note that the initial state can be determined from measurements provided by the microscopic traffic flow model.

[7] The notion of feedback states that the control is a function of state.

accurately represented by a linear system. Although highly desirable, the feedback structure of the integrated control system of Fig. 1 is not (and neither could be for relatively large networks) justified by a corresponding analytical solution. The question that arises then is can the optimal control be embedded in a feedback structure for practical applications such as in our case?

As it is mentioned in [12] this can be accomplished using repetitive optimization (with rolling horizon). According to this procedure, the optimal control problem can be embedded in a feedback control structure, whereby its numerical solution is effectuated in real-time in the following way. At time t_0 based on an initial condition $\mathbf{x}(t_0)$ and on available disturbance predictions $\mathbf{w}(t)$, $t \in [t_0, t_0+T]$, with T denoting the optimization horizon, the formulated problem is solved numerically to obtain the optimal trajectories $\mathbf{u}^o(t)$,and $\mathbf{x}^o(t)$, $t \in [t_0, t_0+T]$, but only a part of the control trajectory is actually applied to the process, namely $\mathbf{u}^o(t)$, $t \in [t_0 + \hat{\tau},\ t_0 + \hat{\tau} + \tilde{\tau}]$, where $\hat{\tau}$ is the computation time for the numerical problem solution, and $\tilde{\tau}$ which is the time interval between two consecutive prediction runs is chosen sufficiently shorter than T (typically it suffices to have $\tilde{\tau} \approx \hat{\tau}$) in order to avoid "myopic" control actions. Then, at time $t_0 + \tilde{\tau}$, based on a new initial condition $\mathbf{x}(t_0+\tilde{\tau})$ and updated disturbance predictions $\mathbf{w}(t)$, $t \in [t_0 + \tilde{\tau},\ t_0 + \tilde{\tau} + T]$, the formulated problem is solved again to obtain the trajectories $\mathbf{u}^o(t)$,and $\mathbf{x}^o(t)$, $t \in [t_0 + \tilde{\tau},\ t_0 + \tilde{\tau} + T]$, but only $\mathbf{u}^o(t)$, $t \in [t_0 + \hat{\tau} + \tilde{\tau},\ t_0 + \hat{\tau} + 2\tilde{\tau}]$ is actually applied to the process, and so forth. A necessary condition for application of the repetitive optimization is that the state variables $\mathbf{x}(t)$ should be measurable or estimated in real-time. The rolling horizon represents a feedback control structure because the control actions are obtained every $\tilde{\tau}$ based on updated state measurements[8]. It should be noted again, that the states are updated using measurements from the microscopic traffic flow model. In a rolling horizon context $\tilde{\tau}$ may be either constant, so there are periodic updates and runs, or may be determined by the operator according to his/her judgement. Although the rolling horizon scheme provides a suboptimal solution, this solution is considered quite efficient for practical applications such as in integrated control systems.

A final issue that needs to be discussed is that of the real-time application of the integrated control system. As mentioned above there are microscopic simulators that simulate traffic in transportation networks faster than real-time (e.g. PARAMICS). For the optimal control problem on the other hand, there exist powerful methods that allow the determination of the optimal control in shorter time than the interval between two consecutive prediction runs (e.g. if, additionally, to the dynamical system the performance index and the constraints are linear, view the dynamic problem as a static linear programming problem and apply suitable solution algorithms). Therefore, real-time application of the integrated control strategy in corridor networks of reasonable size (containing for example 4 to 5 on-ramps) appears feasible.

[8] The reader should observe, that the optimal control problem is defined for any initial event.

REFERENCES

[1] M. Athans and P. L. Falb, Optimal control: An Introduction to the Theory and Its Applications, McGraw-Hill, 1966.

[2] G.-H. Chang, P.-K. Ho, and C.-H. Wei, "A dynamic system-optimum control model for commuting corridors," Transportation Research, vol. C, no. 1, pp. 3-22, 1993.

[3] G.-L. Chang, J. Wu, and H. Lieu, "Real-time incident-responsive corridor control: A succesive linear programming approach," Proceedings of the 1994 annual meeting of IVHS America, Atlanta, Georgia, Vol. 2, pp. 907-918, 1994.

[4] D. Cuneo, J. Mithilesh, and M. Ben-Akiva, "An evaluation of integrated freeway traffic control and route diversion using microscopic simulation," Preprints of the 78th annual meeting of the Transportation Research Board, Washington, D.C., Jan. 1999, 15 pages in CD-ROM format.

[5] N. H. Gartner and C. Stamatiadis, "Integration of dynamic traffic assignment with real-time traffic adaptive control system," Transportation Research Record, vol. 1644, pp. 150-156, 1998.

[6] R. E. Kallman, P. L. Falb, and M. A. Arbib, Topics in Mathematical System Theory, McGraw-Hill, 1969.

[7] H. S. Mahmassani and Y.-H. Liu, "Dynamics of commuting decision behavior under advanced traveler information systems," Transportation Research, vol. C, no. 7, pp. 91-107, 1999.

[8] A. Messmer and M. Papageorgiou, "Automatic control methods applied to freeway network traffic," Automatica, vol. 30, no.4, pp. 691-702, 1994.

[9] A. Messmer and M. Papageorgiou, "Route diversion control in motorway networks via nonlinear optimization," IEEE Transactions on Control Systems Technology, vol. 3, no.1, pp. 144-154, 1995.

[10] M. Papageorgiou, Applications of automatic control concepts to traffic flow modeling and control. New York: Springer Verlag, 1983.

[11] M. Papageorgiou, "An integrated control approach for traffic corridors," Transportation Research, vol. 3C, pp. 19-30, 1995.

[12] M. Papageorgiou, "Automatic control methods in traffic and transportation," Internal Report, no. 1997-10, Chania, Greece, 1997.

[13] R. A. Reiss, N. H Gartner., and S. L. Cohen, "Dynamic control and traffic performance in a freeway corridor: A simulation study," Transportation Research, vol. C, no. 25, pp. 267-276, 1991.

[14] Y. J. Stephanedes and K.-K. Chang, "Optimal control of freeway corridors," ASCE Journal of Transportation Engineering, vol. 119, pp. 504-514, 1993.

[15] Y. J. Stephanedes and E. Kwon, "Adaptive demand diversion prediction for integrated control of freeway corridors," Transportation Research, vol. C, no. 1, pp. 23-42, 1993.

[16] M. Van Aerde and S. Yagar, "Dynamic integrated freeway/traffic signal networks: A routing based modeling approach," Transportation Research, vol. A, no. 22, pp. 445-453, 1998.