A Framework for Real-Time Traffic Management with Case Studies

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ABSTRACT
This paper focuses on real-time traffic management facilitated by modern telecommunication technologies and advanced real-time optimization algorithms. The discussion begins with a recent European project, which provides a real-time decision support system for the reduction of traffic congestion and emissions. The workflow and techniques involved therein are explained, with issues and potential gaps identified. We then introduce a more generic real-time decision-making framework based on decision rules and distributionally robust optimization. We illustrate the wide applicability and unique advantages of such a framework with several case studies in responsive signal control, adaptive variable message sign, and air traffic management.

KEYWORDS
Real-time traffic management; decision support system; decision rule; distributionally robust optimization
1. Introduction

The landscape of real-time traffic management is evolving by leaps and bounds due to the rapid growth of telecommunication in both capacity and variety.¹ During this process challenges arise alongside opportunities. The emergence of new data types (e.g. from new sensors and social media) and collection/communication apparatus have brought much potential to perceive and react to the transportation system in ways not envisaged before. At the same time, they have the potential to yield more robust, and fundamentally new, theories and algorithms to cope with heterogeneous and multi-source data and handle highly uncertain and complex decision environments. This paper presents some case studies of real-time traffic management, with a common methodological framework known as the decision rule (DR) approach. We begin with a brief introduction of a project on sustainable traffic management with some key challenges or issues highlighted (Section 2), followed by a detailed illustration of the DR framework and distributionally robust optimization (Section 3). A few case studies are described to show how the DR approach addresses some of the common challenges in real-time traffic management (Section 4).

2. Adaptive traffic management with environmental impact

Our discussion of real-time traffic management departs from a recent European project CARBOTRAF (http://www.carbotraf.eu). The project aims to adaptively influence traffic in real time to reduce carbon dioxide (CO₂), nitrogen oxides (NOₓ) and black carbon (BC) emissions caused by road transportation in urban and inter-urban areas. The analytical relationships between traffic congestion and emissions were explored using advanced data sensing techniques and communication infrastructure, as well as multi-scale models that link traffic states to different levels of congestion and emission. This is underpinned by a chain of modeling tools based on traffic microsimulation, emission calculation, and pollutant concentration estimation. A decision support system (DSS) is developed to use real-time and simulated traffic/emission data for predicting congestion and emission levels, and suggesting appropriate intelligent transportation system (ITS) measures including variable message sign and coordinated signal control.

The realization of the project goals depends on the offline modeling and simulation of traffic and air quality for the test sites (Section 2.1), as well as the real-time acquisition, communication, and management of streaming data for decision support (Sections 2.2 and 2.3). The overall workflow of the project is shown in Figure 2.1 and explained in greater details in the following sections.

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¹ In this paper, the term telecommunication refers to the acquisition, communication, and processing of transportation-related data, their relevant infrastructure and algorithms.
2.1. Offline modeling and estimation of traffic and emissions

The CARBOTRAF system has an offline module, which performs extensive traffic microsimulation (S-Paramics, VISSIM), emission estimation [1, 2], and pollutant dispersion modeling [3]. Input data from the test sites include network characteristics, demand profile, meteorological conditions, etc., see [4]. Suitable ITS actions with the potential to reduce CO₂, NOₓ, and BC emissions while maintaining the efficient flow of traffic have been identified and incorporated in the traffic simulation. The offline module provides, as part of its output, a look-up table containing pointwise interpretation of the inter-relationship among traffic states, emission, congestion, and ITS actions.

Figure 2.2 illustrates one of the two test sites located at the West end of Glasgow, which is often affected by severe congestion and deteriorated air quality, as it not only connects the radial routes to the city center for drivers approaching Glasgow from the west, but also provides access to the university and other local destinations. Suitable ITS actions for this test site have been identified as:

- Traffic signal control (TSC) at the key junction (see Figure 2.2) with new signal plans while maintaining coordination with adjacent arterials.
- Variable message sign (VMS), which provides real-time route guidance that diverts traffic from the main route (highlighted in red in Figure 2.2) to a less congested, yet longer route (in blue).
Figure 2.2. The Glasgow test site. Upper left: Roadside air quality monitor. Lower left: Road gradient modeling (for emission estimation) based on Digital Elevation Model. Right: The test site with the key traffic signal control and the variable message sign.

The efficacy of these ITS actions in reducing emission and congestion varies with traffic conditions such as demand scenario, fleet composition, traffic congestion situation on designated detection units, and weather, which need to be telecommunicated in real time. For example, Figure 2.3 shows the reduction in BC concentrations for the test network with the same ITS action but under different demand scenarios. It clearly shows that what works in the first demand scenario is less effective in the second one, and that the improvement in air quality varies across different spatial references (i.e. junction, corridor, network levels). This observation necessitates a real-time data sensing network and an online decision support system to identify the right traffic situation and control strategies in a timely fashion.

Figure 2.3. Reduction of BC concentration in West Glasgow after applying TSC and VMS. Negative values indicate reduction.

Several valuable managerial insights are drawn from the offline simulation, with more details documented in [4]. Firstly, the benefits of the ITS actions are more pronounced at the local level than globally. The reduction of congestion or emission is minor at the network level (typically below 3%), but the impact is far greater at the corridor or junction levels (between 5% to 30%). Quite often, the ITS actions tend to shift congestion and emission
spatially; and such trade-offs need to be well understood when formulating control policies. Secondly, compared to the average flow or speed, speed distribution and stop-and-go patterns caused by signal controls play a more significant role in traffic emission. For example, under certain conditions, diverting more traffic to certain corridor through VMS could reduce speed variability and reduce the total emission. Finally, fleet composition needs to be carefully estimated and considered in emission estimation: our results show that the contribution to BC emission of bus/LGV/HGV can be over 70% when they constitute less than 15% of the traffic.

2.2. Online data collection

The online module of the CARBOTRAF system serves two main purposes: (1) to provide access to real-time data through traffic, meteorological, and air quality sensors and online databases; (2) to determine in real time the optimal traffic control measure(s) for an effective reduction of congestion and emissions.

The data collection for CARBOTRAF in Glasgow is performed via the AQWEB internet-based data collection and management system\(^2\). It has been deployed in the Glasgow air quality network and across Scotland. The system allows air quality and meteorology sensors to be connected wirelessly to a cloud network through a gateway that standardizes data formats (open CSV, SQL, Excel) for easy integration. In addition, traffic sensors including loop detectors (for collecting flow and occupancy data) and the Smart Eye cameras (for detecting fleet composition and car acceleration) have been added to the gateway allowing traffic and environmental data to be gathered via the same interface, e.g. [5].

As shown in Figure 2.1, the look-up table (LUT), which provides structured scenario data, is an essential input for the decision support system and is based on the traffic and air quality modeling discussed in Section 2.1. A large number of simulated traffic scenarios were stored in the LUT in the database, which also contains the catalogue of ITS measures made available for the traffic operator.

2.3. Real-time decision support system

The decision support system (DSS) combines streaming data and the LUT to rank different candidate ITS actions, and make suggestions to the traffic operator accordingly. The following information is required by the DSS in operation: (1) the current ITS action deployed; (2) the probability distributions of traffic/emission objectives for the complete set of alternative actions, which are derived from the LUT; and (3) operational constraints on the set of ITS actions. In real-time operation, the DSS determines the optimal control plan, by solving the following minimization problem (with much mathematical details omitted here):

\[
\min_{x=(x_a; a \in A)} \sum_{a \in A} S(\bar{a}, a)x_a + \mathbb{E}_x[Q(x, \varepsilon)],
\]

where \( A \) denotes the set of ITS actions, the binary decision variables \( x_a \) indicate adoption of action \( a \in A \), \( \bar{a} \) is the current ITS action, and \( S(\bar{a}, a) \) is the operational cost for switching from \( \bar{a} \) to \( a \). \( Q(x, \varepsilon) \) is the random objective value associated with given ITS action choice \( x \) and randomness \( \varepsilon \) inherent in the model, which can be inferred from the LUT. \( \mathbb{E}_x(\cdot) \) represents expectation.

The application of this approach has the following potential issues/challenges:

a) Sparsely populated LUT due to limited data or computational resources could render the generation of an effective statistical model \( Q(x, \varepsilon) \) infeasible. In this case, no additional insights beyond simple interpolation are available, and (1) reduces to a weighted average.

\(^2\) AQWEB is a featured product of Air Monitors Ltd., which is a partner of the CARBOTRAF project. http://www.airmonitors.co.uk/our-products/data-management
b) The use of expectation in the stochastic optimization may be susceptible to outliers in the model prediction and sensing data, and is not robust enough to handle unknown probability distributions.

c) Solving stochastic optimization is computationally expensive and causes further delays, in addition to those caused by data communication, which may render the suggested ITS action sub-optimal in real time.

d) The current DSS has an inventory of finite number of ITS actions without more refined decision resolution (e.g. control parameters of those ITS actions).

The next section illustrates a more general decision support architecture that (partially) addresses these challenges.

3. An analytical model for real-time operation

For a more general discussion of real-time control, we consider a class of learning-based models. The so-called decision rule (DR) approach relies on predefined functional forms (either explicit or implicit) to convert real-time traffic states to traffic control parameters. The optimality of an arbitrarily defined DR may be trained offline using historical data. Unlike the LUT approach, the DR is based on a continuous interpretation of the response surface in the <state, control, objective> space. Another important distinction is that the DR requires no substantial computation in real time, as all the learning, training, and optimization are conducted off line. Finally, model uncertainties or sensing errors may be incorporated in the offline training phase of the DR in such a way that ensures the robustness of the resulting control. Figure 3.1 illustrates the general idea of the DR approach and compares it with the CARBOTRAF decision support system, with more details to follow in Section 3.1.

3.1. Decision rule approach and distributionally robust optimization

Let us denote by \( \mathbf{q} \) a vector of state variables that describe the traffic system in the present and/or a few moments in the past. Generally speaking, \( \mathbf{q} \) may represent arbitrary quantities such as flow, density, speed, air quality, or any analytical transformation of them through data fusion or system reconstruction techniques. The decision rule is instantiated as the following mapping:

\[
\mathbf{u} = f(x, \mathbf{q})
\]  (2)
where $x$ consists of parameters to be determined via the offline training, and $x$ is constrained within some predefined set that represent feasible controls to be implemented. The functional form of $f(\cdot,\cdot)$ is arbitrary, and can be linear, nonlinear, or implicitly defined (e.g. through artificial neural networks). Such a rule can yield timely decision that allows real-time operation, and its efficacy can be improved to a target degree of optimality through the offline training of the parameters $x$.

Let $\Phi(q,u) = \Phi(q,f(x,q))$ be an arbitrary network performance function, which depends on the system state $q$ and the control $u$ (along with some other uncertain or endogenous variables omitted from the notation for simplicity). For example, $\Phi$ may represent the delay at a particular junction, or the total emission along certain corridor. Without loss of generality we assume that $\Phi$ is subject to minimization in this paper. The offline training of the decision rule may be conceptually formulated as an optimization problem with uncertainties. In particular, we consider the so-called distributionally robust optimization (DRO) problem:

$$
\min_{x} \max_{\mathbb{D} \in \mathcal{Q}} \mathbb{E}_{\mathbb{D}} \Phi(q,f(x,q))
$$

where we assume that $q$ follows some unknown distribution $\mathbb{D}^*$. In practice, this distribution may be difficult to estimate due to insufficient sample size and data quality. Thus there is much uncertainties associated with the underlying distribution, which needs to be approximated using a set $\mathcal{Q}$ of candidate distributions $\mathbb{D}$. A data-driven calibration of the uncertainty set based on the Kolmogorov-Smirnov (KS) test will be presented in Section 3.2. The DRO addresses the inexact nature of our knowledge of the underlying distributions in a robust way to ensure a sound performance of the resulting decisions. Its goal is to minimize the expectation of $\Phi$ under the most adversarial realization of the uncertain distribution, as expressed by the “min-max” operator. (3) is identified as the offline training phase of the DR approach, in which a computationally expensive optimization problem needs to be solved. On the other hand, the online operation becomes rather simple as it only involves analytical transformation from $q$ to $u$, and the performance of such a DR is guaranteed by the offline training.

**Remark 1.** Normally, the vector $q = (q(t),q(t-1),...,q(t-m))$, meaning that the decision made at time $t$ depends on the traffic state up to $m$ time steps in the past. If there is a delay of $n$ time steps in data communication, we may take it into account in the training stage by writing $q = (q(t-n),q(t-n-1),...,q(t-m))$, and the resulting DR automatically incorporates such delays. This offers a potential solution for the data communication delay issue c) in Section 2.3.

### 3.2. Computational issues

Problem (3) is a nonconvex, infinite-dimensional optimization problem. In the simplified case where the decision rule $f(\cdot,\cdot)$ and the performance function $\Phi$ are both affine, special techniques such as weak duality and finite-sampling approach may be applied to reduce this problem to a mixed integer linear program; see [6] for more details. However, in a realistic and complex traffic environment, for which the DR needs to be highly nonlinear and sophisticated, more practical computational methods need to be invoked, such as metaheuristic methods (e.g. simulated annealing, particle swarm optimization, genetic algorithm). These algorithms require only zeroth-order information, which means that it suffices for us to successively evaluate the objective function $\max_{\mathbb{D} \in \mathcal{Q}} \mathbb{E}_{\mathbb{D}} \Phi(q,f(x,q))$ for a given $x$. In order to evaluate the objective function, we employ a Monte-Carlo approach as follows.

The key is to treat the performance function $\Phi(q,f(x,q))$ as a single-valued random variable parameterized by $x$; its randomness is due to the random state variable $q$ (and possibly some other random variables endogenous to the system). We then focus on characterizing the unknown distribution $\mathbb{D}^*(x)$ of $\Phi(q,f(x,q))$. The corresponding DRO problem becomes
Consider a set of $K$ sampled historical data: $\{q^{(1)}, ..., q^{(K)}\}$. For each given $x$, we can obtain a sequence of objective values $\Phi^i(x) = \Phi(q^{(i)}, f(x, q^{(i)}))$, $1 \leq i \leq K$, which are $K$ independent samples drawn from $\mathbb{D}^*(x)$. The uncertain distribution set $\mathbb{Q}(x)$ can be constructed as follows. We first fix a priori lower bound $L$ and upper bound $U$ of the objective value $\Phi$, and partition $[L, U]$ into $n$ equal sub-intervals of size $\Delta$. The candidate distributions are then expressed in terms of their discrete probability density functions (PDFs) defined on these sub-intervals; see Figure 3.2. The PDF value in the $i^{th}$ sub-interval, expressed as $F_i$, must be bounded from above by $U_i$ and below by $L_i$, which are given by the KS test based on $\Phi^i(x)$, $1 \leq i \leq K$; see [6] for further details. Therefore, the set of candidate distributions is readily written as

$$\mathbb{Q}(x) = \left\{ (F_1, ..., F_n) : \Delta \sum_{i=1}^{n} F_i = 1; F_i \geq 0; F_i \in [L_i, U_i] \right\}$$

(5)

which is expressed using linear constraints. Finally, the objective of the original problem (4) (i.e. the inner maximization problem) can be easily evaluated by solving a linear program if we approximate the expectation as $\Delta \sum_{i=1}^{n} y_i F_i$.

![Figure 3.2. Discrete PDFs of the candidate distributions.](image)

We use Figure 3.3 to illustrate the DRO and its distinction with stochastic programming (SP) and robust optimization (RO). Consider an abstract objective function $g(x, q)$ where $x$ denotes the decision variable and $q$ represents uncertain variables. The SP stipulates a known distribution $\mathbb{D}^*$ that characterizes $q$ exactly and seeks to minimize the expectation of the objective over $\mathbb{D}^*$; the RO finds upper and lower bounds of $q$ and minimizes the maximum (worst-case) value of the objective over the uncertainty set $\Lambda$; the DRO minimizes the maximum expectation of the objective over a set $\mathbb{Q}$ of candidate distributions that capture the ambiguity inherent in the sample data for $q$. Clearly, the DRO is advantageous in treating the uncertainty when the sample size is small or the underlying distribution is too complex to estimate; it also remedies the conservatism of RO illustrated in Figure 3.3.

![Figure 3.3. Different treatment of uncertainty based on stochastic programming (SP), robust optimization (RO) and distributionally robust optimization (DRO). The bars represent sample data of the uncertain parameter $q$.](image)
4. Application to real-time traffic management

The theoretical framework presented in Section 3 presents a wide range of applications in real time traffic control and management. A few examples are presented in this section, which vary in context and technique, as well as requirements for data communication and processing.

4.1. Real-time signal control for throughput maximization

As the first application, we devise a responsive signal control strategy for a sub-network of the Glasgow test site shown in Figure 2.2, with 5 signalized intersections. For this example, we use the link transmission model [7] to describe traffic dynamics. Historical data on traffic flow and vehicle turning movements are used to conduct data-driven calibration of the uncertain distribution set. The study period spans one hour during the morning peak (8:00-9:00 am).

The objective is to maximize the throughput of the entire test network, given real-time vehicle flow data collected at several loop detectors in the network. As discussed in Section 3.2, we use particle swarm optimization [8] as a metaheuristic for solving the outer optimization problem of (4). Two types of decision rules are considered:

1. A linear decision rule where the function in Eqn (2) is an affine transformation; the coefficients of this transformation are treated as \( x \);

2. A nonlinear and implicit decision rule based on artificial neural network, where we fix the number of layers and neurons, as well as the activation functions. The weights of the connections among neurons are treated as \( x \) to be trained off line.

In addition, as part of the decision rule we apply a projection onto the set of feasible signal parameters \( \Omega \) to ensure the feasibility of the signal controls (e.g. fixed cycle length and inter-green, minimum green time, etc.):

\[
u = P_{\Omega}[f(x, \mathbf{q})]
\]  

(6)

Here, the decision variable \( u \) includes the stage green times for all the signals in the network, and is dynamically updated every 5-10 min depending on the real-time traffic condition. The performances of these two decision rules, together with three other benchmark signal control strategies, are shown in Table 1. All the throughput values and CPU times in the table are averaged over 30 independent testing data. It is clearly seen that the fixed timing strategies (I - III) are outperformed by adaptive signal controls (IV - V). In addition, ignoring the daily variation in traffic flows could severely deteriorate the efficacy of the signal control, as is the case in Strategy I. The nonlinear decision rule works slightly better than the linear decision rule; its effectiveness is expected to be more significant if the network dynamics are sufficiently nonlinear and complex.

<table>
<thead>
<tr>
<th>Signal Strategy</th>
<th>Description</th>
<th>Throughput</th>
<th>CPU time (offline/online)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Deterministic, pre-timed</td>
<td>1498 veh</td>
<td>24 hrs / -</td>
</tr>
<tr>
<td>II</td>
<td>DRO, pre-timed</td>
<td>3382 veh</td>
<td>24 hrs / -</td>
</tr>
<tr>
<td>III</td>
<td>Glasgow field parameter, pre-timed</td>
<td>3576 veh</td>
<td>- / -</td>
</tr>
<tr>
<td>IV</td>
<td>LDR-DRO, responsive timing</td>
<td>3910 veh</td>
<td>24 hrs / 0.01 s</td>
</tr>
<tr>
<td>V</td>
<td>NDR-DRO, responsive timing</td>
<td>3951 veh</td>
<td>24 hrs / &lt;5 s</td>
</tr>
</tbody>
</table>

Table 1. Performance of five signal control strategies. Signal strategy I is non-responsive, and is obtained by solving a deterministic optimization problem with flow data that is averaged over the historical samples. Strategy II is also non-responsive, but is obtained by applying DRO to the historical dataset, thereby taking uncertainties into account. Strategy III is provided by the Glasgow City Council as a field parameter when SCOOT is off line. Strategy IV is linear
4.2. Real-time signal control for emission reduction

As the second application, we implement the decision rule approach for on-line signal control in a synthetic, 2×2 grid network, which is set up in the S-Paramics microsimulation software. The objective is to simultaneously reduce total travel time and total carbon emission on the network (the carbon emission is calculated using the AIRE model). We prescribe the average dynamic demands for 28 origin-destination pairs, which are randomly perturbed in multiple simulation runs to fully test the robustness of the LDR and the DRO approach. As this is a multi-objective optimization problem, the following four alternatives are considered (SC=Signal Control):

i. [SC\textsubscript{TT}] The LDR-DRO responsive control with average vehicle travel time as the objective to minimize.

ii. [SC\textsubscript{E}] The LDR-DRO responsive control with network-wide total carbon emission as the objective to minimize.

iii. [SC\textsubscript{W}] The LDR-DRO responsive control with a weighted sum of travel time and emission and the objective to minimize.

iv. [Webster] The non-responsive signal control based on the Webster formula and average O-D route flow information.

In iv, we use the Webster formula to calculate the optimal cycle time and green splits aiming at minimizing vehicle delays at individual intersections. The four signal control strategies are tested in a simulated environment with the same 30 random seeds. Some preliminary results are shown in Figure 4.1 (a)-(b). The proposed responsive signal control strategies, regardless of their intended objectives, all significantly outperform the fixed-time signal control based on Webster’s formula in terms of travel time and carbon emissions. Moreover, the three responsive signal controls have similar performances in terms of both objectives, based on a 95% t-test, except one case where SC\textsubscript{W} outperforms SC\textsubscript{TT} and SC\textsubscript{E} in terms of travel time. The relatively significant alignment between travel time and carbon emission may be because the latter is not as sensitive to vehicle micro-dynamics as other pollutants like NO\textsubscript{X} or PM\textsubscript{10}; rather it is dependent on the average travel speed. The trade-off between traffic and environmental objectives is expected to be more pronounced for other pollutants, and is subject to further investigation.
Figure 4.1. (a)-(b): Box-plot (based on 30 independent runs) comparison of total travel time and carbon emissions. (c)-(d): Empirical distribution of the objectives.

We use Figure 4.1 (c)-(d) to illustrate the distributionally robust optimization. The empirical distributions of the objectives are shown as the histograms, which are irregular and contain outliers, making the probability distribution rather ambiguous and difficult to estimate. Thus, traditional methods like stochastic optimization do not apply. Robust optimization, which does not rely on any knowledge of the distribution, is susceptible to outliers due to its conservatism. On the other hand, the DRO is more suitable for this situation by estimating the worst-case expectation of the uncertain distributions, shown as the red vertical lines in the figures. The DRO can tolerate irregular empirical distributions and filter outliers in a way that is adjustable by selecting different significance levels, and yields a much less conservative interpretation of the uncertainties, resulting in a better system performance.

4.3. Variable message sign

The third application is variable message sign (VMS) display that is responsive to real-time traffic situation. A case study is carried out in Haining, China, to provide adaptive route guidance to reduce congestion during afternoon peak. The test site, including two alternative routes and the VMS, is shown in Figure 4.2. Five route recommendation can be displayed: Route 1 (strong/weak); Route 2 (strong/weak); and no message (neutral). Each display is associated with a given compliance rate. It is envisaged that, in real-time operation, any of these messages may be displayed and does not necessarily reflect the true traffic condition as intuition suggests.³

³ This is an ideal situation. In practice, messages that frequently changes may cause unwanted oscillations in traffic and reduce drivers’ compliance rates. However, this is beyond the scope of this study.
Traffic flow data on 12 links on 20 days between December 2015 and March 2016 were collected from remote traffic microwave sensors. These data were further processed to extract demand information for the test network. To increase the potential impact of the VMS route guidance, we coordinate the VMS with traffic signal controls at the four junctions shown in Figure 4.2. By invoking the decision rule approach and same notations, we may express the control as:

\[ u = (u_{\text{signal}}, u_{\text{VMS}}) = P_{\Omega}[f(x, q)] \]  

where \( \Omega = \Omega_{\text{signal}} \times \Omega_{\text{VMS}} \), and \( \Omega_{\text{VMS}} \) is a finite set with five elements representing the five display status.

A study based on agent-based simulation shows that the adaptive VMS display designed by the decision rule approach significantly reduces the network travel time, with or without coordination with the traffic signals ([9]). Interestingly, the optimal adaptive display deviates from the genuine display, which makes route recommendation based on the actual traffic condition on the two alternative routes. In addition, the level of improvement (either over the no-VMS case or the genuine VMS case) depends on the compliance rate, which are often associated with the effectiveness of the VMS. Although this study needs further development in terms of driving behavior of those influenced by the VMS, the results reveal the complex decision environment for VMS and necessitate an intelligent design of dynamic route guidance to account for its global impact on the network. The reader is referred to [9] for more detailed results of this study.

4.4. Air traffic control in terminal manoeuvring areas

We move on to air traffic management for the final discussion of the decision rule framework. This research project focuses on multi-airport systems (MAS), which serve air traffic demand in large metropolitan areas. Due to the spatial proximity of the airports, MAS airspaces are characterized by heavy demand and enormous complexity. An ongoing project ([10, 11]) seeks to implement the dynamic route service policy (as opposed to the static route structure) for terminal airspaces, by designing 3-D and conflict free dynamic routes that accommodate time-varying and uncertain air traffic demands throughout the day of operation. The goal is to reduce delay, fuel burn, and controller workload compared to the status quo. This involves (1) the temporospatial characterization and clustering of dynamic traffic demand; (2) the prioritization of flight groups in case of conflict; and (3) the design of 3-D routes following a multi-objective optimization problem (see [12]). Figure 4.3 illustrates such a framework with design parameters \( u_1, u_2, u_3 \), which may be deployed on a pre-tactical (e.g. 24 hrs in advance) or operational (e.g. up to 2 hrs in advance) level.

On the operational level, even with 2-hrs-ahead traffic demand prediction, the computational burden does not
allow the optimization of $u_1, u_2, u_3$ in real time, especially considering the prediction errors. To address these issues, we consider a conceptual DR approach:

$$\begin{align*}
\min_x \quad & u = f(x, p) \\
\max_{p(x) \in D(x)} & \mathbb{E}_{p(x)} \Phi(p, q, f(x, p))
\end{align*}$$

(8)

where $p$ represents the demand prediction, and $q$ represents errors associated with the prediction $p$. Per Figure 4.3, the adaptive control $u = (u_1, u_2, u_3)$, which is responsive to $p$, is applied to different stages of the design, leading eventually to the Key Performance Indicator $\Phi$ (i.e. delay, fuel burn, controller workload). The error $q$ between the predicted and realized demand is factored into the objective function $\Phi$.

The main source of uncertainty lies in the traffic demand forecast, which encompasses numerous attributes including (1) operation type (arrival/departure); (2) origin/destination airport; (3) weight class (small, large, heavy, super-heavy); (4) user type (passenger, cargo); (5) OD type (domestic, international); and (6) direction. It is extremely difficult to estimate the marginal or joint distribution of the prediction error associated with these attributes. To resolve this, we again invoke the DRO approach by calibrating the uncertainty set for the objective $\Phi$ through simulation using historical TBFM data provided by the Port Authority of New York and New Jersey.

5. Conclusion

This paper presents a general methodology framework for real-time traffic management; this is motivated by a recent project on the same subject, and some issues identified therein. The decision rule (DR) approach combined with distributionally robust optimization (DRO) offers a range of solutions for tackling some of the challenges listed in Section 2.3. In particular,

a) The DR approximates the response surface with linear or nonlinear forms which, when combined with DRO, yields more reliable decisions compared to a possibly sparse LUT with finite number of scenarios.

b) The DRO is a very effective approach to handle uncertainties not only in the variables but also in their
distributions, which cannot be accurately estimated in practice due to insufficient sample or complex dependence structure. The conservatism of the robust optimization can be adjusted to balance solution optimality and computational overhead (see Figure 3.3).

c) The DR framework allows all the expensive computations to be done off line, making on-line decision rather efficient and suitable for real-time operation. In addition, the issues of delays in transmitting data in real time can be addressed by a careful design of the decision rule, as suggested by Remark 1.

d) The generic form of the decision rule (see (2)) allows user-defined control space and resolution. For example, the DR can be applied to optimize both continuous (e.g. signal parameters) or discrete (e.g. VMS message) control variables.

In addition, thanks to the offline training with metaheuristic optimization, the DR can handle different forms of the objective (such as travel time and emission) and aim at global optimality. This is a feature not shared by many responsive traffic control systems such as SCOOT (Split Cycle Offset Optimization Technique); a preliminary comparison between DR and SCOOT can be found in [13]. Finally, Section 4.4 demonstrates the capability of the DR approach to handle data errors (i.e. prediction error) without any a priori knowledge of their empirical distribution.

References