Control Engineering Practice 32 (2014) 73–86

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

Multiobjective model predictive control for dynamic pickup and delivery problems

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ARTICLE INFO

Article history:
Received 9 August 2013
Accepted 11 July 2014
Available online 23 August 2014

Keywords:
Multiobjective-model-based predictive control
Dynamic pickup and delivery problems
Intelligent transportation systems
Dial-a-ride services
Genetic algorithms

ABSTRACT

A multiobjective-model-based predictive control approach is proposed to solve a dynamic pickup and delivery problem in the context of a potential dial-a-ride service implementation. A dynamic objective function including two relevant dimensions, user and operator costs, is considered. Because these two components typically have opposing goals, the problem is formulated and solved using multiobjective model predictive control to provide the dispatcher with a more transparent tool for his/her decision-making process. An illustrative experiment is presented to demonstrate the potential benefits in terms of the operator cost and quality of service perceived by the users.

1. Introduction

The dynamic pickup and delivery problem (DPDP) considers a set of online requests for service for passengers traveling from an origin (pickup) to a destination (delivery) served by a fleet of vehicles initially located at several depots (Desrosiers, Soumis, & Dumas, 1986; Savelsbergh & Sol, 1995). The final output of such a problem is a set of routes for the fleet that dynamically change over time and must be determined in real time. Progress in communication and information technologies has allowed researchers to formulate such dynamic problems and to develop efficient algorithms of high computational complexity to solve these problems. The DPDP has been intensely studied in the last few decades (Cordeau & Laporte, 2007; Psaraftis, 1980, 1988) and corresponds to the embedded problem behind the operation of most dial-a-ride services. With regard to real applications, Madsen, Raven, and Rygaard (1995) adopted insertion heuristics from Jaw, Odoni, Psaraftis, and Wilson (1986) and solved a real-life problem for moving elderly and handicapped people in Copenhagen. Dial (1995) proposed a distributed system for the many-to-few dial-a-ride transit operation Autonomous Dial-a-Ride Transit (ADART), which is currently implemented in Corpus Christi, TX, USA. A complete review of DPDPs can be found in Berbeglia, Cordeau, and Laporte (2010), where general issues and solution strategies are described. These authors conclude that it is necessary to develop additional studies on policy analysis associated with dynamic many-to-many pickup and delivery problems.

A well-defined DPDP should be based on an objective function that includes the prediction of future demands and traffic conditions in current routing decisions. Regarding dynamic routing formulations that consider the prediction of future events in real-time routing and dispatch decisions, the works of Branke, Middendorf, Noeth, and Dessourky (2005), Ichoua, Gendreau, and Potvin (2006), Mitrovic-Minic and Laporte (2004), Mitrovic-Minic, Krishnamurti, and Laporte (2004), Powell, Bouzaïene-Ayari, and Simão (2007, Chap. 5), Topaloglu and Powell (2005) can be mentioned. In previous studies (Cortés, Núñez, & Sáez, 2008; Cortés, Sáez, Núñez, & Muñoz, 2009; Sáez, Cortés, & Núñez, 2008), an analytical formulation for the DPDP as a model-based predictive control (MPC) problem using state-space models was proposed. In the previously mentioned MCP schemes, the dynamic feature of the problem appears as the system to be controlled considers future requests that are not known in advance; instead, the availability of historical information is assumed, from which future scenarios with certain probabilities of occurrence are created. Different authors treat the dynamism of the routing decisions in DPDPs differently; most of the methods in the literature are developed to be problem dependent (Ichoua et al.,

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http://dx.doi.org/10.1016/j.conengprac.2014.07.004
0967-0661/

2006; Powell et al., 2007, Chap. 5). However, in those studies, the trade-off between users' levels of service and the associated additional operational costs was completely unknown to the dispatcher. Moreover, issues regarding users' levels of service, such as delayed users (experiencing long travel or waiting times), were not considered.

In real-life implementations of DPDPs, the quality of service is critical. Paquette, Cordeau, and Laporte (2009) concluded that most dial-a-ride studies are focused on the minimization of operational costs and those additional studies on user policies must be performed. It is then reasonable that the objective function properly quantifies the impact on the users' levels of service as affected by real-time routing decisions and the effect on the associated additional operational costs. These two dimensions represent opposite objectives. On the one hand, the users want to obtain good service, implying more direct trips, which results in lower vehicle occupancy rates and higher operational costs to satisfy the same demand for a fixed fleet. More efficient routing policies from the operator's standpoint will reflect higher occupation rates, longer routes, and thus longer waiting and travel times for users. Thus, both components in the objective function must be properly balanced to make appropriate planning and fleet-dispatching decisions. The method of achieving such a balance has not yet been clarified in the literature; it depends on who makes the decisions and in what context. In this work, to guide the decision maker, the use of a multiobjective-MPC (MO-MPC) approach to solve the pickup and delivery problem is proposed. Whenever a request appears, a set of Pareto-optimal solutions are presented to the dispatcher, who must express his/her preferences (criteria in a progressive way manner (interactively), seeking the best compromise solution from the dynamic Pareto set. The final performance of the system will be related to the dispatcher and the criterion used to select the re-routing decisions. Because a set of Pareto-optimal solutions is available, the dispatcher will have additional flexibility to change the criterion on-line based on new, different circumstances, including the impact of the communications (Dotoli, Fanti, Mangini, Stecco, & Ukovich, 2010), driver behavior (Ma & Jansson, 2013), and traffic predictions using insufficient data (Chang, Chueh, & Yang, 2011), among many other real-life situations, and to select the Pareto solution that better addresses those new conditions.

Multiobjective optimization has been applied to a large number of static problems. Farina, Deb, and Amato (2004) presented several dynamic multiobjective problems found in the literature, noting the lack of methods that allow for adequate testing. The use of multiobjective optimization is not new in vehicle routing problems (VRPs; Garcia-Najera & Bullinaria, 2011; Osman, Abo-Sinna, & Mousa 2005; Paquete & Stützle, 2009). For a static VRP, Yang, Mathur, and Ballou (2000) also realized the different goals pursued by users and operators regarding their costs. Tan, Cheong, and Goh (2007) considered a multiobjective stochastic VRP with limited capacity; the authors proposed an evolutionary algorithm that incorporates two local search heuristics to determine a near-optimal solution using a fitness function. The authors demonstrated that the algorithm is capable of finding useful trade-offs and robust solutions. For a comprehensive review of multiobjective VRPs, the interested reader is referred to Jozefowiez, Semet, and Talbi (2008), who classified the different problems according to their objectives and the multiobjective algorithm used to solve them. Most of the multiobjective applications in VRPs in the literature are evaluated in static scenarios; therefore, one of the aims of this paper is to contribute to the analysis of using multiobjective optimization in dynamic and stochastic environments. In a dynamic context, multiobjective optimization can be applied in the framework of multiobjective optimal control. Many examples using multiobjective optimization in control have appeared in various fields, such as the parameter tuning of PID controllers, assignment of eigenvalues by the multiobjective optimization of feedback matrices, robust control, supervisory control, fault tolerant control, multiloop control systems, and within the framework of MPC (Gambier & Badreddin, 2007; Gambier & Jipp, 2011). For the case of multiobjective optimization in MPC, the methods can be classified into two groups.

- The most common methods are those based on (a priori) transformations into scalar objective. Those methods are overly rigid in the sense that changes in the preference of the decision maker cannot be easily considered. Among those methods, some formulations based on prioritizations (Hu, Zhu, Lei, Platt, & Dorrell, 2013; Kerrigan, Bemporad, Mignone, Morari, & Maciejowski, 2000; Kerrigan & Maciejowski, 2003; Li, Li, Rajamani, & Wang, 2011) and some based on a goal-attainment method (Zambrano & Camacho, 2002) can be highlighted; the most often used in the literature of MPC is the weighted-sum strategy.
- The second family of solutions is based on the generation and selection of Pareto-optimal points, which enables the decision maker to obtain solutions that are never explored under a mono-objective predictive control scheme, where only one solution (either optimal or near-optimal through heuristics) is obtained. This variety of options makes routing decisions more transparent and aligned with the service provider goals. The additional information (from the Pareto-optimal set) is a crucial support for the decision maker, who seeks reasonable options for service policies for users and operators. For further details, the book by Haimes, Tarvainen, Shima, and Thadatnil (1990) describes the tools necessary to understand, explain and design complex, large-scale systems characterized by multiple decision makers, multiple non-commensurate objectives, dynamic phenomenon, and overlapping information.

In the present paper, a method of the last type described above is proposed to solve a DPDP and to implement a solution scheme for the operation of a dial-a-ride service. The MO-MPC approach together with a properly well-defined objective function allows the dispatcher to make more educated dispatch and routing decisions in a transparent manner. The multiobjective feature provides more flexibility to the dispatcher when making decisions, although the problem to be solved becomes more difficult, highlighting the fact that the generation of a set of solutions instead of only one solution, as in a mono-objective formulation, is needed. In addition to the dynamic feature, a speed distribution associated with the modeled area, which is dependent on both time and space, was included. One important contribution of the present approach is the manner in which the waiting and re-routing times were modeled; an expression based on weights that are variable and that depend on previous wait times and impatientness due to rerouting actions is proposed.

All of the aforementioned features of this formulation generate a highly non-linear problem in the objective function and in the operational constraints; the dynamic feature and uncertainty regarding future demands are reasons to address the problem through a heuristic method instead of an exact solution method to provide a solution set (pseudo Pareto front) to the dispatcher, who must make adequate, real-time routing decisions. An efficient algorithm based on genetic algorithms (GA) is proposed in this context and is validated through several simulation experiments under different dispatching criteria.

The remainder of this paper is organized as follows. In the next section, the MO-MPC approach is presented. The DPDP, including the model, objective functions and MO-MPC statement, are then discussed. Next, the simulation results are presented and analyzed. Finally, conclusions and future work are highlighted.