An Efficient Algorithm for Line Balancing in Baggage Handling Systems

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1 Introduction

Advanced automated baggage handling systems in large airports are often based on destination coded vehicles (DCVs), which are high-speed carts moving on a network of tracks. A DCV-based baggage handling system consists of several parts: loading stations (where the bags enter the system after having cleared the check-in and security check), unloading stations (which are the final destinations of the bags from where the bags are loaded onto the planes), a network of single-direction tracks, and the early baggage storage, where the bags that enter the system too early can be stored. There are three main issues regarding such baggage handling system: (i) route choice control for DCVs, (ii) line balancing, and (iii) empty cart management. In this paper, we focus on the line balancing problem.

In [1, 2] methods were developed for predictive route choice control of DCVs by assuming there is always a sufficient number of free DCVs at the loading stations such that the bags are immediately transported upon arrival. In practice, the number of free DCVs is limited, necessitating dynamical assignment of free DCVs to the loading stations. In this context, line balancing is the problem of assigning a limited number of free DCVs in the central or local depots to the loading stations. Thereby, one would like to achieve minimum overall waiting time of the baggage in the loading stations while keeping the number of DCVs dispatched as small as possible. The first part of this requirement concerns the overall time delay in the loading stations and the second part concerns the energy consumption and the wear and tear due to DCVs moving around in the network.

One particular solution to the line balancing problem is based on Model Predictive Control (MPC), where a finite-horizon constrained optimal control problem is solved in a receding horizon fashion using the dynamic model of the system [3, 4]. We consider a simple configuration of the baggage handling system as depicted in Fig. 1. The proposed control scheme can achieve an acceptable balance between the overall baggage waiting time and the energy consumption. The optimization problem based on our developed model is a nonlinear optimization problem. However, we show that the problem can be recast as a mixed integer linear programming (MILP) problem and as a linear programming (LP) problem by making some approximations. The performance and computational effort of control scheme based on LP will be compared with the ones of the scheme based on the nonlinear optimization, highlighting the trade-off between optimality and computational efficiency.

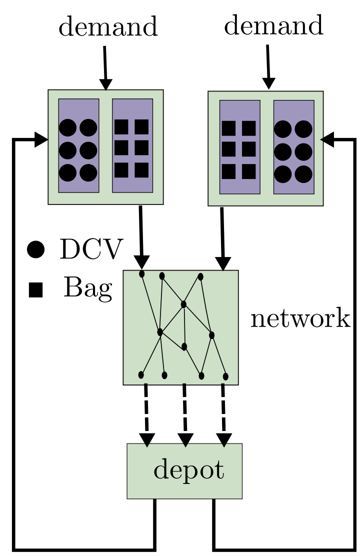

Figure 1: A simple layout of the baggage handling system

2 Methodology

2.1 Dynamical Model

For the configuration of Fig. 1, we derive a continuous-time event driven model, to be used within the context of MPC, by making the following assumptions:

A1 The network of tracks that connects the loading stations to the unloading stations is modeled as a time delay system. Moreover, regardless of the assigned route for each DCV, the travel time between a given loading station and unloading station pair through the network is considered to be known and equal for all DCVs (i.e., we do not take into account the routing of DCVs).

A2 The return path of DCVs from the depot to the loading stations through the network is also considered as a time delay system with known delays.

A3 For each loading station we associate a baggage queue and a DCV queue. Moreover, it is assumed that only fully loaded DCVs can leave the loading station. This implies that the baggage queue outflow must be equal to the DCV queue outflow.

A4 Continuous variables are used for the number of DCVs in the depot and for the queue lengths.

Note that these assumptions are necessary to keep the control design problem tractable, allowing us to make a trade-off between accuracy of the model and tractability of the control problem. Nevertheless, they can be justified for many practical cases.

2.2 Optimization Problem

Based on our developed model, we define an MPC optimization problem that is solved at every control step. The cost function penalizes the overall baggage queue lengths as well as the number of DCVs running around in the network. The optimization problem is a constrained nonlinear optimization problem, which can be solved using multi-start sequential quadratic programming.

2.3 Linear Programming Approximation

The optimization problem based on the original event-driven model, is a nonlinear optimization problem, which cannot be solved efficiently for large instances of the problem or for a large prediction horizon. We approximate the continuous-time even-driven model of the configuration of Fig. 1 with a discrete-time model that is used to recast the problem as an MILP problem [5] and an LP problem. The LP formulation is obtained by expressing the non-negativity requirement of the queue lengths as optimization constraints, whereas in the nonlinear model such requirement is integrated in the model. The MILP formulation is obtained by making some simplifying assumptions on the evolution of the queue lengths within the sampling interval. One should note that the LP and MILP formulations are approximations of the nonlinear one. Therefore, their solutions may be suboptimal with respect to the one of the nonlinear optimization problem. For a small sampling time, inaccuracies due to this approximation would be negligible at the cost of increased computational complexity of the model.

3 Conclusions and Future Work

The MPC controller based on our developed model can achieve a trade-off between the overall baggage waiting time and the energy consumption. The MILP and LP approaches were developed, by making some approximations, to achieve a more computationally efficient solution. When the sampling time is chosen sufficiently small, particularly for the LP approach, it turns out that it achieves a good performance with respect to the nonlinear approach while significantly decreasing the computational complexity of the problem.

In future, we will consider relaxing some of the assumptions of Section 2.1, particularly assumption A3. The MPC objective function will also be modified to penalize the terminal cost as well.

References

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