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Model Predictive Control for Scheduling and Routing in a Solid Waste Management System

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Abstract: Solid waste collection and hauling account for the greater part of the total cost in modern solid waste management systems. In a recent initiative, 3,300 Swedish recycling containers have been fitted with level sensors and wireless communication equipment thereby giving waste collection operators access to real-time information on the status of each container. In a previous study (Johansson, 2006), analytical modeling and discrete-event simulation have been used to evaluate different scheduling and routing policies utilizing the real-time data, and it has been shown that dynamic scheduling and routing policies exist that have lower operating costs, shorter collection and hauling distances, and reduced labor hours compared to the static policy with fixed routes and pre-determined pick-up frequencies employed by many waste collection operators today. This study aims at further refining the scheduling and routing policies by employing a model predictive control (MPC) framework on the system. In brief, the MPC controller should minimize an objective cost function consisting of fixed and variable collection and hauling costs for a fixed future horizon by calculating a sequence of tactical scheduling and routing decisions that satisfies system constraints using a receding horizon strategy.

1. INTRODUCTION

Over the last 20 years, car traffic has grown at a rate of 3.3 percent per annum and road freight traffic has grown almost at 5 percent per annum (OECD, 1995). Consequently, freight transportation-related problems are mounting (OECD, 1997). Solid waste collection and hauling are estimated by municipal planners in Malmoe, Sweden, to account for 10-15% of the total freight transportations in the city, but due to the low average speed of vehicles used, and numerous stops during collection, the effect they have on congestion, air pollution, and noise is higher than that of other types of freight transportation.

The most important achievements in reducing traffic-related problems to date have been effected through advances in technology; e.g. developments in engine technology to reduce fuel consumption, noxious emissions and noise; and cleaner fuels. The gains made have in some cases, however, been offset by changes in behavior, e.g. savings in fuel through engine design has been offset by the trends towards more powerful engines, higher speeds, and increased congestion (OECD, 1995). Policy-makers and scientists alike agree that technology alone cannot solve the problems; habits and behaviors need to change too. This makes telematics technology an interesting topic as it can be used to enable and aid changes in traffic behavior. The word telematics was "originally coined to mean the convergence of telecommunications and information processing, the term later evolved to refer to automation in automobiles. GPS navigation, integrated hands-free cell phones, wireless communications and automatic driving assistance systems all come under the telematics umbrella." (Definition from TechEncyclopedia; www.techweb.com, 2004-06-28). Recent developments have extended the concept to equipment fitted on the load carrier. Examples of such equipment are the level sensors and alarm systems for recycling containers for corrugated board and cardboard in Sweden.

Since 1994, Sweden has had producer's responsibility regulations for packaging waste. All companies that manufacture, import or sell packaging are responsible for ensuring that packaging waste can be collected and recycled. Together, these companies have formed five material handling companies working together under the name Packaging Collection Service, with the task of organizing and administering this responsibility. In order to collect packaging waste, the Packaging Collection Service has set up recycling stations at more than 7,000 locations throughout the country. A typical recycling station has a number of containers where nearby households can discard plastic, paper, cardboard, corrugated board, metal, and glass packaging. The collection, hauling, and sorting of packaging waste is contracted out to local entrepreneurs. The containers are typically collected by front-loading compacting vehicles. Due to heavy congestion, this vehicle type cannot, however, be used in downtown areas and consequently some inner city containers are of a different design and are collected using smaller, less efficient, non-compacting, open-sided vehicles which use a crane for waste collection. Recently, the material handling companies for corrugated board and cardboard, Returwell and Svensk Kartongåtervinning respectively, fitted their containers with level sensors and wireless communication equipment in order to assess the quality of the service provided. The investment was paid in full by the material handling companies. Approximately 3,300 containers of this type have been distributed to recycling stations around the country. The sensor is mounted under the lid of the container. It is activated once an hour and assesses the level of the container by means of four infrared light-emitting diodes. If three of the four beams are broken, an alarm is raised and transmitted through the GSM network, and an automatically generated email is sent to the waste collection operator. A second alarm is raised when all four beams are broken and a reset signal is sent when a tilt-sensor indicates that the container has been emptied. In order to assure the quality of service, the operator is charged a penalty if the time between the second alarm and the reset signal exceeds 24 hours on weekdays and 48 hours on a weekend.

Studies of solid waste management systems report that waste collection and hauling represent the greater part of the total cost of such systems (Baht, 1996; Leander in Sonesson 2000). Although the equipment fitted on the recycling containers in Sweden has given waste collection operators access to real-time information on container status, many operators have chosen not to use the data to improve the planning and control of their operations. Instead, they continue to rely on their traditional static planning approach, employing fixed routes with predetermined pick-up frequencies. The situation where some waste collection operators have embraced technology raises many questions on how real-time data can be used for planning and control purposes.

The purpose of this paper is therefore to evaluate if model predictive control can be used to improve the scheduling and routing of solid waste transports in the system. This problem is characterized by the simultaneous presence of three fundamental aspects:

- Scheduling: to specify a time or set of times when a certain route should be executed.
- Routing: to organize the physical movement of goods between different geographical sites.
- Dynamicity: the two aspects above embedded in a framework of constantly changing information, a time horizon, and where decisions influence later decisions.

It should be pointed out that the study is primarily related to waste collection from a relatively small number of discrete points, and does not apply directly to house-to-house curbside collection of residential wastes.

1.1 Vehicle scheduling and routing

Vehicle scheduling and routing problems have been extensively researched during the last three decades. The classical vehicle routing problem (VRP) aims to minimize the total cost of routing a multiple number of vehicles from a depot to service customer nodes and then return. The problem can be further characterized by, for example, type of fleet, number of depots, and type of operations (pure pick-ups, pure deliveries, and mixed). The vehicle scheduling and routing problems (VSRP) are an extension of the VRP with a time horizon, additional time constraints, place requirements on the order of operations (Bodin and Golden, 1981). Most work in this area has, however, focused on static problem formulations where all information is known to the planner beforehand despite its stochastic and dynamic characteristics.

Stochastic vehicle routing and scheduling problems arise when elements of the problem are modeled as random variables, e.g., stochastic travel time and stochastic demand. The typical solution approach to this class of problems is a priori optimization of the probability that the tour(s) can be completed given the constraints of the problem. With support for real-time decision making, such as wireless communication, geographic information systems (GIS), and global positioning systems (GPS), the importance of simultaneously handling the temporal aspects of uncertainty is growing. Dynamic data is characterized by its constantly changing nature and includes e.g. real-time traffic conditions, customer demands, driver and vehicle statuses. Psaraftis (1988) and Powell et al (1995) feature comprehensive surveys of stochastic and/or dynamic vehicle routing problems.

The problem domain belongs to a class of optimization problems that are intrinsically hard to solve. Lund et al (1996) introduced the concept of degree of problem dynamism, measured by the ratio of dynamic distance over static distance, and evaluated its effect on the quality of the solutions. This concept was further explored by Larsen et al (2001) who also proposed a taxonomy for dynamic routing systems where the ratio between dynamic requests and total number of requests is used as the key determinant of the system's degree of dynamism. In the context of this study, only containers where the sensors have raised alarms and initiated a tour are regarded as dynamic requests. Other containers that might be collected on the same tour are regarded as non-dynamic, planned events, although the planning takes place ad hoc at the time when the tour is initiated. Applications of VRP and VSRP related to waste collection can be found in Bommisetty and Dessouky (1998), Tung and Pinnoi (1999), Shih and Chang (2001), Baptista et al (2001), Angelelli and Speranza (2002), Zografos and Androutsopoulos (2002). However, none of the articles deals with dynamic scheduling and routing, nor the underlying system characteristics or how they are connected to different scheduling and routing policies.

1.2 Model Predictive Control

MPC is an optimal control strategy utilizing an internal forecasting model to generate predictions of future system behavior and an optimization model. Applications of MPC have been widely used in industry, and also some contributions of MPC can be found supply chain and logistics literature (Bose and Pekny, 2000; Braun *et al.*, 2003; Perea-López *et al.*, 2003; Tzafestas *et al.*, 1997; Wang et al., 2007; Zafra-Cabeza *et al.*, 2007).

2. METHODOLOGY

The research methodology used in this study is a blend of analytical and simulation modeling combined with empirical case research. The first approach was to construct analytical models in an attempt to reflect an ideal system, thus isolating vital system characteristics which determine the effect of dynamic planning in a waste collection context. The second modeling approach, stochastic discrete-event simulation, was used to build more realistic models of the system. The simulation approach allowed a relaxation of the assumptions made in the analytical models and more advanced geometries, heterogeneous sets of containers, and more complex planning policies could therefore be evaluated. The final simulation case study is built on observations and interviews with planners and drivers operating the downtown recycling stations in Malmoe. Supplementary interviews were conducted with two other operators of similar systems in order to investigate their usage of real-time data.

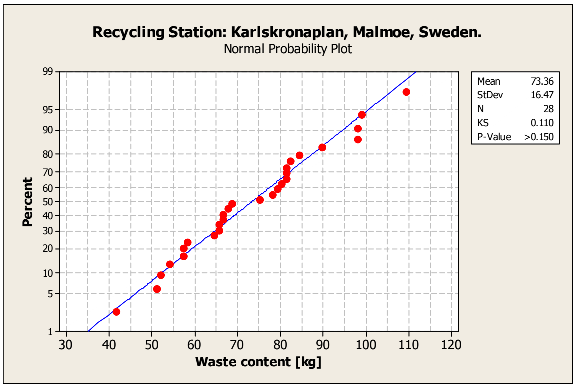

Figure 1. Normal probability plot of the waste collected from the recycling station at Karlskronaplan, Malmoe, Sweden. The mean weight of the waste collected in a week is 73.36 kg with a standard deviation of 16.47 kg, or 10.5 kg/day, with a standard deviation of 6.2 kg/day$^{0.5}$.

2.1 Analytical model

In order to evaluate the benefits of adopting dynamic scheduling in solid waste collection, an analytical model of a system with N containers was developed using probability theory. The container contents weight after a certain time was assumed to follow a normal distribution, an assumption supported by the empirical data collected (Fig. 1). The goal of the static scheduling is to collect all containers before the capacity of any one is expected to exceed its limits. In order to compute the optimal static collection frequency, an acceptable risk-level, α, has to be set. The α-level is the risk that any of the N containers exceeds its capacity. It is assumed that all N containers are emptied on the same tour and that the containers are independent but identical in terms of capacity, mean fill rate, and its standard deviation. The mean time between collections [MTBC] is then defined by

$$MTBC = \frac{2 \cdot M \cdot \bar{x}_{day} / Z^2 + s_x^2 - \sqrt{4 \cdot M \cdot \bar{x}_{day} \cdot s_x^2 / Z^2 + s_x^4}}{2 \cdot \bar{x}_{day}^2 / Z^2} \quad (1)$$

Where:

$Z = F^{-1}(p \mid p = (1-\alpha)^{\frac{1}{N}})$: inverse cumulative standardized normal distribution

α : risk of exceeding any container capacity

$\bar{x}_{day}$: mean inflow per container and day [kg/day]

s_x : standard deviation of inflow per container and day [kg/day$^{0.5}$]

M : container capacity [kg]

N : number of containers

This time should be compared to the MTBC for a dynamic system where the collection occurs when the first container exceeds its capacity and an alarm is raised. It is assumed that the dynamically controlled system has sufficient capacity to respond to the alarm and that the time for collection is negligible. The MTBC for the dynamic system can then be calculated by using equation 1 with an α-value of 0.50, which corresponds to a 50% chance (or risk) that at least one of the N containers is 100% full and triggers the alarm (Fig. 2).

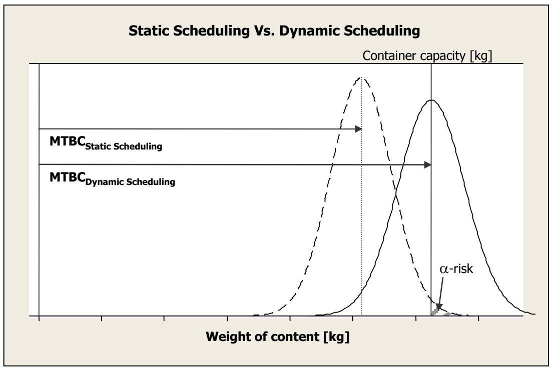

Figure 2. A theoretical representation of the additional container weight expected when comparing a system with optimal static scheduling for a given risk-level versus a system with event-driven, dynamic scheduling.

Since the real system does not operate 24 hours a day, seven days a week, the equation has to be adapted to operating only in the daytime on weekdays. Since the model assumes that all N containers are emptied on the same tour, regardless of whether the tour is initiated by a static schedule or triggered by a level sensor, the cost of the individual tours is the same, but since the frequency of tours differs, the long-term cost will be different. The ratio between the $MTBC_{static}$ scheduling and the $MTBC_{dynamic}$ scheduling is a measure of the potential cost reduction of adopting dynamic planning.

2.2 Simulation model

The simulation model consists of containers, vehicles, and a recycling facility. The key attributes of the containers are mean waste fill rate [kg/day], standard deviation of fill rate [kg/day$^{0.5}$], current weight [kg], capacity [125 kg], and location. Each container is fitted with a level sensor that triggers an alarm signal when the container exceeds the 75% level ("yellow alarm"), and when it is 100% full ("red alarm"). The key attributes of the vehicles are the current weight of its load [kg], capacity [2500 kg], average speed [20 km/h], time to perform different actions, e.g. check station and set up vehicle for collection [2.5 min], collect [2.5 min/container], reset vehicle and leave station [2 min], empty vehicle at recycling facility [10 min], distance cost [0.6 EUR/km], and hourly cost [39 EUR/h].

Two different city geometries were used. The first geometry was a hypothetical city model where the collection points were equidistantly located around a circle with a recycling plant outside the circle. The simulation results reported were based on a geometry with a city center radius of 2 km and a distance to the recycling plant of 15 km. The second geometry used in the simulation was a model of the actual system in Malmoe, Sweden (Fig. 3). Based on input values for system size, a random system was created in terms of the number of containers and geometry parameters, minimum and maximum values for the waste generation, and standard deviation of fill rate. The mean waste fill rates per container were drawn from a uniform distribution with the minimum and maximum value as parameters. The simulation results reported in this article are based on a waste generation minimum value of 4 kg/day, a maximum value of 20 kg/day, and a standard deviation of 50% of the mean fill rate.

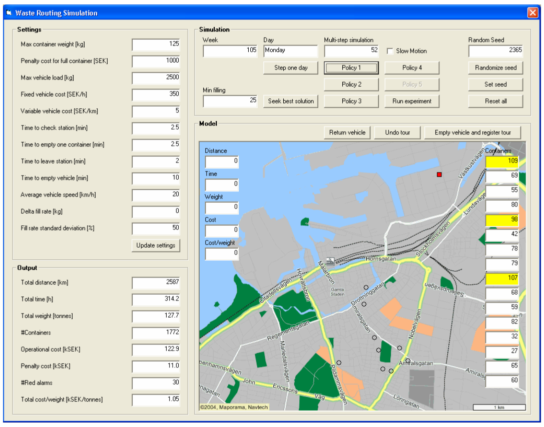

Figure 3. The Malmoe Simulation Model

During the simulation, each location generates waste according to a normal distribution and adds it to the containers on an hourly basis. It should be pointed out that the inflow model of having a normally distributed amount of waste added to the container once an hour is not a true representation of the variation in inflow to the containers. On an aggregated level, the normal distribution appears to adequately resemble the real system over time and in particular in the later stages when the container's content is approaching the critical levels where the sensor raises alarms.

When the waste quantity exceeds the threshold values of 75% and 100%, alarms are raised and depending on which planning policy is used, vehicles might be scheduled and routed to the recycling point. If a container is full and not collected within a specified time, 24 hours on weekdays and 48 hours during the weekend, a penalty is charged. As with the real system, collection and hauling are only conducted in the daytime on weekdays. The duration was 104 weeks. The primary performance indicators used included the total operational cost of the system, penalty cost, labor hours, collection and hauling distance, number of tours, and number of containers collected, all on an annual basis. The variations in outputs between runs were small, and five replicates appeared sufficient to allow an estimate of the system behavior. Five different collection policies were used in the evaluation:

Policy 1: Static scheduling and static routing. This policy mimics the actual operations of the system practiced today with fixed collection days and routes. The procedure for solving the static routing problem is based on the heuristic algorithm proposed by Christofides and Beasley (1984).

Policy 2: Dynamic scheduling and dynamic routing to full containers. This policy is fully event-driven and initiates a tour to full containers within 24 hours from the receipt of a "red alarm". In order to avoid overfull containers and subsequent penalties during weekends, a special rule for Fridays was introduced so that containers where the "yellow alarm" has been triggered were also collected. An alarm that is received while a vehicle is already collecting waste will not re-route that vehicle, but will instead initiate a new tour within 24 hours. As with all dynamic scheduling policies, it is assumed that the system has sufficient vehicles and manpower to handle the collection requests within 24 hours.

Policy 3: Dynamic scheduling and dynamic routing to "almost" full containers. This policy is similar to policy 2, and initiates a tour to full containers within 24 hours from the receipt of a "red alarm" or a "yellow alarm" on a Friday. The vehicle is, however, not routed exclusively to full containers, but also to nearby containers which have an estimated level greater than a set threshold value.

Policy 4: Static scheduling and dynamic routing to "almost" full containers. The static scheduling and routing to "almost" full containers policy is based on a static scheduling using the same collection days as policy 1 has chosen. The routing is, however, done to full and "almost" full containers using the same logic as policy 3. The policy aims to maintain the benefits of static schedules for the drivers, while using the real-time data for improving the demand prediction and routing.

Policy 5: Employing model predictive control. The scheduling and routing is done by MPC controller using a prediction and control horizon of each 14 days. The controller calculates a sequence of tactical scheduling and routing decisions satisfying system constraints by means of a receding horizon strategy while minimizing the collection and hauling cost. The policy aims to investigate if it is beneficial to modify the policy given a specific state of the system, rather than having fixed the policy as in 1-4.

The second simulation model is built on empirical data from the Malmoe downtown recycling system and features a realistic geometry and waste generation. The system consists of nine recycling stations located in the downtown area and comprises 16 containers for cardboard and corrugated board. Currently, a static approach to scheduling and routing is employed; every Monday, a vehicle is routed to all 16 containers, and on Fridays, a vehicle is routed to two of the containers with above-average fill rates. The full Monday tour is 12.5 km long and takes approximately 3 hours to complete. The mean fill rates of the containers vary from 4.5 to 21.7 kg/day and the standard deviation is estimated to be between 44% and 59% of the mean fill rate.

Validation and verification of the simulation model The goal of the verification and validation process is twofold; (1) to create a model that represents the true system closely enough to be used as a substitute for the purpose of experimenting and predicting system behavior, and (2) to create credibility of the model (Banks et al, 2001). One of the most critical data assumptions in the solid waste collection model was related to modeling of waste generation that created the demand for collection. Data on recycling waste per recycling point in the real system was therefore collected over a period of 6 months, from November 2003 until May 2004. In the model, it was assumed that the amount of waste in a container after a certain time would follow a normal distribution. With the exception of the time around Christmas, when the generation of packaging waste is extremely high, this assumption was validated using a Kolmogorov-Smirnov test. The hypothetical city simulation model was also quantitatively validated by comparing it to the analytical model. In total 6,724 simulation runs of varying system sizes ranging from 5 to 50 containers, mean fill rates ranging from 5 to 25 kg/day, and standard deviations ranging from 0 to 10 kg/day$^{0.5}$ were compared to the analytical model with a mean average percent error [MAPE] of 0.18% indicating a very good match between the models.
A quantitative validation of the model and the Malmoe system was not done due to the lack of data on individual tours. Instead, aggregated data on a yearly basis was available, allowing the model to be validated (and calibrated) on this level. As expected, policy 1 and policy 4 produce identical results when the threshold value is set to 0%.

3. RESULTS AND DISCUSSION

In the analytical model, the savings potential is given by the increased MTBC in the dynamically controlled system versus the system with static planning. This is shown in Fig. 4 where the savings potential is plotted as a function of the mean fill rate and the standard deviation of the fill rate for a system operating 24 hours a day, 7 days a week. Evidently, dynamic planning offers the greatest savings potential for systems exhibiting high variation and low mean fill rates, while the potential for systems with low variation is negligible.

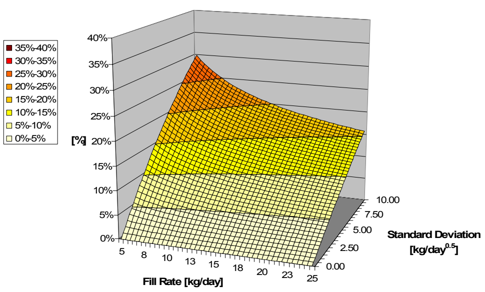

Figure 4. Savings potential for dynamic scheduling and routing vs. static scheduling and routing, for a 10-container system operating 24/7, calculated using the analytical model [%].

Figure 5 displays the savings potential for a system where operations are allowed on weekdays only. The jagged nature of the surface merits explanation. Due to constraints posed by working hours, the static scheduling policy operates with spare capacity for most combinations of inflows. Since the savings potential is given by the quotient between the operating cost of a static scheduling system and a dynamically controlled system, a saw-like surface appeared.

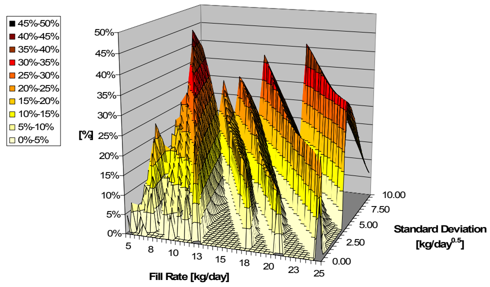

Figure 5. Savings potential for dynamic scheduling and routing versus static scheduling and routing, for a 10-container system operating on weekdays only, calculated using the analytical model [%].

The result that variability has a significant impact on the savings potential is also confirmed by the simulation results of the hypothetical city model.

The dynamic policy 2 has the greatest container utilization, but for small systems, the process comes at the expense of frequent tours, long distances, and low utilization of the vehicle. For a larger system, however, this policy proves to be the most cost efficient although the distance is slightly higher than for the other policies. In fact, it can be shown that policy 2 is optimal for large, dense systems. For smaller systems, however, policy 1 is superior to policy 2. Since most systems for recycling containers are smaller than 100 containers, this comparison explains the reluctance of waste collection operators to adopt the dynamic policy 2.

For systems smaller than 100 containers; policy 3, and to a lesser degree policy 4, manage to reduce the collection and hauling distance and increase both vehicle and container utilization compared to policy 1. It should be pointed out that the results of operating according to policy 3 and policy 4 are highly dependent on the threshold value for what should constitute an "almost" full container. In the simulations reported in this study the threshold values of 40% and 75% respectively were used. The relatively low value of 40% for smaller systems indicates the importance of fully utilizing the vehicle once it has been decided that a tour should be initiated. The policy 5 produces similar results as policy 3 for smaller systems, and as policy 2 for larger systems, i.e. the MPC controller seems to switch to the optimal policy automatically given the size of the system.

Operating cost has been used as an aggregated measure of the efficiency of a system. The simulation results from the hypothetical city model reveal that there is a strong link between the system size and the cost of operating the different policies. Further, the results show that policy 4 mirrors the cost of policy 1 closely. The results obtained from the hypothetical city model are confirmed by the result from the simulation of the actual system in Malmoe. The result shows that policy 3 reduces collection and hauling distances by 17%, the number of stops to collect containers is decreased by 14% and the operational cost reduced by 15%. As expected, policy 2 is much less efficient due to the small size of the system. In this simulation the total cost of operating with policy 4 is 17% higher, with 5% of the costs due to penalties for overfilling containers.

4. CONCLUSIONS

In this study, the effect of some basic scheduling and routing policies in the collection of solid waste has been examined, both for a hypothetical city model and a model of a real system. From the study, it can be concluded that dynamic scheduling and routing policies exist that have lower operating costs, shorter collection and hauling distances, and which collect fewer containers compared to the static policy employed by many waste collection operators, for all system sizes and realistic levels of variation. Further, dynamic scheduling and routing have the highest potential to decrease cost in the face of irregular demand. For large, dense systems, the dynamic scheduling and routing policy 2 is the optimal solution. When the number of containers is decreased and/or the distance between the containers is increased, this policy rapidly loses its benefits however. For smaller systems, the dynamic policy 3 is more suited and cost reductions in the range 10% to 20% can be expected for the type of systems evaluated in this study. The policy 5 of using an MPC controller will automatically determine when the switch from policy 2 to policy 3 should be done. Policy 5, however, does not outperform any of the other policies. This may be a bit surprising, but is likely to be caused by the static nature of the waste inflow. The inflow for each container is modeled as a stochastic variable, *i.e.*, once “optimal” settings have been established for policy 2 or 3, they remain “optimal” and the MPC controller is not able to improve the system further.

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