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Control-based integration of rejection rates into endogenous demand ride-pooling simulations

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Abstract—The potential of Mobility-on-Demand systems has frequently been studied in the literature, often in combination with dynamic demand models that respond to the obtained service levels. However, the endogenous demand usually does not respond to generated rejection rates. The paper discusses potential ways of integrating this dimension into a behavioral demand model. A linear control-based approach is proposed that penalizes choices for the on-demand service until a maximum desired rejection rate is obtained. The practical value of the method is demonstrated on a large-scale agent-based transport simulation and pathways for future improvements are provided.

Index Terms—ride-pooling, mobility on demand, rejections, simulation, endogenous demand, linear control

I. INTRODUCTION

Mobility-on-Demand (MoD) refers to a type of mobility system that consists of a fleet of on-demand vehicles that are available to the users as needed, offering more flexibility and an alternative to owning private cars. The development of MoD is closely related to the development of autonomous vehicles [1] which are expected to render on-demand mobility business models more viable and profitable.

The design of MoD systems involves decisions on the strategic, tactical and operational levels [2], [3] such as number and characteristics of vehicles, operation strategies and pricing. Agent-based simulation is a tool that is increasingly used in mobility studies for the design and prospective assessment of future mobility systems. Various agent-based simulation tools and frameworks with different capabilities and levels of details have been proposed, many of which are open-source [4]. Consequently, various studies based on agent-based simulations considering MoD systems can be found in the literature [1]. Various aspects of MoD systems have been addressed, from fleet sizing [5], [6] to operation strategies [7], [8].

Most of the studies of MoD systems in agent-based simulation consider static demand for MoD where a predefined set of requests is submitted to a service. Various indicators such as wait times, travel times and the empty distance ratio are used

to assess the quality of service. In the majority of existing studies, all requests must be served by the operators, which means that the demand level directly impacts those indicators. Fewer studies allow requests to be rejected [9]. In those cases, the service metrics are decoupled from the demand level and a new indicator, the rejection rate, is introduced.

More recent studies use endogenous demand, where the requests are adjusted by a behavioral model that recursively takes into account the level of service of the MoD system [10]–[13]. Typically, those studies make use of rejection-free fleet control algorithms. To our knowledge, no endogenous demand study has been proposed that integrates observed rejection rates into its demand estimation, although this case represents more closely future deployments of MoD systems in reality.

In this work, we propose a method to integrate rejection rates into such an endogenous demand simulation model. Section II formally introduces the type of simulation we consider. Potential solutions for integrating rejection rates are discussed, and their individual shortcomings are identified. Section III presents our method based on a linear proportional controller to address the identified issues. Section IV describes our simulation environment to evaluate the approach and presents a use case for the area of Paris-Saclay. Section V discusses our approach, edge cases, and proposes policy-relevant interpretations. Finally, Section VI concludes the study with perspectives on future improvements.

II. PROBLEM

Formally, we consider simulation set-ups as shown in Figure 1. In an iterative way, a set of requests is generated using a demand model, which is then processed in a mobility simulation. In a closed loop, the obtained information on waiting times, detours, and also the rejection rate, are fed back to the decision process in order to generate a new adapted set of requests. Generally, low levels of service will lead to lower demand while reduced wait times, travel times and rejection rates should yield higher demand.

In most endogenous demand studies, discrete mode choice models are used. In those models, users can choose for each of their trips between a set of modes, for instance, using the car, public transport, using the bicycle, or walking. For each mode, a utility function is defined, with higher utilities indicating more interesting alternatives.

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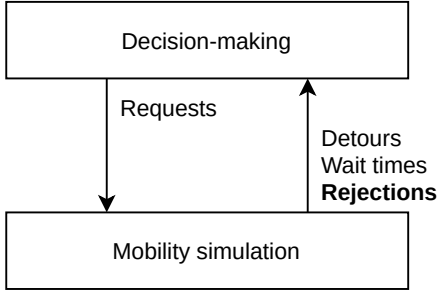


Fig. 1. Endogenous demand loop

For instance, [11] uses the following equation to simulate MoD in Paris:

$$\begin{aligned} \tilde{v}_{\text{MoD}}(\mathbf{x}) = & \beta_{\text{ASC,MoD}} \\ & + \beta_{\text{travelTime,MoD}} \cdot x_{\text{travelTime,MoD}} \\ & + \beta_{\text{waitingTime,MoD}} \cdot x_{\text{waitingTime,MoD}} \\ & + \beta_{\text{cost}} \cdot p \cdot x_{\text{distance,MoD}} \end{aligned} \quad (1)$$

Variables denoted as x describe estimated choice dimensions for a specific trip, and behavioral parameters (usually negative) denoted as β quantify their share in the overall generalized costs for the trip. Furthermore, a price p is defined, and similar utility functions are defined for the other modes of transport that compete with the on-demand service.

A commonly used discrete choice model type that is also used in [11] is the multinomial logit model which yields a probability to choose each alternative based on the calculated utilities for each mode [14]. Additionally, an availability $a_k \in \{0, 1\}$ can be defined which defines whether an alternative is available for a specific trip k or whether the choice probability is zero.

While some choice dimensions (like the distance) can be obtained directly through routing, others, such as the waiting time can be estimated from the mobility simulation, for instance in time bins and on a hexagonal grid such as in [11] or [12].

Additionally, we now assume that a fleet control algorithm with rejections is used in the simulation, which allows us to calculate a global rejection rate $\rho \in [0, 1]$ as the quotient of the rejected number of requests and the total amount.

The resulting question is how to feed back this rejection rate like the other choice dimensions (Figure 1). In the following, let $i \in \mathbb{N}$ denote the currently executed iteration from which information has been obtained. Intuitively, there are three pathways to achieve the feedback:

- (i) The rejection rate can be integrated into the utility function as another **choice dimension**, weighted by the parameter $\beta_{\text{rejection}}$:

$$v_{i+1} = \tilde{v}(\mathbf{x}_i) + \beta_{\text{rejection}} \cdot \rho_i \quad (2)$$

Economically, the formulation is not realistic, as a rejection rate of 100% should lead users to never consider

the service. However, then $\beta_{\text{rejection}}$ should be quite high, and it is not intuitively clear which value to put for the parameter. There is also a conceptual contradiction: The idea of the parameter is that $\beta_{\text{rejection}} < 0$ would penalize rejections. However, if a state is reached at which rejections are avoided, ρ_i will be zero and the additional term will have no impact.

- (ii) The **availability** of the MoD mode can be sampled according to

$$a_{k,i+1} \sim \text{Bernoulli}(1 - \rho_i) \quad (3)$$

indicating that the number of trips for which MoD is available follows the acceptance rate. However, applying this approach will not yield the desired rejection rate in the following iteration, since choices should be discarded *after* being chosen based on the utilities. This could be a viable approach, but would imply complex structural changes to the choice process.

- (iii) Similar to the first option, a new **penalty** term $\pi \in \mathbb{R}$ can be introduced to the utility function:

$$v_{i+1} = \tilde{v}(\mathbf{x}_i) + \pi_{i+1} \quad (4)$$

Being a simple constant (but iteration-dependent) term to the utility function, it can be interpreted easily in a multinomial logit context and even converted to monetary units. If π_{i+1} is chosen close to zero, there will be little impact on the overall demand and the rejection rate. If a strongly negative value is chosen, demand will be suppressed and (assuming same fleet size) the rejection rate will decrease. We assume that a value π^* can be found that pushes the rejection rate below a predefined threshold ρ^* .

Due to its flexibility and interpretability, we choose the last approach. The correct value of π^* to reach a rejection rate of ρ^* depends on external configuration inputs, such as the fleet size. One would, hence, need to run multiple simulations for each new configuration to find the optimal π^* and even repeat the process for different target rates ρ^* .

Therefore, we propose an iterative approach to auto-calibrate the parameter π^* over the course of one iterative simulation.

III. APPROACH

The approach proposed in this paper draws from the field of control theory and concretely makes use of a Linear Proportional Controller [15] in order to dynamically find a penalty that drives the rejection rate below ρ^* .

The control process is formalized by defining an update rule for the penalty:

$$\pi_{i+1} = \pi_i + \Delta\pi_i \quad (5)$$

In a purely linear control application, a proportional controller can be defined through the update rule

$$\Delta\pi_i = K \cdot \Delta\rho_i \quad \text{with} \quad \Delta\rho_i = \rho^* - \rho_i \quad (6)$$

leading to a positive update if the current rejection rate ρ is too low and to a negative update otherwise, assuming a positive proportional gain $K > 0$, which specifies how fast the penalty is adjusted.

For stability reasons (see below), we propose an extended update rule as

$$\Delta\pi_i = \begin{cases} K \cdot \Delta\rho_i & \text{if } \rho_i \geq \rho^* \\ 0 & \text{else} \end{cases} \quad (7)$$

Accordingly, the penalty is only updated if the current value is larger than the target value. The initial penalty π_0 is set to zero.

IV. CASE STUDY

We consider in this work the use case of a future mobility system in the Paris-Saclay area presented in [16]. Alongside future rail-based public transport lines that are considered, the use case features a MoD system that is used as a feeder to and from train, metro and tramway lines including those of the future Grand Paris Express, one of the largest infrastructure projects in Europe.

The case study is based on the MATSim simulation framework [17], and the demand is determined using a multinomial logit model that is used to update the mode decisions of a random selection of 20% of a total of 700,000 agents in each iteration. They represent 100% of the travelers observed on an average day in the study area. The simulated travelers can choose between performing trips using their own car (if available), public transport, slow modes or a MoD system that is integrated with public transport.

During the mobility simulations, an insertion-based algorithm is used to assign vehicles to waiting customers. It searches points in all vehicles' schedules where an incoming requests can be inserted, while obtaining arrival times as early as possible and adhering to maximum wait time and detour constraints for each assigned passenger [18]. If no suitable insertion is found, a request can be rejected by the operator.

In the case study [16], only requests which have origin or destination at a rail-based public transport stop can be submitted. Hence, the MoD system is operated in feeder mode. Furthermore, decisions are based on a tour-based (rather than a trip-based) model, which means that accumulated utilities over multiple individual trips, for instance, along a home-based round-trip, are considered. The control-based approach proposed in this study easily generalizes to such complex scenarios without any specific adjustment (as would be the case for the second approach described above).

In contrast to the case study [16], where rejection rates were merely reported and not fed back into the agent decisions, here we perform simulations making use of the proposed control approach. The simulations are performed with 400 iterations, requiring about 3 days of runtime on 10 cores and using 40GB of RAM for one full simulation. Therefore, an approach that is integrated into the simulation dynamics, rather than an offline calibration of π^* , is beneficial.

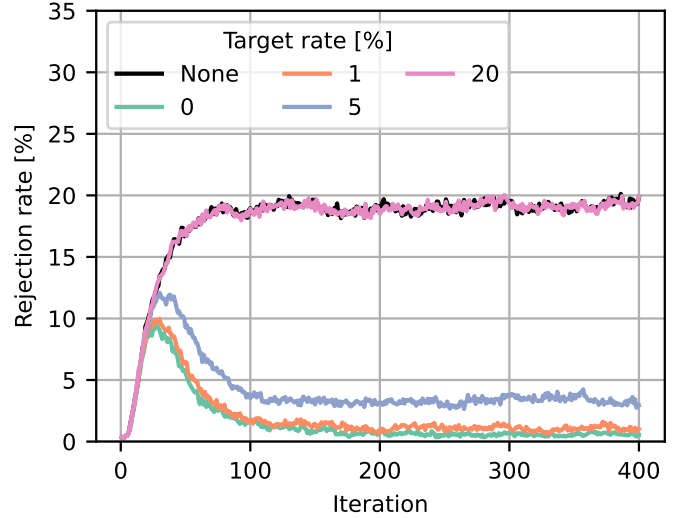


Fig. 2. Observed rejection rates during simulations with 200 vehicles varying target rejection rates compared to the base simulation

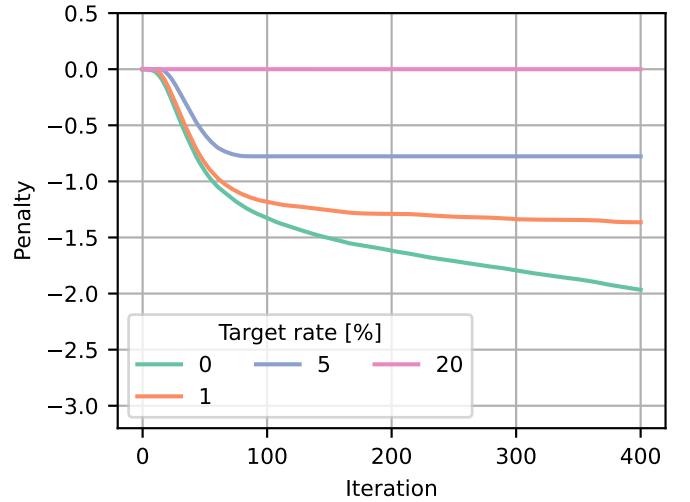


Fig. 3. Evolution of the penalty during simulations with 200 vehicles varying target rejection rates

Figure 2 shows observed rejection rates through simulations of a fleet of 200 vehicles and different values of the target rate $\rho^* \in \{0\%, 1\%, 5\%, 20\%\}$. The trajectory of the observed rejection rate is compared to the base simulation where no controller is used and where a demand is generated that leads to about 20% of the requests being rejected. With $\rho^* = 5\%$, Figure 2 shows that our approach is able to lower the demand as to obtain rejection rates below the value of ρ^* .

However, when the target rejection rate is very low ($\rho^* \in \{0\%, 1\%\}$), the observed rejection rates do not drop consistently below ρ^* . This is an artifact of the demand model, which is probabilistic and, even when the MoD mode is strongly penalized, may choose it for a specific trip. Those trips are usually characterized by poor other options, for instance,

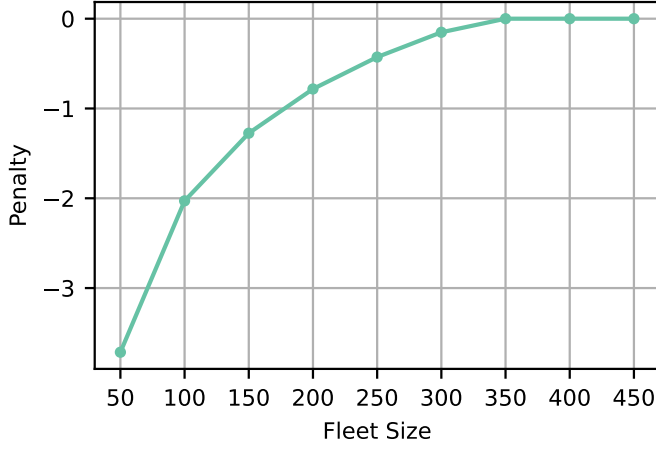


Fig. 4. Obtained penalty value to ensure a rejection rate less than 5% with various fleet sizes

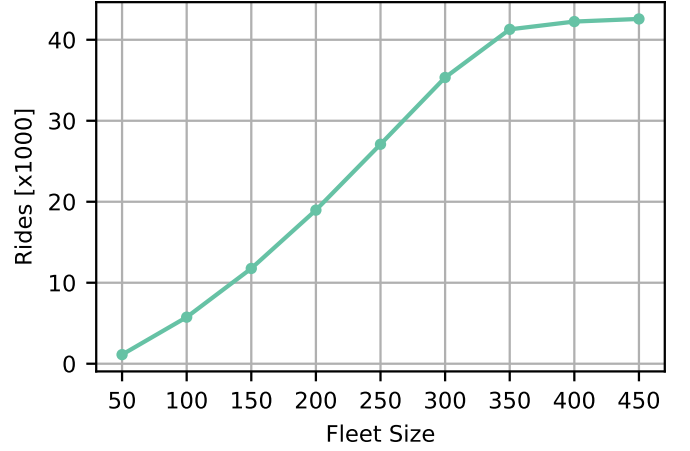


Fig. 5. Number of MoD trips performed with various fleet sizes when using a penalty to ensure less than 5% of rejected requests

without car access, but also not having a viable public transport alternative. Based on the particular set-up of the case study, these trips are also those which are likely to be rejected by the operator because operational constraints (delay, wait time) cannot be fulfilled.

Moreover, we note that when the target rejection rate is above the one already observed in the base case ($r^* = 20\%$), our controller does not reduce the observed rejection rate.

These results are mirrored in Figure 3 where the evolution of the penalty in those simulations is shown. The penalty remains at zero when $\rho^* = 20\%$. As expected, the penalty decreases with lower values of ρ^* . For $\rho^* \in \{5\%, 10\%\}$, the converged value of the penalty is achieved after about 100 iterations. As the required rejection rate cannot be reached, for $\rho^* \in \{1\%, 0\%\}$, the penalty decreases continuously.

For properly chosen target rejection rates, these results show that our approach is able to find a penalty value that lowers the demand just enough to achieve an acceptable rejection rate for a fixed fleet size. From another perspective, it is interesting to analyze what penalty is needed to reach the same target rejection rate at different fleet sizes. In order to do so, we perform simulations with fleet sizes between 50 and 450 vehicles and a target rejection rate of $\rho^* = 5\%$.

Figure 4 shows the obtained penalty values after 400 iterations. With higher fleet sizes, the penalty approaches zero, indicating that after 350 vehicles the fleet is large enough to provide rejection rates below 5%. Figure 5 shows the number of trips performed in these simulations. Below the fleet size of 350 vehicles, the number of trips increases almost linearly with the number of vehicles, with a clear saturation of demand.

V. DISCUSSION

The results shown in section IV demonstrate the effectiveness of our approach and its ability to lower the observed rejection rates below a certain value. However, the obtained rejection rate can be somewhat lower than the target (Figure 2). This is due to an overshooting by our method that reduces

the penalty more than necessary. The overshooting behavior is directly related to the value of K that is used. Lower values for this parameter will overshoot less, but take longer to converge. The problem can be tackled by making use of the default update rule introduced in Equation 8.

Figure 6 shows the evolution of the penalty when using the standard controller. As is common for purely proportional controllers [15], the penalty value shows oscillations. Its amplitude seems to be decreasing, but the penalty does not reach convergence within 400 iterations. This issue could further be mitigated by making use of a PI (proportional integral) controller using the update rule:

$$\Delta\pi_i = K_P \cdot \Delta\rho_i + K_I \cdot \sum_{j=0}^i \Delta\rho_j \quad (8)$$

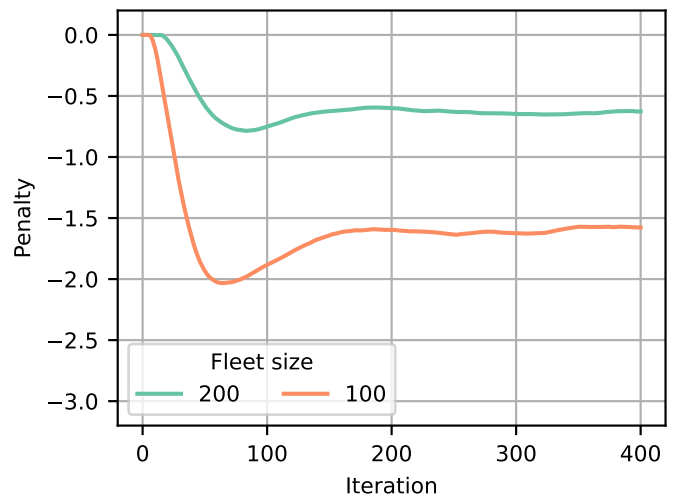


Fig. 6. Evolution of the penalty when enabling backward adjustment during simulations with 200 vehicles and $r^* = 0.05$

However, this approach would require additional (and computationally costly) fine-tuning of the two gain parameters K_P and K_I .

Our results also allow observations related to edge cases: When the fleet size is large enough to handle the demand without a penalty, the service does not become more attractive and the rejection rate always stays below the target. On the other hand, when the fleet size or the target rejection rate are too low, the penalty can decrease infinitely, and the demand is driven close to zero.

Regarding the interpretation of the obtained penalty values, a few alternatives are possible:

- The penalty can be understood as an addition to the alternative-specific constant (β_{ASC}) that is defined for the mode and captures preference effects that are not explained explicitly by the choice dimensions. However, this is a bare conceptual interpretation that does not allow any economic interpretation.
- In a multinomial logit model, the marginal effects β can be converted into marginal (monetary) costs by dividing the whole utility function by β_{cost} [12]. Hence, $\pi^*/\beta_{\text{cost}}$ represents a price. In the case study [16], a penalty of $\pi^* = -1$ would, according to the values of the choice model, represent an additional cost of about 4.85 EUR per trip. This is the price that an operator would need to ask to avoid excessive rejection rates in the system (for a given fleet size).
- Analogously, π^* can be translated into any other choice dimension in a multinomial logit model with a linear utility function. For instance, the penalty of $\pi^* = -1$ represents 20 minutes of additional wait time per trip in [16]. This is the delay that an operator can allow its vehicles if rejection rates should be capped.

An interesting development pathway for this method is to adjust penalties based on user characteristics, zones, or time of day. This would allow differentiating between situations with varying demand. When interpreting the penalty as a price, this idea links to the topic of dynamic pricing for MoD systems that has been addressed in literature [19].

VI. CONCLUSION

In this study, a linear control approach is proposed to achieve feedback of rejection rates generated by MoD simulator to an endogenous demand model. It can be integrated into classic discrete choice demand models without complex modifications of the choice logic. Also, it generalizes well to complex use cases, as is demonstrated with our case study on a MoD feeder system.

The results detailed in this work show the practical use of the method as it is able, for well-defined target values, to find penalty values that yield rejection rates below a specified threshold. However, we note that certain issues remain: The approach is not able to achieve target rejection rates too close to zero, as it becomes subject to artifacts inherent in the fleet operational strategies and the endogenous demand model. Furthermore, it presents overshooting behavior that results in

not exactly reaching the target rejection rate, but one that is lower (but close to) the requested service level. The problem can be mediated using a classic proportional or proportional-integral control approach, which, however, needs additional calibration.

A major benefit of our approach is the potential to interpret the obtained results. Interesting operational insights on monetary costs and wait times can be derived from the obtained penalty values, as shown in our case study. Finally, combining our approach with feedback of other system performance indicators (wait times and detours) to the endogenous model demand, it is possible to fully assess the impact that existing and novel operational strategies have on the attractiveness of an MoD system.

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