Optimization of Mobility Policies in Port-City Scenarios Through Simulation and Surrogate Models

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Abstract A port located within a city is a paradigmatic example of an area where logistic and mobility flows interact systematically, giving rise to negative phenomena like pollution and congestion. Thus, the adoption of innovative mobility policies is a key factor to mitigate the externalities and maximize the economic benefits. Here we focus on the optimization of lane-restriction policies, which is far from trivial because of the complexity of the traffic dynamics in an area shared by trucks and mobility flows. Therefore, the optimization process needs to take into account all the factors influencing the network, e.g. traffic light timings, for the new policy to be beneficial. Thus, in this paper we propose a method, based on the combination of traffic micro-simulation and deep learning models, to evaluate and optimize the impact of mobility policies acting in port-city contexts. In the paper we provide a case study focused on the port-city context of Genova, Italy, one of the most important ports of the Mediterranean Sea. Our simulation tests show how the proposed methodology can be a useful tool to evaluate a priori the possible adoption of a new policy, allowing many insights on its impact and maximizing its benefits.

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1 Introduction

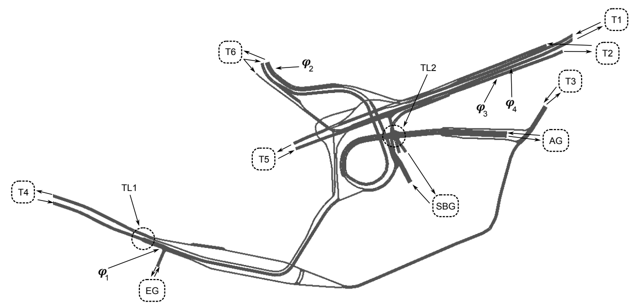
A port located near a city center is a paradigmatic example in which the urban infrastructure is shared by mobility flows and traffic from large logistics hubs. This kind of interaction generates serious externalities like pollution and congestion, with critical impact on the many involved stakeholders like citizens, city managers, logistics operators and port authorities. The goal of mitigating these unwanted phenomena requires the definition of smart mobility policies able to optimize the competing flows [9, 12]. In this work we propose a method to evaluate and optimize the application of new policies in port-city contexts to manage the flow of trucks generated by the port. The methodology is based on two main elements: *i*) a simulation model of traffic dynamics and *ii*) surrogate modelling techniques. The first one has the purpose of generating a few scenarios of application of the given policy in operative conditions, yielding outcomes of interest such as pollution and throughputs. Because of their computational burden, simulations cannot be directly used in an optimization routine, thus we propose a surrogate model to provide a fast approximation of the simulator outcomes. This approximation allows to cope with the several evaluations required by the optimization routines employed to find the best parameters of the policy. The rationale for the analyses is linked to the societal need to lower down emissions while maximizing transport flows in an environment in which mixed freight-passenger vehicles are present. In most scenarios, dedicated lanes with fixed constraints would be introduced to streamline the flow (see e.g. [11]). Such solutions usually offer some improvement, but they permanently impact the network capacity without a serious assessment of the actual network performance. The proposed model aims at filling in such gap.

Concerning the traffic simulation models, we consider in particular models of the microscopic kind (see e.g. [4] and the references therein). These tools, nowadays routinely employed in research and practical applications, allow the detailed dynamic representation required for our purposes, including the simulation of different vehicle classes, emission profiles and traffic lights. For the surrogate model we focus in particular on deep neural networks, state-of-the-art architectures endowed with excellent approximation properties, that have recently shown impressive performance in surrogate modeling of traffic scenarios [3].

There is a consolidated literature on the use of simulation models for policy evaluation and assessment in mobility scenarios (see e.g. [1,5] and the references therein). However, the combination of simulation and surrogate modelling for optimization is quite new in port-city contexts. A recent example is [2], where micro-simulation and deep learning are employed for the model-predictive control of emissions in a port-city area. In that article the goal is the real-time management of the logistic and mobility flows, while in the present work we want to optimize a policy at a strategic level, considering a more composite performance index not limited to emissions reduction.

In the paper we consider a case study inspired by the port-city context of the city of Genova, in northwest Italy. We focus in particular on a lane-restriction policy, optimized through efficient choice of the phase duration of the two main traffic lights

Fig. 1: The considered port-city area for the case study.



in the considered area. Our simulations show how the application of the policy can be an improvement, highlighting the importance of coordination at the network level. In particular, our tests show that a lane-restriction policy can indeed be beneficial for the overall sustainability of the area, yet it requires a careful optimization of the traffic light timings to become truly effective, due to a tradeoff between increased mobility throughput and truck emissions. At the same time, the tests show how the proposed methodology can be a valuable tool to achieve this optimization, being able to assess and control this tradeoff arising from the adoption of the new policy.

2 The Reference Scenario

In this section we present our reference case study, which is located in the port-city context of Genova. More specifically, we consider the San Benigno port area, illustrated in Figure 1, which includes the main portions of the urban network characterized by the concurrent presence of logistic and mobility traffic, where phenomena of pollution and congestion occur regularly. In particular, we focus on the flows of containers generated by the port terminals located in the zone, and implement the entire area in the ECLIPSE/SUMO micro-simulator [8].

The ‘T’ labels in the figure represent traffic directions to/from zones outside the area, corresponding to points of origin/destination for both mobility and logistic traffic. In particular, T1, T2 and T3 mark main paths for mobility vehicles to/from eastern parts of the town. T4 marks a direction for traffic to/from Lungomare Canepa, also collecting logistic flows from port gates and highway entry points located in near western parts of the town. T5 involves mainly mobility traffic to/from western areas, while T6 is the direction to/from the Genova Ovest highway toll boot, shared by both mobility and logistic traffic. The labels ‘SBG’ and ‘EG’ denote the San Benigno and Etiopia Gates, respectively, acting as both source and destination for logistic traffic, while ‘AG’ denotes the Albertazzi Gate, involving mainly ferry passenger traffic. The ‘TL’ labels denote the positions of the two main traffic lights acting on the area, namely the one at the end of Lungomare Canepa (TL1) and the one at the Via

Ballaydier junction (TL2), that will be involved in the optimization test as detailed below. The labels φ_j denote throughput check points that will be discussed below.

Concerning the traffic demand, we assume that the flows of trucks follow fixed routes between gates and highway toll booths. In particular, we consider 6 logistic routes, namely (SBG $\rightarrow$ T6), (T4 $\rightarrow$ EG), (T4 $\rightarrow$ T6), (EG $\rightarrow$ T4), (EG $\rightarrow$ T6) and (T6 $\rightarrow$ SBG). To these truck routes corresponds, at each simulation stage t, a 6-dimensional vector $\boldsymbol{F}_t^{\mathrm{log}}$ of hourly vehicle demand rates. Mobility vehicles instead can follow arbitrary routes depending on the desired destination and traffic status. In particular we consider 19 origin/destination pairs, i.e., (T4 $\rightarrow$ T1), (T4 $\rightarrow$ T2), (T4 $\rightarrow$ T3), (T4 $\rightarrow$ T6), (T5 $\rightarrow$ T6), (T5 $\rightarrow$ T1), (T5 $\rightarrow$ T2), (T5 $\rightarrow$ AG), (T6 $\rightarrow$ T4), (T6 $\rightarrow$ AG), (T6 $\rightarrow$ T1), (T6 $\rightarrow$ T2), (T2 $\rightarrow$ T5), (T1 $\rightarrow$ T5), (T2 $\rightarrow$ T6), (T2 $\rightarrow$ T4), (AG $\rightarrow$ T6), (T3 $\rightarrow$ T4) and (T3 $\rightarrow$ T6). To these mobility routes correspond, at each simulation stage t, a 19-dimensional vector $\boldsymbol{F}_t^{\mathrm{mob}}$ of hourly vehicle demand rates. In order to add flexibility to the traffic management task, we consider also a decision variable corresponding to the length (in seconds) of the two phases of traffic lights TL1 and TL2. We denote the corresponding 4-dimensional vector $\boldsymbol{p}_{\mathrm{TL}} = [p_1, p_2, p_3, p_4]$.

2.1 Policy Scenario Simulation

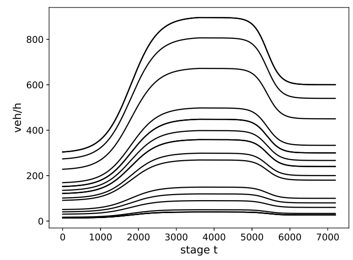
As said, the port-city area considered for the paper has been implemented in the Eclipse/SUMO traffic micro-simulation urban model [8]. The simulator is a popular open source model through which detailed traffic dynamics can be obtained, allowing the representation of various elements such as car following behavior, lane changes, traffic lights, adaptive routing procedures, junction priorities, etc. An important feature of a micro-simulation model such as SUMO is that it allows to define multiple vehicle classes. For our particular case, we considered two classes, namely logistic and general mobility, implemented in the simulator through the definition of standard truck and car vehicles, respectively, each with specific size, speed, acceleration, etc. These standard vehicles are also used to define the equivalent unit of accumulation for each traffic kind in our model.

For the purpose of our analysis, we can formally define a simulation run as a process implementing the function

$$\boldsymbol{y}_1, \ldots, \boldsymbol{y}_T = S(\boldsymbol{F}_1, \ldots, \boldsymbol{F}_T, \boldsymbol{p}_{\mathrm{TL}}) \tag{1}$$

where T is the number of steps of length dt of the simulation horizon (in our implementation, $dt = 1s$), $\boldsymbol{F}_t = [\boldsymbol{F}_t^{\mathrm{log}}, \boldsymbol{F}_t^{\mathrm{mob}}]$ is the vector combining the hourly rates of demand for logistic and mobility traffic for period t, and $\boldsymbol{p}_{\mathrm{TL}}$ is the vector of traffic light phases introduced above, kept fixed for all the simulation. The vectors $\boldsymbol{y}_t$ represent quantities evolving during the simulation that we take as outcomes we are interested in. In this paper we focus on two quantities, namely a vector of pollutant emissions $\boldsymbol{E}_t = [e_t^{\mathrm{CO}}, e_t^{\mathrm{HC}}, e_t^{\mathrm{PM}_x}, e_t^{\mathrm{NO}_x}, e_t^{\mathrm{CO}_2}]$ where e_t^{χ} denotes the overall

Fig. 2: Demand rates of vehicles in the 2-hours scenario considered. Each line depicts one of the 19 demand rate patterns considered for the tests.



emissions of kind χ in mg/s from vehicles in the network during stage t, estimated by the simulator, and a vector of throughputs $\boldsymbol{\varphi}_t = [\varphi^{\text{log}}_{t,1}, \varphi^{\text{log}}_{t,2}, \varphi^{\text{mob}}_{t,1}, \varphi^{\text{mob}}_{t,2}, \varphi^{\text{mob}}_{t,3}, \varphi^{\text{mob}}_{t,4}]$ where $\varphi^{\text{log}}_{t,j}$ and $\varphi^{\text{mob}}_{t,j}$ denote the number of trucks and cars, respectively, that during stage t leave edges of interest that are affected by the interaction of logistic and mobility flows, through points denoted in Figure 1. In particular, $j = 1$ is Lungomare Canepa eastbound before the Etiopia Gate, $j = 2$ is towards the Genova Ovest highway booth, and $j = 3, 4$ are on the two main paths to leave the area towards eastern parts of the town. Accordingly, we define $\boldsymbol{y}_t = [\boldsymbol{E}_t, \boldsymbol{\varphi}_t]$. Notice that in the definition of S we assumed that the simulator seed is fixed, so that the simulation outcome is ruled only by the demand rates $\boldsymbol{F}_t$ and the traffic light phases $\boldsymbol{p}_{\text{TL}}$.

Concerning the demand rates, for our analysis we considered a basic 2-hours scenario in which the mobility demand transitions from quiet to peak, then tends to medium intensity. Then, each component $\boldsymbol{F}^{\text{mob}}_t$ of hourly demand rates follows a curve of $T = 7200$ stages (with $dt = 1s$) having a shape like the ones depicted in Figure 2. For the logistic demand rates, instead, we assume that the hourly demand of trucks $\boldsymbol{F}^{\text{log}}_t$ remains fixed during the 2-hour window.

For the purpose of our optimization task, we aggregate the variables involved in the simulation run in K blocks of 5 minutes, to obtain more stable outcomes and mitigate noise due to traffic light dynamics. In particular, for the vector $\boldsymbol{F}_t$ we take the mean over non-overlapping blocks of 300 stages, while for the emission and throughput vectors $\boldsymbol{E}_t$ and $\boldsymbol{\varphi}_t$ we consider the sum. Thus, with a little abuse of notation, in equation (1) we replace $\boldsymbol{y}_t$ with $\boldsymbol{y}_k$, for $k = 1, \ldots, K$, where the transition from k to $k + 1$ entails a block of 300 stages of length dt.

In this work we are interested in evaluating and optimizing the adoption of a dynamic lane restriction policy for traffic management. In our specific case study, the policy implements the following rule: if the average speed in Lungomare Canepa falls below a given threshold v^*, then the left lane is strictly reserved to mobility vehicles, while the right lane is strictly reserved to trucks. When the average speed gets back to $v^* + \delta$, the restrictions are removed. Notice that the parameter δ is introduced to avoid a continuous switching behaviour of the system. Lungomare Canepa has been chosen because there the main disruptive interactions between mobility and logistic flows happen, often giving rise to heavy congestion. This policy has been implemented in the SUMO simulator through the TraCI system. Formally, we denote by S_0 the simulation run in a standard scenario, while we denote by S_1 a simulation run with the new policy in place. Accordingly, we denote by $\boldsymbol{y}_t^0$ and $\boldsymbol{y}_t^1$ the outcomes from S_0 and S_1 in equation (1) for the same values of $\boldsymbol{F}_t$ and $\boldsymbol{p}_{\mathrm{TL}}$, respectively, and we do the same for the definition of $\boldsymbol{E}_t^0$, $\boldsymbol{E}_t^1$ and $\boldsymbol{\varphi}_t^0$, $\boldsymbol{\varphi}_t^1$.

2.2 Performance Index Optimization

For the purpose of evaluating the effect of the policy and for its optimization, we define the following performance index as a convex combination of emissions and throughputs

$$J(\boldsymbol{F}_1, \ldots, \boldsymbol{F}_T, \boldsymbol{p}_{\mathrm{TL}}) = \alpha \cdot \varphi^* + (1 - \alpha) \cdot E^* \tag{2}$$

where

$$\varphi^* = \frac{1}{K} \sum_{k=1}^{K} \sum_{i=1}^{6} \varphi_{k,i} w_i^{\varphi}, \quad E^* = \frac{1}{K} \sum_{k=1}^{K} \sum_{i=1}^{5} E_{k,i} w_i^{E}$$

where $\varphi_{k,i}$, $E_{k,i}$ denote the i-th component of $\boldsymbol{\varphi}_k$, $\boldsymbol{E}_k$, respectively, and w_i^{φ}, w_i^{E} are normalizing factors to fix the different scales of the various components.

The index J, aggregating the outcome of a simulation run, reflects an expected tradeoff due to a lane-restriction policy. In fact, while mobility throughput is expected to increase due to the reserved lane in the most congested street, trucks are expected to be penalized, which generally increases some of the pollutant emissions (in particular, PM_x and NO_x). Maximizing the performance index J enables to obtain the best effect from the application of the policy, maximizing the overall throughput while keeping emissions as small as possible. The parameter $\alpha \in [0, 1]$ controls the importance given to the two elements of this tradeoff.

In this paper we consider, for our analysis, a basic scenario characterized by a given set of demand rates $\{\boldsymbol{F}_t^*\}_{t=1}^T$, representing a standard weekday cycle. Thus, we perform the optimization over the set of traffic light phases, i.e., we can formalize the policy optimization problem as finding

$$\max_{\boldsymbol{p}_{\mathrm{TL}} \in [\boldsymbol{p}^{\min}, \boldsymbol{p}^{\max}]} J(\boldsymbol{p}_{\mathrm{TL}}) = J(\boldsymbol{F}_1^*, \ldots, \boldsymbol{F}_T^*, \boldsymbol{p}_{\mathrm{TL}})$$

where $\boldsymbol{p}^{\min}$, $\boldsymbol{p}^{\max}$ are minimum and maximum allowed values for the phases.

Since a micro-simulation run is very time-consuming, in order to perform the many evaluations required by the optimization routine to find the optimal 4-dimensional vector of phases, we take advantage of a surrogate model. More specifically, we consider a parametrized approximation of J having form $\hat{J}(\boldsymbol{p}_{\mathrm{TL}}, \boldsymbol{\beta})$, where $\hat{J}$ is a data-driven model and $\boldsymbol{\beta} \in \Lambda$ is a set of model parameters that need to be trained to provide an approximation of J. In our paper we consider the class of feedforward neural network models, due to their excellent properties of approximation [6] and the success in surrogate modeling tasks related to traffic dynamics [3]. To train the parameters $\boldsymbol{\beta}$, we select a set $\{\boldsymbol{p}_{\mathrm{TL}}^{(1)}, \ldots, \boldsymbol{p}_{\mathrm{TL}}^{(L)}\}$ of L phase vectors, with $\boldsymbol{p}_{\mathrm{TL}}^{(l)} \in [\boldsymbol{p}^{\min}, \boldsymbol{p}^{\max}]$, and perform L simulation runs, obtaining, for each l

$$\boldsymbol{y}_1^{(l)}, \ldots, \boldsymbol{y}_K^{(l)} = S(\boldsymbol{F}_1^*, \ldots, \boldsymbol{F}_T^*, \boldsymbol{p}_{\mathrm{TL}}^{(l)})$$

From the set $\{\boldsymbol{y}_1^{(l)}, \ldots, \boldsymbol{y}_K^{(l)}\}$ we derive $\varphi^{*(l)}$, $E^{*(l)}$ by which we compute $J(\boldsymbol{p}_{\mathrm{TL}}^{(l)})$.

Eventually, the set of L pairs $\{\boldsymbol{p}_{\mathrm{TL}}^{(l)}, J(\boldsymbol{p}_{\mathrm{TL}}^{(l)})\}_{l=1}^{L}$, can be employed as a training set for the supervised training of the neural model. In particular, this can be obtained by the optimization of an empirical cost, to obtain the set $\boldsymbol{\beta}^* \in \Lambda$ that minimizes $\sum_{l=1}^{L} \ell(\hat{J}(\boldsymbol{p}_{\mathrm{TL}}^{(l)}, \boldsymbol{\beta}), J(\boldsymbol{p}_{\mathrm{TL}}^{(l)}))$ where $\ell(\boldsymbol{x}, \boldsymbol{y})$ is a loss function, which measures the distance between $\boldsymbol{x}$ and $\boldsymbol{y}$ (e.g. $\ell(\boldsymbol{x}, \boldsymbol{y}) = \|\boldsymbol{x}-\boldsymbol{y}\|_2^2$, or the L1 norm $\ell(\boldsymbol{x}, \boldsymbol{y}) = \|\boldsymbol{x}-\boldsymbol{y}\|_1$). Once the network has been trained, we can replace the original optimization problem with: find $\max_{\boldsymbol{p}_{\mathrm{TL}} \in [\boldsymbol{p}^{\min}, \boldsymbol{p}^{\max}]} \hat{J}(\boldsymbol{p}_{\mathrm{TL}}, \boldsymbol{\beta}^*)$.

3 Experiments

In this section we present results from simulation tests performed on the port-city scenario described in the previous section. For the tests, a total of $L = 1000$ simulation runs have been performed. The values of the demand rates $\{\boldsymbol{F}_t^*\}_{t=1}^{T}$ have been chosen from knowledge of the area, to reflect the typical dynamics of a 2-hour cycle of mobility patterns in a busy weekday. The set of traffic light phases $\{\boldsymbol{p}_{\mathrm{TL}}^{(1)}, \ldots, \boldsymbol{p}_{\mathrm{TL}}^{(L)}\}$ has been taken from a uniform distribution within $[\boldsymbol{p}^{\min}, \boldsymbol{p}^{\max}]$. In particular, for the actual sampling we employed the Sobol' sequence [10], a deterministic approximation of the uniform distribution that belongs to the family of so-called low-discrepancy sequences, and has already proved to be successful in surrogate modeling tasks [3]. More specifically, we employed the standard non-scrambled sequence skipping the first 4096 points.

Figures 3 and 4 contain the boxplots over the 1000 runs of the outcomes $\boldsymbol{E}$ and $\boldsymbol{\varphi}$ from S_0 (base scenario without the policy) and S_1 (scenario with the new policy), summed over the K stages, before introducing the surrogate model. For the definition of the performance index J, in order to be able to compare the performance from S_0 and S_1, the normalizing factors w_i^{ϕ} and w_i^{E} have been taken equal to $w_i^{\phi} = \max\{\max_{l,k} \varphi_{k,i}^{(0,l)}, \max_{l,k} \varphi_{k,i}^{(1,l)}\}$ and $w_i^{E} = \max\{\max_{l,k} E_{k,i}^{(0,l)}, \max_{l,k} E_{k,i}^{(1,l)}\}$, where the superscript (h, l) denotes the l-th simulation run with scenario S_h, with $h \in \{0, 1\}$. This normalization, employed both for S_0 and S_1, ensures that J is limited to 1 and comparable for both scenarios. Figure 5 contains the boxplots over the 1000 runs of the performance index J for S_0 and S_1, again before introducing the surrogate model, for various levels of α (chosen to span uniformly the ranges between the 'emissions only' and the 'throughput only' balance of priorities). The plots underline the importance of choosing the right values of the traffic light phase durations, in order for the lane restriction policy to be advantageous.

Fig. 3: Boxplots of the emissions in the scenario S_0 (without policy) and S_1 (with the policy). The lower the better.

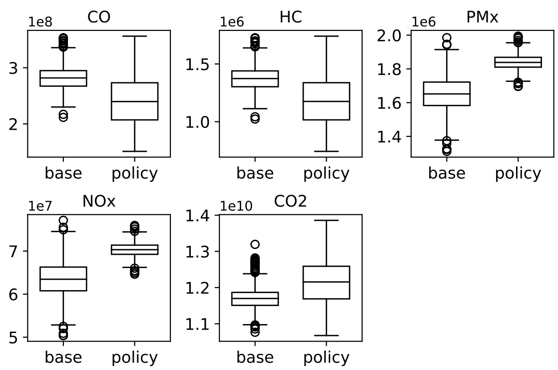
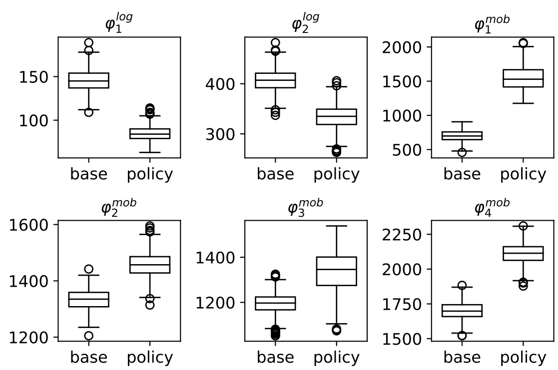


Fig. 4: Boxplots of the various throughputs in the scenario S_0 (without policy) and S_1 (with the policy). The higher the better.

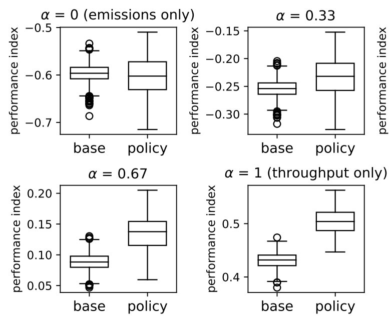


For the surrogate model $\hat{J}$ used to optimize the lane-restriction policy we employed a deep feedforward neural network with 2 layers of 500 'ReLu' units, trained using data from S_1 with a loss function ℓ corresponding to the L1 error. The training was performed through the ADAM algorithm [7], with 1000 epochs and batch size equal to 64. All the neural network code was implemented in Pytorch[1].

The optimal phase durations that maximize $\hat{J}$ within the considered range $[\boldsymbol{p}^{\min}, \boldsymbol{p}^{\max}]$ turn out to be equal to $[40, 20, 40, 13]$ seconds for $\alpha = 0, 0.33, 0.5$, equal to $[37, 20, 40, 11]$ seconds for $\alpha = 0.66$ and equal to $[39, 20, 40, 10]$ seconds for $\alpha = 1$. As a preliminary assessment of the quality of the maximum provided by the surrogate, for each α the closest phase values in the training set actually correspond to the best values of $\hat{J}$. Concerning computational times, a single simulation

[1] https://pytorch.org/

Fig. 5: Boxplots of the performance index for different values of α in the scenario S_0 (without policy) and S_1 (with the policy). The higher the better.



run in our implementation on a Apple M2 CPU with 64 Gb of RAM takes about 530 s, while the output of the surrogate model is generated in about 6 μs, i.e., 10^8 times faster. This clearly shows how a surrogate model is mandatory for the several evaluations required to compute the optimal phase durations. The training time of the surrogate model takes about 28 s.

3.1 Discussion and Plans for Future Work

From the simulation results we can draw many interesting outcomes. The main outcome is that the lane-restriction policy has the potential to be beneficial for the overall performance of the considered port-city network. In fact, as shown in Figure 5, for any value of α the maximum value of the performance index is always attained in scenarios where the policy is in place. At the same time, the boxplots underline the importance of choosing the right values of the traffic light phase durations, in order to make the lane restriction policy advantageous. Indeed, choosing the wrong durations for the considered phases can undermine the impact of the policy completely, even yielding worse performance with respect to the base scenario. This proves that, in such a complex scenario with two conflicting classes of traffic, devising a smart mobility policy is not enough, if we do not optimize other important factors in a logic of interconnected network. It is also interesting highlighting how performance - in terms of either flow or environment - could be effectively optimized through dynamic solutions that allow the network to adapt to specific circumstances rather than using rigid static constraints that impact on network capacity permanently.

Concerning the choice of α, Figures 3 and 4 show that there is clear tradeoff between mobility throughput and total pollutant emissions when the policy is in place. Then, the choice of α in the performance index can modulate this tradeoff depending on the goals of the involved stakeholders. Once the value is set, the optimization of the traffic light phases allows to minimize the negative impact of the emissions within the chosen tradeoff balance. In conclusion, the proposed methodology proves to be a useful and principled tool to evaluate the impact of new policies in scenarios where logistic and mobility traffic interact.

Future work will be aimed at investigating different mobility policies for the port-city context, and more tests involving various operative scenarios of interest. A more thorough testing of the performance of the surrogate model optimization will be carried out as well.

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