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# Optimal Management of Electrified and Cooperative Bus Systems

*Francesco Viti, Marco Rinaldi and Georgios Laskaris*

## Abstract

This chapter presents an integrated management approach exploiting the potentials of the new Cooperative Intelligent Transportation Systems (C-ITS) to meet the requirements of the next generation Public Transport (PT). This approach considers the additional complexity of electrification—for instance electric busses need to periodically recharge during operation using dedicated infrastructure. This not only can impact service level, but also extend operating costs with complex electric charges. We develop new strategies explicitly optimizing the interactions within the PT ecosystem consisting of vehicles, traffic signals, and e-bus charging infrastructure. To achieve these goals, we rely on vehicle control rather than on the use of transit signal priority, which in congested urban scenarios can have negative effects on overall traffic performance. The main research challenges are in formulating and solving complex multi-objective optimization problems and real-time control. The proposed system is tested and evaluated in simulation showing the benefits of electrified and cooperative bus systems.

**Keywords:** public transport, integrated charging and scheduling, cooperative intelligent transportation systems, real-time control, electrification

## 1. Introduction

Sustainable urban development motivates investments in environment-friendly and user-centered Public Transport (PT) services. Three trends towards next generation PT systems are observed, namely 1) introduction of greener vehicles such as electric/hybrid busses (e-busses), 2) focus on high service quality (e.g. increased ride comfort via mitigation of stop-and-go driving) and 3) reduction of emissions and operating costs related to fuel/energy consumption and equipment wear and tear. These trends however bring new challenges. The first challenge is posed by different operational characteristics and constraints of e-busses, e.g. they need to periodically recharge batteries at e-charging stations placed in selected stops and terminals. This brings additional constraints into PT operations and its cost dynamics. The existing approaches lack the required degree of modeling detail necessary to capture the complex interactions emerging between bus operations and charging infrastructure. The second challenge is how to guarantee comfort- and cost-effective operations without negatively impacting general traffic performance. Relying solely on strategies such as Transit Signal Priority (TSP), which prioritize PT vehicles at signalized intersections, might cause congestion effects that could backfire on the PT system itself.

The main contribution of this work is that we jointly address constraints and control capabilities of all entities of the PT ecosystem, which consists of signal control, (e-)busses, and e-bus charging infrastructure. The developed methods combine cooperation and negotiation between all actors thanks to connectivity, in order to effectively achieve mutual goals. Thanks to bus real-time positioning systems (Automatic Vehicle Location, AVL) and vehicle-to-infrastructure communication (Signal Phase and Timing, SPaT), multi-objective optimization is employed to determine bus dispatching time, operating speeds, dwell time plans, e-bus charging schedules, and TSP requirements. Regarding the interaction between buses and e-charging infrastructure, the objective is to minimize electricity costs and adhere to the planned bus dispatching times. From the online/operational perspective, the problem is to model and optimize a connected and cooperative system with a set of heuristic tools and actions, such that real-time system disturbances can be addressed, in order to maximize the adherence to the offline plans. For example, busses can use information on upcoming green times to adapt their speeds or hold at a stop in order to avoid stopping at signals. Consequently, stop-and-go is mitigated in an efficient and non-invasive way.

This chapter is structured as follows. Chapter 2 provides an overview of the e-bus eco-system, and the integrated design approach we developed in this work. Chapter 3 focuses on the integrated scheduling and charging problem at the planning phase, in particular considering a hybrid fleet of electric and hybrid busses. Chapter 4 deals with the operational phase, and in particular it shows the benefits of the cooperative ITS-based control strategies. Finally, chapter 5 provides an outline and the potential future research directions for this research.

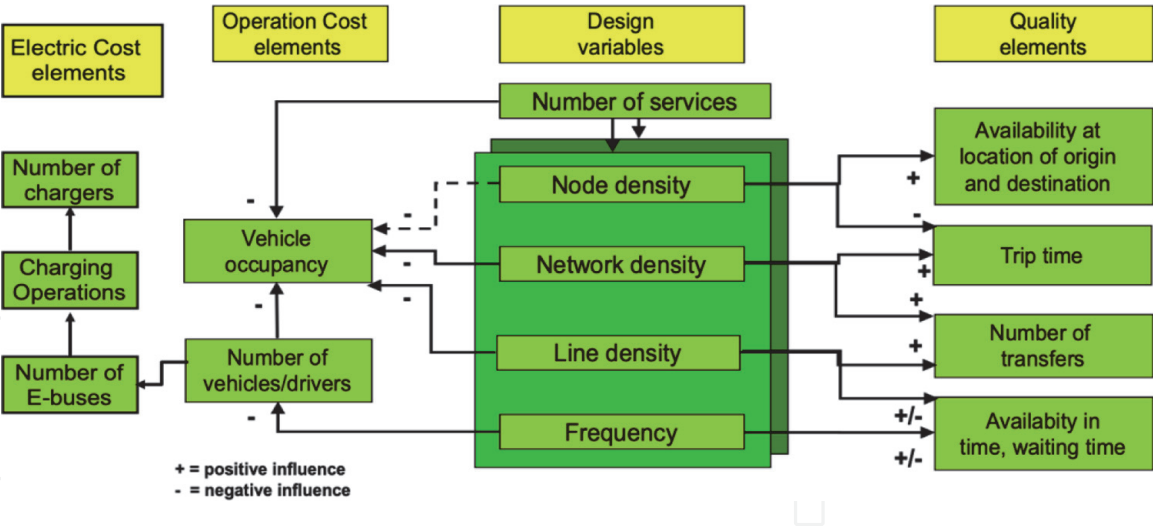
## **2. The electrified and cooperative bus system**

The quality and service level of bus systems often rely on the interaction of different lines, in order to provide optimal frequencies and hence acceptable waiting times for the users, and to offer sufficient capacity to accommodate the demand, measured in terms of passenger flows. These flows vary across the network due to the variability of the demand, which differs depending on the origin and the destination of the users, and in time. To match the demand with the supply, bus operators aim to manage efficiently their fleet of vehicles, identifying at any time the most opportune vehicle type and the number of vehicles to be assigned to a line, together with their dispatching times. This decision has consequences on the way lines run smoothly and provide a certain level of service quality to the passengers, as well as it impacts the operational costs (**Figure 1**). In this study we consider design decisions (node density, network density and line density) as given.

Allocating a small number of vehicles limits the service frequency, which affects the waiting time. However, increasing this number will have a negative impact on the operating costs, since more vehicles and drivers will need to be employed. Too many vehicles on the other hand may result in under-utilizing vehicle capacities, reducing the marginal profits for the operators. Hence, optimally allocating fleet resources in the network is a fundamental planning problem that impacts both operators' costs and passengers' experience.

### **2.1 Electrification opportunities and challenges**

Emerging trends in green PT systems offer new benefits: e-busses reduce emissions, energy use, noise as well as offer smoother rides. There are three types of e-busses—hybrid electric, plug-in hybrid electric, and battery electric. The last two



**Figure 1.**  
*Integrated design of bus systems.*

are able to recharge their batteries from an electric power grid via an *opportunity charging*—a bus periodically charges at bus stops or terminals. This allows to down-size battery and extend bus range to a desirable value. E-bus systems are currently moving from pilot projects to small-scale deployments with single line/operator with very few charging stations. The potentials and needs of large-scale e-bus systems have been investigated by the EU's Zero Emission Urban Bus System (ZeEUS) project [1] as well as Volvo's City Mobility Program [2]. More recent EU projects investigated the impact of fleet mix and configuration parameters to the operation costs [3].

When introducing e-busses, additional costs need in fact to be accounted for, since current battery-capacitated e-busses need to be recharged multiple times a day (e.g. a Volvo 6700 bus can perform a trip in full electric mode for around 30 km, and each vehicle can run distances of a few hundreds of km each day). Current opportunity charging technologies allow a bus to recharge up to 80% in a matter of 6-10 min, while novel flash charging technologies can recharge in less than a minute, but it extends the range of only few more kilometers. An example is the TOSA system in Geneva, a single line that uses both opportunity (3-4 min with low power) and at bus stops e-charging (15-second each 1-1.5 km with high power) [4]. Given the costs of fast and flash charging, bus operators charge their e-busses overnight, when the cost of electricity is lowest, and then use opportunity charging stations, typically located at line terminals, to recharge during the short resting times of the drivers. Flash charging are up to date very rarely implemented, given the very high costs of the relatively small gain in terms of range extension.

The charging infrastructure creates a strong link between infrastructure planning and bus operations [5]. The location and charging operations in fact influences the dispatching times of the vehicles, and in turn irregularities in the operations with recurrent phenomena of bus bunching may result in busses queuing at the charging station, with additional propagation of delays and overall degradation of service levels. Therefore, past research focused on developing a proper system design including strategic locations of e-charging stations [6, 7]. Energy efficiency was also addressed via energy management strategies for the engine [8], and regenerative braking technologies [9], and taking into account environmental policies such as zero-emission zones [10].

In this study we contribute to this stream of research by focusing on the problem of integrating vehicle scheduling and dispatching times with recharging needs and operations of the e-bus fleet. In particular, we consider the problem of managing a



mixed fleet of vehicles, which will be likely to be the case for the next years to come, since full electrification will require heavy investments in the electrical grid and current batteries and chargers are considered a relatively immature technology to completely replace combustion engines. We show in Chapter 3 that optimally assigning vehicle types in the network will provide benefits for both service quality (mitigation of delays due to charging) and operating costs (more e-busses used in daily operations are likely to bring lower energy consumption costs).

## **2.2 Cooperation opportunities and challenges**

The main PT service quality objective is expressed in terms of punctuality (for schedule-based operations) and/or headway regularity (for headway-based operations). Current methods are based upon in-vehicle support systems, managing holding strategies and preferential signal control (TSP) and providing PT vehicles with preferential treatment at intersections via temporary traffic signal timing adjustments [11, 12]. For schedule-based operations, holding strategies (delaying departure of a bus from a bus stop until the scheduled time) ensure punctuality by managing slack times (extra “backup time” inserted into schedules) [13]. The problem of existing methods is that they slow down busses due to the fact that they add delays to the planned trip time [14]. They also address isolated lines and ignore any disturbances observed in real-world PT operations [15]. Headway-based operations are more difficult to control, as the strategies need to account for several busses [16, 17] and multiple interacting lines [18]. Thus, additional ITS systems such as Automated Vehicle Location (AVL), Automated Passenger Count (APC) and a central coordination entity are used to control busses in real time [15, 19].

The core reliability objective is also supported by TSP strategies capable of providing conditional priority. However, since TSP influences the traffic flow reliability [20] its acceptance is limited. Future improvements of TSP exploiting AVL can be achieved. This allows previously unfeasible continuous exchange of information between vehicles and traffic signals [21], allowing cooperation bus-signal through e.g. speed advisory [22, 23]. Such systems are one of the few ITS applications that would provide benefits even at early stages of CV technology [24].

Recent advances in V2I communication enable developing a new promising efficiency-oriented class of driving support systems aiming at improving driving efficiency, comfort and reducing unnecessary stops at signals [25]. Opposite to signal control, which uses CV technology to collect information about the approaching vehicles, in V2I-based systems vehicles use signal control information to optimize their own speeds accordingly. The two SPaT-based DASs researched in literature are the Green Light Optimal Speed Advisory (GLOSA) and Green Light Optimal Dwell Time Advisory (GLODTA). GLOSA provides vehicles with speed guidance, while GLODTA advises additional holding at bus stops. Their main advantage is that these systems improve bus performance with respect to traffic signals, but, unlike TSP, they are non-intrusive (i.e. do not influence signal timings). The two V2I-based advisory systems can be combined to mutually increase their effectiveness [26] and they can be combined with traditional holding strategies. These integrated controls have been shown to meet both objectives of service regularity and reducing the number of stops, as well as they reduce the number of TSP requests [27, 28].

## **2.3 The eCoBus integrated ecosystem**

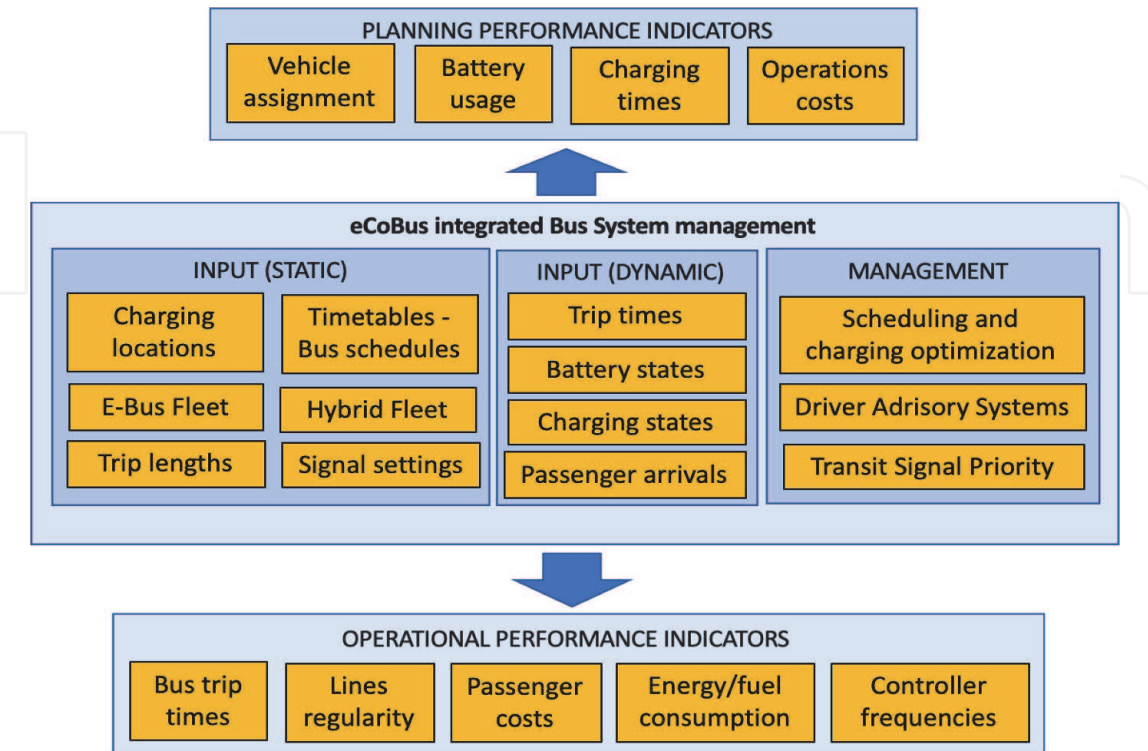
In this work we adopt a cooperative system approach, following the C-ITS paradigm, reinforced by an energy-aware decision support system. This approach

allows to manage the interplay between PT ecosystem actors (vehicles, signals, and e-infrastructure). Secondly, it enables joint optimization and coordination of actions carried out by the different actors, in order to achieve system goals.

**Figure 2** provides an overview of the eCoBus integrated system developed in this project. The core module consists of collecting *static* input, namely the location of charging stations, lines timetables, together with the characteristics of the fleet (number of e-busses and hybrid vehicles), the characteristics of the lines (trip lengths) and of the signal infrastructure. We also assume to collect in real time trip times through AVL technology, battery states from the busses, status of each charging (occupied, available) and to have a good estimate of the passenger arrivals at stops (via e.g. APC information). These are input to the *scheduling and charging optimization* module, which is presented in detail in Section 3, whereas the *driver advisory system* combining holding and C-ITS based control and TSP are used at the operational phase to manage the vehicles in real time. The integrated system is shown to provide significant benefits both for planning objectives (better use of the fleet and the charging infrastructure, lower operations costs), and management goals (lower trip time variability and passenger costs, less fuel or energy consumed, less use of TSP requests). These benefits will be showcased in simulations using realistic scenarios in the next sections.

### 3. Mixed Fleet vehicle scheduling and charging optimization

Vehicle scheduling problems in public transportation have been approached as part of the “full operational planning process” [29]. From a modeling perspective, these problems are usually formulated as Mixed-Integer Linear Programs (MILP), under the name of Single/Multi-Depot Vehicle Scheduling Problem (SDVSP/MDVSP) [30]. The impact of electrification on bus scheduling problems has been recently taken into consideration by researchers, e.g. [31, 32], in preparation and support towards widespread Public Transport electrification. In this Section we



**Figure 2.**  
*The eCoBus integrated management ecosystem.*

present results stemming from our own recent research efforts [33–35] concerning the development of mixed-fleet vehicle scheduling models and algorithms tailored to the ongoing electrification of the bus fleet in the City of Luxembourg.

Compared to combustion, a fleet of electric or partially electric busses brings novel challenges to transit planning. Within the four decisional stages as discussed in [29] (line planning, timetabling, vehicle scheduling and crew rostering), electrification especially influences scheduling. The problem faces an increase in complexity, as recharging operations must be included without introducing disturbances in the existing schedule, to both ensure that busses have sufficient charge to perform trips and to avoid conflicts at the charging infrastructure. When handling a mixed fleet, optimal scheduling policies should therefore seek to take as much advantage as possible from both coexisting technologies.

In this Section we introduce mathematical models and methodologies to address the problem of scheduling a mixed fleet of conventional and electric busses. We begin by introducing the offline, planning stage optimization problem related to both single and multi-terminal instances. Subsequently we discuss a potential extension towards online, reactive rescheduling in the presence of disturbances, such as delays. Finally, we present a multi-terminal case study based on the city of Luxembourg, in the eponymous country.

### 3.1 Offline optimization: The SDEVSP and MDEVSP optimization problems

We formulate the problem of assigning a mixed fleet of  $I = \{1, \dots, i\}$  electric busses and  $H = \{1, \dots, h\}$  hybrid busses to a set of scheduled trips  $J = \{1, \dots, j\}$ , each characterized by desired departure time  $D_j = \{1, \dots, d_j\}$  [time steps], duration  $T_j = \{1, \dots, t_j\}$  [time steps] and total energy required  $U_j = \{1, \dots, u\}$  [kWh]. Time is subdivided in consecutive steps  $\tau = \{0, 1, \dots, N\}$ , with a discretization step  $T_s$ . For each trip, decision variables  $y_{i,j}^t$  and  $z_{h,j}^t$  describe respectively whether trip  $j$  is initiated at time step  $t$  by electric bus  $i$  or hybrid bus  $h$ , while variable  $x_{i,m}^t$  represents whether e-bus  $i$  is recharging at charging station  $m$  at time step  $t$ .

Throughout this Section we adopt the assumption that full charging of e-busses happens within a single time step, as will be detailed later. **Table 1** introduces the meaning of each variable and parameter, as well as their domain.

The formulation's objective function, in Eq. (1), is that of minimizing the total operational cost:

$$\begin{aligned} \min \sum_t \sum_i \sum_j & \left( y_{i,j}^t \cdot (c + r \cdot (t - d_j)) \right) + \sum_t \sum_h \sum_j \left( z_{h,j}^t \cdot (\hat{c} + r \cdot (t - d_j)) \right) \\ & + \sum_m \sum_i \sum_t q_i^t \cdot x_{i,m}^t \end{aligned} \quad (1)$$

Trip costs  $c$  and  $\hat{c}$  are determined following Eq. (2), adopting average cost rates per kWh of energy components  $\eta_1$  and  $\eta_2$  for e-busses and h-busses respectively:

$$\begin{aligned} c &= \eta_1 \cdot u_j \\ \hat{c} &= \eta_2 \cdot u_j \end{aligned} \quad (2)$$

Energy component  $\eta_2$  includes a coefficient to represent the difference in consumption rates between electric and conventional combustion (hybrid) busses. The penalty term  $r$  [EUR] is applied to trips being performed later than their preferred departure time, to allow, at a cost, trade-offs between schedule adherence and operational performance. We consider  $M = \{1, \dots, m\}$  charging stations available at

Var.	Domain	Explanation
$y_{ij}^t$	$\{0, 1\}$	1 if trip $j$ is initiated by e-bus $i$ at time $t$ , 0 otherwise
$z_{hj}^t$	$\{0, 1\}$	1 if trip $j$ is initiated by h-bus $h$ at time $t$ , 0 otherwise
$x_{i,m}^t$	$\{0, 1\}$	1 if e-bus $i$ is being recharged at charging station $m$ at time $t$ , 0 otherwise
$\epsilon_i^t$	$\leq E, \in \Re^+$	Total energy in kWh that e-bus $i$ has at time $t$
$u_j$	$\Re^+$	Total energy in kWh required to perform trip $j$ , considering e-bus as a means of transport
$d_j$	$\mathbb{Z}^+$	Preferred departure time step for trip $j$
$t_j$	$\mathbb{Z}^+$	Duration of trip $j$ in time steps
$s_i^t$	$\leq E, \in \Re^+$	Slack variable, necessary to ensure that constraint (12) does not violate the domain of $\epsilon_i^t$
$E$	$\Re^+$	Total battery capacity in kWh for all electric busses
$\mu$	$\leq 1, \in \Re^+$	Minimum battery charge in percentage for each electric bus
$A_i^t$	$\{0, 1\}$	1 if e-bus $i$ is not available to perform any trip nor recharge at time $t$ , 0 otherwise
$H_h^t$	$\{0, 1\}$	1 if h-bus $h$ is not available to perform any trip at time, 0 otherwise

**Table 1.**  
Problem variables and parameters.

selected terminals, and take into account the time dependent cost  $q_i^t$  of recharging bus  $i$  at time  $t$ . System dynamics are captured by constraints (3)–(14):

$$\sum_j y_{ij}^t + \sum_m x_{i,m}^t \leq 1 - A_i^t \forall i, t \quad (3)$$

$$y_{ij}^t + \frac{1}{t_j - 1} \sum_{\bar{t}=t+1}^{t+t_j-1} \left( \sum_{\bar{j}} y_{i,\bar{j}}^{\bar{t}} + \sum_m x_{i,m}^{\bar{t}} \right) \leq 1 \forall i, \forall j : t_j > 1, \forall t : t \geq d_j \quad (4)$$

$$\sum_j z_{hj}^t \leq 1 - H_h^t \forall h, t \quad (5)$$

$$z_{hj}^t + \frac{1}{t_j - 1} \sum_{\bar{t}=t+1}^{t+t_j-1} \sum_{\bar{j}} z_{h,\bar{j}}^{\bar{t}} \leq 1 \forall h, \forall j : t_j > 1, \forall t : t \geq d_j \quad (6)$$

$$\sum_t \left( \sum_i y_{ij}^t + \sum_h z_{hj}^t \right) = 1 \forall j \quad (7)$$

$$\sum_{t < d_j} \left( \sum_i y_{ij}^t + \sum_h z_{hj}^t \right) = 0 \quad \forall j \quad (8)$$

$$y_{ij}^t - \frac{\epsilon_i^t}{u_j + \mu E} \leq 0 \forall i, j, \forall t : t \geq d_j \quad (9)$$

$$\sum_i x_{i,m}^t \leq 1 \forall m, t \quad (10)$$

$$\epsilon_i^0 = \bar{\epsilon}_i \forall i \quad (11)$$

$$E \cdot \sum_m x_{i,m}^t - \sum_j y_{ij}^t \cdot u_j + \epsilon_i^t - s_i^t = \epsilon_i^{t+1} \forall i, t \quad (12)$$



$$\sum_m x_{im}^t - \frac{s_i^t}{E} \geq 0 \forall i, t \quad (13)$$

$$\frac{1}{E} \cdot s_i^t - \frac{1}{E} \varepsilon_i^t \leq 0 \forall i, t \quad (14)$$

Constraint (3) ensures that an e-bus can be assigned to at most one trip at a time, or recharge in at most one charger at a time, only in those time steps in which the bus is available. Constraint (4) implies that an e-bus which initiates a trip  $j$  whose duration in time steps is greater than one cannot be used to perform any other trip nor recharged throughout the entire duration of trip  $j$ . Constraints (5) and (6) enforce similar dynamics for trips being performed by hybrid busses. Note that matrices  $A_t^i$  and  $H_t^i$  represent exogenous sources of unavailability (e.g., during a scheduled maintenance). Constraint (7) guarantees that each trip be performed exactly once, by either kind of bus, and constraint (8) implies that no trip  $j$  can be initiated before its preferred departure time. Constraint (9) guarantees that an e-bus will not perform a trip unless it has enough energy to do so. Constraint (10) implies that a charger can charge at most one e-bus at any given time. Constraint (11) controls the initial state of battery charge of each electric bus, which is set to the exogenously given input value  $\varepsilon_i$  for all e-busses. Constraint (12) represents recharging and discharging dynamics of electric bus  $i$  at time  $t$ : if it is assigned to a trip  $j$  at time  $t$ , its available charge at time  $t + 1$  will be reduced by the trip's required energy  $u_j$ . Conversely, if the electric bus  $i$  is being recharged at time  $t$ , total battery capacity  $E$  is assumed to be restored at time  $t + 1$ . We operate under the assumption that a single time step is sufficient to fully recharge an electric bus, although this condition can rather trivially be relaxed by altering this constraint, or by assuming a large enough time step. We consider the availability of charging stations at selected terminals, powerful enough to meet the required electricity demand. To ensure that the total battery capacity is not exceeded during charging, when the residual charge level  $\varepsilon_i^t$  is greater than zero, a “slack” variable  $s_i$  is introduced, with consideration of the domain feasibility for variables  $\varepsilon_i^t$  and  $\varepsilon_i^{t+1}$ . When a bus is being recharged, the slack variable  $s_i$  must assume a value at least equal to  $\varepsilon_i^t$ , enforcing that  $\varepsilon_i^{t+1} \leq E$ . Constraint (13) implies that the slack variable  $S_i$  can be non-zero only during recharging operations, and constraint (14) ensures that its maximum value can be  $\varepsilon_i^t$ . Therefore, the combination of constraints (12)–(14) governs the behavior of the slack variable  $S_i$  such that the latter variable is either 0, if bus  $i$  is not recharging at time  $t$ , or exactly  $\varepsilon_i^t$  if the bus is recharging.

By supplying a set of lines with accompanying timetables, the model can be employed to determine the optimal scheduling for a mixed-fleet of e-busses and h-busses. Parameters such as fleet size, fleet composition (% of electrics, % of hybrids), charging stations' availability and capacity are supplied exogenously.

### 3.1.1 MDEVSP: Multi-depot electric vehicle scheduling problem

In order to correctly represent realistic Public Transport services, we improve and extend the model showcased in the previous section to appropriately represent multi-terminal schedules featuring deadheading trips.

For each trip  $j$  we therefore introduce a departure terminal  $\alpha_j$  and arrival terminal  $\beta$  both within a given set of bus terminals  $B = \{1, \dots, b\}$ . The set of bus terminals can also include any number of bus depot(s), where busses are stored when not in service. The subset  $\bar{B} \subseteq B$  of bus terminals is equipped with charging stations. We assume that each terminal of the  $\bar{B}$  subset is equipped with the same

amount of  $m$  chargers. Deadheading trips are possible between any combination of terminals, with required total energy  $\hat{u}_{b1,b2}$  and duration  $\hat{t}_{b1,b2}$ .

We discretize time in consecutive time steps  $\tau = \{0, 1, \dots, N\}$ , with a discretization step  $T_s$ . For each trip, decision variables  $y_{ij}^t$  and  $z_{hj}^t$  describe respectively whether trip  $j$  is initiated at time step  $t$  by electric bus  $i$  or hybrid bus  $h$ , variable  $g_{i,b}^t$  controls execution of deadheading trips, and variable  $x_{i,b,m}^t$  captures recharging decisions. We adopt the assumption that full charging of e-busses happens within a single time step. Locations of the electric and hybrid busses are captured by variables  $\omega_{i,b1,b2}^t$  and  $p_{h,b}^t$  respectively.

In this work, we allow deadheading trips for electric busses only. Deadheading is, in fact, critical to optimize usage of electric busses, which have cheaper operational costs, and to optimize their charging dynamics, allowing them to move to terminals equipped with charging stations when needed, while it is not strictly necessary for optimal dispatching of hybrid/conventional combustion busses. The model could anyway be easily extended to consider deadheading for hybrid busses.

The updated formulation's objective function is as follows:

$$\begin{aligned} \min \sum_t \sum_i \sum_j c \cdot (1 + r \cdot (t - d_j)) \cdot y_{ij}^t + \sum_t \sum_h \sum_j \hat{c} \cdot (1 + r \cdot (t - d_j)) \cdot z_{hj}^t \\ + \sum_t \sum_i \sum_{b_1} \sum_{b_2} \bar{c} \cdot \omega_{i,b1,b2}^t + \sum_t \sum_i \sum_b \sum_m q_i^t \cdot x_{i,b,m}^t \end{aligned} \quad (15)$$

Cost vectors  $c$ ,  $\hat{c}$  and  $\bar{c}$  are computed as shown in Eq. (16), considering average cost rates per kWh of energy components  $\eta_1$ ,  $\eta_2$  and  $\eta_3$  for e-busses, h-busses and deadheading trips respectively:

$$\begin{aligned} c &= \eta_1 \cdot u_j \\ \hat{c} &= \eta_2 \cdot u_j \\ \bar{c} &= \eta_3 \cdot \hat{u}_{b1,b2} \end{aligned} \quad (16)$$

Energy component  $\eta_2$  includes an adaptation coefficient to consider the difference in consumption rates between e-busses and h-busses. A penalty term  $r$  [EUR] is applied to trips being performed later than their preferred departure time, to evaluate trade-offs between schedule adherence and operational performance. Regarding the cost of recharging, we take into account the time dependent cost  $q_i^t$  of recharging bus  $i$  at time  $t$  as part of the operational cost needing minimization. Updated system dynamics are captured by constraints (17)–(41) as follows:

$$\sum_j y_{ij}^t + \sum_{b_1, b_2 \in B} \omega_{i,b1,b2}^t + \sum_b \sum_m x_{i,b,m}^t \leq 1 - A_i^t \quad \forall i, t \quad (17)$$

$$\begin{aligned} y_{ij}^t + \frac{1}{t_j - 1} \sum_{\bar{t}=t+1}^{t+t_j-1} \left( \sum_{\bar{j}} y_{i\bar{j}}^{\bar{t}} + \sum_{b_1, b_2 \in B} \omega_{i,b1,b2}^{\bar{t}} + \sum_{b \in \bar{B}} \sum_m x_{i,b,m}^{\bar{t}} \right) \\ \leq 1 \forall i, \forall j : t_j > 1, \forall t : d_j \leq t \leq d_j + \theta \end{aligned} \quad (18)$$

$$\begin{aligned} \omega_{i,b1,b2}^t + \frac{1}{\hat{t}_b - 1} \sum_{\bar{t}=t+1}^{t+\hat{t}_b-1} \left( \sum_{\bar{j}} y_{i\bar{j}}^{\bar{t}} + \sum_{\bar{b}_1, \bar{b}_2} \omega_{i,\bar{b}_1,\bar{b}_2}^{\bar{t}} + \sum_{\bar{b} \in \bar{B}} \sum_m x_{i,\bar{b},m}^{\bar{t}} \right) \\ \leq 1 \forall i, \forall b_1 \in B, \forall b_2 \in B, \forall t : \hat{t}_b > 1 \end{aligned} \quad (19)$$

$$\sum_j z_{h,j}^t \leq 1 - H_h^t \forall h, t \quad (20)$$

$$z_{h,j}^t + \frac{1}{t_j - 1} \sum_{\bar{t}=t+1}^{t+t_j-1} \sum_{\bar{j}} \bar{z}_{h,j}^{\bar{t}} \leq 1 \forall h, \forall j : t_j > 1, \forall t : d_j \leq t \leq d_j + \theta \quad (21)$$

$$\sum_t \left( \sum_i y_{ij}^t + \sum_h z_{h,j}^t \right) = 1 \forall j \quad (22)$$

$$\sum_{t < d_j \cup t > d_j + \theta} \left( \sum_i y_{ij}^t + \sum_h z_{h,j}^t \right) = 0 \quad \forall j \quad (23)$$

$$\sum_i x_{i,b,m}^t \leq 1 \forall m, t, \forall b \in \bar{B} \quad (24)$$

$$y_{ij}^t - \frac{\varepsilon_i^t}{u_j + \min_{\beta_j \notin \bar{B}, b_2 \in \bar{B}} (\hat{u}_{\beta_j, b_2}) + \mu E} \leq 0 \forall i, j, \forall t : d_j \leq t \leq d_j + \theta \quad (25)$$

$$\omega_{i,b_1,b_2}^t - \frac{\varepsilon_i^t}{\hat{u}_{b_1,b_2} + \mu E} \leq 0 \forall i, \forall t, \forall b_1, \forall b_2 \quad (26)$$

$$\varepsilon_i^0 = \bar{\varepsilon}_i \forall i \quad (27)$$

$$E \cdot \sum_{b \in \bar{B}} \sum_m x_{i,b,m}^t - \sum_j y_{ij}^t \cdot u_j - \sum_{b_1, b_2 \in \bar{B}} \omega_{i,b_1,b_2}^t \cdot \hat{u}_{b_1,b_2} + \varepsilon_i^t - s_i^t = \varepsilon_i^{t+1} \forall i, t \quad (28)$$

$$\sum_{b \in \bar{B}} \sum_m x_{i,b,m}^t - \frac{s_i^t}{E} \geq 0 \forall i, t \quad (29)$$

$$\frac{1}{E} \cdot s_i^t - \frac{1}{E} \varepsilon_i^t \leq 0 \forall i, t \quad (30)$$

$$\sum_m x_{i,b,m}^t - g_{i,b}^t \leq 0 \forall t, i, \forall b \in \bar{B} \quad (31)$$

$$\sum_{j:\alpha_j=b_1} y_{ij}^t + \sum_{b_2} \omega_{i,b_1,b_2}^t - g_{i,b_1}^t \leq 0 \forall i, b_1, t \quad (32)$$

$$\sum_{j:\beta_j=b_2} y_{ij}^t + \sum_{b_1} \omega_{i,b_1,b_2}^t - g_{i,b_2}^{t+1} \leq 0 \forall i, b_2, t \quad (33)$$

$$\sum_{j:\beta_j=b_2} y_{ij}^t + \sum_{b_1} \omega_{i,b_1,b_2}^t - (g_{i,b_2}^{t+1} - g_{i,b_2}^t) \geq 0 \forall i, b_2, t \quad (34)$$

$$\sum_b g_{i,b}^t = 1 \forall i, t \quad (35)$$

$$g_{i,b}^0 = \begin{cases} 1 & \text{if } b = G_i \\ 0 & \text{otherwise} \end{cases} \forall i, b \quad (36)$$

$$\sum_{j:\alpha_j=b} z_{h,j}^t - p_{h,b}^t \leq 0 \forall h, b, t \quad (37)$$

$$\sum_{j:\beta_j=b} z_{h,j}^t - p_{h,b}^{t+1} \leq 0 \forall h, b, t \quad (38)$$

$$\sum_{j:\beta_j=b} z_{h,j}^t - (p_{h,b}^{t+1} - p_{h,b}^t) \geq 0 \forall h, b, t \quad (39)$$

$$\sum_b p_{h,b}^t = 1 \forall h, t \quad (40)$$

$$p_{h,b}^0 = \begin{cases} 1 & \text{if } b = P_h \\ 0 & \text{otherwise} \end{cases} \forall h, b \quad (41)$$

Constraints (17)–(21) avoid conflicts in the usage of resources. Constraints (22)–(23) model when the scheduled trips should be executed. Constraints (24)–(30) control the charging and discharging dynamics and ensure that the trip execution is consistent with battery status. Constraints (31)–(41) control the location dynamics of each bus.

### 3.2 Online optimization: Decomposition scheme and model predictive control

The optimization model described in the previous section is aimed at determining full day bus schedules in the Public Transport planning stage, i.e. assuming a specific trip timetable and considering no deviations arising from operations. However, the model has been designed with the explicit objective of enabling the application of time-based decomposition schemes, for the sake of scalability in seeking solutions at the planning stage. In this Section we showcase how this decomposable nature can be further exploited, in combination with a Model Predictive Control scheme, to compute real-time rescheduling in case of major disruptions arising from operations (e.g. delays due to overcrowding, bunching, congestion, ...).

#### 3.2.1 Time-wise decomposition scheme for the SDEVSP/MDEVSP models

The two models described earlier can be rather straightforwardly decomposed along the time variable  $\tau = \{0, 1, \dots, N\}$ , arbitrarily choosing both the frequency of sub-problem (defined henceforth as time-lapse) definition and the effective points in time where decomposition should happen. In order to ensure that the decomposed time-lapses effectively capture the original formulation, coupling constraints must be added to the formulation, as follows:

$$A_i^t|_f = A_i^{t+l(f-1)}|_{f-1} + \lambda_i^t|_{f-1} \forall i, f, t \quad (42)$$

$$H_i^t|_f = H_i^{t+l(f-1)}|_{f-1} + \zeta_i^t|_f \forall i, f, t \quad (43)$$

$$\lambda_i^t|_f = \begin{cases} 1 & \forall i, t : \exists j, \bar{t} : y_{i,j}^{\bar{t}}|_f = 1 \wedge (l_f < t \leq \bar{t} + t_j) \\ 0 & \text{otherwise} \end{cases} \quad (44)$$

$$\zeta_i^t|_f = \begin{cases} 1 & \forall i, t : \exists j, \bar{t} : z_{i,j}^{\bar{t}}|_f = 1 \wedge (l_f < t \leq \bar{t} + t_j) \\ 0 & \text{otherwise} \end{cases} \quad (45)$$

$$\begin{aligned} \bar{\epsilon}_i|_f &= \epsilon_i^{l(f-1)}|_{f-1} \forall i, f \\ \bar{\epsilon}_i|_0 &= E \forall i \end{aligned} \quad (46)$$



These constraints communicate the status of the fleet along different time-lapses, informing the later time periods on both availability and battery status of the busses as a result of the scheduling decisions performed in the earlier time periods.

By correctly configuring the frequency of time decomposition (at each time step), the width of the time lapses (chosen equal to the desired prediction horizon) and the appropriate bus availability data (busses are marked available only after the effective trip completion, rather than following a pre-determined trip duration), a Model Predictive Control application can be devised, as shown in **Figure 3**.

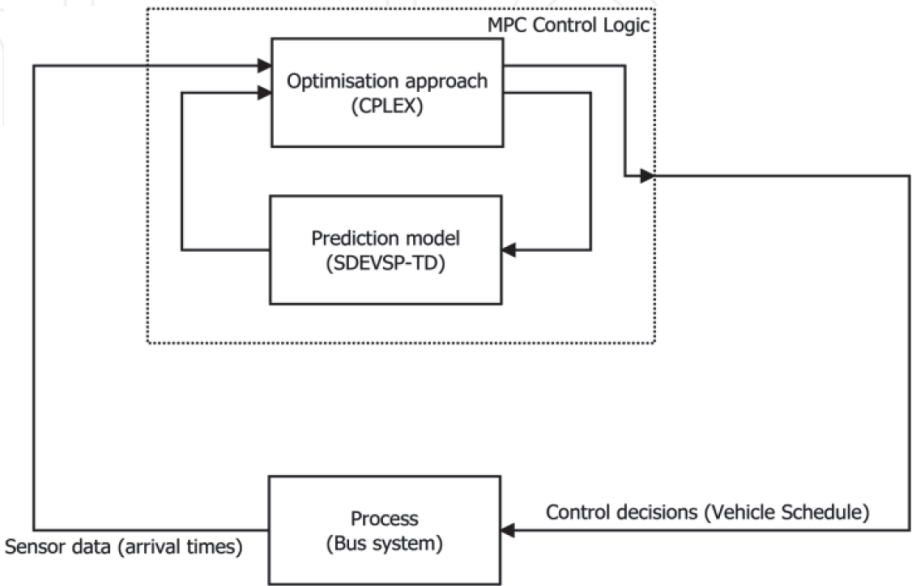
### 3.3 Multi-terminal mixed-fleet scheduling in the city of Luxembourg

The proposed model and solution framework have been implemented in Matlab™, employing IBM’s ILOG Cplex 12.7 as optimization software. We validated our multi-terminal model against a real-life instance arising in the city of Luxembourg, considering several urban bus lines, as shown in **Figure 4**. Four of the terminals are currently equipped with two opportunity charging stations each. We employ our model on two different sets of tests: one addressing a subset of bus lines (lines 1, 16, 9 and 14, comprising 536 daily trips across 5 bus terminals, 2 of which are equipped with chargers), and one representing the complete instance (10 bus lines, 1034 daily trips across 12 terminals, 4 of which are equipped with chargers).

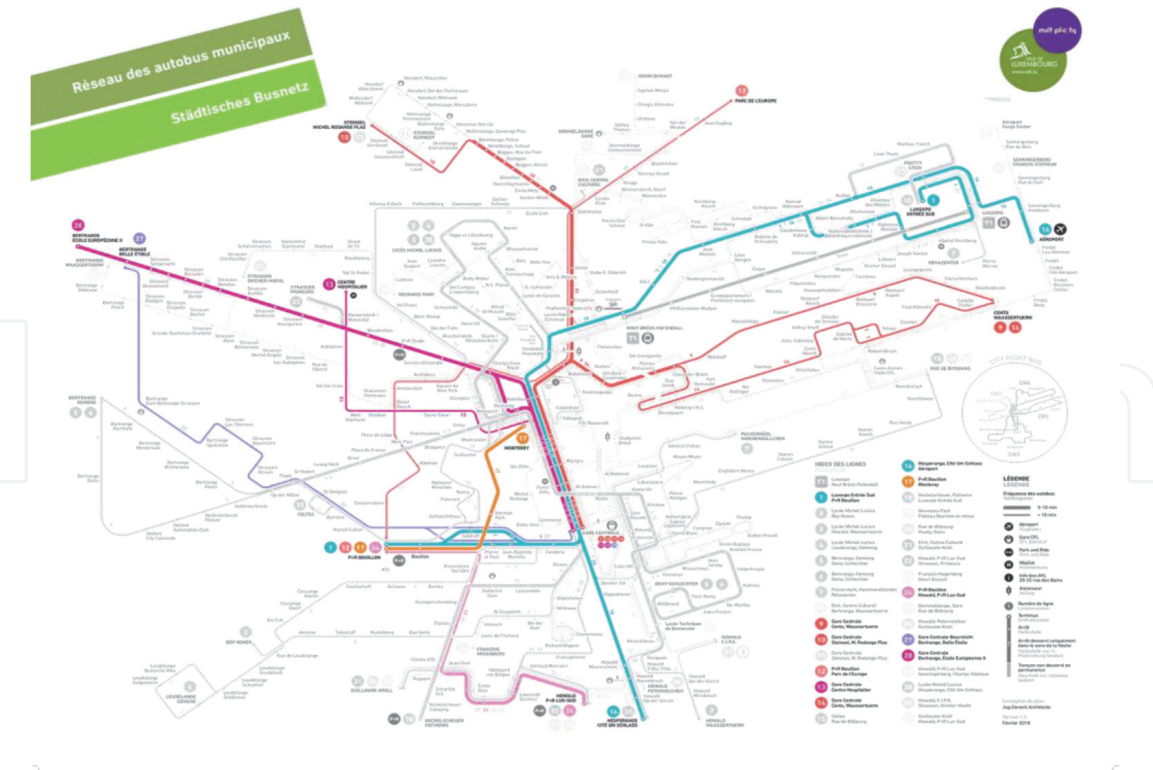
The results shown in **Figures 5 and 6** show consistently that, as the fleet transitions towards full electrification, the overall operational cost decreases and the number of total recharges increases accordingly.

It is interesting to note that the rate at which operational costs decrease and the total amount of recharging operations increase both exhibit an inflection point: in the set of tests addressing all the 10 lines, the gradient decreases at about 30% of electrified fleet, while in the reduced problem addressing 4 bus lines it becomes actually flat at about 70% of electrified fleet.

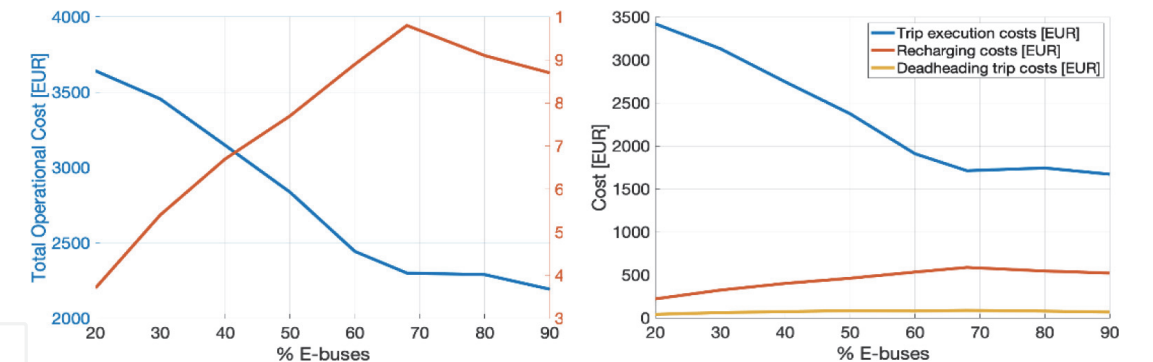
These results showcase that a diminishing returns effect might arise when approaching full electric operations. The effect is however less impactful in the full-scale scenario, implying that complex instances might lead to larger potential gains to be attained through electrification.



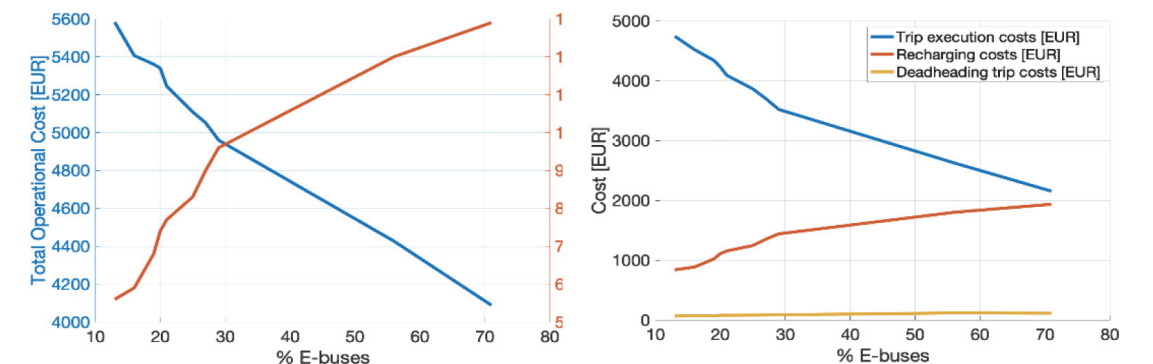
**Figure 3.**  
*MPC scheme.*



**Figure 4.**  
*Case study: 10 bus lines in the City of Luxembourg.*



**Figure 5.**  
*Bus lines, 536 trips – Total operational costs and recharge operations (left); distinct cost factors (right).*



**Figure 6.**  
*10 bus lines, 1034 trips – Total operational cost and recharge operations (left); distinct cost factors (right).*

## 4. Real-time cooperative control

Operation is the last pillar, following design and planning. The nature of public transport operations is stochastic, with disruptions occurring due to irregularities in travel times and variation in passenger demand. Thanks to the advances in Intelligent Transportation Systems (ITS), the performance of a transit network can be monitored in real time, and corrective actions can be applied to restore the targeted level of service. All different applications have widened the spectrum of real time control strategies that can be deployed [13]. Until now, C-ITS Driver Advisory Systems have exclusively focused on assisting vehicles traverse signalized intersections and reducing the number of TSP requests, disregarding the consequences of their control actions to the regularity of the transit line [27]. The regularization of a line is the main objective of many real time strategies for public transport, with holding to be one of the thoroughly investigated in literature and applied in practice [17, 36]. We investigate how C-ITS can complement holding strategy and achieve a synergy to address both the objectives of regularity and the mitigation of the number of stops at signalized intersections.

We combine two DAS, namely GLOSA and GLODTA, with a rule-based holding criterion at stops prior to signalized intersections, to provide a pair of holding time and speed advisory or a holding time to achieve both objectives. The combined controllers are presented in the following sections, followed by the results obtained from a real-world case study.

### 4.1 Regularity based driver advisory systems

#### 4.1.1 Reliability green light optimal speed adaptation (R-GLOSA)

The first regularity based advisory system is R-GLOSA. At the bus stops applied, it instructs a vehicle to be held to regulate the operation and depart with the speed needed to traverse the next green phase. After the arrival of a vehicle at a bus stop prior to a signalized intersection and the completion of dwell time, its position subject to the preceding and the succeeding vehicle is checked. If the headway from the preceding vehicle is short enough, then the vehicle will be held until the consecutive headways are even. We use the same rule-based holding criterion with [36], which regulates the departure time of a vehicle and limits the maximum allowed headway based on the planned headway.

After holding time is calculated, the departure time from the stop is updated and the expected arrival to the first downstream signalized intersection is estimated. The expected arrival time at the first signalized intersection downstream  $t_{ijk}^{arr,tl}$  is estimated by adding to the updated exit (departure) time  $t_{ijk}^{exit}$ , the time the bus needs between the stop and the intersection. The time corresponds to the expected running time derived by the ratio of the distance  $d_{j,tl}$  between current bus stop  $j$  and the signalized intersection  $tl$  and  $V_k$  the average speed of vehicle  $k$  at the link downstream of stop  $j$ . The expected arrival time is expressed by Eq. (43):

$$t_{ijk}^{arr,tl} = t_{ijk}^{exit} + \frac{d_{j,tl}}{V_k} \quad (47)$$

After the expected arrival time is calculated, information of the signal timing and phasing are transmitted, to estimate if the vehicle will stop or not by the time of the arrival at the intersection. If the current indication is red then the remaining

time for red  $t^{Red,remain}$  is estimated and added to the expected arrival time  $t_{ijk}^{arr,tl}$ . Then the recommended speed is calculated using Eq. (44):

$$V_k^{RGLOSA} = \frac{d_{j,tl}}{(t_{ijk}^{arr,tl} - t_{ijk}^{exit} + t^{Red,remain})} \quad (48)$$

In case of green, the vehicle should either accelerate to catch the current phase or wait for the next green phase. Therefore, two candidate speeds can be recommended, one for the estimated arrival time  $t_{ijk}^{arr,tl}$  and one for the expected arrival at the next green phase, given by Eqs. (45) and (46), respectively.

$$V_1^{RGLOSA} = \frac{d_{j,tl}}{(t_{ijk}^{arr,tl} - t_{ijk}^{exit})} \quad (49)$$

$$V_k^{RGLOSA} = \frac{d_{j,tl}}{(t_{ijk}^{arr,tl} - t_{ijk}^{exit} + t^{Green,remain} + t^{Red})} \quad (50)$$

where  $t^{Red}$  the red time of the cycle of the current traffic light.

In case of two candidate speeds, the one respecting the speed limits is selected. If both speeds are within the speed limits,  $V_1^{RGLOSA}$  is selected since vehicle accelerates to arrive during current green phase. If both speeds are outside the speed limits, no speed advisory is given by the controller. In contrast, if there is no need to restore regularity, the controller is treated as GLOSA.

#### 4.1.2 Reliability green light optimal dwell-time adaptation (R-GLODTA)

R-GLODTA is the second hybrid controller, combining holding and GLODTA. In principle, holding and GLODTA are using the same control logic, by extending the time at stop to achieve their objectives to restore regularity and mitigate stops at traffic lights respectively. Therefore, with this controller, the prolongation of dwell time at stops aims to satisfy both objectives. After the vehicle arrives at the stop and completes dwell time, two candidate holding times are calculated to restore regularity. Then, the expected arrival time to the next signalized intersection is estimated using Eq. (43).

If the expected arrival time is during green phase, then no GLODTA time is needed. In contrast, if the vehicle is expected to arrive during red, then the waiting time at traffic light  $t_{ijk}^{wait,tl}$  is calculated by subtracting the current red time  $t^{Red,c}$  from the red time  $t^{Red}$  as in Eq. (51):

$$t_{ijk}^{wait,tl} = t^{Red} - t^{Red,c} \quad (51)$$

The waiting time at the traffic light corresponds to the GLODTA time  $t^{GLODTA}$ . The waiting time at traffic light is transferred at the bus stop and utilized as dwell time for the passengers. GLODTA time  $t^{GLODTA}$  with the duration of green phase define a time interval, within a vehicle will traverse the downstream signalized intersection without stopping (Eq. 52).

$$[t^{GLODTA}, t^{GLODTA} + t^{Green}] \quad (52)$$

The hybrid controller can work as holding or GLODTA alone depending on the current performance and needs of the system. If both candidate holding times (for



regularity and GLODTA) meet the criteria, then the shorter time is selected. If with both holding times, the vehicle is expected to arrive during red, then the holding time with the less estimated remaining time at the traffic light is selected and the controller counts simply as a regularity controller:

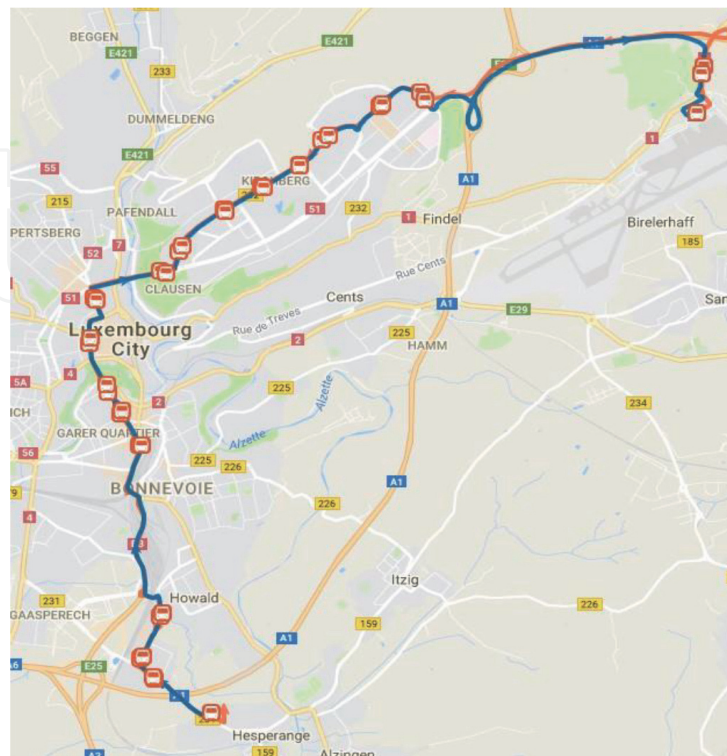
$$t^{hold} = \min \left( t_{ijk}^{exit} + t_{ijk,1}^{hold} + \frac{d}{V_k}, t_{ijk}^{exit} + t_{ijk,2}^{hold} + \frac{d}{V_k} \right) \quad (53)$$

In case of on time or late arrival, the vehicle will depart after  $t^{GLODTA}$  in order to recover by saving time at traffic light, again if needed. This joint strategy, which we name R-GLODTA.

## 4.2 Cooperative control in the City of Luxembourg

The two hybrid controllers are tested for one of the busiest lines of the city of Luxembourg, AVL Line 16. Line 16 is the backbone of the bus network of the city of Luxembourg. As depicted in **Figure 7**, The line consists of 19 stops, among which there are stops in the city center, the central business district of Kirchberg and the new activity zone of Cloche d'Or at the south. Additionally, Line 16 connects the central railway station, the airport and the Kirchberg multimodal transport hub. The line is running in high frequency and double articulated busses are used. In addition, the busses run in dedicated lanes and are equipped with AVL technology. We assume that all traffic lights have the same signal program with cycle of 120 s (80 green and 40 red) with the red indication first at the simulation environment. No coordination has been considered between signals.

Two case studies, one for each of the newly introduced controller, were conducted. In both cases, a do-nothing scenario is used as a benchmark scenario. In addition, the hybrid controllers are compared with a holding strategy and the individual application of GLOSA and GLODTA. Moreover, different levels of TSP are put into test. For the R-GLOSA scenarios, three different levels are tested. The



**Figure 7.**  
Line 16 in Luxembourg City.

first level, referred as weak TSP, the scenario in which both green extend and green recall are up to 5 s. With strong TSP, green phase can be modified by 15 s. In the R-GLODTA scenarios only strong TSP is tested. Lastly, in the R-GLODTA scenarios, the hybrid controller is combined with GLOSA and TSP.

The main performance indicators used in this study are the adherence of headway of the line as well as the total trip time and its variability. Moreover, we will also analyze the delay at the signalized intersections and the times the vehicles managed to pass through a green phase. Finally, for the performance of the joint controller, the number of times requested is given and the share of each sub-controller are recorded. In summary, these are the performance indicators selected for the study:

- Regularity indicators: Coefficient of variation of headways; bunching;
- Passengers' cost indicators: in-vehicle time; waiting time at stops;
- Link performance indicators: stop frequency and delay at traffic light, average speed and running time;
- Controller performance: share of control requests and of controller choice.

4.2.1 Results

All regularity indicators are summarized in **Table 2**. It is clear from the results that the control schemes, the objective of which is to regulate the operation, dominate the regularity indicators. The coefficient of variation of headway and the level of bunching are chosen as regularity indicators. It should be noted that R-GLOSA has a minor difference from holding control since it is based on the same criterion to calculate holding time. The additional gaining comes from the speed recommendation given by the GLOSA part of the controller. Among strategies there are no significant differences in waiting time of passengers at stops. The independent application of the two DASs has no effect on system's regularity. Both have the same performance with the benchmark scenario. The regularity indicators remain unchanged regardless the TSP strength and similar to the do-nothing scenario. R-GLOSA manages to integrate the performance of holding strategy in terms of regularity and GLOSA in terms of cycle time. The cycle time with R-GLOSA is better than weak TSP and results to the least variable cycle time among all

	CV Line	Bunching	Waiting time [s]	In vehicle time [s]	Cycle time [s]	Cycle time deviation [s]
NC	0.599	0.372	302.98	204.74	4096.91	415.61
HOLDING	0.486	0.269	302.38	211.90	4042.55	415.61
GLODTA	0.628	0.382	302.40	212.49	4166.16	505.49
GLOSA	0.597	0.351	302.63	200.66	4050.49	480.16
RGLOSA	0.466	0.254	302.30	212.73	4042.09	394.56
TSP5	0.607	0.378	303.14	204.00	4060.26	472.07
TSP10	0.590	0.358	302.22	203.25	4013.18	472.07
TSP15	0.613	0.370	301.45	198.51	4012.75	490.94

**Table 2.**  
*Regularity performance indicators.*

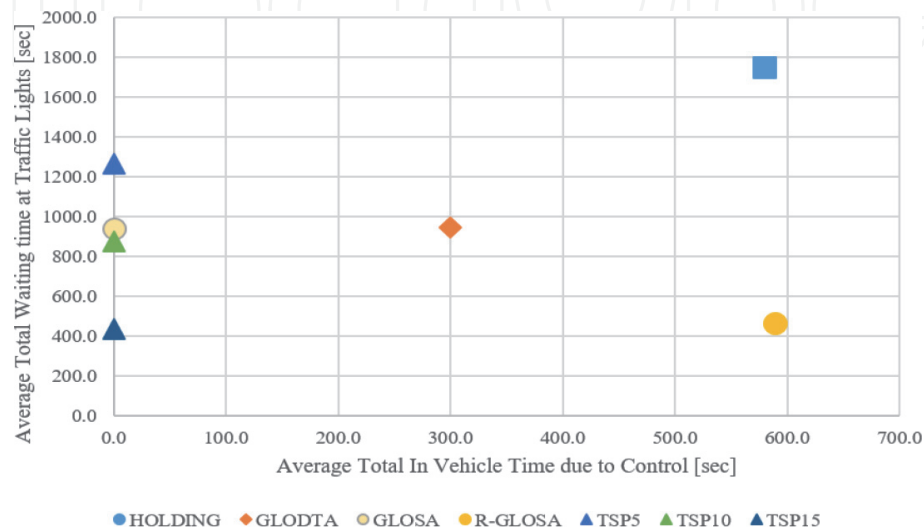
	Frequency of stop at traffic lights	Total average delay at traffic lights [s]	Running time	Average speed [km/h]
NC	0.309	1778.8	2821.0	18.8
HOLDING	0.302	1751.0	2817.0	18.8
GLODTA	0.237	947.6	2790.6	19.1
GLOSA	0.305	942.3	2808.3	19.0
RGLOSA	0.374	465.2	2828.7	18.6
TSP5	0.223	1265.9	2781.0	19.2
TSP10	0.152	876.5	2757.2	19.4
TSP15	0.076	435.5	2738.2	19.7

**Table 3.**  
 Link performance indicators.

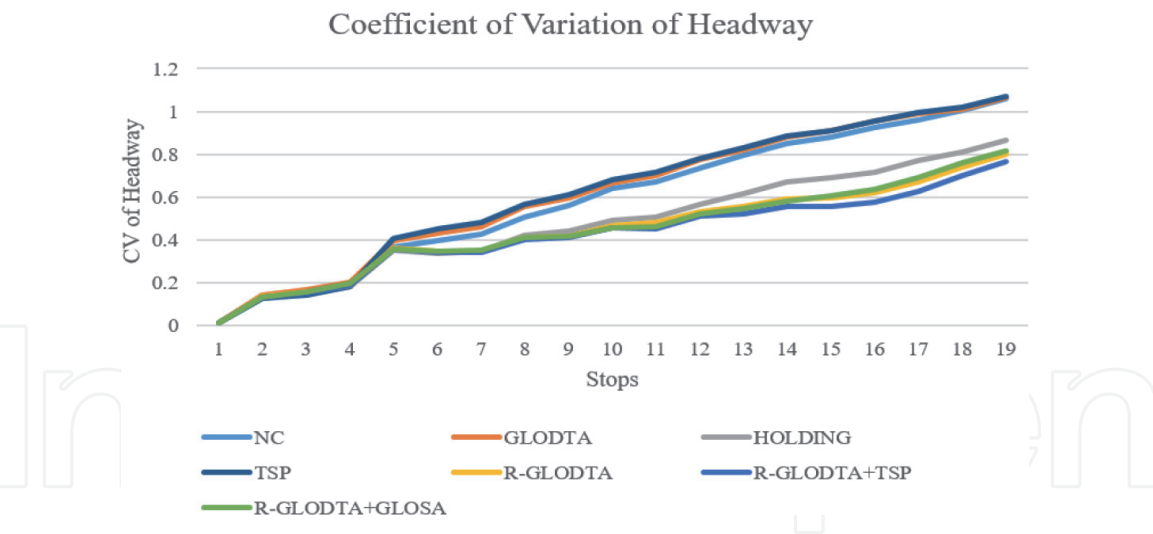
strategies, giving the operator the opportunity to administer more efficiently the available resources and construct a more robust schedule.

The performance indicators for the links are documented in **Table 3**. It is worth noting that R-GLOSA reports the highest frequency of stops at traffic lights. However, the total average delay at traffic lights is comparable to strong TSP, which has the best performance in these two indicators. GLOSA and GLODTA perform better than holding in reducing the number of stops and the delay at traffic signals. The running time on the signalized links is also lower, meeting the objectives of both GLODTA and GLOSA. R-GLOSA reduces the running time at signalized links at the same level of weak TSP. The average speed of the vehicles increases only at the scenarios with TSP.

**Figure 8** shows the trade-off between the average delay at traffic lights and the additional time due to control. When holding is applied, the travel time increases and the additional delay at signalized intersections is not taken into account. TSP heavily prioritizes PT neglecting the impact on regularity by increasing bunching. Obviously, the application of TSP or GLOSA do not introduce any control delay at stops. GLODTA and GLOSA results to similar performance as with intermediate TSP. In contrast to TSP and GLOSA, holding is not causing any delay at traffic lights but increases significantly the additional time added due to control at stops. The delay of R-GLOSA is similar to the one holding, but delay at traffic signals is



**Figure 8.**  
 Tradeoff between waiting time at traffic light and holding time at stop.



**Figure 9.**  
Coefficient of variation of headway per stop.

significantly reduced to the level of strong TSP. Therefore, the savings obtained in running time can compensate the additional delay at stops. The results can vary subject to the chosen holding criterion.

In **Figure 9**, the coefficient of variation (CV) of headway of all R-GLODTA case study scenarios is depicted. Strategies that target the mitigation of stops at traffic lights neglect the regularity of the line. Between GLODTA or TSP scenarios can be found with minor differences compared to the benchmark scenario, reporting high level of variability which propagates along the line. On the other hand, holding, All the R-GLODTA scenarios show significant improvement on maintaining the propagation of headway low. R-GLODTA outperforms holding and its performance improves further with weak TSP. Although R-GLODTA with GLOSA performs better than GLODTA and TSP, the combination is not the most effective compared to R-GLODTA and TSP.

Regularity performance indicators at line level are summarized in **Table 4**. Similarly to the results in terms of coefficient of variation per stop, R-GLODTA outperforms the other strategies with minor differences from holding and R-GLODTA with TSP. GLOSA has a significant impact on the regularity of the line This can be explained by the fact the GLOSA adjusts the speed in order to traverse green. Acceleration and deceleration can shorten the headway between consecutive vehicles and cause platoons. Again, R-GLODTA has the lowest level of bunching between all scenarios. Passenger indicators are also recorded during simulation. As expected, differences between strategies can be observed in in-vehicle times. The

	CV of Headway	Bunching	Waiting time [s]	In vehicle time [s]
NC	0.59	0.37	300.03	204.87
GLODTA	0.62	0.37	300.98	211.2
HOLDING	0.48	0.27	300.08	212.71
R-GLODTA	0.44	0.20	299.96	215.00
R-GLODTA + TSP	0.42	0.19	301.9	212.36
R-GLODTA + GLOSA	0.43	0.21	301.64	226.26
TSP	0.62	0.38	302.75	202.77

**Table 4.**  
Regularity performance indicators.



	Stop at traffic light frequency per segment	Total waiting time at traffic light per segment [s]	Total running time [s]	Average speed [km/h]	Times GLOSA triggered per segment	Number of TSP requests per segment
NC	5.6	113.9	2160.3	18.8	0.0	0.0
GLODTA	4.3	60.7	2135.7	19.0	0.0	0.0
HOLDING	5.4	109.2	2154.2	18.8	0.0	0.0
TSP	1.3	26.1	2084.6	19.7	0.0	4.1
R-GLODTA	4.7	69.4	2132.4	19.0	0.0	0.0
R-GLODTA+TSP	2.9	52.7	2115.9	19.3	0.0	1.7
R- GLODTA+GLOSA	4.7	49.6	2172.1	18.7	2.1	0.0

**Table 5.**  
*Link performance indicators.*

additional time added due to control actions increases the time passengers spend on board. The higher in-vehicle time can be compensated with a more robust travel time and the overall improved performance of the line.

One of the objectives of the proposed scheme is the mitigation of stop and go at signalized intersections, therefore the performance of each scenario at a link level is assessed. The results are summarized in **Table 5**.

Unquestionably, providing unconditional signal priority to PT can reduce dramatically the number of stops at signals and the corresponding delay at signalized intersections. However, this reduction will potentially penalize the rest of the traffic. R-GLODTA shows slightly increased number of stops compared to GLODTA alone. This can be explained by the fact that the combined controller prioritizes regularity over stopping at signals. Therefore, it will not exchange holding for regularity to secure passing during green. Weak TSP improves substantially the performance of R-GLODTA in terms of frequency of stops and delay at intersections. Speed adjustment with GLOSA transfers waiting time at traffic lights to running times to the links. A GLOSA advises to decelerate in order to arrive at the intersection during green, prolongs the running time between stops. All R-GLODTA scenarios result in lower total running time compared to an independent application of GLODTA or holding but higher than TSP, but they compensate with their regularity indicators, especially bunching. Among scenarios the differences of the speed are marginal.

We compare the number of TSP requests between the TSP and the R-GLODTA with TSP scenarios. The number of TSP requests is halved with R-GLODTA and with the combination of weak TSP can achieve comparable results with TSP in reducing stop and go actions at traffic lights while it contributes to the regularity of the line.

A final analysis is performed to check how many times the strategies are adopted in the simulated scenarios. **Table 6** shows the share of each control decision, i.e. when each control was needed. Fixing regularity is prioritized over reducing stops at traffic lights. Controlling actions are reduced when R-GLODTA is combined with TSP. R-GLODTA aims to address both objectives and the number of independent applications of holding or GLODTA. On the other hand, the combination with TSP or GLOSA reinforces the objective of GLODTA. The need of holding alone intensifies in these scenarios to restore regularity. With GLOSA, holding is triggered more than half of the times a controller was requested. If the changes of speed do

	Control request	Controller choice		
		GLODTA	Holding	R-GLODTA
R-GLODTA	61%	38%	42%	19%
R-GLODTA + TSP	58%	37%	49%	14%
R-GLODTA + GLOSA	62%	37%	51%	13%

**Table 6.**  
*Controller frequency.*

not account for the sequence of vehicles, undesired phenomena as formation of platoons are more likely to occur and impact the performance of a bus line.

5. Conclusions

This chapter has presented an integrated approach to manage electrified bus systems using Cooperative ITS. We first discussed the challenges and opportunities brought by next generation public transport systems, which require to manage the system in an integrated way. Then we introduced novel optimization methods for joint bus scheduling and charging, and real-time operational control strategies. Results in realistic simulations show how the integrated systems achieves cost effective, reliable and energy efficient operations.

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