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A decentralized optimization approach employing cooperative cycle-regulation in an intersection-centric manner: A complex urban simulative case study

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ABSTRACT

The upcoming high population density rise in metropolitan areas is anticipated to further deteriorate the traffic conditions. To tackle this problem, advanced ICT applications have been employed, able to monitor and manage traffic in real time. In practice, to efficiently correspond to dynamic traffic conditions those applications require to be frequently reconfigured – an operation that usually involves expert-teams manually adjusting the traffic-regulating strategies regularly. However, these manual procedures are not adequately aligned with the traffic situation since complicated stochastic dynamics, model unavailability and data inner-transmission constraints usually emerge. In order to overcome such cumbersome and expensive adjustment procedures modern decentralized adaptive optimization is widely accepted and recognized as an efficient automated solution for tuning the control strategy on-the-fly. Motivated by the above, L4GCAO, a decentralized, model independent, flexible optimization technique has been designed for optimizing cycle management at a local level to improve network performance at the global level, by automatically adjusting the cycle-regulating parameters in an intersection-centric manner, through cooperating self-learning agents.

This paper studies L4GCAO's first application on a realistic traffic-network simulation scheme that examines the online fine-tuning process of the cycle-regulating parameters. Moreover, in order to evaluate the decentralized L4GCAO performance, two levels of performance benchmarking have been considered: a comparison with CAO - its well-established centralized counterpart; an already well-designed fixed-time management plan. In all cases, L4GCAO exhibits an almost equivalent performance improvement compared to CAO, both with respect to a properly fixed-time traffic management plan, while utilizes less parameters in a non-centralized manner.

1. Introduction

Since human population shift continuously to urban areas, traffic congestion levels are anticipated to growth accordingly, resulting low quality levels of life and reducing regional economic health. To this end traffic management has become a key issue in urban living areas generating a lot of studies that examine the efficiency of such tactics and approaches (Cameron et al., 2004; Newman and Kenworthy, 2011; Huo et al., 2012; Gargett and John, 2004). Traffic congestion may seem only a technical/engineering problem, it affects, however, in a negative way many aspects of everyday life. To reduce the negative effects of congestion, Advanced Traffic Management Systems (ATMS) are developed and utilized. ATMS are able to collect data from several different types of sensors (cameras, speed meters, connected vehicles, detector loops, etc.) and exploit them through specialized ICT tools which are capable of aggregating and evaluating these data to create informative insights for the operator. The operator is then called to make decisions aiming at reducing congestion levels, smoothening traffic flow, and enhancing drivers' safety.

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Abbreviations: ATMS, Advanced Traffic Management System; ADTPV, Average Delay Time Per Vehicle; BCS, base case scenario; CAO, Cognitive Adaptive Optimization; CR, cycle regulation; ES, extremum seeking; ITS, Intelligent Transportation System; L4GCAO, Local for Global Cognitive Adaptive Optimization; LIP, linear in parameters; MPC, model predictive control; ND, Network Demand; NP, network productivity; NMS, network mean speed; SC, split control; TCC, Traffic Control Center.

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Nomenclature

k	positive integer counter of current optimization iteration
L	positive integer number of total random perturbations
N	positive integer number of total constituent/local optimizers
w	positive integer index of specific constituent optimizer
T_h	defined control parameters update period (optimization iteration time interval)
ct	constant number/value
$a(k)$, $a_w(k)$	positive perturbation amplitude for centralized CAO and decentralized L4GCAO approach, at the k-th iteration, respectively
H_{gk}, H_{wk}	set of control parameters (tunable parameters) for centralized CAO and decentralized L4GCAO approach, at the k-th iteration, respectively
J_{gk}, J_{wk}	objective function value for the overall (global) and local w-th constituent systems, performance, at the k-th iteration, respectively
$\hat{J}_{gk}$	estimated objective function value for the overall (global) performance, at the k-th iteration
θ_k, θ_{wk}	estimator parameters for centralized CAO and decentralized L4GCAO approach, at the k-th iteration, respectively
H^j_{gk}, H^j_{wk}	perturbed candidate control parameters set for centralized CAO and decentralized L4GCAO approach, at the k-th iteration, respectively
ΔH^j_{gk}, ΔH^j_{wk}	random perturbation of the control parameters set for centralized CAO and decentralized L4GCAO approach, at the k-th iteration, respectively
$\hat{J}^j_{gk}$	estimated overall (global) objective function for each perturbed candidate control parameters set, at the k-th iteration, respectively
q	current control cycle
C(q)	the current calculated cycle time [*sec*]
σ(q)	the average maximum load [veh] of some pre-specified links
C_{min}	is the minimum permissible cycle time [*sec*]

decisions aiming at reducing congestion levels, smoothening traffic flow, and enhancing drivers' safety.

Decision-support techniques suggest that skilled personnel and expert traffic control engineers based on field observations, previous data and empirical design accumulations are usually adopted to manually apply actions with an acceptable and satisfactory behavior. Unfortunately, heuristic-based decision-making (Hunt et al., 1982; Lowrie, 1982; Liu et al., 2015; Smith, 2015) is particularly difficult or not feasible at certain times, due to system complexity, size and uncertain dynamics imposed by weather conditions and driving behavior. As a result, satisfying performance in an emerging environment such as urban traffic networks at a permanent basis cannot be guaranteed. Emerging traffic-affecting conditions lead to highly uncertain behavior which hinders static and non-adaptive approaches' applicability in practice. Moreover, other literature studies are simplifying the optimization problem dynamics to linearized ones (Mehrabipour and Hajbabaie, 2017); considering the overall performance index as a linear and analytically known function of the observable states (Wang, 2005), which imposes lower accuracy and reduced applicability in practice where highly stochastic, unknown and complex/nonlinear dynamics may affect the behavior of the system.

To this end a large number of innovative adaptive optimization approaches, utilizing standard Stochastic Approximation parameters have been suggested in literature (Kiefer and Wolfowitz, 1952; Ermoliev, 1969; Robbins and Monro, 1951; Spall, 1992) and also multiple Stochastic Approximation algorithms have been identified for their capability to adequately fine-tune traffic simulation modelled schemes (Lu et al., 2015; Koch et al., 1997; Chin and Smith, 1994). Although, despite their improved performance in comparison with traditional approaches they are depended on simplified methods for analytically calculating the general gradient of the objective function that concerns the overall performance of the system. That inevitably reveals their inefficiency as concerns complicated ITS (Kosmatopoulos et al., 2007; Kosmatopoulos and Kouvelas, 2009), such as the sophisticated traffic control approaches of metropolitan areas. Extremum Seeking (ES) decentralized optimization schemes considering dynamically changing challenges - where only a small portion of systems' information is available - have also been indicated in literature (Kutadinata et al., 2016; Guay et al., 2004; Adetola and Guay, 2007; Tan et al., 2006; Liu and Krstic, 2012; Krstic and Wang, 2000; Pan et al., 2002; Stankovic et al., 2011; Guay et al., 2015). In those cases, the overall objective function is considered analytically known despite the cooperative optimization topology as the weighed summation of the locally available ones. Additionally, ES schemes assume direct interaction among neighboring agents similar to Multi-Agent Reinforcement Learning (Chu et al., 2019; Chu et al., 2016; Aziz et al., 2017) where the Q-function values are observed from the field (Chu and Wang, 2017) while large-scale deep-learning tedious techniques are considered (Van der Pol and Oliehoek, 2016) which is not usually the case in real-life applications; fact which renders the volume of data transmitted along with the corresponding communication rates among neighboring agents (agent-clusters) to be high. Normally, the scale of the identified intercommunicating neighboring agents is oppositely proportional to the adaptation degree and the recurrence of the periodic signal that is utilized to determine extremum seeking in order to guarantee reduced communication weights/costs. Moreover due to their design scheme, those approaches also suffer from the hypothesis of a linear explicit dependence of the overall objective function with the local ones (weighted summation) – an assumption that is regularly adopted in decentralized ES but cannot be applicable considering the present real-life applications.

Contrary to the aforementioned approaches, the Local for Global Cognitive Adaptive Optimization (L4GCAO) approach is able to efficiently address quite complicated and large in scale traffic cycle regulation calibration challenges, that uncertain dynamics emerge (Kosmatopoulos et al., 2015) presenting low computational and operational costs. Considering L4GCAO optimization methodology, only a single data point is required – a single data point that is able to exhibit the overall performance of the system and can be systematically distributed within all constituent agents, while the analytic form of the overall objective function is totally analytically unknown but observable. The circulation of the same single data point among all constituent local systems minimizes to almost zero the required communication resources related to the respective infrastructure, energy, time, and maintenance. However, one differentiating feature, if not the most important, of L4GCAO is its ability to operate in a plug-n-play manner i.e. without any previous pre-application efforts. L4GCAO has been designed to serve as a calibrating engine for virtually any kind of large scale traffic control system, being agnostic to the actual internal dynamics of the plant. The results demonstrated L4GCAO's ability to effectively hash down the large-scale optimization problem to several cooperative locally-driven ones. An optimizing agent is dedicated for managing each sub-problem to improve the overall performance of the system. The decentralized algorithm L4GCAO that is based on CAO - Cognitive

Adaptive Optimization (Kosmatopoulos and Kouvelas, 2009; Kosmatopoulos, 2009; Baldi et al., 2014) – is able to function effectively in cases where the model that describes the traffic network is totally unknown. The use of its parallel centralized algorithm approach that utilized CAO, has previously been assessed in equivalent cases of traffic optimization control (simulation scenarios and real-life cases) exhibiting remarkable operational success (Baldi et al., 2015a; Sangi et al., 2016; Baldi et al., 2015b). To this end CAO algorithmic solution is utilized in order to define an efficient and reliable system for L4GCAO comparison. The goal of the current study is to extensively test and evaluate L4GCAO in cycle-regulation applications where real-time centralized control – due to communication and data-transmission limitations – can become impractical as the number of interconnected entities and network scale is constantly growing. As a result, the decentralized algorithm is utilized to locally adjust the variables of the control approach for improving its efficiency at the global network: the approach employs a local signal control strategy towards the optimization control of the Chania City urban traffic network that is located in the island of Crete - Greece. It should be mentioned that this study research portrays an expanded and continued report of a respective research introduced in 5th International Conference on Control, Decision and Information Technologies (CoDIT), 2018 (Michailidis et al., 2018). It should also be noted that the current study considers a simulation model of the Chania city network that has already been created under a previous research and the demand scenario was configured based on real-life measurements in order to exhibit efficiently the actual conditions in the urban road network: the aforementioned scenario that concerns a congested traffic environment is able to be directly transferred to the actual traffic network plant effort (Kouvelas et al., 2011). Is noteworthy that the actual application of the current approach wouldn't require the employment of any extra infrastructure additions where each junction controller could may behave as a decentralized calculation hosting platform for the respective local agent. Moreover, operational costs concerning real-time data transmission from every part of the traffic network, would also be significantly reduced since the system requires a smaller amount for central information.

This study is integrated in 5 sections:

- Section 2 (Problem Formulation In Urban Traffic Networks) describes briefly the optimization problem formulation;
- Section 3 (Simulative Traffic Network Testbed) describes the traffic network that concerns the current research effort;
- Section 4 (Distributed Automated Fine-Tuning Method) exhibits the primary features of the proposed L4GCAO approach;
- Section 5 (The Signal Control Method & The Respective Optimization Parameters) presents the application case study of L4GCAO, emphasizing on the optimization goals, adopted simulation schemes and performance measurements;
- Section 6 (Simulation Results & Discussion) presents and discusses the results of the simulation study;
- Section 7 (Conclusions) presents the final conclusions of the current research.

2. Problem formulation in urban traffic networks

In this section the main ideas behind the dynamic control-strategy optimization problem formulation is presented. The mathematical details behind this approach have already been published in Kosmatopoulos et al. (2015) where the interested reader is referred to, for more details. We will assume in the general case; that the traffic network can be described by the dynamics

$$\dot{\chi}(t) = F(\chi(t), u(t)) + d(t)$$

$$u(t) = S\big(H_g(t), \sigma_q(t)\big)$$

where $\chi = [\chi_1^T, \chi_2^T, \ldots, \chi_N^T]^T$ denotes the system augmented state vector (e.g. the vehicle-numbers and flows of all links), while χ_i denotes the respective constituent/local states and $H_g = [[\sigma_{w01}, \sigma_{cr1}, K_{11}, K_{21}]^T, [\sigma_{w02}, \sigma_{cr2}, K_{12}, K_{22}]^T, \ldots, [\sigma_{w0N}, \sigma_{crN}, K_{1N}, K_{2N}]^T]^T$ is the augmented control vector comprised by the respective local ones (intersection centric) $H_i = [\sigma_{w0i}, \sigma_{cri}, K_{1i}, K_{2i}]^T$, $d(t)$ is a stochastic noise affecting the network (e.g. the effect of stochastic traffic demand) and $\sigma_q(t)$ is the augmented vector of the network links occupancy (see Section 5 for more details). Finally, function F is – in the general practice case – highly nonlinear and complex (rendering it almost unknown) and function S is a known control formula designed to implement the cycle-regulating strategy (see Section 5 for more details).

As a result, from the above analysis, the dynamics of the traffic network plant involve unknown, complex, nonlinear and stochastic behavior in the general case. In the current study the function F is implemented by a modelled instance of the Chania City traffic network model, implemented in AIMSUN environment (see Section 3 for more details). Moreover, the cost-to-go criterion – indicating the system performance - to be optimized (in particular to be maximized) is formulated as follows:

$$J = \int_0^\infty \Pi\Big(\chi(s), u\big(H_g(s), \sigma_q(s)\big)\Big) ds$$

where, for the specific traffic control problem at hand, the function Π represents the network productivity function, calculated from the network mean speed (NMS) and demand (ND).

However, in order to solve the aforementioned problem using CAO, the manipulation of the augmented scale H_g problem (overall network scale) would be intractable as the plant's scale and complexity increases (more intersections involved, more complex CR algorithms considered, etc.). For this reason, in Section 4 we propose the decentralized L4GCAO dynamic optimization approach to effectively distribute the computational workload and reduce the communicational workload without jeopardizing the achieved network efficiency, at the same time.

3. Simulative traffic network testbed

As it has been already noted, the decentralized L4GCAO algorithm aims at tuning the parameters of several parallel (local intersection-driven) cycle regulating strategies to improve the overall traffic performance of the network. In order to evaluate this procedure properly an AIMSUN-based realistic simulation model (Barcelo et al., 1999) emulating the traffic network of Chania city (Fig. 1. Simulation test case site, Chania, Crete.) is employed. The modelled instance was already developed and evaluated for the purposes of previous studies (Baldi et al., 2015b; Manolis et al., 2015) and as a result AIMSUN was considered as the most convenient simulation environment for testing. Chania is considered an attractive touristic destination for many people especially during summertime, when the number of actual residents is being doubled. The traffic grid overall concerns almost 8 km in length and includes 13 controlled junctions (each consisted by 3 to 5 links) having its detector loops primarily placed around the center of the respective links or almost 40 m upward the stop line (Fig. 2. Chania Traffic Network AIMSUN model. portrays in detail the network model) (Baldi et al., 2015b).

Previous historical data available from the 2008 traffic flow measurements, have been utilized in order to construct a challenging test-scenario that comprises congested traffic conditions as described in Section 6 (Baldi et al., 2015b). Consequently, the proposed traffic system is defined as a high complicated network that concerns uncertain dynamics since altering weather conditions and uncertain driver behaviors are significantly affecting the system. The L4GCAO strategy represent a great opportunity for providing efficient real-time optimization control that, besides achieving improved travel times, average speed, productivity and reduced delays it is able to reduce the environmental impact and fuel consumption and promote the economic activities of a community overall (e.g. transportation).

Fig. 1. Simulation test case site, Chania, Crete.

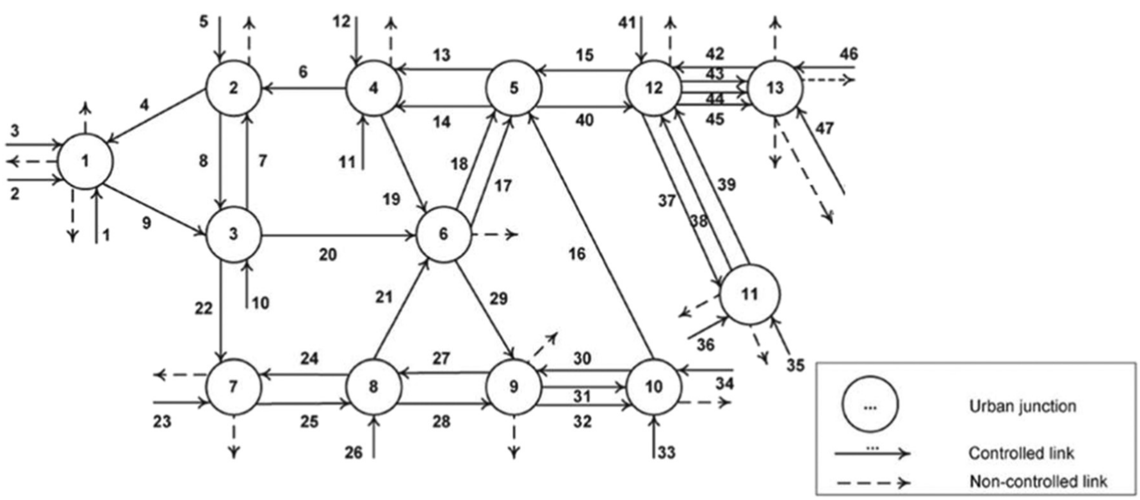

Fig. 2. Chania Traffic Network AIMSUN model.

4. Distributed automated fine-tuning method

L4GCAO was designed based on the same principles as its centralized counterpart, therefore L4GCAO inherits the same properties from its basic ingredient, the Cognitive Adaptive Optimization tool (CAO). CAO is a centralized optimization tool with self-learning capabilities. The algorithmic workflow of this tool; utilized for adjusting the control parameters of a given cycle regulation strategy; is briefly described in the following table (see Fig. 3).

CAO algorithm description	Analytic presentation of CAO algorithm
(i) Initialize the central[a] control parameters (usually to well-tuned or the ones used in practice) $H_g = H_{g0}$ (see Eq. (1)), define a reasonable iteration period interval T_h (depending on the application characteristics and particularities) (see Eq. (2)), define a continuous smooth time-decaying function representing the random perturbation area size *α(k)* and define the respective initial value $\alpha_0 > 0$ (see Eq. (3)), also let *k* A1]∈ ℕ denote the number of the current iteration (see Eq. (4)).	Initialize: $H_g = H_{g0}$ (Eq. 1) $T_h = ct$ (Eq. 2) $a(k) = \frac{a_0}{k+1}$ (Eq. 3) $k = 0$ (Eq. 4)
(ii) Apply the set of the central control parameters H_{gk} of the current iteration to the system and commute the overall performance J_{gk} at the end of the current iteration.	STEP 1. Apply H_{gk} to the system and calculate the respective value of the overall objective function J_{gk}.
(iii) Feed CAO with the set of central control parameters used and the respective total performance calculated.	STEP 2. Create sets of respective: $H_{gk} - J_{gk}$.
(iv) Calculate a central linear in the parameters estimator of the total performance: $\hat{j}_{gk} = f(H_{gk})$ (see Eqs. (5) and (6)).	STEP 3. Based on these sets, calculate, using common least squares techniques, a linear in the parameters – LIP - estimator of the objective function as follows: $\hat{j}_{gk} = \theta_k H_{gk}$ (Eq. 5) $\theta_k = argmin\{\sum_{i=0}^{i=k} [J_{gi} - \theta H_{gi}]^2\}$ (Eq. 6)

(*continued*)

CAO algorithm description	Analytic presentation of CAO algorithm
(v) Generate $L \in \mathbb{N}$ random perturbations of central H_{gk} (see Eq. (7)) and evaluate them utilizing the resulted central estimator from the previous step (see Eq. (8)).	STEP 4. Generate $L \in \mathbb{N}$ random perturbations of H_{gk} as follows: $H^j_{gk} = H_{gk} + a(k)\Delta H^j_{gk}, j = 0, 1, \ldots, L$ (Eq. 7) and evaluate them through the estimator resulted from the previous step as follows: $\hat{J}^j_{gk} = \theta_k H^j_{gk}$ (Eq. 8)
(vi) The set of central control parameters presenting the best estimated performance i.e. the smallest value of the cost criterion considered or, equivalently, the largest value of the performance criterion considered, is selected and applied to the system for the next interval/iteration (see Eq. (9)).	STEP 5. Select the one presenting the most efficient estimated performance, to be applied to the system for the next optimization iteration k + 1: $H_{g(k+1)} = H^j_{gk} = argmin\{[\hat{J}^j_{gk}]^2\}$ (Eq. 9)
(vii) Repeat the process described within (ii)–(vii) until convergence is reached.	STEP 6. Check if convergence has been achieved. IF true THEN: STOP ELSE: Set k = k + 1 and GO TO STEP 1.

[a] “Central” term is repeated several times in an emphatic manner in order to stress out the main differences between CAO and L4GCAO methodologies.

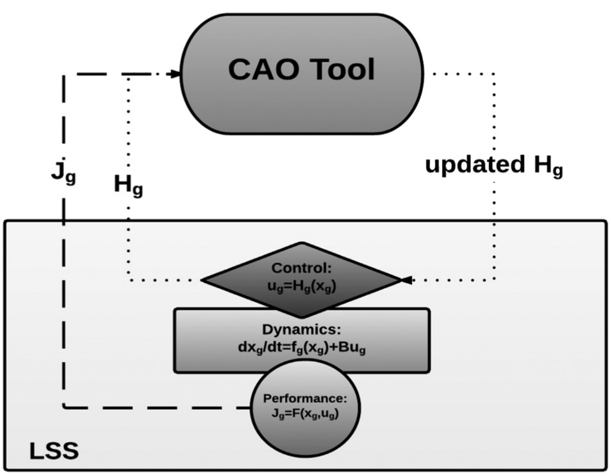

Fig. 3. Cognitive Adaptive Optimization (CAO) centralized setup.

CAO can be practically deployed in an easy and straightforward manner without any tedious pre-application effort. Several application cases have accounted for CAO's ability to converge early and effectively both in simulation and realistic conditions (Kosmatopoulos, 2009) (Baldi et al., 2014). However, being a centralized approach, CAO requires all information to be processed centrally; fact which severely intensifies the data-communication rate and processing power at the central node.

To tackle the aforementioned problems while preserve all principal advantages of CAO, a decentralized counterpart – namely L4GCAO (Kosmatopoulos et al., 2015) - was developed, by unburdening the central node from solving the global optimization problem in very large-scale networks. L4GCAO was designed to solve several smaller yet equivalent optimization subproblems in parallel. Therefore, instead of solving a high dimensional optimization problem centrally, $N \in \mathbb{N}$ smaller (in scale, processing power and data-rates) subproblems are defined to equivalently optimize the exact same overall performance index (see Fig. 4).

The main architectural principle comprises of two basic elements: the local optimizers (CAO instances) and the single cloud/central node which simply calculates the overall performance index. L4GCAO's algorithmic workflow is briefly described in the following table.

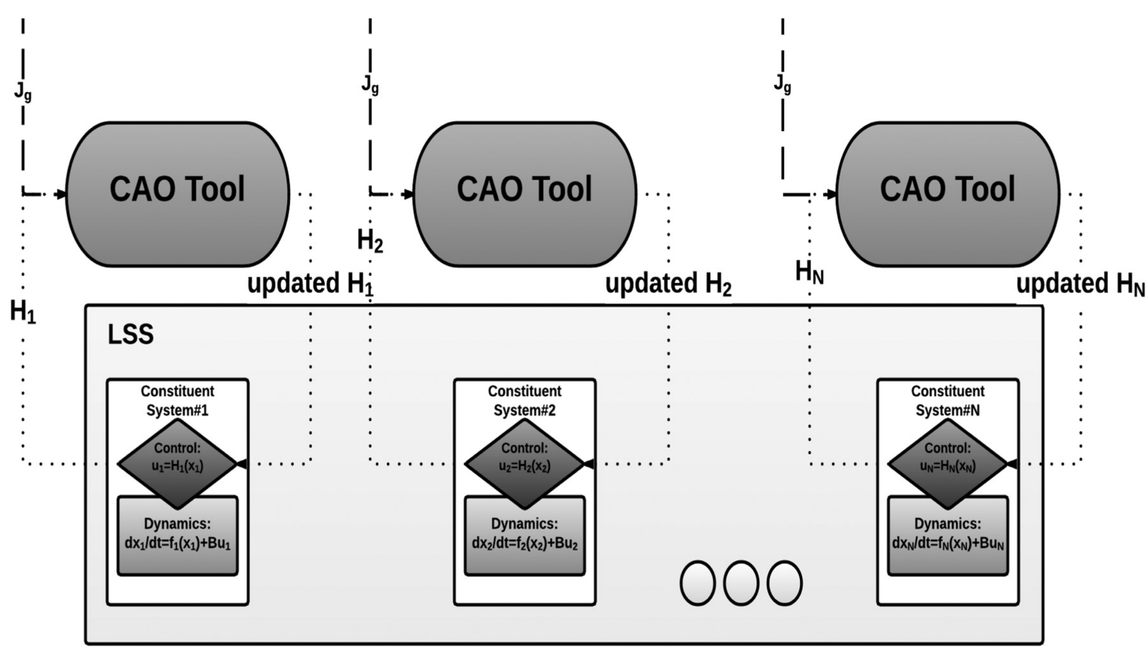

Fig. 4. Local 4 Global CAO distributed setup.

L4GCAO algorithm description	Analytic presentation of L4GCAO algorithm
(i) Initialize the control parameters in each constituent[a]/local[b] system (usually to the ones used in practice) $H_{wk} = H_{w0}$ (see Eq. (10)), define a reasonable iteration period interval T_h (depending on the application characteristics and particularities) (see Eq. (11)), define a continuous smooth time-decaying function representing the random perturbation area size $\alpha(k)$ and define the respective initial value $\alpha_{w0} > 0$ (see Eq. (12)), also let $k \in \mathbb{N}$ denote the number of the current iteration and $N \in \mathbb{N}$ the number of constituent systems (see Eq. (13)).	Initialize (for each constituent system): $H_{wk} = H_{w0}$ (Eq. 10) $T_h = ct$ (Eq. 11) $a_w(k) = \frac{a_{w0}}{k+1}$ (Eq. 12) $k = 0$ (Eq. 13)
(ii) Apply each local set of the control parameters $[H_{1k}, H_{2k}, \ldots, H_{Nk}]$ of the current iteration to each respective constituent system and commute the overall performance $J_{gk} = F(J_{1k}, J_{2k}, \ldots, J_{Nk})$ at the end of the current iteration (at the "cloud" central level).	STEP 1. Apply H_{wk} to each respective constituent system and calculate the overall system performance J_{gk}.
(iii) Feed each local optimizer/agent (constituent CAO) with the respective set of local control parameters H_{wk} used and the achieved overall performance J_{gk}.	STEP 2. Commute the achieved overall performance back to all constituent optimizers and create locally sets of respective: $H_{wk} - J_{gk}$
(iv) Calculate at the local level a linear in the parameters estimator of the overall performance: $\hat{j}_{gk} = f(H_{wk})$ (see Eqs. (14) and (15)).	STEP 3. Based on these sets, calculate, using common least squares techniques, a linear in the parameters – LIP - estimator of the overall objective function at a local level, as follows: $\hat{j}_{gk} = \theta_{wk} H_{wk}$ (Eq. 14) $\theta_{wk} = argmin\{\sum_{i=0}^{i=k} [J_{gi} - \theta_w H_{wi}]^2\}$ (Eq. 15)
(v) Generate $L \in \mathbb{N}$ random perturbations of local H_{wk} (see Eq. (16)) and evaluate them utilizing the resulted respective local estimator from the previous step (see Eq. (17)).	STEP 4. Generate $L \in \mathbb{N}$ random perturbations of H_{wk} as follows: $H^j_{wk} = H_{wk} + a_w(k)\Delta H^j_{wk}, j = 0, 1, \ldots, L$ (Eq. 16) For all constituent optimizers and evaluate them through each respective local estimator resulted from the previous step as follows: $\hat{J}^j_{gk} = \theta_{wk} H^j_{wk}$ (Eq. 17)
(vi) The set of local control parameters presenting the best estimated overall performance i.e. the smallest value of the cost criterion considered or, equivalently, the largest value of the performance criterion considered, is selected and applied to the respective local system for the next interval/iteration (see Eq. (18)).	STEP 5. Select the ones presenting the most efficient locally estimated performance, to be applied to each respective local system for the next optimization iteration k + 1: $H_{w(k+1)} = H^j_{wk} = argmin\{[\hat{J}^j_{gk}]^2\}$ (Eq. 18)
(vii) Repeat the process described within (ii)-(vii) until convergence is reached.	STEP 6. Check if convergence has been achieved. IF true THEN: STOP ELSE: Set k = k + 1 and GO TO STEP 1.

[a] The terms "constituent" and "local" are considered having equivalent/similar meanings herein.
[b] "Local" term is repeated several times in an emphatic manner in order to stress out the main differences between CAO and L4GCAO methodologies

From the simulation results and the comparison between the centralized (CAO) and distributed (L4GCAO) versions, it can be derived that L4GCAO achieves successfully to deal with such a high-dimensional, complex optimization problem (for more details see Section 6).

5. The signal control method & the respective optimization parameters

Current real-life practice for the management of metropolitan traffic networks suggests centralized signal control and monitoring approaches that demand common cycle times at every junction for coordination reasons. Opposing to that, the current study involves an intersection-driven, cycle-regulating strategy that is able to perform without such limitation while the only restraints imposed refer to a predetermined sequence of the signal cycle stages, their minimum permitted green times as well as the min and max cycle times for every junction. The selected signal regulation approach includes two low-cost algorithms that are utilized for updating two different levels of the signal control settings: (a) the cycle time and; (b) the green splits (e.g. the respective green period of every stage) - as part of the cycle time - at each local junction level. The aforementioned algorithmic strategies operate once in every adjusted cycle period in order to react in-time when unexpected stochastic traffic network alterations occur. In order to refresh the signal parameters at the beginning of cycle, the well-established, feedback-based cycle regulation (CR) algorithm of TUC (Traffic-responsive Urban Control) (Kouvelas et al., 2011; Diakaki et al., 2003) is being utilized. Moreover, for the green split control (SC) the back-pressure algorithm - adopting a variant of the max pressure (MP) partitioning the respective cycle times in the related cycle stages for maximizing throughput – is considered (Xiao et al., 2015; Varaiya, 2013). MP originates from the communication network control domain (Tassiulas and Ephremides, 1992) but has already been thoroughly tested for managing the cycle regulation problem (Kouvelas et al., 2014). It should be noted that in all individual junctions, the SC and CR approaches are operating locally, absolutely independent from any other.

The local CR considers a control rule that comprises parameters for every junction point, fact which influences the intensity of its control response and consequently its operation and effectiveness. The cycle control module is a piecewise linear bimodal function of σ_w (occupancy norm). In the first mode the cycle time is increased linearly with the norm of the normalized occupancy: in the second mode the cycle time is decreased linearly with the norm of the normalized occupancy. It has been observed empirically; there exists a critical occupancy σ_{cr} such that that below this threshold increased cycle time (and increased portion of green time) will make traffic smoother. Above the critical occupancy the increased portion of red time will create longer queues, so it is more beneficial to decrease the cycle time. The CR formula utilizes the following control rule (Kouvelas et al., 2011; Diakaki et al., 2003):

$$C_w(q) = \begin{cases} C_{w,\,min} + K_{w1}(\sigma_w(q) - \sigma_{w0}), & \sigma_w(q) \le \sigma_{w,cr} \\ C_{w,\,min} + K_{w1}(\sigma_{w,cr} - \sigma_{w0}) - K_{w2}(\sigma_w(q) - \sigma_{w,cr}), & \sigma_w(q) > \sigma_{w,cr} \end{cases} \tag{19}$$

where q is the current control period, $C_w(q)$ the calculated cycle time [s], $\sigma_w(q)$ the mean value of the space occupancies of the most loaded junction links, and $C_{w,\min}$ represents the minimum permissible cycle time [s]. Additionally, σ_{w0}, $\sigma_{w,cr} \in [0,1]$ and K_{w1}, $K_{w2} > 0$ consider factors that influence the intensity of the control rule responses towards the observed saturation levels via $\sigma_w(q)$ - and so they need to be adequately calculated in order to guarantee control efficiency. After applying the regulation law, the calculated cycle time $C_w(q)$, is confined between $[C_{w,\min}, C_{w,\max}]$ limits. C_{max} portrays the maximum acceptable cycle time [s], to become feasible, if necessary.

In order to adjust the CR parameters ($H_w = [\sigma_{w0}, \sigma_{w,cr}, K_{w1}, K_{w2}]$) at every junction CAO and L4GCAO optimization strategies are being utilized and compared to each other as shown in Fig. 3. Cognitive Adaptive Optimization (CAO) centralized setup. and Fig. 4. Local 4 Global CAO distributed setup. The main goal of the optimization procedure is to increase a representative performance index using a frequent re-configuration of these parameters in every junction. In similar application cases the usual performance indicator considered is the Network Mean Speed (NMS) [km/h]. However, optimizing NMS alone is not efficient since the Network

Demand (ND) affects significantly the NMS in an approximately disproportional manner - altering over time. To this end, the Network Productivity (NP) [km·veh/h^2] index, has been considered (Eurostat et al., 1997; B. Australian Transport Safety, 2005; Australian Bureau of Statistics, 2004), formulated as the multiplication product of Network Mean Speed (NMS) [km/h] and Average Network Demand (ND) [veh/h], in order to evaluate the NMS optimizations in situations where ND is altering. To determine this index, the required ND and NMS values are estimated based on flow and occupancy measurements from the network. The goal was to calculate these indexes in a practically feasible manner – considering the replicability of the approach in real-life networks; and avoid utilizing values estimated directly from AIMSUN which would not be available in practice. More specifically, the daily total demand (i.e. ND) is calculated as the sum of the time-averaged flows measured by the detectors located at the network origins. On the other hand, NMS is estimated as the ratio TTD/TTS, where TTD is the total travelled distance and TTS is the total time spent by all vehicles in the network. TTD is on its turn estimated by multiplying the flow measurement with the respective length of each junction's link, while TTS is estimated through the occupancy measurements, using a function that considers the length of the links and the position of the detectors. This procedure was proven quite robust, providing accurate enough estimations for the actual network mean speed and demand based only on loop detector measurements.

6. Simulation results & discussion

6.1. Simulation scenarios and reference case

For performance comparison purposes the efficiency achieved both by CAO and L4GCAO tools is evaluated. Both solutions were utilized in order to fine-tune the parameters deciding the CR strategy – as presented in Section 5 – under diversified simulation test-scenarios conducted using the AIMSUN-based plant of the Chania city traffic network, as mentioned earlier in Section 2. The complete experimental setup adopted is schematically depicted in Fig. 5, where locally driven L4GCAO agents – one per junction – fine tune the respective local CR parameters towards maximizing the shared overall performance index level which reflects the global productivity of the network. At a second stage, the resulted cycle duration is then split among the respective incoming links of each specific junction through the SC module (see Section 4).

The simulation horizon considered a period of 17 consecutive working days (no weekends or other type of special days were considered) presenting similar demand levels and peaks, while each simulation day considered only the peak midday period of 1.5 h duration. As explained in Section 2, the daily demand considered in the experimental scenarios is derived by historical congested traffic conditions from 2008 (see Fig. 8a) during a 30-min peak period within the total 1.5 h horizon during each simulation day. The centralized CR parameters (H_g) and all decentralized CR parameters (H_w) are updated at the end of each simulation day, while the parameter a_0 (for the centralized case) and all a_{w0} (for the decentralized case) were set equal to 1 (see initialization steps both for CAO and L4GCAO in Section 3). The choice of such scenario has been adopted since potential improvements will impose a higher impact in practice during congested conditions.

For comparison and benchmarking purposes, three different CR-deciding strategies were adopted:

- Reference case: A set of CR-deciding parameters – designed especially for congested conditions in a previous study (Dinopoulou et al., 2005) and projects: Traman21 (http://www.traman21.tuc.gr/), Nearctis (http://www.nearctis.org/) - was considered for all junctions constant during the whole simulation scenario without daily optimized re-calibration (see Table 1).
- Case 1 – CAO: The global H_g set of cycle-regulating parameters is fine-tuned at the end of each simulation day utilizing the centralized CAO algorithm. The initial values for the H_{g0} are set equal to the reference case ones (see Table 1).
- Case 2 – L4GCAO: One local optimizing agent linked to each local CR strategy is responsible for optimizing its cycle-regulating set H_w of parameters at the end of each simulation day by utilizing the L4GCAO algorithm. The initial values for every H_{w0} are set equal to the reference case ones (see Table 1).

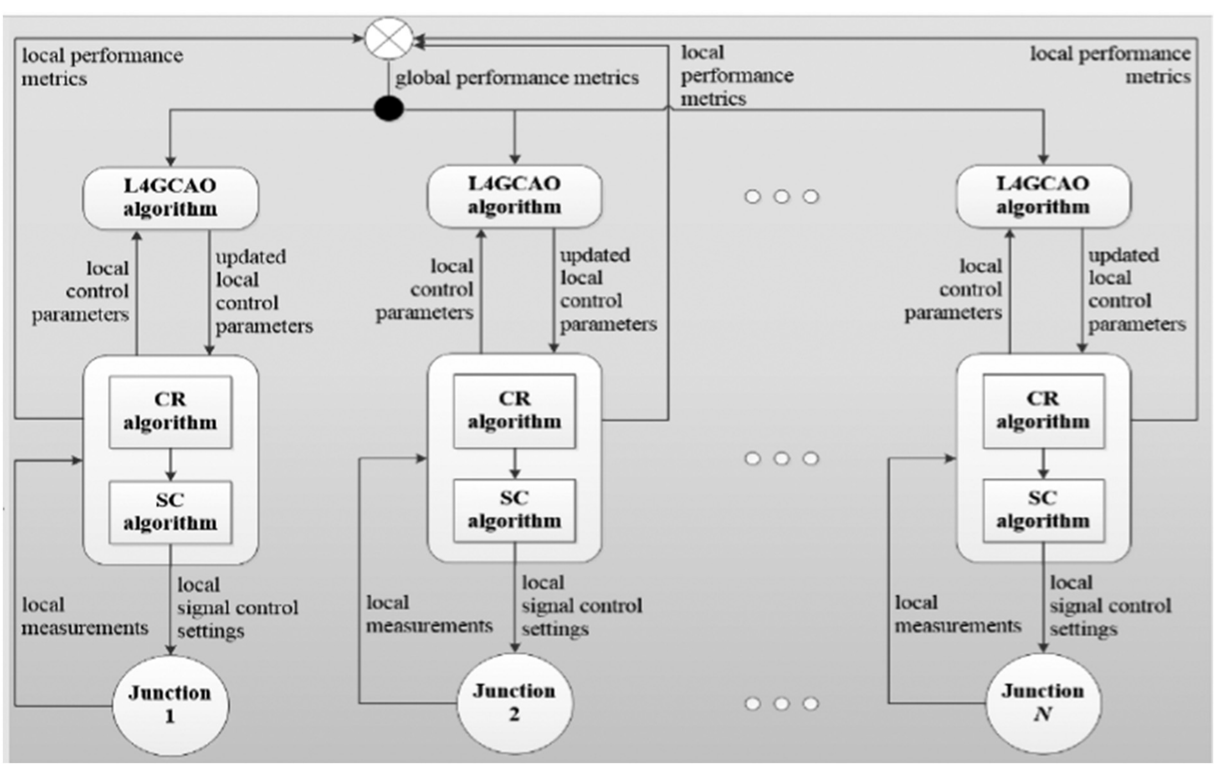

Fig. 5. Experimental setup adopted (CR: cycle regulation, SC: split control).

Table 1
Reference cycle regulation parameter values.

Symbols	Minimum bounds	Reference values	Maximum bounds
σ_{w0}	0.05	0.15	0.4
$\sigma_{w,cr}$	0.1	0.65	0.7
K_{w1}	60	80	120
K_{w2}	10	20	30

Table 2
Fixed-time TCC and reference case performance indicators.

Metric/index	Fixed-time TCC case - average absolute values		Reference case - average absolute values	
	Days: 1–7	Days: 8–17	Days: 1–7	Days: 8–17
ND [veh/h]	5782.6	5800.3	5823.1	5751
NMS [km/h]	17.75	17.11	17.69	17.66
ADTPV [s/km]	144	153	135	133
NP [km*veh/h^2]	102,517	99,134	102,938	101,546

As a remark, the simulation of consecutive days – with diversified daily network demand - was considered in the tests in order to impose the real-life application limitation of replicating the exact same application day several times (Fig.6). This fact enhances the real-life applicability of both solutions. Moreover, the base case performance which both CAO's and L4GCAO's performance is compared to is calculated using the reference case strategy. To ensure that the considered reference case CR-strategy is an acceptable comparison basis for CAO and L4GCAO, a tuned fixed-time strategy was considered for comparison purposes with the reference case parameter selection. The fixed-time strategy considers 90 s fixed cycle-time plans, with balanced offset among all network junctions. The fixed-time plans were defined by the Traffic Control Center (TCC) operators of Chania city in a past study (Kouvelas et al., 2011). As Fig. 7 exhibits, the fixed cycle-time strategy presents comparable but slightly worse performance levels when compared to the reference case in terms of NP, NMS and Average Delay Time Per Vehicle (ADTPV) (see Table 2).

The reference case traffic conditions are shown in Table 2 while the optimization results both from the centralized (CAO) and decentralized (L4GCAO) optimization cases are shown in Fig. 8. The numerical values observed for the respective indicative metrics during case 1 (CAO) and 2 (L4GCAO) are listed in Table 3. Finally, Tables 4 and 5 summarize the percentage improvements with respect to the reference case achieved values, presenting small variance and narrow performance deviations.

To discretize between the transient and the converging periods, the performance observed after each iteration (i.e. simulation day) was split to 2 phases according to the estimators' discrepancies and trend approximation accuracy. The estimators' approximation accuracy was calculated by comparing the estimated/approximated performance to the actual AIMSUN performance values. The 2 phases are defined as follows:

(i) 1st phase: comprised by the first 7 application days (i.e. day 1 to 7) when larger estimator discrepancies occur (see the grey shaded area in Fig. 8);
(ii) 2nd phase: comprised by the remaining application days (i.e. day 8 to 17) when smaller estimator discrepancies are observed (see the white shaded area in Fig. 8).

As shown in Fig. 8, both CAO and L4GCAO present significantly better overall traffic network performance than the reference case during the majority of the 17 application days. However, a more elaborate presentation of the performance values observed, for each phase, is discussed in the following sub-sections.

6.2. 1st phase period analysis

The summarizing numerical values observed, during the first phase (i.e. simulation days 1 to 7) both for the centralized CAO and decentralized L4GCAO application cases, for the traffic performance metrics follow an increasing/improving trend but with quite large discrepancies (see Table 5 and Fig. 8e) since the built-in self-learning regression modules (centralized one and decentralized ones) were not able to achieve an accurate enough

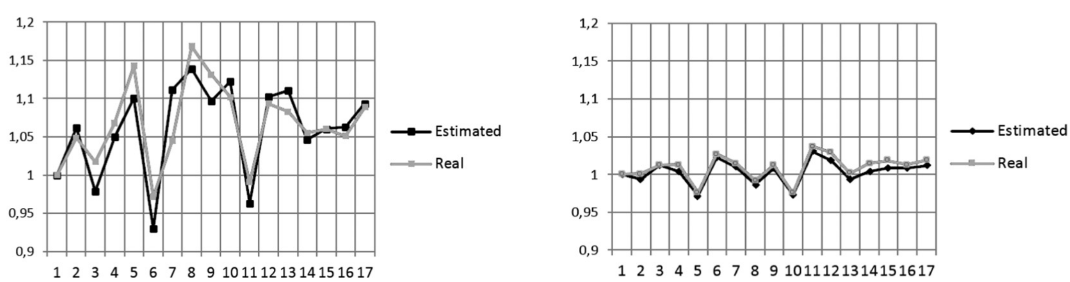

Fig. 6. Comparison of actual and estimated normalized MNS (left) and ND (right) throughout the 17 simulation days.

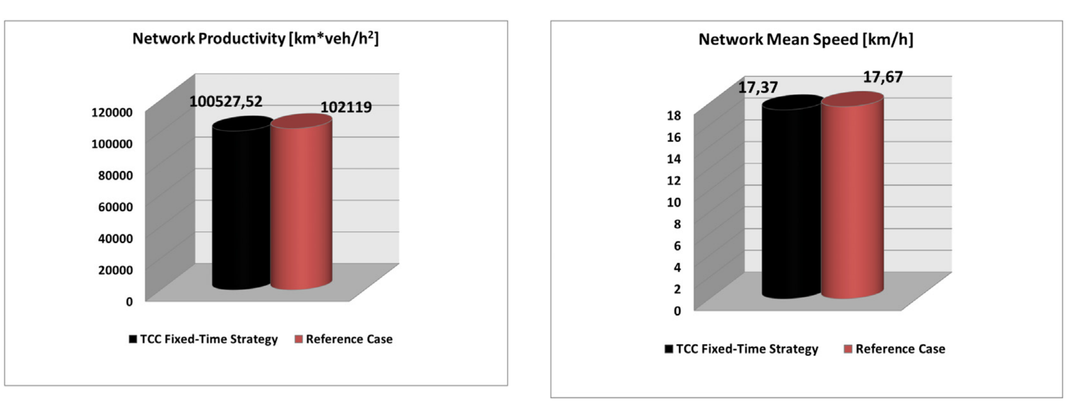

Fig. 7. Average network performance (over 17 iterations) between reference case and real-life practice in terms of: (a) Network productivity (NP) [km*veh/h^2] (left); (b) Network Mean Speed (NMS) [km/h] (right).

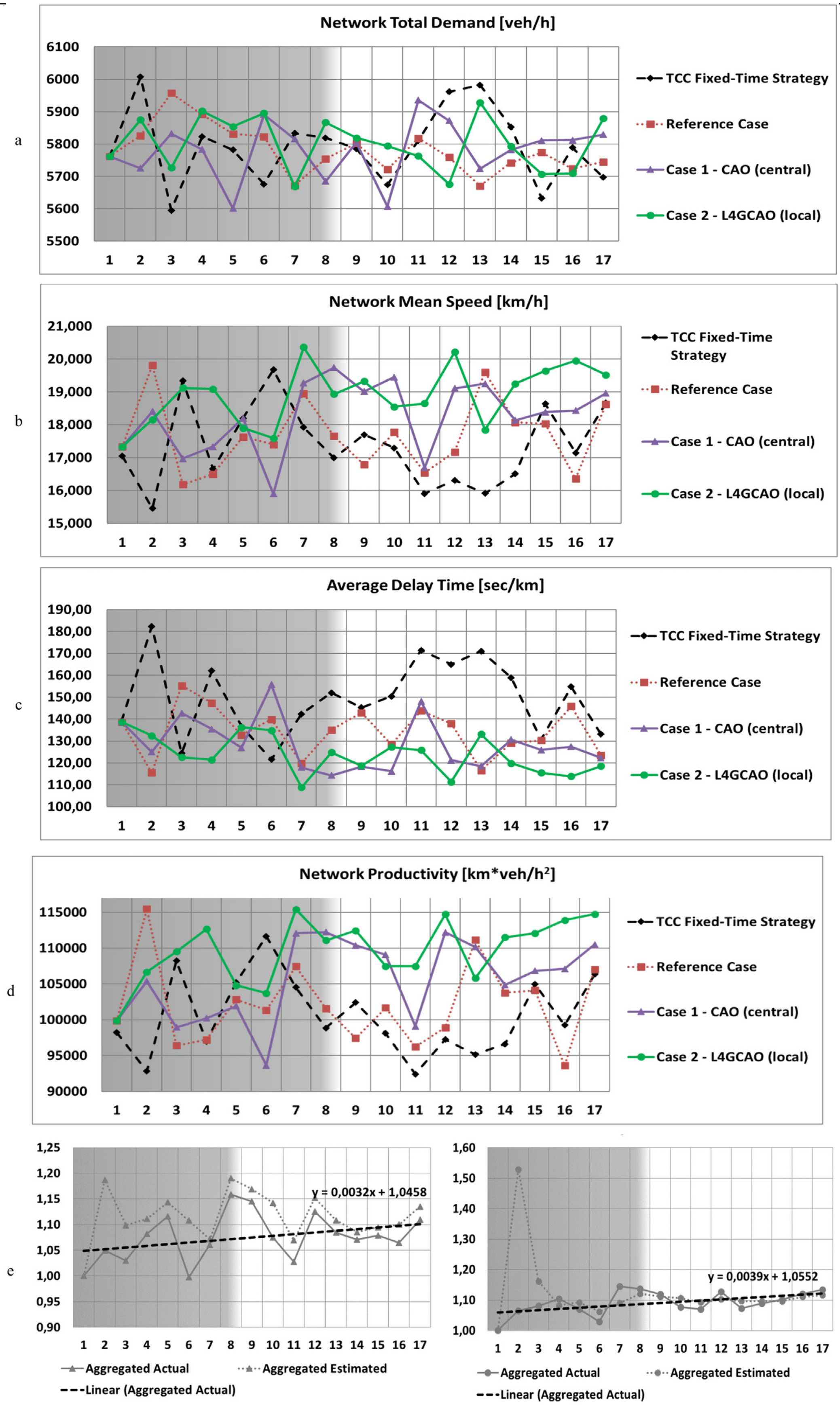

Fig. 8. Centralized and Decentralized optimization application results (1st phase period: grey shaded area – 2nd phase period: white shaded area) throughout the 17 simulation days: (a) Network Demand [veh/h]; (b) Network Mean Speed [km/h]; (c) Average Delay Time [sec/km]; (d) Network Productivity [km·veh/h^2]; (e) Normalized Centralized Estimator performance (left) and Normalized Average Decentralized Estimators performance (right).

Table 3
CAO and L4GCAO cases performance indicators.

Metric/index	Centralized CAO - average absolute values		Decentralized L4GCAO - average absolute values	
	Days: 1–7 (1st phase period)	Days: 8–17 (2nd phase period)	Days: 1–7 (1st phase period)	Days: 8–17 (2nd phase period)
ND [veh/h]	5772.8	5786.3	5812	5793
NMS [km/h]	17.63	18.72	18.51	19.19
ADTPV [s/km]	134.6	124.3	127.8	120.9
NP [km*veh/h^2]	101,727	108,246	107,518	111,127

(small discrepancies) performance yet. As a result, no mentionable solid improvements could be observed during this transient period (see Table 4). As imposed by the analysis of this phase's absolute numerical performance-metrics' values (see Tables 2 and 3), the average performance improvements are comparably the same in respect to the reference case (see also the grey shaded area in Fig. 8b, c, d). However, in both application cases (CAO and L4GCAO) a quite short transient period of only 7 days was achieved without severe/catastrophic performance fluctuations, denoting the quite efficient feature selection and definition of the regressor vector in the design of the estimators. In specific, such restrained and short transient period can be considered practically acceptable even in real-life traffic applications, fact which supports both CAO's and L4GCAO's real-life applicability.

6.3. 2nd phase period analysis

The second phase comprises the nominal operation of both CAO's central estimator and L4GCAO's local estimators. According to the numerical analysis for the specified period (i.e. simulation days 8 to 17) the achieved traffic conditions improvement during both case 1 (centralized CAO) and case 2 (L4GCAO decentralized) is significant (see Table 5). Moreover, the traffic network performance achieved to converge rapidly within only the 10 days of this phase utilizing the substantially accurate built-in estimation modules (see Table 5). The respective percentage improvements (normalized in respect to the reference case) are exhibited in all evaluation metrics values (see Fig. 8b for the NMS, C. ADTPV, D. NP) while network demand (ND) levels are similar and comparable during the whole 17-day simulation horizon (see Fig. 8a and Table 4).

As already explained, L4GCAO's local estimators utilize the reduced set of only locally-measured data and the global performance in contrast to the centralized estimator of CAO where data from across the whole network are collected and utilized. As a result L4GCAO's total estimation error is expected to be larger than CAO's (see Table 5 and Fig. 8e). However, L4GCAO achieves to sufficiently identify locally the influence of each respective local CR parameter set to the overall estimated/aggregated system performance and is proven capable of achieving a quite efficient performance-improving trend throughout the duration of the simulation tests, reaching eventually a performance comparable to the centralized case's (see linear trend-lines in Fig. 8e). To summarize the results, comparable improvement levels - with respect to the reference case - were achieved in both cases (the centralized CAO and decentralized L4GCAO). CAO converged to a CR set of parameters reaching, in average, almost +6% NMS improved level, a −6.8% ADTPV reduction level and a +6.6% overall NP improvement level, while the average ND levels were increased slightly by +0.6% (see Table 4). L4GCAO achieved to improve NMS levels by +8.6%, reduce ADTPV by −9.3% and improve NP by almost +9.4%, while ND was slightly increased by around +0.75% (see Table 4).

6.4. Why L4GCAO over CAO?

As already presented, both CAO and L4GCAO achieved comparable results in terms of traffic network performance with just a few iterations/days. This fact translates to a practically feasible and directly applicable solution without requiring tedious preparatory efforts: the two solutions can be interfaced digitally to the Chania Traffic Network infrastructure and automatically fine-tune the existing cycle-regulation strategies (in every intersection) for congested periods of the day within just a few weeks of operation. Despite the fact that both CAO and L4GCAO are able to effectively perform such a task; the main difference between the two approaches relies on their design architecture: (a) CAO follows a centralized topology where all measured data from across the network should be transmitted at a central node; while the optimized cycle-regulation decisions are distributed from the central node back to each intersection controller in a real-time manner; (b) L4GCAO follows a decentralized topology where one fine-tuning agent is dedicated to each intersection; the necessary measured data are locally utilized to regulate the respective intersection's cycle in a real-time manner while at a periodic basis (e.g. daily) only the global network performance (scalar value) is calculated/measured at a central node and distributed back to each constituent agent (see also Figs. 3 and 4).

Let us consider, for fair comparison purposes that in all cases: the cycle-regulation control modules (as described in Section 4) are hosted at a local intersection station while the global network performance is calculated centrally; where the overall network mean speed and demand (at the origins) are available. The decentralized topology of L4GCAO allows to host the optimizers at a local intersection level as well. Therefore, instead of transmitting all parameters $H_w = [\sigma_{w0}, \sigma_{w,cr}, K_{w1}, K_{w2}]$ as well as the locally calculated performance index from every intersection to a central station (i.e. the CAO case) to centrally fine-tune them and return back their

Table 4
CAO and L4GCAO improvements (with respect to fixed-time TCC and reference case).

Metric/index	CAO [% w.r.t. fixed-time TCC case/% w.r.t. reference case]		L4GCAO [% w.r.t. fixed-time TCC case/% w.r.t. reference case]	
	Days: 1–7 (1st phase period)	Days: 8–17 (2nd phase period)	Days: 1–7 (1st phase period)	Days: 8–17 (2nd phase period)
ND [veh/h]	−0.17/−0.8	−0.24/+0.6	+0.5/−0.2	−0.12/+0.7
NMS [km/h]	−0.7/−0.3	+9.4/+6	+4.25/+4.6	+12.1/+8.6
ADTPV [s/km]	−6.5/−0.7	−18.9/−6.77	−11.25/−5.7	−21.1/−9.3
NP [km*veh/h^2]	−0.77/−1.2	+9.2/+6.6	+4.9/+4.4	+12.1/+9.4

Table 5
Indicative optimization application metrics.

Metric/index	Centralized CAO - average absolute values		Decentralized L4GCAO - average absolute values	
	Days: 1–7 (1st phase period)	Days: 8–17 (2nd phase period)	Days: 1–7 (1st phase period)	Days: 8–17 (2nd phase period)
Maximum NP [km*veh/h^2]	115,418.3097	114,766.782	112,083.3365	112,240.5802
Minimum NP [km*veh/h^2]	99,883.17498	105,791.8541	93,647.43769	99,094.81501
Normalized NP variance [%]	0.29%	0.08%	0.33%	0.13%
Total performance estimation squared error	0.03752	0.00138	0.22706 (all 13 local agents)	0.00340 (all 13 local agents)

Table 6
CAO and L4GCAO central communication requirements comparison.

Annotation	CAO [1 centralized optimizer for the entire network]	Centralized communication load	L4GCAO [13 local agents; one per network intersection]	Centralized communication load
$\sigma_{w0}(k)$	Being locally available the	13	All cycle-regulating	0
$\sigma_{w,cr}(k)$	4 cycle-regulating parameters	13	parameters are available	0
$K_{w1}(k)$	need to be transmitted from	13	locally at **every local**	0
$K_{w2}(k)$	every local intersection **to the central station**	13	**intersection** level	0
$\sigma_{w0}(k+1)$	After fine-tuning centrally these	13	All cycle-regulating	0
$\sigma_{w,cr}(k+1)$	parameters they need to be	13	parameters are fine-tuned	0
$K_{w1}(k+1)$	transmitted back from the central	13	locally at **every local**	0
$K_{w2}(k+1)$	station/node **to every local intersection** cycle controller	13	**intersection** level	0
NP(k)	No need to distribute locally the overall performance	0	**Only** the global/overall network performance is required to be distributed across all 13 agents	13
	Total [every day]	9 parameters * 13 intersections = 117	**Total [every day]**	1 parameter * 13 intersections = 13

Bold data indicate the core differences between the centralized and the decentralized/distributed approaches.

updated values from the central station to every intersection; L4GCAO allows to significantly reduce the communication load and distribute the computation load to each cooperative local station; without jeopardizing the traffic network conditions and performance as indicated by the comparative evaluation analysis discussed in the previous subsections.

As a result, the communication workload as well as the necessary communication infrastructure to support this workload is significantly different. In particular, as shown in Table 6, to achieve comparable traffic network performance improvements L4GCAO requires **only** the locally calculated performance index to be distributed locally. **L4GCAO required 9× less data transactions, compared to its centralized counterpart CAO, to fine-tune the exact same number of CR parameters in a decentralized manner**. L4GCAO achieves to unburden the central traffic control center from severe communication workloads, enabling smoother operation, allowing for smaller infrastructure investments, reducing maintenance costs, increasing the reliability and resilience of the network. L4GCAO's workload decentralization benefits become more significant as the scale of the network (number of intersections) increases as well as more IoT devices (mobile phones, vehicles, wearables, cameras) are interconnected to form the next generation urban transportation systems.

7. Conclusions

The aim of the current work is to demonstrate the efficiency of a novel model-free decentralized adaptive optimization approach (L4GCAO) compared to its thoroughly verified centralized counterpart (CAO). As shown in Section 6.3, both CAO and L4GCAO were able to perform more efficiently – by 10% and 12% respectively - as compared to the reference case CR scenario even within a very simulation number of daily iterations (only 17 days).

As shown in Table 5, by compromising on the efficiency of the constituent built-in estimator which uses only locally available data and the overall objective function at a periodic basis, L4GCAO achieved substantial overall learning performance (around 7 iterations) at a local level compared to the centralized CAO within phase 1 (day 1 to 7). The required transient period was quite short for both cases (CAO and L4GCAO) leading to short payback period and practical traffic improvement within a few days of application.

It must be underlined that due to limitations of computational power and data transmission rates, centralized optimization topologies are expected to lead to data-traffic bottleneck when scaling up to larger network cases. Therefore, to ensure their applicability and allow CAO's and L4GCAO's comparison, the utilization of the Chania traffic network (medium size) made the application of both CAO and L4GCAO feasible. The analysis in Section 6.4 demonstrated the significant savings in this domain, during the operation of L4GCAO: the number of the communication transactions required centrally were 9× less resulting a significant reduction in the communication workload of around 88.8%.

The authors have already identified future research tasks such as continuation of the optimization process and extending the application period to more than 17 days to achieve even greater improvement levels, as expected. In addition, other application domains where complex emerging dynamics are involved in very large-scale systems where the centralized approach deals with severe applicability issues are already under consideration for L4GCAO performance evaluation.

CRediT authorship contribution statement

Iakovos T. Michailidis: Conceptualization, Methodology, CAO and L4GCAO Software, Data curation, Writing- original draft preparation, Conducting simulative tests, Coordinating manuscript write-up, Visualization, Validation, Investigation, Formal analysis. **Diamantis Manolis**: Simulation model development; Conducting simulative tests, Data curation. **Panagiotis Michailidis**: Writing- reviewing and editing. **Christina Diakaki**: Writing- original draft preparation, Simulative testbed concept preparation, Conceptualization. **Elias B. Kosmatopoulos**: Methodology, Conceptualization, Supervision, Funding acquisition, Project administration.

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