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Event-triggered adaptive OFDMA protocol for multi-vehicle clusters

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Abstract— **We present an event-triggered based OFDMA resource allocation algorithm in conjunction with the solution to a distributed optimization problem. The optimal OFDMA subcarriers assignment is supported by the sensitivity function of the objective function to exchange information between the nodes of the underlying network. The resulting sensitivity-based event-triggered policy invokes a cross-layer communication protocol by introducing sensitivity-dependent weights in the resource sharing optimization problem at the MAC layer. For practical evaluation purposes, we consider steering of wireless multi-vehicles, where each vehicle on its own is controlled by a cluster of collaborative on-board distributed processors communicating over a single wireless link.**

I. INTRODUCTION

A distributed wireless network control system consists of a set of wireless nodes connected via a wireless network channel, which is used to exchange state information between its dynamical subsystems. Typically, the exchange of states over a wireless channel requires extensive consumption of communication resources [1]. At the same time, the wireless channel suffers from limited resources in terms of bandwidth, data rate, and channel capacity. Therefore, with an increasing number of wireless nodes requiring service from the channel, resource allocation techniques are needed for implementing proper distribution of the channel resources among the connected nodes. This channel resource allocation has to guarantee that all connected nodes receive at least a minimum of the required service, and must ensure that their requests are handled in accordance with the quality-of-service (QoS) requirements [2]. Moreover, in networked control systems they additionally ought to guarantee certain levels of control performance at the application layer.

Event-based communication mechanisms in network control applications introduce a purposeful reduction of the communication in accordance with the dynamic evolution of the local subsystem states. To the present paper, of relevance is the work in [3] which considers sensitivity-based event-triggered communication policies in the context of model-predictive-control (MPC) by making use of a sensitivity analysis of the utilized optimization scheme. We use a similar idea to design event-triggered policies for resource allocation in Orthogonal Frequency-Division Multiple Access (OFDMA) protocol.

In a series of the authors' previous works [4], [5] and the references therein, various distributed optimization schemes utilizing event-based communication to optimal tire friction force allocation for electric cars were investigated. Therein we proposed the idea of wireless cars supported by an on-board wireless network of sensors, actuators, and control units. In this context, we provided an extensive analysis of Time Division Multiple Access (TDMA) schemes in connection with the guidance and stabilization problem of vehicle dynamics. Here, we extend these ideas in two directions. The first one refers to the adaptive OFDMA resource allocation protocol, and the second extension to applying this idea to the control of multi-vehicles. Note that here we rather contribute the basic conceptual idea and demonstrate its usability by extensive numerical evaluations.

The paper is organized as follows. A brief recap of OFDMA-based wireless communication networks along with description of the multi-vehicles and event-triggered OFDMA based system structure is given in Section II. In Section III, an overview of event-triggered wireless-based communication is introduced, and the formulation of the event-triggered adaptive OFDMA resource allocation protocol based on a sensitivity analysis of the underlying optimization problem is discussed. Section IV introduce the optimization problem for the guidance of a single- and multi-vehicle and subgradient solver. Finally, in Section V, the simulation results are given and discussed.

II. OFDMA BASED WIRELESS NETWORKED SYSTEM

A. Overview of OFDMA protocol

Using a wireless channel as a communication medium in the networked control systems has the advantage of offering mobility, distribution, flexibility, and easy maintenance [6]. On the other hand, it introduces wireless communication issues such as limited bandwidth, time delay, and packet loss into the system structure. Moreover, the complexity of the system increases with respect to the number of connected nodes, which in turn increases the demand for service over the limited wireless channel resources, such as frequency, time, and data rate. Therefore, it is necessary to optimally assign the channel resources to those nodes that have a high impact on the system performance. OFDMA is considered as an essential multiple users technique and is the main Medium Access Control (MAC) protocol used in the fourth generation of wireless communication (4G and LTE) [7]. The basic principle of OFDMA is to divide the available bandwidth into a number of low data rate subcarriers. The OFDMA-based wireless network includes an Access Point (abbr. AP) that controls the communication between the interconnected nodes, a transceiver which handles the communication between the nodes, and scheduler that deals with

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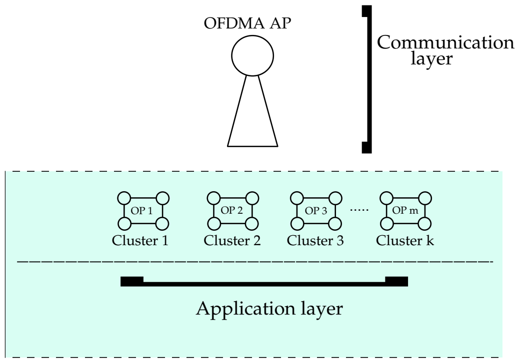

Fig. 1. System structure consisting of two layers: the communication layer and the application layer. Note that here, a cluster refers to the nodes hosted within a single vehicle.

scheduling of communication resources by updating the resource block (RB) table. Communication and data exchange between the nodes and the AP is performed in two phases, the uplink phase and the downlink phase. In the uplink phase, the AP uploads the data from the nodes that are assigned with the subcarriers, and in the downlink phase, it delivers the transmitted data to the destination nodes. The scheduler deals with nodes' communication request by solving a resource allocation optimization problem. The optimization problem is generally resolved with respect to the node's Channel State Information (CSI), which includes the Signal to Noise Ratio (SNR) measurement over all available subcarriers. As a result, the scheduler optimally assigns a resource block to the selected node including a subcarrier in a fixed time slot.

B. System structure

We consider a distributed wireless system depicted in Fig. 1, which consists of AP and a set of V multi-vehicles. Each vehicle is presented as a cluster with $n = 4$ wireless nodes connected to the AP. The system structure consists of two layers, the communication layer at the AP level and the application layer at the wireless nodes level. The first layer consists of event-based resource allocation algorithm for subcarriers assignment, where the OFDMA scheduler builds the resource allocation table (RB) by solving the resource allocation optimization problem that maximizes the node rate over the available subcarriers. The application layer consists of nV wireless nodes located within the AP coverage area. As a result of the limited number of subcarriers, the AP needs to assign the subcarriers to the nodes that have a higher effect on the convergence of the distributed optimization problem. We introduce the sensitivity based event-triggered scheme into the problem solver, where each node *i* approximates the effect of its state update on its neighbor $j \in \mathcal{N}_i$ state by computing and exchanging the state sensitivity with respect to the changes on its neighbors' state.

III. Event-triggered adaptive sensitivity-based OFDMA resource allocation protocol

A. Sensitivity analysis

We consider a networked system presented as a distributed convex optimization problem, where the cost function f_i^0 and inequality constraints $f_p^i \leq 0$ are convex, and the equality constraints $h_q^i = 0$ are affine:

$$\begin{aligned} \underset{x_i}{\text{minimize}} \quad & f_i^0(x_i, \hat{x}_j^i) \\ \text{subject to} \quad & f_p^i(x_i, \hat{x}_j^i) \leq 0, \; p = 1, \ldots, P_i, j \in \mathcal{N}_i \\ & h_q^i(x_i, \hat{x}_j^i) = 0, \; q = 1, \ldots, Q_i, j \in \mathcal{N}_i, \end{aligned} \tag{1}$$

where $i = 1, \ldots, n$, $x_i \in \Re^{n_i}$ and n_i are the local state, and the local state space dimension of sub-problem f_i^0, respectively. The local cost function f_i^0 is updated based on its own state x_i and on the received state $\hat{x}_j^i$ (corresponding to x_j), from its neighborhood $\mathcal{N}_i$, which includes the set of subproblems that exchange their state with the ith optimizing subprocess. The Lagrangian $L_i(x_i, \hat{x}_j^i, \lambda_p^i, \nu_q^i)$ corresponding to ith cluster (1) is then given by:

$$L_i(x_i, \hat{x}_j^i, \lambda_p^i, \nu_q^i) = f_i^0 + \sum_{p=1}^{P_i} \lambda_p^i f_p^i + \sum_{q=1}^{Q_i} \nu_q^i h_q^i \tag{2}$$

where, $\lambda_p^i \geq 0$ and ν_q^i are the dual multipliers. Now let $y_i^* = [x_i^*, \lambda_p^{i*}, \nu_q^{i*}]^T$ represent the minimizer to the above Lagrangean L_i and consider $\varepsilon_j := x_j - \hat{x}_j^i$ as a perturbation. Here x_j is to stand for an update of $\hat{x}_j^i$ in the (2). If f_0^i is twice continuously differentiable, f_p^i and h_q^i are continuously differentiable, then the gradients ∇f_p^i and ∇h_q^i are linearly independent, and the second order sufficient optimality condition holds at y^*, yielding a once continuously differentiable vector function $y_i(\varepsilon_j) := [x_i(\varepsilon_j), \lambda_p^i(\varepsilon_j), \nu_q^i(\varepsilon_j)]^T$ for small ε_j in the neighborhood of the received variables $\hat{x}_j^i$. Technically, we can approximate the change of the neighbors' $j \in \mathcal{N}_i$ state based on the change of node i state by computing the sensitivity matrix S_i^j and solve the following sensitivity equation [8]:

$$S_i^j = M_i^{-1} N_i^j, \tag{3}$$

where M_i is the Jacobian matrix of (2) with respect to x_i, λ_p^i, and ν_q^i of node *i*, and N_i^j is the negative Jacobian matrix with respect to x_j^i received at node *i*. The sensitivity matrices M_i and N_i^j are computed as follows:

$$M_i = \begin{bmatrix} \nabla_{x_i}^2 L_i & -\nabla_{x_i}^T f_1^i & \ldots & -\nabla_{x_i}^T f_{P_i}^i & \nabla_{x_i}^T h_1^i & \ldots & \nabla_{x_i}^T h_{Q_i}^i \\ \lambda_1^i \nabla_{x_i} f_1^i & f_1^i & 0 & 0 & 0 & 0 & 0 \\ \vdots & 0 & \ddots & 0 & 0 & 0 & 0 \\ \lambda_{P_i}^i \nabla_{x_i} f_{P_i}^i & 0 & 0 & f_{P_i}^i & 0 & 0 & 0 \\ \nabla_{x_i} h_1^i & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & 0 & 0 & 0 & 0 & 0 & 0 \\ \nabla_{x_i} h_{Q_i}^i & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

and

$$\begin{aligned} N_i^j = \big[& -\nabla_{\hat{x}_j^i x_i}^{2,T} L_i, -\lambda_1^i \nabla_{\hat{x}_j^i}^T f_1^i, \ldots, -\lambda_{P_i}^i \nabla_{\hat{x}_j^i}^T f_{P_i}^i, \\ & -\nabla_{\hat{x}_j^i}^T h_1^i, \ldots, \nabla_{\hat{x}_j^i}^T h_{Q_i}^i \big]^T. \end{aligned}$$

B. State approximation $\tilde{x}_j^i$

The decision of assigning communication resources to node *i* will depend on the approximation of the state approximation $\tilde{x}_j^i$ for the state x_j, $j \in \mathcal{N}_i$, as computed at the node i. The approximated state $\tilde{x}_j^i$ of the neighbor j is computed at node i using the last received state $\hat{x}_j^i$ and the received sensitivity $\hat{S}_j^i$ (note that the roles of i and j are switched now, cf. Eq. (3)). The approximation of the state $\tilde{x}_j^i$ is computed as follows:

$$\tilde{x}_j^i[k+1] = \hat{x}_j^i[k] + \hat{S}_j^i(x_i[k+1] - \hat{x}_i^j[k]), \tag{4}$$

where, $\hat{x}_j^i[k]$ is the last transmitted state of node *j* received at node *i*, whereas $\hat{x}_i^j[k]$ is the last transmitted state of the node *i* to the node *j*. Also note that $\hat{S}_j^i$ is the most recent received copy of the sensitivity matrix S_j^i received at the node i from the node j. Again, S_j^i reflects the effects of the "perturbing" state x_i into the state x_j. The matrix S_j^i need to be computed at the node j and it has to be shared with the node i.

C. Event-triggering condition

The event-triggering condition of node *i* is based on how the transmission of the state x_i will affect the optimization convergence. We introduce the approximated event-triggered condition of the changes of the overall cost function with respect to the approximated value of the state $\tilde{x}_j^i$ of all neighbors. To this end, we compute the cost function increment $\Delta\tilde{J}_0^i$ of (11) at node *i* as follows:

$$\Delta\tilde{J}_0^i \cong \nabla_{x_i} f_i^0(x_i, \hat{x}_j^i)\Delta x_i + \sum_{j\in\mathcal{N}_i} \nabla_{x_j} f_j^0(\tilde{x}_j^i, \hat{x}_i^j)\Delta\tilde{x}_j^i, \tag{5}$$

where $\nabla_{x_i} f_i^0$ and $\nabla_{x_j} f_j^0$ are the gradients of the cost function assigned to nodes *i*, and node *j*, respectively, while $\Delta x_i = x_i[k+1] - x^i[k]$ and the estimated state increment $\Delta\tilde{x}_j^i$ is computed as the difference of the approximated value of the state $\tilde{x}_j^i$ from equation (5) at the time $k+1$ and the last transmitted state $\hat{x}_j^i$ known by the node *i*:

$$\Delta\tilde{x}_j^i = \tilde{x}_j^i[k+1] - \hat{x}_j^i[k]. \tag{6}$$

The estimated increment $\Delta\tilde{J}_0^i$ of the cost function J_0^i is used to define the triggering criterion of the node *i*, as well as for the computation of the node weight w_i (see below) which is utilized for the resource allocation. More specifically, the node *i* activates the Request To Send RTS_i signal acquiring subcarriers from the AP to transmit its state x_i to the neighbors *j* if $\Delta\tilde{J}_0^i$ fulfills the following condition:

$$\left\|\Delta\tilde{J}_0^i\right\| \geq \beta_0 \left\|h_q^i(x_i, \tilde{x}_j^i)\right\| + \beta_1, \tag{7}$$

where $0 < \beta_0 \leq 1$ and $0 < \beta_1 < 0.01$ are the triggering parameter which tune the acceptability of the state error level.

D. Resource allocation optimization problem

Based on the findings from our previous work [4], application layer performance is highly correlated with optimal use of the communication resources. The key question is how to map the relation between application performance and efficient use of the communication resources. Therefore, mapping the resource allocation optimization problem to the sensitivity of the optimization problem at the application level is done by utilizing the computed w_i in the cost function of the resource allocation problem. So, we couple the effect of the convergence rate of the distributed optimization problem at the application layer with the optimal resource allocation at the communication layer. In particular, the weight w_i of node *i* is used to reflect the effect of the changing of the state x_i of node *i* on the convergence of the overall cost function. Consequently, the value of the weight w_i of the node *i* should be proportional to the incremental participation of the node *i* (i.e. of Δx^i) in the entire cost increment ΔJ_0^i, for instance, as defined by the quotient:

$$w_i = \frac{\|\nabla_{x_i} f_i^0\, \Delta x_i\|}{\|\Delta\tilde{J}_0^i\|}. \tag{8}$$

As a case study, we consider a standard optimization problem to maximize the node rate based on the measured signal to noise ratio e_{is} of node *i* over all available subcarriers $s \in \mathcal{K}$, and with respect to the constraint of the assigned power p_{is} to node *i* over the subcarrier s:

$$\sum_s p_{is} \leq \mathcal{P}_i, \quad i \in \mathcal{N} \tag{9}$$

With respect to that, the subcarrier s assigned to only node *i*. In order to use the maximum capacity of the wireless channel operating in B Hz frequency band and divided into k subcarriers, the standard resource allocation optimization problem [9], [10] with respect to the SNR measured by each node over all subcarriers to maximize the node i data rate over the assigned subcarriers is formulated as follows:

$$\begin{aligned} \underset{p_{is}, z_{is}}{\text{maximize}} \quad & \sum_i w_i \sum_s z_{is} \log\left(1 + p_{is} e_{is}\right), \\ \text{subject to} \quad & \sum_s p_{is} \leq \mathcal{P}_i, \quad i \in \mathcal{N} \\ & p_{is} \geq 0, \quad i \in \mathcal{N}, s \in \mathcal{K} \\ & X_i \cap X_j = \emptyset, \quad i \neq j, i, j \in \mathcal{N} \end{aligned} \tag{10}$$

where w_i is the computed weight associated with node *i*, p_{is} is the power assigned to node *i* over the subcarrier $s \in k$, z_{is} indicating the subcarrier s assigned to node *i*, X_i and X_j are the set of subcarriers assigned to the nodes i and j, and e_{is} is the SNR measured by node *i* over subcarrier s.

We consider the multi-vehicle wireless distributed system depicted in Fig. 2. The system block diagram consists of an AP and set of vehicle clusters. The AP collects the SNR_i measurements from nodes $i \in \mathcal{N}$ over all subcarriers $s \in \mathcal{K}$, and RTS_i request. Then the AP computes the node *i* weight w_i based on its state sensitivity S_i^j on the approximated state $\tilde{x}_j$ of its neighbor *j*. The AP solves the resource allocation optimization problem (10) using the iterated subgradient method to optimally assign a subcarrier s with maximum data rate to the node *i*. Generally, we assume that each subcarrier is assigned to only one node. The overall system operation is presented in Algorithm 1.

IV. Case study: optimal control problem of vehicle dynamics

A fully distributed event-triggered optimization scheme in the context of global chassis control with a redundantly

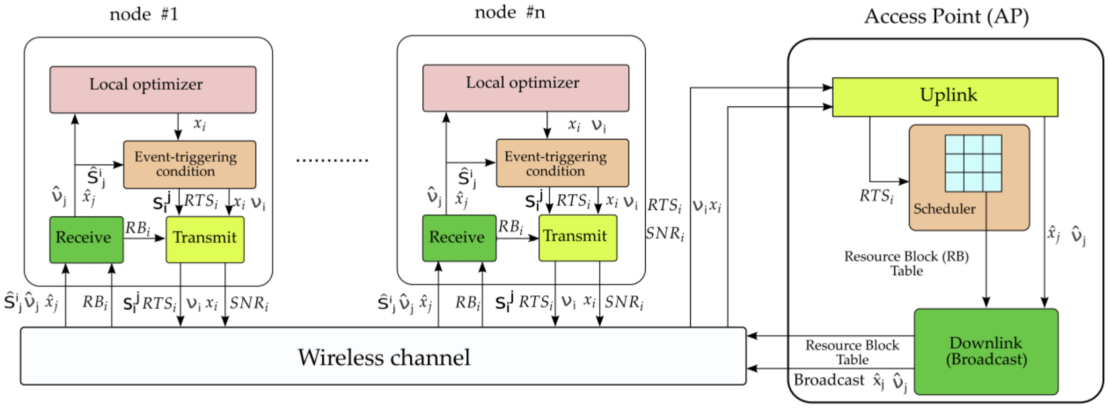

Fig. 2. OFDMA based event-triggered distributed wireless network system. Note that the resource allocation at the Access Point (AP) is based upon the state evolution at the local optimizer controllers. Following the sensitivity-based policy, more resources are allocated to the nodes with the states associated with a higher sensitivity of the objective function w.r.t. the information exchange.

actuated electric cars was proposed in the authors' previous works [4]. There, we considered distributed optimal control of vehicle dynamics and studied the effect of different communication protocols on the convergence of the underlying optimization algorithms. The optimal control task consists of achieving the smallest possible utilization of the adhesion potential η_i and keeping it below the physical adhesion limit. The optimal control problem for minimizing the maximal adhesion potential $\eta := \max_{i\in\{1,\dots,n\}}\eta_i$ is formulated as follows:

$$\begin{aligned}
\underset{\eta_i}{\text{minimize}} \quad & J_0 = \sum_{i=1}^{n} \eta_i^2 + \epsilon^2\left(F_{xi}^2 + F_{yi}^2\right), \\
\text{subject to} \quad & f_1 = \eta_i - \mu_{\max} \leq 0, \\
& f_2 = \sqrt{F_{xi}^2 + F_{yi}^2} - \eta_i N_i \leq 0, \\
& h_1 = A_x \hat{F}_{xj} + A_y \hat{F}_{yj} - Y_d = 0, \\
& h_2 = \eta_i - \hat{\eta}_j = 0, j \in \mathcal{N}_i,
\end{aligned} \tag{11}$$

where η_i is the adhesion potential, F_{xi} and F_{yi} are the longitudinal and lateral forces, respectively, $\epsilon \ll 1$ is a regularization term add to the cost function, A_x and A_y matrices are defined by vehicle geometric parameters, Y_d is the reference trajectory, $\hat{F}_{xj}$, $\hat{F}_{yj}$ are the received longitudinal and the lateral forces vectors, N_i is the normal force, and $\mu_{\max}$ is the maximum friction coefficient parameter. The optimization problem (11) is distributed into $i = 1,\dots,n$ sub-problems, and the Lagrangian L_i of the sub-problem i is:

$$\begin{aligned}
L_i(\eta_i, F_{xi}, F_{yi}, \lambda_i, \sigma_i, \nu_i, \theta_i) = \eta_i^2 + \epsilon^2\left(F_{xi}^2 + F_{yi}^2\right) + \lambda_i(\\
\sqrt{F_{xi}^2 + F_{yi}^2} - \eta_i N_i) + \sigma_i(\eta_i - \mu_{\max}) + \nu_i^T(A_x \\
\hat{F}_{xj} + A_y \hat{F}_{yj} - Y_d) + \theta_i^T(\eta_i - \hat{\eta}_j), \forall j \in \mathcal{N}_i,
\end{aligned} \tag{12}$$

where, η_i, F_{xi}, and F_{yi} are the primal variables, and $\lambda_i, \sigma_i, \nu_i$, and θ_i are the dual multipliers. The corresponding dual function $g_i(\lambda_i, \sigma_i, \nu_i, \theta_i) = \text{Inf}_{\eta_i, F_{xi}, F_{yi}} L_i(\eta_i, F_{xi}, F_{yi}, \lambda_i, \sigma_i, \nu_i, \theta_i)$ of the distributed sub-problem i is written as:

$$\begin{aligned}
g_i(\lambda_i, \sigma_i, \nu_i, \theta_i) = \inf\big(\eta_i^2 + \epsilon^2\left(F_{xi}^2 + F_{yi}^2\right) + \lambda_i(\\
\sqrt{F_{xi}^2 + F_{yi}^2} - \eta_i N_i) + \sigma_i(\eta_i) + \nu_i^T(A_x \\
\hat{F}_{xj} + A_y \hat{F}_{yj}) + \theta_i^T \eta_i\big) - \nu_i^T Y_d - \sigma_i \mu_{max} - \theta_i^T \hat{\eta}_j, \forall j \in \mathcal{N}_i.
\end{aligned} \tag{13}$$

Using the subgradient method to solve the dual problem (13), and perform the subgradient update of the dual variables $\lambda_i, \sigma_i, \nu_i$ and θ_i associated with each sub-problem i as follows:

$$\begin{aligned}
\lambda_i[k+1] &= (\lambda_i[k] - \alpha f_1[k])_+, \\
\sigma_i[k+1] &= (\sigma_i[k] - \alpha f_2[k])_+, \\
\nu_i[k+1] &= \nu_i[k] - \alpha h_1[k], \\
\theta_i[k+1] &= \theta_i[k] - \alpha h_2[k],
\end{aligned} \tag{14}$$

where $i = 1,\dots,n$, $x_+ := \max(0, x)$, and α is the step size [11]. The subgradient of $f_1[k], f_2[k], h_1[k]$, and $h_2[k]$ are defined as:

$$\begin{aligned}
f_1[k] &= -f_1(\eta_i^*[k], F_{xi}^*[k], F_{yi}^*[k]), \\
f_2[k] &= -f_2(\eta_i^*[k], F_{xi}^*[k], F_{yi}^*[k]), \\
h_1[k] &= -h_1(\eta_i^*[k], F_{xi}^*[k], F_{yi}^*[k]), \\
h_2[k] &= -h_2(\eta_i^*[k], F_{xi}^*[k], F_{yi}^*[k]),
\end{aligned} \tag{15}$$

where, $\eta_i^*[k] = \eta_i(\lambda_i[k], \sigma_i[k], \nu_i[k], \theta_i[k])$, $F_{x/y}^*[k] = F_{x/y}(\lambda_i[k], \sigma_i[k], \nu_i[k], \theta_i[k])$ are the right-hand side expressions represent analytical solutions to $(\eta_i^*, F_{xi}^*, F_{yi}^*) = \arg\inf_{\eta_i, F_{xi}, F_{yi}} L_i(\eta_i, F_{xi}, F_{yi}, \lambda_i[k], \sigma_i[k], \nu_i[k], \theta_i[k])$. Due to the scope limitations, they are not shown here.

V. Simulation and Discussion

In order to evaluate the proposed event-triggered OFDMA resource allocation protocol, an extensive simulation study was carried out in a distributed multi-vehicle dynamics scenarios. First, we point out that the simulation study considers the convergence of the distributed optimization problem at the application layer and the communication

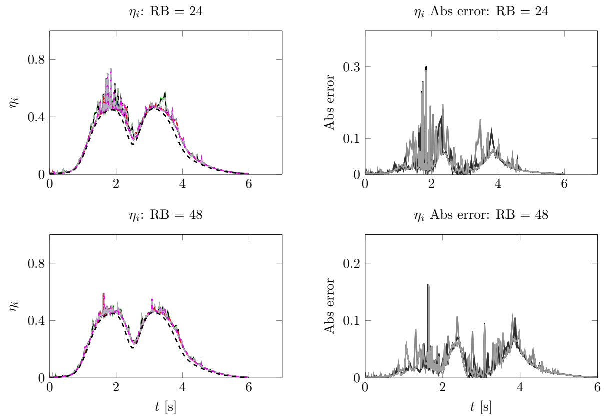

Fig. 3. Algorithm performance over the complete maneuver: η_i for all nodes (top) and absolute error (bottom) for the AP for capacities with (RB = 24) and (RB = 48). Naturally, larger resource capacities yield smaller errors and improved performance.

behavior of the interconnected nodes according to the optimal resource allocation algorithm at the AP. The efficiency of the proposed algorithm is evaluated in terms of the communication reduction, convergence to optimal solution, and the optimal resource allocation. In the application layer, a set of $V = 1, 2, 3$ clusters, each of which consists of $n = 4$ nodes, each node internally solves a distributed vehicle dynamics optimization problem. A lane change maneuver under braking is used as a reference trajectory for the vehicle dynamics optimization problem, and the parametrization of the maneuver scenario defined in [4]. The distributed dual subgradient method is used with the step size $\alpha = 0.1/\sqrt{k}$, and the triggering parameters of the event-triggered condition are set to $\beta_0 = 0.004$, and $\beta_1 = 0.00001$.

The convergence rate of the distributed optimization problem was computed according to the relative error $= \frac{\|x[k+1]-x^*\|}{\|x^*\|}$. The relative error traces the performance of the proposed distributed algorithm by computing the convergence rate of η_i with respect to the optimal adhesion potential η_i^* computed by centralized algorithm.
For the OFDMA wireless network, we used LTE standard AP parameters. The access point operates on the frequency band $B = \{5, 10\}$ MHz, which provides a set of resource blocks $RB = \{24, 48\}$. The SNR is randomly distributed over the subcarriers with maximum value up to 130 dB.

Fig. 3 presents the computed η_i for $i = 1, ..., 12$ of the three clusters and the absolute error computed in reference to a centralized optimal algorithm. We see that the algorithm performance is highly improved with an increasing number of resource blocks $(RB = 48)$ and a decrease in the absolute error value. We notice that with small numbers of subcarriers $(RB = 24)$, the resource allocation algorithm maintains the system performance with noticeable increase in the absolute error value especially in extreme driving maneuver instance. Fig. 4 presents the effect of the optimal node weights on the resource assignment. Fig. 4-(a) shows an example of the computed weights of node 1, whereas Fig. 4-(b) shows the corresponding number of resource blocks assigned to node 1

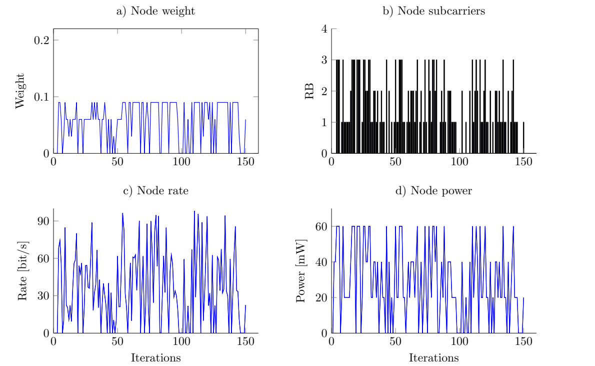

Fig. 4. Weights, assigned rate, and power of Node 1 related to the number of subcarriers for an AP with a capacity of 24 resource blocks.

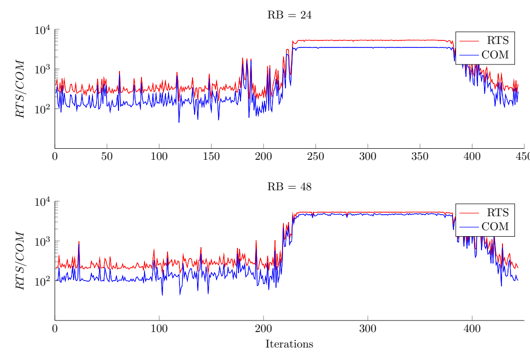

Fig. 5. RTS and communication activities for all nodes; AP with 24 and 48 resource blocks.

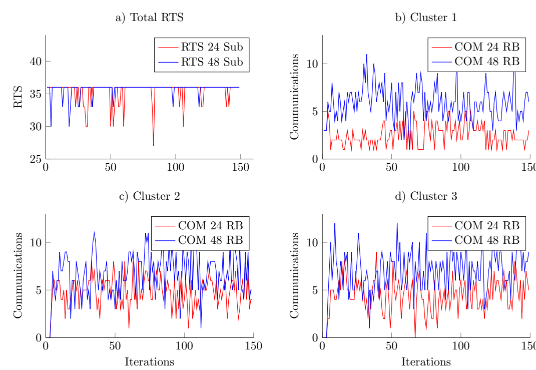

Fig. 6. RTS and communication intensity for the whole network involving three clusters and individual correspondents for an AP with a capacity of (RB = 24) and (RB = 48). Less capacity naturally leads to lower communication intensity.

according to the changes in its weight. Fig. 4-(c) presents the sum of optimal rate assigned to the node over the assigned subcarriers, while Fig. 4-(d) depicts the total optimal power assigned to node over the assigned subcarriers. Here, we comment that the changes in node 1 weights highly affect its communication activities with respect to the assigned subcarriers, rate, and power.

Fig. 5 presents the nodes' communication request RTS, and the communication activities in the case of AP is operating on (RB = 24) and (RB = 48) capacity. Fig. 6 shows the communication request analysis of the three clusters over an extreme maneuver instance and the AP operating on (RB = 24) and (RB = 48) capacity. We observe that in the extreme maneuver, the resource demands is increased and

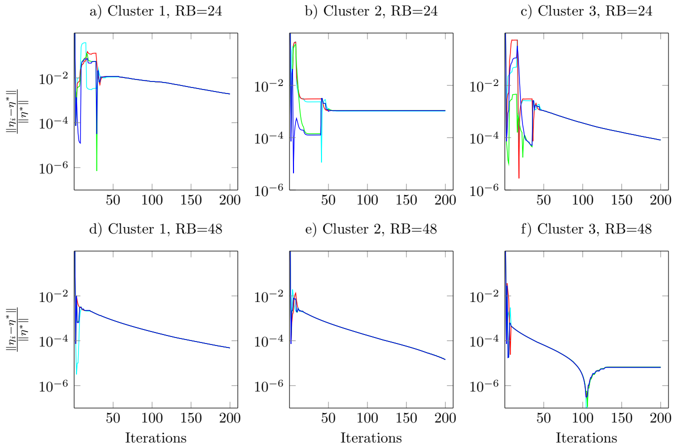

Fig. 7. Convergence rate of η_i for the three clusters with AP operating on 24 resource blocks (top) and 48 resource blocks (bottom). Obviously, larger resource block capacity produces solutions with smaller errors.

the scheduler assigns the available resources to those nodes that have higher weight. Fig. 6-(a) presents the total number of RTS of all nodes, and Figs. 6-(b), 6-(c), and 6-(d) show the transmission activities of the clusters 1,2, and 3.

Finally, Fig. 7 presents the relative error measure of the convergence rate of η_i for each node within the three clusters. The communication is conducted with AP operating with (RB = 24) and (RB = 48). Observe that the convergence rate is improved when more resource blocks are used, while the performance of the system is maintained even with fewer communication resources by optimally assigning the communication resources to nodes.

VI. Conclusions

In this paper, we presented an event-triggered adaptive OFDMA resource allocation protocol with application to multi-vehicles. In particular, the sensitivity of the distributed optimization problem was mapped to the weighting factor of the node in the resource allocation optimization problem. While this idea has been borrowed from an earlier work in the literature, our main contribution consists of its application to the design of adaptive OFDMA protocols. The event-triggered scheme couples the communication and application layers of the proposed OFDMA protocol. We have demonstrated the utilization of the protocol in the case study of a multi-vehicle, but in principle, it can be readily extended to other network control systems, as well. The simulation results demonstrate that the proposed protocol for the communication reduction combined with the optimal resource allocation of the available subcarriers maintains the system performance even during critical driving maneuvers, which are typically associated with high resource demands.

Adaptive OFDMA protocol with sensitivity based event-triggered resource allocation

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initialization;
set $\mathcal{N} = \{1, ..., n\}$; $\mathcal{N}_i = \{1, ..., N_i\}$;
while *subgradient* **do**

For all nodes;

1) **Update** x_i, ν_q^i, and λ_p^i ;
2) **Compute** sensitivity S_i^j : $S_i^j = M_i^{-1} N_i^j$;
3) **Transmit** sensitivity S_i^j, $\forall j \in \mathcal{N}_i$:
4) **Compute** state approximation $\tilde{x}_j^i[k+1]$: $\tilde{x}_j^i[k+1] = \hat{x}_j^i[k] + \hat{S}_i^j(\tilde{x}_i[k+1] - \hat{x}_i^j[k])$;
5) **Compute cost function difference** $\Delta\tilde{J}_0^i \cong \nabla_{x_i} f_i^0(x_i, \hat{x}_j^i)\Delta x_i + \sum_{j\in\mathcal{N}_i} \nabla_{x_j} f_j^0(\tilde{x}_j^i, \hat{x}_i^j)\Delta\tilde{x}_j^i$;
6) **Assign** node weight $w_i = \frac{\|\nabla_{x_i} f_i^0 \Delta x_i\|}{\|\Delta\tilde{J}_0^i\|}$;
7) **Event-triggered condition**: **if** $\left\|\Delta\tilde{J}_0^i\right\| \geq \beta_0 \left\|h_q(x_i, \tilde{x}_j^i)\right\| + \beta_1$ **then** $RTS_i \leftarrow True$;

Access Point:;

1) **Collect** w_i, e_{is}, RTS_i, $\forall i \in \mathcal{N}$, $\forall s \in \mathcal{K}$;
2) **Solve** resource allocation problem: $$\underset{p_{is}, z_{is}}{\text{maximize}} \quad \sum_i w_i \sum_s z_{is} \log\left(1 + \frac{p_{is}e_{is}}{z_{is}}\right);$$
3) **Update** the resource allocation table (RB);
4) **Broadcast** the RB table, $\forall\ i \in \mathcal{N}$;
5) **Broadcast** x_i, $\forall\ j \in \mathcal{N}_i$;

end

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