# Delay-Aware Network Optimization in LTE Based High-Speed Railway Wireless Networks

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***Abstract*—This paper presents an extended joint resource optimization framework for multi-service transmissions in high-speed railway (HSR) wireless networks by introducing the average delay constraint into the dynamic resource management problem. The system utility is maximized under the constraints of average delay, queue stability and average power by formulating a joint stochastic problem, which is transformed into a queue stability problem. Using Lyapunov drift theory, the queue stability problem is decomposed into separate convex subproblems. Golden section search method is used to achieve a globally optimal solution for the resource allocation subproblem. Finally, a distributed dynamic resource management technique is proposed, and its performance is evaluated under realistic conditions for HSR wireless networks. Numerical simulations show that our approach provides an improved throughput performance while satisfying the average delay requirements.**

***Keywords*—*High-speed railway wireless networks; Delay requirements.***

## I. INTRODUCTION

High-speed railway (HSR) has been deployed worldwide as the dominant fast public transportation system [1][2]. HSR infrastructure features an increasing amount of control and multimedia transmissions to ensure the safety and efficiency of the transportation, and to support the increasing demand from passengers for the Internet services. Since GSM for railway (GSM-R) offers limited data transmission capabilities and inefficient radio resource usage [3], alternative communication systems should be investigated to support the increasing traffic demand. Therefore, the deployment of wideband wireless communication technologies is an urgent need for the operation of HSR to provide reliable and robust connection with the central control systems, and to offer seamless Internet access for passengers. Long Term Evolution (LTE) is envisioned as the leading candidate to replace GSM-R for the future railway infrastructures due to its packet-switched network architecture with high data transmission capacities and low latency [4].

In a conventional cellular network infrastructure, mobile terminals have a direct communication with the base stations. This type of direct communication fails in HSR environment due to high penetration loss, severe Doppler frequency shift, and high rate of drop calls and handovers [5]. Figure 1 shows an LTE-based HSR network architecture, which avoids the drawbacks of the conventional HSR infrastructure by providing a two-hop communication between the passengers and base stations [1][5]. In this architecture, multiple access points (APs) are placed within the train, and a relay station (RS) with powerful antennas is mounted on top of the train. APs provide the passengers with an indirect communication with a high transmission rate to the RS, which in turn, directly communicates with the LTE-compliant base stations (eNBs) located along the rail line. The evolved packet core (EPC) network of LTE is connected to eNBs via wired lines, and provides a high performance communication between the train and Internet to support the operational and multimedia traffic along the journey. EPC is composed of Mobility Management Entity (MME), Serving Gateway (S-GW) and Packet Data Network Gateway (PDN-GW). The increasing amount of wireless traffic in HSR [6] necessitates the development of radio resource management (RRM) techniques to enable the efficient resource utilization [1]. However, the design of such techniques is quite challenging due to the very dynamic channel conditions between the fast moving train and eNBs, and the operational and passenger services with heterogeneous QoS requirements [7][8]. RRM techniques for HSR wireless networks should jointly optimize the different aspects of resource allocation, admission and power control while observing different network constraints to maximize the

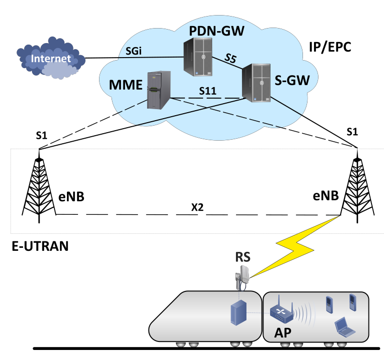


Figure 1. LTE-based HSR network infrastructure

system performance. This optimization should be performed in a cross-layer manner by considering the distinctive parameters of the physical, medium access control (MAC), and application layers. Furthermore, it should manage the inherent trade-offs between these layers in a comprehensive close-to-optimal manner.

The work in [9] investigates the downlink resource allocation in relay-assisted HSR communication systems. It aims to minimize the average end-to-end delay through scheduling actions under the service delivery ratio constraints. In [10], an admission control scheme with the complete-sharing resource allocation model is proposed for LTE-R system to maximize the number of admitted services while guaranteeing their related QoS requirements of each service class. The proposed admission control scheme gives high priority to on-going services and guarantees the full use of system bandwidth resource. The work in [11] studies the utility-based resource allocation problem in HSR wireless networks by jointly considering the power control and packet allocation among services. A joint optimal design of admission control and resource allocation for multimedia service delivery in HSR wireless networks is studied in [12]. A stochastic network optimization problem is formulated to maximize the system utility while stabilizing all transmission queues under the average power constraint. Using the same approach as [12], the work in [13] introduces average delay constraints to the multi-service transmission problem, with a focus only on resource allocation and power control.

In this paper, we combine the cross-layer RRM schemes in [12] and [13] in a more general optimal framework. Thus, we present a delay-aware optimization framework, which jointly optimizes the resource allocation, admission and power control in LTE-based HSR wireless networks. Our framework extends the previous work [12] by introducing an additional delay constraint, inspired by [13], to the dynamic network management of HSR infrastructure, and, hence, maximizing the throughput performance of the network while jointly optimizing the aforementioned aspects. Specifically, we formulate and investigate a cross-layer optimization problem to jointly optimize the network resources under the constraints of average delay, queue stability and power to maximize the system utility. Finally, we propose a dynamic resource management algorithm to guarantee the joint optimization of the studied aspects, and evaluate its performance through numerical simulations showing that our algorithm provides an improved throughput performance while considering the delay requirement.

The rest of this paper is organized as follows. In Section II, HSR network constraints are discussed. In Section III, the stochastic optimization problem is formulated. In Section IV, the application of the Lyapunov drift theory to solve the optimization problem is explained. In Section V, problem decomposition is described, and our dynamic resource management algorithm is presented. In Section VI, our numerical results are reported. In Section VII, our paper is concluded.

## II. HSR Network Constraints

In this paper, we aim at improving the throughput performance in HSR wireless networks by dynamically optimizing the management functions. Our optimization framework considers certain constraints whose averages are evaluated over the journey of the train. Assuming that a set $\mathcal{K} \triangleq \{1, 2, ..., K\}$ of services is supported by a slot-based HSR wireless transmission network, and $\bar{x}$ represents the long-term time average expectation for any quantity $x$, time average constraints are explained below:

### A. Average Delay

LTE-based HSR wireless networks are envisioned to offer broadband multimedia services for both passengers and railway operators. These services may be sensitive in varying degrees to the transmission delay so that heterogeneous delay requirements must be taken into account when optimizing the network resources.

Let $\overline{W_k}$ denote the average time that a packet spends in a queue $k$. According to the Little's law in queuing theory [14], $\overline{W_k} = \overline{Q_k}\ \lambda_k$, where $\overline{Q_k}$ and $\lambda_k$ represent the average number of packets located in the queue (i.e. average queue backlog), and the average arrival rate of the packets, respectively. Average delay constraint for any queue requires that $\overline{W_k}$ be upper bounded by the maximum time $W_k^{\max}$ during which a packet can stay in any queue. $W_k^{\max}$ depends on the type and QoS requirements of the services. Average delay constraint for any queue $k$ can be expressed as:

$$\overline{Q_k} \leq W_k^{\max} \lambda_k, \quad \forall k \in \mathcal{K}. \tag{1}$$

### B. Queue Stability

Since the LTE-based HSR infrastructure has a packet-switched network architecture, buffering is involved at networking devices requiring the stability of the queues to be taken into consideration. According to [14], a queue is strongly stable if it has a bounded time average backlog, $\overline{Q_k} \leq \infty$.

Intuitively, if the inequality (1) holds for any queue, it implies the stability of the queue. Thus, the satisfaction of the average delay constraint implies the satisfaction of the queue stability constraint [13].

### C. Average Power

In an LTE-based HSR wireless network, channel conditions dynamically change with respect to the time-varying distance between the eNBs and the train [6][8]. Therefore, the transmit power $P(t)$ should be dynamically adjusted according to this time-varying distance to ensure a reliable communication. However, at any time slot $t$ during the trip, $P(t)$ must be limited between the maximum and average transmit powers, namely, $P_{\max}$ and $P_{\text{av}}$, respectively. The average power constraint can be expressed as:

$$\overline{P} \leq P_{\text{av}}. \tag{2}$$

## III. Problem Formulation

The throughput performance of a multi-service stochastic network can be improved by maximizing:

$$\sum_{k \in \mathcal{K}} \phi_k(\overline{r_k}), \tag{3}$$

where $\phi_k$ is a nondecreasing concave continuous utility function representing the throughput benefit for a service $k$ while $\overline{r_k}$ represents the average throughput. It is difficult to maximize this objective function since it requires the maximization of individual functions of time averages [7]. Therefore, it can be transformed into the following problem to facilitate the maximization process:

$$\begin{aligned}
&\text{maximize} && \sum_{k \in \mathcal{K}} \overline{\phi_k(\gamma_k)} && \text{(4a)}\\
&\text{subject to} && \overline{P} \leq P_{\text{av}}, && \text{(4b)}\\
& && \overline{Q_k} \leq W_k^{\max}\lambda_k, \quad \forall k \in \mathcal{K}, && \text{(4c)}\\
& && \overline{\gamma_k} \leq \overline{r_k}, \qquad \forall k \in \mathcal{K}, && \text{(4d)}
\end{aligned}$$

where $\gamma_k(t)$ is an auxiliary variable upper bounded by the average throughput [12].

The dynamics of each queue $Q_k(t+1)$, that is, the number of packets located in a queue at time slot $t+1$, are controlled by admission control action $r_k(t)$ and resource allocation action $\mu_k(t)$ as follows:

$$Q_k(t+1) = Q_k(t) - \mu_k(t) + r_k(t), \quad \forall k \in \mathcal{K}, \tag{5}$$

where $r_k(t)$ and $\mu_k(t)$ represents the number of newly arrived packets to be stored into the queue and number of packets removed from the queue for transmission, respectively. These control actions should be jointly decided to maximize the objective function (4a) under the time average constraints.

## IV. Lyapunov Optimization

In this section, similar to [12] and [13], Lyapunov optimization theory is used to transform the original problem into a queue stability problem by introducing virtual queues. Then, Lyapunov drift is applied to jointly stabilize these queues. Our Lyaponuv drift is different from [12] and [13] since we use a different combination of virtual queues.

### A. Queue Stability Problem Transformation

To facilitate the problem transformation and the satisfaction of the time average constraints, the work in [12] and [13] introduces the virtual queues $X_k(t)$, $Y_k(t)$ and $Z_k(t)$ with the following dynamic update equations:

$$X_k(t+1) = \max[X_k(t) - W_k^{\max}\lambda_k, 0] + Q_k(t+1), \tag{6}$$

$$Y_k(t+1) = \max[Y_k(t) - P_{\text{av}}, 0] + P(t), \tag{7}$$

$$Z_k(t+1) = \max[Z_k(t) - r_k(t), 0] + \gamma_k(t). \tag{8}$$

The stabilization of the virtual queues $X_k(t)$, $Y_k(t)$ and $Z_k(t)$ ensures that the respective inequalities (4c), (4b) and (4d) hold [14].

### B. Lyapunov Drift

Assuming that $\mathbf{X}(t)$, $\mathbf{Y}(t)$ and $\mathbf{Z}(t)$ represent the respective vectors of $X_k(t)$, $Y_k(t)$ and $Z_k(t)$, and $\mathbf{\Theta}(t) \triangleq [\mathbf{X}^T(t), \mathbf{Y}^T(t), \mathbf{Z}^T(t)]^T$ denotes the combined vector, the quadratic Lyapunov function is defined as:

$$L(\mathbf{\Theta}(t)) \triangleq \frac{1}{2} \sum_{k \in \mathcal{K}} (X_k(t)^2 + Y_k(t)^2 + Z_k(t)^2). \tag{9}$$

The one-slot conditional Lyapunov drift $\Delta(\mathbf{\Theta}(t))$ at time $t$ is given by:

$$\Delta(\mathbf{\Theta}(t)) \triangleq \mathbb{E}[L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t)) | \mathbf{\Theta}(t)]. \tag{10}$$

Minimizing the drift (10) ensures that all virtual queues are jointly stable and the desired constraints are satisfied.

In [12] and [13], the following inequalities are obtained by squaring the equations (6), (7) and (8) to further simplify the drift:

$$\begin{aligned}X_k(t+1)^2 - X_k(t)^2 \leq{}& Q_k(t+1)^2 + (W_k^{\max}\lambda_k)^2\\ &+ 2X_k(t)(Q_k(t+1) - W_k^{\max}\lambda_k),\end{aligned} \tag{11}$$

$$\begin{aligned}Y_k(t+1)^2 - Y_k(t)^2 \leq{}& P(t)^2 + P_{\text{av}}^2\\ &+ 2Y_k(t)(P(t) - P_{\text{av}}),\end{aligned} \tag{12}$$

$$\begin{aligned}Z_k(t+1)^2 - Z_k(t)^2 \leq{}& \gamma_k(t)^2 + r_k(t)^2\\ &+ 2Z_k(t)(\gamma_k(t) - r_k(t)).\end{aligned} \tag{13}$$

Replacing the inequalities (9) and (10), the following inequality is obtained:

$$\Delta(\mathbf{\Theta}(t)) \leq \frac{1}{2} D + \mathbb{E}[G(t) | \mathbf{\Theta}(t)], \tag{14}$$

where $D$ is a finite constant and $G(t)$ is defined to be:

$$\begin{aligned}G(t) \triangleq \sum_{k \in \mathcal{K}} [&X_k(t)(Q_k(t) - \mu_k(t) + r_k(t) - W_k^{\max}\lambda_k)\\ &+ Z_k(t)(\gamma_k(t) - r_k(t)) + Y_k(t)(P(t) - P_{\text{av}})].\end{aligned} \tag{15}$$

Minimizing the drift (10) can be facilitated by minimizing the upper bound of inequality (14). Since $D$ is constant, it is sufficient to minimize the expectation $\mathbb{E}[G(t)|\mathbf{\Theta}(t)]$, which can be achieved by only minimizing $\mathbb{E}[G(t)]$ [14]. All queues can be stabilized while maximizing the sum of the utility functions by greedily minimizing the following "drift-plus-penalty" expression [12]:

$$\mathbb{E}[G(t) - V \sum_{k \in \mathcal{K}} \phi_k(\gamma_k(t))], \tag{16}$$

where $V$ is a non-negative control parameter that balances between the maximization of the system utility and the satisfaction of the constraints.

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## V. Our Dynamic Resource Management Algorithm

The objective function (16) can be minimized by jointly optimizing $\mu_k(t)$, $r_k(t)$, $P(t)$ and $\gamma_k(t)$ at each time slot $t$. By isolating these control variables, the objective function can be easily decomposed into three separated subproblems, namely, utility maximization, admission control, and resource allocation.

In [12], utility maximization subproblem is solved by tracking $Z_k(t)$ to determine the optimum $\gamma_k(t)$, while a simple threshold-based admission control strategy is proposed for solving the admission control subproblem to obtain $r_k(t)$. Since a larger $\mu_k(t)$ demands a larger $P(t)$, a mixed integer programming (MIP) problem with a continuous variable $P(t)$ and an integer variable $\mu_k(t)$ is designed in [13] to jointly optimize $P(t)$ and $\mu_k(t)$. This MIP problem is then transformed into an equivalent single variable problem, and a static resource management algorithm, based on the golden section search method, is proposed to solve the problem with a guaranteed global optimality.

We propose a distributed dynamic resource management algorithm to jointly optimize the network resources by combining the solutions to utility maximization, admission control, and resource allocation subproblems provided in [12] and [13]. Our algorithm aims at improving the system utility under average delay, queue stability, and power constraints.

The distributed algorithm is described in Figure 2. All system parameters and queue vectors are initialized before the beginning of the trip. Then, during the trip, for each time slot $t$ and each service $k$, the three aforementioned subproblems are solved to obtain the optimal control variables. The auxiliary variable $\gamma_k(t)$ is determined according to [12], while admission control action $r_k(t)$ is decided via a threshold-based admission control strategy by tracking $X_k(t)$. Resource allocation action $\mu_k(t)$ and power control action $P(t)$ are jointly obtained by calling Static Resource Management Algorithm in [13]. At the end of each slot $t$, each queue vector $k$ is updated according to (5), (6), (7), and (8). This algorithm will be repeated for all time slots, from the origin station to the destination station.

**Algorithm 1** Dynamic Resource Management Algorithm

1: Initialize $V$, $Q_k(0) = 0$, $X_k(0) = 0$, $Y_k(0) = 0$, $Z_k(0) = 0$ for all $k \in \mathcal{K}$;
2: **while** $t \in [0, T]$ **do**
3: **for** $k = 1$ *to* $\mathcal{K}$ **do**
4: Obtain the optimal $\gamma_k(t)$ inspired by [12];
5: Obtain the optimal $r_k(t)$ by using threshold-based admission control strategy [12];
6: Obtain the optimal $P(t)$ and $\mu_k(t)$ by calling Static Resource Management Algorithm [13];
7: Update $Q_k(t+1)$, $X_k(t+1)$, $Y_k(t+1)$, and $Z_k(t+1)$ according to (5), (6), (7), and (8), respectively;
8: **end for**
9: **end while**

Figure 2. Distributed Dynamic Resource Management Algorithm.

## VI. Simulation Results

Our algorithm for dynamic resource management is implemented using MATLAB. Table I summarizes the realistic parameters, according to [7][11][12], used in our simulations. To perform each simulation, our algorithm is executed for 30,000 time slots during which the train moves between the centers of two adjacent cells. In this section, we present comparison results for our scheme and the reference model in [12]; therefore, we use the piecewise linear utility function for all services, namely, $\phi_k(r_k) = \nu_k \min[r_k, \lambda_k]$, where $\nu_k$ represents the service priority.

TABLE I. SIMULATION PARAMETERS.

| Parameter | Description | Value |
|---|---|---|
| $P_{\text{av}}$ | Average power constraint | 35 W |
| $P_{\text{max}}$ | Maximum transit power | 45 W |
| $H$ | System bandwidth | 5 MHz |
| $L$ | Packet size | 240 bits |
| $T_s$ | Slot duration | 1 ms |
| $\alpha$ | Pathloss exponent | 4 |
| $\lambda_k$ | Packet arrival rate | 25 packet/slot |
| $v$ | Constant moving speed | 350 km/h |
| $R$ | Cell radius | 1.5 km |
| $d_0$ | Distance between BS and rail | 50 m |
| $K$ | Number of services | 6 |

Figure 4 shows the average delay and average power consumption achieved by our algorithm for different values of $V$. The priority for all services is selected to be $\nu_k = 10$ in this simulation. Figure 4a shows that, in all cases, our algorithm achieves an average delay which increases with respect to $V$ until it reaches a saturation point. However, as shown in the figure, a larger $W_k^{\max}$ leads to a higher average delay for a certain value of $V$. Since the work in [12] does not consider the delay constraint, the average delay achieved by the reference model keeps increasing for all values of $V$ without reaching a saturation point. These results indicate that our algorithm fully satisfies the average delay constraints in our simulations. On the other hand, Figure 4b demonstrates that our scheme will cause a slightly larger average power consumption for the small values of $V$ compared to the reference model while still satisfying the average power constraint.

Figure 3 presents the throughput performances of our scheme and the reference model for varying values of $V$. $W_k^{\max}$ is selected to be 10 in all cases for this simulation. For the small values of $V$ within the range $[0, 15]$, the average throughput for all service priorities ($\nu_k$) increases with respect to $V$. However, Figure 3a shows that the services of higher priorities achieve a larger throughput performance. On the other hand, for the larger values of $V$, the average throughput achieved by the services with low priorities has a slightly decreasing trend while continuing to increase for the services with high priorities. The results in Figure 3a indicate that our scheme mostly yields better throughput performance than the reference model for the low values of $V$. Figure 3b shows that the performance improvement achieved by our algorithm costs a slight increase in the average power consumption within the range of 5 watt. Providing better performance for the low values of $V$ is favorable since high values of $V$ result in more packets to be admitted into the buffers, which necessitates larger buffer size and higher power consumption.

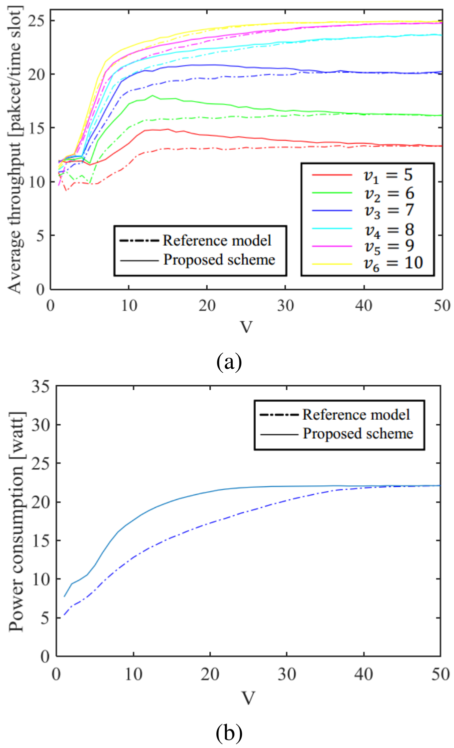


Figure 3. Average throughput and average power consumption achieved by our algorithm for different service priorities.

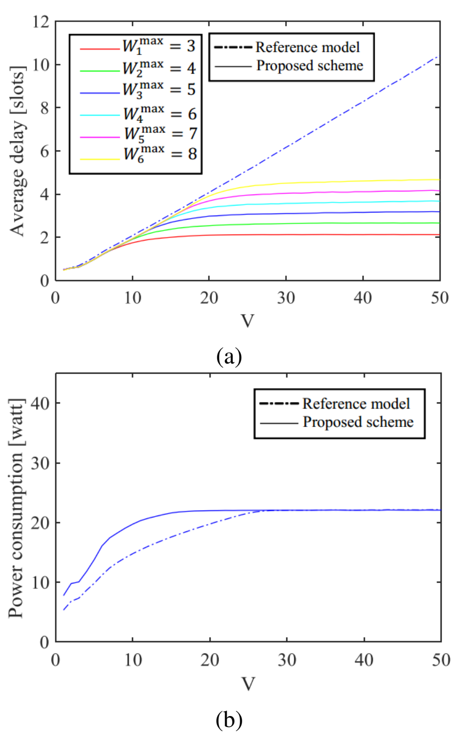


Figure 4. Average delay and average power consumption achieved by our algorithm for different delay requirements.

## VII. Conclusion

This paper presents an extended joint resource optimization framework for admission control, power control and resource allocation in LTE-based HSR wireless networks. Our work introduces an average delay constraint to the formulation of dynamic management problem of HSR wireless networks. A joint optimization problem is designed to maximize the system utility under the constraints of average delay, queue stability and average power. The problem is then transformed into a queue stability problem, which is decomposed into the separable convex subproblems using Lyapunov drift theory. Golden section search method is used to solve the resource allocation subproblem, and a dynamic resource management algorithm is proposed to achieve the joint optimization of the network resources. Finally, we perform numerical simulations which show that our proposed model fully satisfies the average delay requirements and significantly improves the throughput performance of HSR wireless networks.

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