# DYNAMIC RESOURCE OPTIMIZATION FOR DECENTRALIZED SIGNAL ESTIMATION IN ENERGY HARVESTING WIRELESS SENSOR NETWORKS

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## ABSTRACT

We study decentralized estimation of time-varying signals at a fusion center (FC), when energy harvesting sensors transmit sampled data over rate-constrained links. We propose a dynamic strategy based on stochastic optimization for selecting radio parameters, sampling set, and harvested energy at each node, with the aim of estimating a time-varying signal with guaranteed performance while ensuring stability of the batteries around a prescribed operating level. Numerical results validate the proposed approach for dynamic signal estimation under communication and energy constraints.

***Index Terms*—** Signal recovery, probabilistic quantization, energy harvesting, stochastic optimization.

## 1. INTRODUCTION

Wireless sensor networks (WSN's) are envisioned to play a key role in the Internet of Things (IoT) paradigm, where trillions of smart devices are expected to be connected with each other while sensing information from the environment [1, 2]. In fact, embedding intelligent signal processing tools in our productive systems will enable distributed proactive sensing and control mechanisms aimed at preventing performance degradation and optimizing the overall production chain. For this reason, decentralized estimation was deeply investigated in several works as, e.g., [3–7], with the aim of optimizing the radio resource allocation while imposing a constraint on the mean-square error (MSE) performance in the case of *static* parameter estimation. Meanwhile, energy harvesting (EH) techniques have attracted a lot of interest in WSN's in order to cope with the battery-limited nature of sensor devices, enabling the possibility to collect energy from renewable sources such as wind, sun, vibration, and heat [8]. EH naturally introduce *dinamicity* in the estimation problem due to the intermittent arrivals of energy from the environment and the variability over time of the battery levels at each sensor. In this context, the works in [9, 10] studied the optimal packet communication strategy to maximize the net bit rates while stabilizing the data queue in EH communications. An energy scheduling strategy for remote estimation in the case of a single EH sensor was proposed in [11]. Finally, the work in [12] proposed a dynamic radio resource allocation for static and dynamic estimation in WSN's with EH devices, in the case of scalar parameter estimation and an analog amplify-and-forward transmission strategy at each sensor.

In this paper, we consider vector signal estimation in EH wireless sensor networks. We propose a dynamic resource allocation strategy that optimally selects radio parameters, the set of sampling sensors, and the harvested energies in order to minimize the average energy expenditure of the WSN, while imposing prescribed performance guarantees in terms of average MSE performance and stability of the battery levels at each node. The method builds on stochastic optimization techniques [13] in order to cope with the dynamic and unknown variability of the energy arrival process and the radio channels. Numerical results illustrate the validity of the proposed approach for decentralized estimation in EH WSN's.

## 2. RATE-CONSTRAINED SIGNAL ESTIMATION

Let us consider a WSN with $N$ nodes that is deployed to monitor a signal over a certain geographic area. We consider a dynamic scenario where time is divided in slots of equal duration $T$. Let $\boldsymbol{x}(t) = [x_1(t), \ldots, x_N(t)]^T$ be the vector collecting the signal values at every node of the network at time $t$. The observed data are assumed to belong to a low-dimensional subspace, i.e., at each time $t$, the vector $\boldsymbol{x}(t)$ can be cast as:

$$\boldsymbol{x}(t) = \mathbf{U}\boldsymbol{s}(t), \tag{1}$$

where $\mathbf{U}$ is an $N \times r$ matrix, with $r \leq N$, and $\boldsymbol{s}(t)$ is an $r \times 1$ column vector. The columns of $\mathbf{U}$ are assumed to be linearly independent and thus constitute a basis spanning the useful signal subspace. In practice, the dimension $r$ of the useful signal subspace is typically much smaller than the dimension $N$ of the observation space. From (1), at time $t$, the network collects measurements $\{y_i(t)\}_{i=1}^N$ given by:

$$y_i(t) = x_i(t) + v_i(t) = \boldsymbol{u}_i^H \boldsymbol{s}(t) + v_i(t), \tag{2}$$

$i = 1, \ldots, N$, where $\boldsymbol{u}_i^H$ is the $i$-th row of matrix $\mathbf{U}$, and $v_i(t)$ is zero-mean, uncorrelated noise with variance $\sigma_i^2$. The measurements in (2) must be transmitted to a FC to evaluate a proper estimate of the signal $\boldsymbol{x}(t)$. Assuming the presence of rate-constrained radio channels, the messages $\{y_i(t)\}$ must necessarily be encoded into a sequence of bits in order to be sent to the FC. Suppose that $[-A, A]$ is the signal range that sensors can observe. At each time $t$, we consider a uniform quantizer at each node $i$, which divides the range $[-A, A]$ into intervals of length $\Delta_i(t) = 2A/(2^{b_i(t)} - 1)$, and rounds the observations in (2) to the neighboring endpoints of these small intervals in a probabilistic manner [3], [4]. Then, if $l\Delta_i(t) < y_i(t) < (l+1)\Delta_i(t)$, with $l \in \{-2^{b_i(t)-1}, \ldots, 2^{b_i(t)-1}\}$, $y_i(t)$ is quantized to $m(y_i(t), b_i(t))$ according to:

$$m(y_i(t), b) = l\Delta_i(t) + \alpha\Delta_i(t), \tag{3}$$

where $\alpha$ is a Bernoulli random variable such that $\mathbb{E}\{\alpha\} = \text{Prob}\{\alpha = 1\} = (y_i(t) - l\Delta_i(t))/\Delta_i(t) \in [0,1]$. Thus, according to (3), the quantized $i$-th observation at time $t$, i.e., $m_i(y_i(t), b_i(t))$, can be equivalently written as:

$$m_i(y_i(t), b_i(t)) \,=\, x_i(t) + v_i(t) + q(y_i(t), b_i(t)), \tag{4}$$

where $q(y_i(t), b_i(t)) = (\alpha - \mathbb{E}\{\alpha\})\Delta_i(t)$ denotes the quantization noise. In particular, it is possible to show that $m_i(y_i(t), b_i(t))$ in (4) is an unbiased estimate of $x_i(t)$, and

$$\mathbb{E}|m_i(y_i(t), b_i(t)) - x_i(t)|^2 \leq \sigma_i^2 + \frac{A^2}{(2^{b_i(t)} - 1)^2} \tag{5}$$

is an upper bound on the estimation variance [3, 4].

Our goal is to build a linear estimator of $\boldsymbol{x}(t)$ from $\{m_i(t)\}_{i=1}^N$ in (4) that guarantees a target value of MSE. In particular, we consider the (quasi-)BLUE given by:

$$\begin{aligned}\widehat{\boldsymbol{x}}(t) \,=\, \mathbf{U}\Big(\mathbf{U}^H\left(\mathbf{C}_v + \mathbf{C}_q(t)\right)^{-1}\mathbf{U}\Big)^{-1} \times \\ \times\, \mathbf{U}^H\left(\mathbf{C}_v + \mathbf{C}_q(t)\right)^{-1}\boldsymbol{m}(t)\end{aligned} \tag{6}$$

where $\boldsymbol{m}(t) = \{m_i(t)\}_{i=1}^N$, $\mathbf{C}_q(t) = \text{diag}\left\{\frac{A^2}{(2^{b_i(t)}-1)^2}\right\}_{i=1}^N$. Notice that $\widehat{\boldsymbol{x}}(t)$ in (6) is an unbiased estimator of $\boldsymbol{x}(t)$ since every $m_i(t)$ in (4) is an unbiased quantization of $x_i(t)$. Now, let us assume that the channel between each sensor and the FC is corrupted with additive white Gaussian noise whose double-sided power spectrum density is given by $N_0/2$. Furthermore, we denote by $h_i(t)$ the channel coefficient between sensor $i$ and the FC at time $t$. If sensor $i$ sends $b_i(t)$ bits with quadrature amplitude modulation with constellation size $2^{b_i(t)}$ at a bit error probability $\text{BER}_i$, then the amount of energy required for the transmission is [4, 14, 15]:

$$e_i(t) = \frac{2N_f N_0 G_d}{h_i^2(t)}\left(\ln\frac{2}{\text{BER}_\text{i}}\right)(2^{b_i(t)} - 1), \tag{7}$$

where $N_f$ is the receiver noise figure, and $G_d$ s a system constant defined in the same way as in [14, 15]. In the sequel, for simplicity, we assume that the BER of each transmission is made sufficiently small such that errors have a negligible effect on the MSE. Thus, letting $c_i(t) = \frac{2N_f N_0 G_d}{h_i^2(t)}\left(\ln\frac{2}{\text{BER}_\text{i}}\right)$, and using (5) and (7), it is possible to prove that the MSE of the estimator in (6) is upper bounded by:

$$\text{MSE}(\boldsymbol{e}(t)) \leq \text{Tr}\left\{\left(\sum_{i=1}^N \frac{\boldsymbol{u}_i\boldsymbol{u}_i^H}{\sigma_i^2 + \dfrac{A^2 c_i^2(t)}{e_i^2(t)}}\right)^{-1}\right\}, \tag{8}$$

where $\boldsymbol{e}(t) = [e_1(t), \ldots, e_N(t)]^T$ is the vector collecting all transmission energies. In the sequel, we illustrate the EH model at each sensor, and the proposed dynamic resource allocation method based on stochastic optimization.

## 3. DYNAMIC RESOURCE OPTIMIZATION

The EH process is modeled as successive energy packet arrivals, i.e., $R_i(t)$ units of energy arrive at sensor $i$ at the beginning of the $t$-th time slot. The energy arrivals $R_i(t)$ are i.i.d. among different slots, and are upper bounded by $R^{\max}$ [16]. In each time slot, part of the arrived energy, say, $r_i(t)$, satisfying $r_i(t) \leq R_i(t)$, will be harvested and stored in the battery, and it will be available for transmission [cf. (7)] from the next slot. Let us denote the battery level of node $i$ at time slot $t$ as $B_i(t)$. In virtue of the energy causality constraint $e_i(t) \leq B_i(t)$ for all $t$, the battery level evolves according to:

$$B_i(t+1) = B_i(t) - e_i(t) + r_i(t), \quad \text{for all } i, t. \tag{9}$$

Of course, from (9), the battery level is determined by the balance between the energy spent for transmission [i.e., $e_i(t)$] and the one harvested from the environment [i.e., $r_i(t)$].

The proposed strategy minimizes the expected sum of transmission energies of all sensors, under a constraint on the average MSE, while also ensuring that all the batteries remain stable over time. The problem can be cast mathematically as:

$$\begin{aligned}
\min_{\boldsymbol{e}(t), \boldsymbol{r}(t)} \quad & \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1}\sum_{i=1}^N \mathbb{E}\left\{e_i(\tau)\right\} \\
\text{s.t.} \quad & \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}\left\{\text{MSE}(\boldsymbol{e}(\tau))\right\} \leq \gamma \\
& \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}\left\{r_i(\tau) - e_i(\tau)\right\} = 0 \quad \forall i; \\
& 0 \leq e_i(t) \leq \min[e_i^{\max}, B_i(t)], \quad \forall i, t; \\
& 0 \leq r_i(t) \leq R_i(t), \quad \forall i, t.
\end{aligned} \tag{10}$$

The first constraint in (10) imposes that the average MSE is lower than a value $\gamma > 0$; the second constraint avoids the battery levels are drained or explode over time (i.e., stability) by enforcing that the average inputs and outputs must be equal; the third constraint puts bounds on the transmitted powers, i.e., the minimum among the battery level $B_i(t)$ and the maximum energy $e_i^{\max}$ that can be transmitted by the radio interface; finally, the last constraint in (10) sets the bounds on the harvestable energy at each time slot.

**Min-Drift-Plus Penalty Algorithm.** To solve problem (10), we exploit tools from stochastic optimization [13]. To this aim, we first introduce the virtual queue $Z(t)$ associated with the MSE inequality constraint in (10), with update equation:

$$Z(t+1) = \max[Z(t) + \mathrm{MSE}(\boldsymbol{e}(t)) - \gamma, 0]. \tag{11}$$

Furthermore, to keep the energy storage stabilized around a maximum battery size, we use the approach from [17, 18], thus defining the virtual queues:

$$\widetilde{B}_i(t) = B_i(t) - \vartheta_i, \quad i = 1, \ldots, N, \tag{12}$$

where $B_i(t)$ evolves as in (9), and $\vartheta_i > 0$ is a parameter to be selected. As illustrated in [18], the use of the virtual queues $\widetilde{B}_i(t)$ in (12) is useful to stabilize the battery levels $B_i(t)$ in (9) around $\vartheta_i$. Then, the algorithmic approach passes through the definition of the Lyapunov function:

$$L(\boldsymbol{\Psi}(t)) = \frac{1}{2}Z(t)^2 + \frac{1}{2}\sum_{i=1}^{N}\widetilde{B}_i(t)^2 \tag{13}$$

where $\boldsymbol{\Psi}(t) = \left[Z(t), \{\widetilde{B}_i(t)\}_i\right]$. We can now define the *one-slot conditional Lyapunov drift* as:

$$\Delta(\boldsymbol{\Psi}(t)) \triangleq \mathbb{E}\{L(\boldsymbol{\Psi}(t+1)) - L(\boldsymbol{\Psi}(t))|\boldsymbol{\Psi}(t)\} \tag{14}$$

where the expectation depends on the control policy, and is taken with respect to the random channels and energy packet arrivals. Since our approach aims at minimizing the energy spent by the network to perform the signal recovery task [cf. (10)], we introduce the *drift-plus-penalty* function as [13]:

$$\Delta_p(\boldsymbol{\Psi}(t), \boldsymbol{e}(t)) = \Delta(\boldsymbol{\Psi}(t)) + V\sum_{i=1}^{N}\mathbb{E}\left\{e_i(t)\right\}|\boldsymbol{\Psi}(t)\} \tag{15}$$

where $V$ is a control parameter used to trade-off power consumption with queues length. Following arguments as in [13], exploiting (11) and (12), the drift-plus-penalty function in (15) can be upper-bounded as:

$$\begin{aligned}\Delta_p(\boldsymbol{\Psi}(t), \boldsymbol{e}(t), \boldsymbol{r}(t)) \;\le\; & C + V\cdot\sum_{i=1}^{N}\mathbb{E}\{e_i(t)|\boldsymbol{\Psi}(t)\} \\ & + Z(t)\cdot\mathbb{E}\big\{\mathrm{MSE}(\boldsymbol{e}(t)) - \gamma|\boldsymbol{\Psi}(t)\big\} \\ & + \sum_{i=1}^{N}\widetilde{B}_i(t)\cdot\mathbb{E}\{\boldsymbol{r}_i(t) - \boldsymbol{e}_i(t)|\boldsymbol{\Psi}(t)\}\end{aligned} \tag{16}$$

where $C$ is a positive constant. Thus, using a stochastic approach where we greedily minimize instantaneous values of (16) at each $t$ [13], we obtain the control policy described by the Min-Drift-Plus Penalty Algorithm in Table 1. The proposed dynamic algorithm determines the optimal transmission energies $\{e_i(t)\}$, the sampling set (i.e., the set of nodes with transmitting energy different from zero), and the energies $\{r_i(t)\}$ to be harvested from the environment. In particular, step [S.1] is obtained by minimizing (16) with respect to $\{r_i(t)\}$, with the constraint $0 \le r_i(t) \le R_i(t)$. Since (16) is linear with respect to $\{r_i(t)\}$, from (17), each node $i$ collects the maximum harvestable energy $R_i(t)$ when $B_i(t) \le \vartheta_i$; whereas, for $B_i(t) > \vartheta_i$, node $i$ does not harvest any energy. Consequently, merging (9) with (17), we have:

$$B_i(t) \le \vartheta_i + R^{\max}, \qquad \text{for all } i, t. \tag{19}$$

Step [S.2] of Algorithm 1 requires the solution of the non-convex optimization problem (18) [cf. (8)]. Thus, at each time slot $t$, we can only find a local optimum solution of (18). Nevertheless, a possible convexification can be obtained reformulating the objective function and the stability constraint in (18) in terms of the *square* energies $\{e_i^2(t)\}$ and $\{r_i^2(t)\}$. Following the same arguments as before, we would achieve an algorithm totally similar to the one in Table 1, with same step [S.1], and [S.2] entailing the solution of:

$$\begin{aligned}\min_{\boldsymbol{e}(t)} \; & \sum_{i=1}^{N}\left(V - \widetilde{B}_i(t)\right)e_i^2(t) + Z(t)\cdot\mathrm{MSE}(\boldsymbol{e}(t)) \\ & \text{subject to} \quad 0 \le e_i(t) \le \min[e_i^{\max}, B_i(t)].\end{aligned} \tag{20}$$

Now, using $z_i(t) = \dfrac{e_i^2(t)}{e_i^2(t)\sigma_i^2 + A^2c_i^2}$, $i = 1, \ldots, N$, and (8) in (20), we obtain the equivalent problem:

$$\begin{aligned}\min_{\boldsymbol{e}(t)} \; & \sum_{i=1}^{N}\left(V - \widetilde{B}_i(t)\right)c_i^2\frac{z_i(t)}{1 - z_i(t)\sigma_i^2} \\ & \qquad + Z(t)\cdot\mathrm{Tr}\left\{\left(\textstyle\sum_{i=1}^{N} z_i(t)\,\boldsymbol{u}_{\mathcal{F},i}\boldsymbol{u}_{\mathcal{F},i}^H\right)^{-1}\right\} \\ & \text{subject to} \quad 0 \le z_i(t) \le \frac{\zeta_i(t)}{1 + \zeta_i(t)\sigma_i^2}\end{aligned} \tag{21}$$

**Table 1: Min Drift-Plus-Penalty Algorithm**

Every slot $t$, observe the queue states $\boldsymbol{\Psi}(t)$ and the random events $\{h_i(t)\}$, $\{R_i(t)\}$, and make the control actions:

[$\mathbf{S.1}$] Set the optimal harvested energies $\{r_i(t)\}$ to

$$r_i(t) = R_i(t)\cdot\mathbb{I}\left(\widetilde{B}_i(t) \le 0\right) \tag{17}$$

where $\mathbb{I}(\cdot)$ is the indicator function;

[$\mathbf{S.2}$] Compute the transmission energies $\{e_i(t)\}$ by solving:

$$\begin{aligned}\min_{\boldsymbol{e}(t)} \; & \sum_{i=1}^{N}\left(V - \widetilde{B}_i(t)\right)e_i(t) + Z(t)\cdot\mathrm{MSE}(\boldsymbol{e}(t)) \\ & \text{subject to} \quad 0 \le e_i(t) \le \min[e_i^{\max}, B_i(t)]\end{aligned} \tag{18}$$

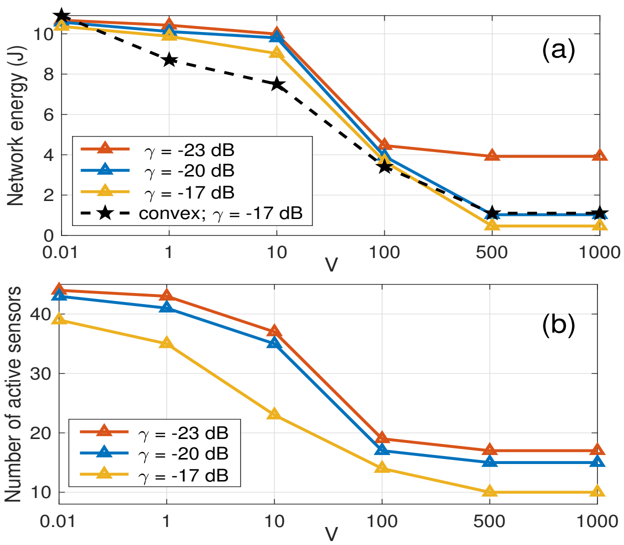


**Fig. 1**: Transmitted energy (a) and number of active nodes (b) versus time, for different values of the parameter $\gamma$.

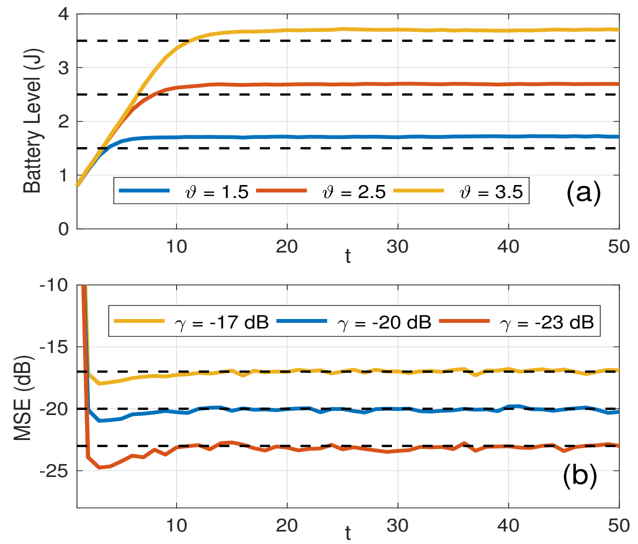


**Fig. 2**: Battery (a) and MSE (b) versus time, for different values of the parameters $\gamma$ and $\vartheta_i$.

where $\zeta_i(t) = \min[e_i^{\max}, B_i(t)]^2/(A^2 c_i^2)$. If $V > \widetilde{B}_i(t)$ for all $t$ [1], problem (21) is convex, and its globally optimal solution can be found using efficient algorithms [19].

## 4. NUMERICAL RESULTS

We consider a WSN with 50 nodes uniformly distributed over a disk of radius 100 meters. The graph signal belongs to the subspace spanned by the first six eigenvectors of the Laplacian matrix of a graph, whose adjacency matrix considers Gaussian weights depending on the relative distance among the nodes. The observation noise in (2) is zero-mean, Gaussian, with a variance $\sigma_i^2 = 10^{-4}$ for all $i$. The radio channels $\{h_i(t)\}$ consider free-space propagation with a carrier frequency equal to 10 MHz. The other parameters are: $A = 1$, $G_d = 10^{-3}$, $N_f = 10$, $\mathrm{BER}_i = 10^{-4}$ for all $i$. The i.i.d. EH variables $R_i(t)$ are extracted from a uniform distribution between 0 and $R^{\max} = 0.5$ for all $i, t$.

To assess the performance of the proposed resource allocation strategy, in Fig. 1(a), we illustrate the behavior of the sum of transmission energies over the network, averaged over 50 independent simulations, versus the control parameter $V$, for different values of the MSE threshold $\gamma$. As expected, increasing the value of $V$, from Fig. 1(a) we can notice how the average transmission energy decreases, until a minimum value that is lower for larger values of $\gamma$. This reduction of overall transmitted energy is also due to the fact that, for large values of $V$, many sensors do not transmit at all. Indeed, from 1(b), we can appreciate how the average number of active nodes (or, equivalently, the average cardinality of the sampling set) becomes smaller by increasing $V$, with floor values that again are lower if we consider larger values of $\gamma$. Also, in Fig. 1(a), using a dashed line we illustrate the behavior of the convex algorithm in (21), which performs similarly to its nonconvex counterpart in (18).

[1]To ensure $V > \widetilde{B}_i(t)$, it is sufficient to set $V > R^{\max}\ \forall i, t$ [cf. 19].

The algorithm behavior in terms of average transmitted energy and number of active nodes is obtained while guaranteeing a prescribed performance in terms of MSE and battery levels. To show this result, in Fig. 2(a), we illustrate the temporal behavior of the battery level, averaged over the sensors and over 50 independent simulations, considering $V = 100$ and different values of $\vartheta_i = \vartheta$ for all $i$. As we can notice From Fig. 2(a), the battery levels quickly become stable around a value slightly greater than $\vartheta$, while satisfying (19). Finally, in Fig. 2(b), we show the temporal behavior of the MSE, averaged over 50 independent simulations, considering $V = 100$ and different values of $\gamma$. As we can notice From Fig. 2(b), the algorithm stabilizes the MSE around $\gamma$, thus guaranteeing a target performance of signal estimation.

## 5. CONCLUSIONS

In this paper we have proposed a dynamic algorithm for optimally selecting radio parameters (i.e., transmission energies, quantization bits) and harvested energies in a WSN with EH devices, with the aim of estimating a time-varying signal with guaranteed average performance, while stabilizing the batteries around a prescribed level. The method builds on stochastic optimization tools and does not need any apriori knowledge of the statistics of the random radio channels and renewable energy arrivals. Interestingly, as a byproduct, the method dynamically selects the sampling set, i.e., the set of transmitting nodes. Numerical examples illustrate the good performance of the proposed dynamic resource allocation technique.

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