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Energy Efficient Traffic Allocation for Resource-constrained Multi-homed WSN Gateway

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Abstract

WSN (Wireless Sensor Network) gateway acts as a bridge between WSN and external networks. Currently, rapid growing demands from various IoTs (Internet of Things) applications are posing critical challenges to the data transmission capability of such gateway. As a promising solution, multi-homed WSN gateway, which is equipped with multiple network interfaces, can obtain enhanced parallel data transmission by jointly utilizing multiple RATs (Radio Access Technologies). However, the multi-homed gateway is a resource-constrained device, so it's crucial to guarantee the efficiency for both data throughput and resource consumption. Delay and buffer size, simulation results validate that the proposed algorithm can allocate To this end, an energy efficient traffic allocation algorithm for resource-constrained multi-homed WSN gateway is proposed in this paper, which aims at minimizing the gateway's power consumption while guaranteeing the transmission the traffic optimally for the gateway with different constraints and configurations, and it can significantly promote the gateway's energy efficiency in comparison to the traditional method.

Keywords: *traffic allocation, energy efficiency, multi-homing, wireless sensor network, optimization, resource management*

1. Introduction

As the bridge between WSN and external networks, WSN gateway acts an important role for the intercommunications of the both networks. In the future, the rapid increasing IoTs applications will enrich the demands for the sensing information, especially on the scale and transmission aspects. Forwarded by the WSN gateway, large amounts of sensing data generated by the sensors inside WSN will be uploaded as efficient as possible to the users from heterogeneous external networks. Therefore, the access to heterogeneous networks and the data forwarding throughput will be major indexes for the WSN gateway. In order to meet the above purpose, a WSN gateway needs to become a multi-homed device, which is equipped with multiple network interfaces for sufficient abilities to access multiple heterogeneous RATs, so the multi-homed WSN gateway not only can communicate with multiple users from heterogeneous external networks, but also can promote the data throughput by utilizing multiple heterogeneous RATs. However, the gateway is a resource-constrained device, such as the relative low computation and memory configurations, and limited power supply, so the gateway also needs to guarantee the efficiency when providing throughput improved data transmission via the multi-homing characteristic. For such a multi-homed WSN gateway, managing the utilization of these heterogeneous RATs efficiently and optimally is one of the key issues to achieve improved communication performance for the resource-constrained WSN gateway.

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There are two ways of multi-homed data transmission: the separated and joint utilization of RATs. The former employs single RAT for data transmission, while the latter splits data traffic into sub-flows and carries out parallel data transmission over multiple RATs simultaneously [1]. The entire transmission efficiency and quality of multi-home device can be effectively promoted by jointly utilizing multiple RATs. Literatures proposed on this field are mainly around the transmission schemes and corresponding architectures, which aim at system capacity maximization [2][3], throughput maximization [4], and QoS optimization [1], [5], etc. Multi-homed WSN gateway appears some particular characteristics, such as limited energy supply, constrained computation and memory capabilities, statistical property of WSN's traffic, etc., however, existing research barely addresses the transmission schemes for multi-homed WSN gateway.

This paper is focused on the resource-constrained multi-homed WSN gateway jointly utilizing multiple RATs. We investigate how to optimize data throughput and resource consumption by adjusting the data traffic allocated to each participating RAT, and we propose an energy efficient traffic allocation scheme while satisfying the data transmission delay requirements of IoTs applications and the buffer size constraints of the gateway. The main contributions of this paper can be summarized as follows: (1) we propose a parallel data transmission model for gateway jointly utilizing multiple RATs. Based on the characteristic of WSN's traffic, a queuing system is adopted for modeling the link over each RAT. A modified Shannon capacity formula is employed as a part of the gateway's power consumption model. (2) we formulate the minimization problem of gateway's total power consumption as a convex optimization problem constrained by total data transmission rate, system average buffer size, and total transmission delay. (3) Based on the solution derived from the problem formula, we give a traffic allocation algorithm, which includes a primal-dual interior point method.

The remainder of this paper is organized as follows: the description and formulation of the traffic allocation problem are described in Section 2. The proposed optimal traffic allocation algorithm is developed in Section 3. Simulation results and evaluations for the proposed algorithm are presented in Section 4. Finally, Section 5 draws conclusions of our work.

2. Problem Description and Formulation

Our system model consists of three parts: external network, WSN, and multi-homed WSN gateway. The external network integrates multiple heterogeneous RATs, which share the same core network system. WSN and external network are interconnected via the multi-homed WSN gateway, which is equipped with multiple network interfaces of RATs in the external network, and the network interface of WSN. The major traffic carried by the gateway is upstream (from WSN to external network), because most of the IoTs applications are based on sensing information collection. For joint utilization of RATs, the gateway gathers data traffic in WSN, then splits it into several sub-flows, and transmits them in parallel over multiple RATs. Finally, data flows are reassembled at the destination.

Power consumption by wireless communication is a major energy consumer in WSN gateway, especially in a multi-homed WSN gateway which integrates multiple baseband modules of RATs. These modules may cause higher-level power consumption when they are jointly utilized for parallel uplink communication. Transmission delay, which can indicate the throughput of the gateway's data forwarding, is an important criterion representing the gateway's support to real-time performance of IoTs applications. The limited computation capability makes the gateway hard to bear complex algorithms, and the limited memory capability further restricts the gateway's data buffer size. For these above factors, the objective of our traffic allocation scheme is to minimize the gateway's total power consumption while keeping the total transmission delay and buffer size within constraints, the corresponding algorithm is also required as efficient as possible.

A scenario is shown in Figure 1, where a multi-homed WSN gateway carries out parallel data transmission over n RATs. In the gateway, the data collected from WSN are split and scheduled via the traffic allocation algorithm, and the split data are queued and then forwarded to the external network through the corresponding RAT. We represent the set of RATs as $\mathbf{N} = \{1, 2, \ldots, n\}$, and RAT $i \in \mathbf{N}$. We define the gateway's data forwarding rate allocated to the interface of RAT i as λ_i, and the serving rate of RAT i as μ_i. The average queue length at the interface of RAT i is represented as L_i. The average packet sizes of RAT i are denoted as S_i. Thus, as the gateway's output, data throughput at interface of RAT i is $r_i = \lambda_i S_i$; as the gateway's input, data throughput at interface of WSN is defined as r_{WSN}. We consider extra overhead is generated by traffic splitting protocol [1], so$k r_{\mathrm{WSN}} = \sum_{i \in \mathbf{N}} r_i$, where the factor k is the ratio of overhead, and $k > 1$.

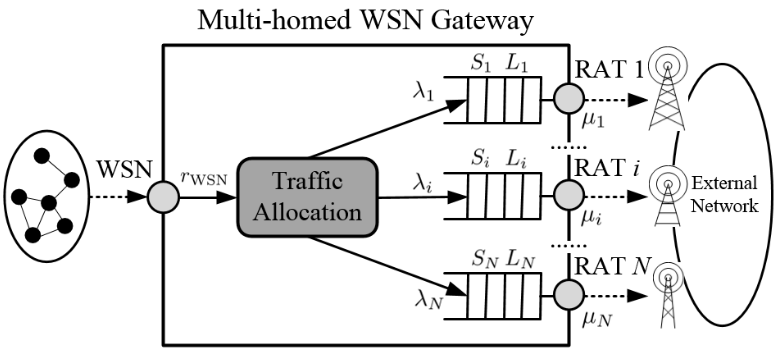

Figure 1. System Model

As same as the assumptions on the characteristic of WSN’s traffic and corresponding serving model in [6]-11], we suppose the sensing traffic generated by WSN follows the Poisson distribution, thus, as for the gateway, the data arrival at the interface of WSN also follows Poisson distribution. We also assume the serving rate at the interface of each RAT satisfies independent exponential distribution. Consequently, the M/M/1 queuing system can be applied for modeling the traffic at the interface of RAT i according to the queuing theory [12]:

Theorem 1: if the M/M/1 queue with arrival rate λ and serving rate μ satisfies$\lambda < \mu$, the probability of x clients staying in the queue exists, and it is independent with initial conditions.

$\lambda_i < \mu_i$ holds, that is, the allocated data arrival rate at the interface of RAT i is upper bounded by the maximum serving ability of RAT i, so based on the **Theorem 1**, the probability of x packets staying in the queue of RAT i exists, and it can be given by [12]:

$$P_i(x) = \left(\frac{\lambda_i}{\mu_i}\right)^x \left(1 - \frac{\lambda_i}{\mu_i}\right), \quad x = 0,1,2, \ldots \tag{1}$$

Then, we can express the average queue length at the interface of RAT i as:

$$L_i = \sum_{x=0}^{\infty} \big(xP(x)\big) = \frac{\lambda_i}{\mu_i - \lambda_i} \tag{2}$$

We assume that the queues of all RATs are shared in the gateway's memory, and all pending packets are stored in a buffer with average size Z. Thus, in order to avoid buffer overflow, the sum of each RAT's average queue size should be restricted by the average buffer size:

$$\sum_{i\in\mathbf{N}}(L_i S_i) < Z \tag{3}$$

Moreover, according to Little's theorem [12], we have the average delay of RATi:

$$d_i = \frac{L_i}{\lambda_i} = \frac{\lambda_i}{\mu_i - \lambda_i} \tag{4}$$

In parallel data transmission, data sub-flows are transmitted simultaneously from the gateway to all RATs. As a result, the total transmission delay is defined as the maximum average delay among all RATs, and it is denoted by:

$$d = \max_{i\in\mathbf{N}} d_i \tag{5}$$

We suppose channels between gateway and base station of each RAT are all AWGN channels. Commonly, all RATs are heterogeneous, and they work on non-overlapping frequencies. Also, RF circuits of these RATs are separately designed and placed in the WSN gateway. The noise power spectral density of the channel between gateway and base station of RAT i is expressed as N_i. B_i is the bandwidth of RAT i. p_i^r is defined as the received power at the base station of RAT i. Adopting the Shannon capacity formula, the gateway's data throughput at the interface of RAT i can be formulated as:

$$r_i = \rho_i B_i \log\left(1 + \frac{p_i^r}{N_i B_i}\right) \tag{6}$$

Where the constant $\rho_i \in (0,1]$ indicates the loss ratio due to the protocol overhead of RAT i. Considering the effect of path loss, we express gateway's transmit power for RAT i as:

$$p_i^t = \theta_i(p_i^r) = \theta_i\left(N_i B_i (2^{\frac{\lambda_i S_i}{\rho_i B_i}} - 1)\right) \tag{7}$$

Where the θ_i is the path loss function for RAT i, and θ_i can be formulated by wireless propagation models. Besides the transmission power, power consumed by the communication baseband module also contains circuit consumption for DA converter, mixer and frequency synthesizer, etc. The circuit power consumption remains fixedly even when the baseband module is in idle state. The circuit power consumption of RAT i can be given by [13]:

$$p_i^c = C_i B_i \tag{8}$$

Where C_i is a constant factor, which depends on the baseband circuit of RAT i. Combining (7) and (8), we can express the gateway's power consumption on RAT i as:

$$p_i(\lambda_i) = p_i^t + p_i^c = \theta_i\left(N_i B_i (2^{\frac{\lambda_i S_i}{\rho_i B_i}} - 1)\right) + C_i B_i \tag{9}$$

According to the above analysis, the minimization problem of gateway's total power consumption with constraints of total data throughputr_{WSN}, system average buffer size Z, and total transmission delay D can be formulated, and the optimal solution is:

$$\boldsymbol{\lambda}^* = \arg\min_{\boldsymbol{\lambda}}(f(\boldsymbol{\lambda})) = \arg\min_{\boldsymbol{\lambda}}\left(\sum_{i\in\mathbf{N}} p_i(\lambda_i)\right) \tag{10}$$

Subject to

$$\sum_{i\in\mathbf{N}} r_i = kr_{\mathrm{WSN}} \tag{11}$$

$$\sum_{i\in\mathbf{N}} (L_i S_i) \le Z \tag{12}$$

$$d \le D \tag{13}$$

$$0 \le \lambda_i \le \mu_i,\ \ i \in \mathbf{N} \tag{14}$$

Where the $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \dots, \lambda_n)^T$ is the $n \times 1$ vector of traffic allocation for each RAT, and $\boldsymbol{\lambda}^* = (\lambda_1^*, \lambda_2^*, \dots, \lambda_n^*)^T$ is the $n \times 1$ vector of optimal allocation.

Further, based on formula (5), formula (13) is equivalent to $d < D$, $i \in \mathbf{N}$. Then, with it substituted into formula (4), we have $\lambda_i < \mu_i - 1/D$. So the formula (13) and (14) can be rewritten as:

$$0 \le \lambda_i \le \mu_i - \frac{1}{D},\ \ i \in \mathbf{N} \tag{15}$$

3. Optimal Traffic Allocation Algorithm

An optimal traffic allocation algorithm using a primal-dual interior point method is proposed in this section.

We first prove the convexity of the optimization problem. Function (9) is convex since $p_i''(\lambda_i) > 0$ when linear or convex propagation models (θ_i is linear or convex) are adopted. The objective function in (10) is a positive weighted sum of formula (9) with independent λ_i, so it can be derived as convex since nonnegative weighted sum of convex formula is also convex [14]. Formula (11) and (15) are linear, and formula (12) is convex. Therefore, the optimal solution $\boldsymbol{\lambda}^*$ of the optimization problem exists and can be obtained.

The Lagrangian relaxation [14] is employed, then, by relaxing (11), (12) and (15), the Lagrangian function l is formulated from (10):

$$\begin{aligned} l(\boldsymbol{\lambda}; \boldsymbol{\omega}, \boldsymbol{\nu}) &= f(\boldsymbol{\lambda}) + \alpha\left(\sum_{i\in\mathbf{N}}(L_i S_i) - Z\right) \\ &+ \sum_{i\in\mathbf{N}}\left(\beta_i(\lambda_i - \mu_i + \frac{1}{D})\right) + \sum_{i\in\mathbf{N}}\big(\gamma_i(-\lambda_i)\big) + \nu\left(\sum_{i\in\mathbf{N}} r_i - kr_{\mathrm{WSN}}\right) \end{aligned} \tag{16}$$

where we define $\boldsymbol{\omega} = \left(\omega_1, \omega_2, \dots, \omega_j, \dots, \omega_{2n+1}\right)^T = (\alpha, \beta_1, \beta_2, \dots, \beta_n, \gamma_1, \gamma_2, \dots, \gamma_n)^T$ and $\boldsymbol{\nu} = (\nu)^T$ as the vectors of Lagrange multipliers, which are associated with inequality constraints (12), (15) and equality constraint (11), respectively. From the KKT conditions [14] of the optimization problem, we can have:

$$\mathbf{A}\boldsymbol{\lambda} = kr_{\mathrm{WSN}} \tag{17}$$

$$\nabla f(\boldsymbol{\lambda}) + (Drv\boldsymbol{g}(\boldsymbol{\lambda}))^T\boldsymbol{\omega} + \mathbf{A}^T\boldsymbol{\nu} = 0 \tag{18}$$

$$\omega_j g_j(\boldsymbol{\lambda}) = 0,\ \ j = 1,2,\dots,2n+1 \tag{19}$$

where $\mathbf{A} = (S_1, S_2, \ldots, S_n)$ is derived from the equality constraint (11), and $\boldsymbol{g}(\boldsymbol{\lambda}) = (g_1(\boldsymbol{\lambda}), g_2(\boldsymbol{\lambda}), \ldots, g_j(\boldsymbol{\lambda}), \ldots, g_{2n+1}(\boldsymbol{\lambda}) = (\sum_{i\in\mathbf{N}}(L_i S_i) - Z, \lambda_1 - \mu_1 + \frac{1}{D}, \lambda_2 - \mu_2 + \frac{1}{D}, \ldots, \lambda_n - \mu_n + \frac{1}{D}, -\lambda_1, -\lambda_2, \ldots, -\lambda_n)^T$ is defined as the vector combined by the inequality constraints (12) and (15). $Drv\boldsymbol{g}(\boldsymbol{\lambda}) = (\nabla g_1(\boldsymbol{\lambda})^T, \nabla g_2(\boldsymbol{\lambda})^T, \ldots, \nabla g_1(\boldsymbol{\lambda})^T, \ldots, \nabla g_{2n+1}(\boldsymbol{\lambda})^T)^T$ is the derivative matrix of $\boldsymbol{g}(\boldsymbol{\lambda})$. We replace the complementarity condition (19) by $-\omega_j g_j(\boldsymbol{\lambda}) = 1/t$, where $t > 0$ is a parameter that sets the accuracy of the approximation [14]. Then, we have the modified KKT conditions of the optimization problem, expressed as:

$$\boldsymbol{h}(\boldsymbol{\lambda}; \boldsymbol{\omega}, \boldsymbol{\nu}) = \begin{pmatrix} \nabla f(\boldsymbol{\lambda}) + \left(Drv\boldsymbol{g}(\boldsymbol{\lambda})\right)^T \boldsymbol{\omega} + \mathbf{A}^T \boldsymbol{\nu} \\ -\mathbf{diag}(\boldsymbol{\omega})\boldsymbol{g}(\boldsymbol{\lambda}) - \left(\frac{1}{t}\right)\mathbf{1} \\ \mathbf{A}\boldsymbol{\lambda} - kr_{\mathrm{WSN}} \end{pmatrix} = 0 \tag{20}$$

In the primal-dual interior point method, we define the current point as $\boldsymbol{p} = (\boldsymbol{\lambda}, \boldsymbol{\omega}, \boldsymbol{\nu})$, and the Newton step as $\Delta\boldsymbol{p} = (\Delta\boldsymbol{\lambda}, \Delta\boldsymbol{\omega}, \Delta\boldsymbol{\nu})$. The latter is characterized by Newton's method [14]:

$$\Delta\boldsymbol{p} = -(Drv\boldsymbol{h}(\boldsymbol{\lambda}; \boldsymbol{\omega}, \boldsymbol{\nu}))^{-1}\boldsymbol{h}(\boldsymbol{\lambda}; \boldsymbol{\omega}, \boldsymbol{\nu}) \tag{21}$$

The primal-dual search direction is the solution of (21), defined as $\Delta\boldsymbol{p}^*$. The process of the primal-dual interior point method is shown in **Algorithm 1**.

Algorithm 1 Primal-dual interior point method

Given

starting point $\boldsymbol{\lambda} := \boldsymbol{\lambda}^{(0)}$ that satisfies inequality constraints (12) and (15), $\boldsymbol{\omega} > 0$, $\xi > 1$, $\epsilon_{\mathrm{feas}} > 0$ and $\epsilon > 0$, where μ is the step size constant, ϵ_{feas} is the dual feasible tolerance, and ϵ is the tolerance of surrogate gap.

Repeat

1. *Determine t.* Set $t := (2n+1)\,\xi/\sigma$, where $\sigma = -\boldsymbol{g}(\boldsymbol{\lambda})^T\boldsymbol{\omega}$.

2. Compute primal-dual search direction $\Delta\boldsymbol{p}^*$.

3. *Line search and update*

   Determine step length $s > 0$ and set solution $\boldsymbol{p} := \boldsymbol{p} + s\,\Delta\boldsymbol{p}^*$.

Until

$||\mathbf{A}\boldsymbol{\lambda} - kr_{\mathrm{WSN}}||_2 \le \epsilon_{\mathrm{feas}}$,

$||\nabla f(\boldsymbol{\lambda}) + (Drv\boldsymbol{g}(\boldsymbol{\lambda}))^T\boldsymbol{\omega} + \mathbf{A}^T\boldsymbol{\nu}||_2 \le \epsilon$.

There is only one loop in the primal-dual interior point method, and the primal and dual iterates are not necessarily feasible. Moreover, the number of iterations to compute an accurate solution is typically small [14] (also confirmed in later simulations). Thus, this relative low complexity and fast convergence makes the method suitable for running in the gateway.

Finally, based on the primal-dual interior point method, we propose an optimal traffic allocation algorithm, which can be carried out via the radio resource management module of the gateway. The algorithm is shown in **Algorithm 2**.

Algorithm 2 Optimal traffic allocation algorithm

Loop

1. Periodically collect total data throughput r_{WSN} at the interface of WSN, and obtain theserving rate $\mu_1, \mu_2, \ldots, \mu_n$ from the base station of each RAT.

if $r_{\mathrm{WSN}} > 0$, **then**

2. Calculate the optimal traffic allocation $\boldsymbol{\lambda}^*$ via the primal-dual interior point method.

3. Feedback the $\boldsymbol{\lambda}^*$ to the traffic splitter [1] of the gateway. The traffic splitter operates traffic allocation by delivering packets to each RAT with different rate. For $i \in \mathbf{N}$, λ_i^* is the optimal packets delivery rate allocated to the interface of RAT i.

end if

end Loop

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4. Simulation Results

The performance of the proposed algorithm is evaluated in numerical simulations. The scenario comprises WSN, one multi-homed WSN gateway and base stations of RAT 1, 2, 3 ($n = 3$). The distance between the gateway and the base station of RAT i is defined as w_i. The overhead ratio of the traffic splitting protocol is $k = 1.1$.

Multiple propagation models can be applied to our proposed algorithm. They can be chosen according to the wireless environment where the WSN gateway is deployed. In the simulations, we suppose the simulation scenario is located in an urban area covered by cellular systems, thus we adopt modified Hata urban propagation models [15], and then the path loss function θ_i for RAT i is given by:

$$\theta_i(p_i^r) = \begin{cases} p_i^r + PL_i + \eta_i \lg\left(\dfrac{w_i}{W_i}\right), & w_i \geq W_i \\ p_i^r + PL_i + \eta_i \lg(W_i), & w_i < W_i \end{cases} \tag{22}$$

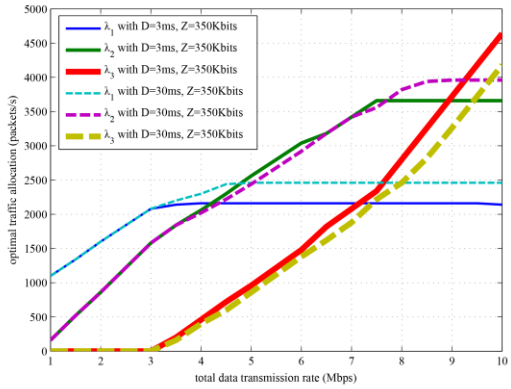
Where w_i is the distance between the gateway and the base station of RAT i. PL_i, η_i and W_i are the reference path loss, path loss factor and reference distance of RAT i, respectively. The parameters in the simulations are shown in **Table 1**, where we set the data throughputs of these RATs as RAT 1 < RAT 2 < RAT 3, and hence the energy consumptions on these RATs are: RAT 1 < RAT 2 < RAT 3.

Table 1. Simulation Parameters

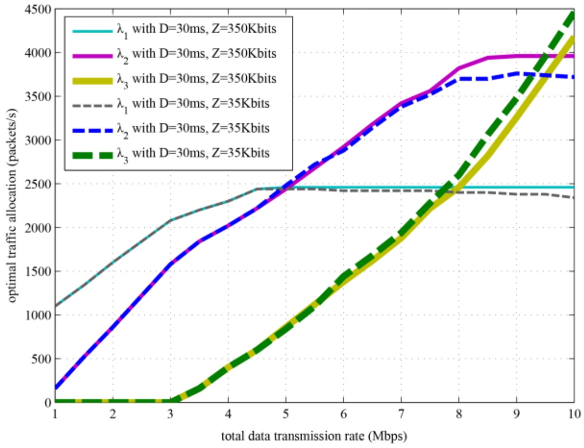
	RAT 1	RAT 2	RAT 3
w_i	120 m	120 m	120 m
r_i	2 Mbps	4 Mbps	6 Mbps
B_i	1 MHz	2 MHz	3 MHz
S_i	800 bits	1 000 bits	1 200 bits
ρ_i	0.8	0.75	0.7
C_i	6^{-8}	8^{-8}	10^{-8}
N_i	-170 dBm/Hz	-170 dBm/Hz	-170 dBm/Hz
PL_i	110	112	114
η_i	35	35	35
W_i	30 m	30 m	30 m

In order to analyze the traffic allocation under different parameters, we employ a multi-homed WSN gateway using RAT 1, 2, 3. r_{WSN} is set from 1 Mbps to 10 Mbps to represent the varying data throughput in WSN.

Figure 2(a) shows the allocation results under different total transmission delay constraints ($D = 3$ ms and$D = 30$ ms), and **Figure 2(b)** shows the allocation results under different average buffer size constraints ($Z = 35$ Kbits and $Z = 350$ Kbits). Overall, it can be observed that the RAT i with lower p_i and lower μ_i (such as RAT1 and RAT2) is primarily allocated. When it gradually reaches its upper bound of traffic allocation constrained by D and Z, the RAT i with higher p_i and higher μ_i (such as RAT3) is allocated with more traffic. In addition, when $Z = 350$ Kbits, as D lengthens from 3 ms to 30 ms, the upper bounds of traffic allocation on all RATs (especially, RAT1 and RAT2) grow due to the relaxation of D. When $D = 30$ ms, as Z narrows from 350 Kbits to 35 Kbits, we can observe that the difference between the allocation results is gradually enlarged, because L_i increases with λ_i (see (2)), it requires larger queue size, which may conflict with Z (such as RAT1 and RAT2, μ_1 and μ_2 are low), thus the allocated traffic arrival rates on RAT 1 and RAT2 with $Z = 35$ Kbits are lower than that with $Z = 350$ Kbits.



(a) Traffic Allocation under Different *D* Parameters



(b) Traffic Allocation under Different Z Parameters

Figure 2. Traffic Allocation under Different Parameters

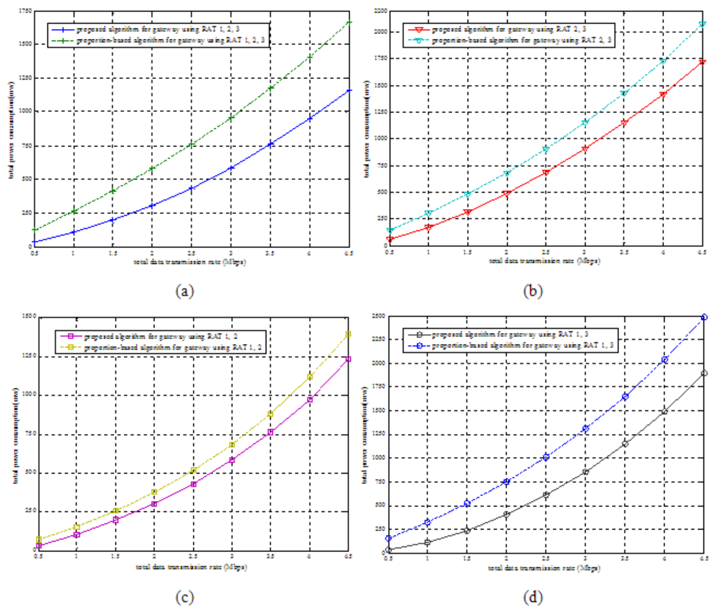


Figure 3. Total Power Consumptions Using the Two Algorithms

The traffic allocation for gateways with different configurations (using RAT 1, 2, 3, RAT 2, 3, RAT 1, 2 and RAT 1, 3, respectively, and $D = 30$ ms, $Z = 350$ Kbits) is evaluated. Firstly, we test the computation efficiency of the proposed algorithm. Due to the high efficiency of the primal-dual interior point method, in the proposed algorithm, numbers of iterations under the four configurations range from 17 to 23, which are very small. Secondly, we compare the energy efficiency between the proposed algorithm and the existing proportion-based algorithm. The proportion-based algorithm allocates the traffic according to the proportion of each RAT's serving rate in the total serving rates, and it can be given by:

$$r_i = k r_{\mathrm{WSN}} \frac{\mu_i}{\sum_{i \in \mathbf{N}} \mu_i} \tag{23}$$

If the allocated λ_i doesn't satisfy the constraint (12) and (15), its extra part will be allocated to other available RAT(s) proportionally. **Figure 3** shows the power consumptions optimized by the two algorithms, and its subfigures (a), (b), (c), (d) show the power consumptions with 4 different configurations, respectively. It can be seen that, with all 4 configurations, the total power consumptions via the proposed algorithm are all significantly lower than that via the corresponding proportion-based algorithm, especially when r_{WSN} is low. In addition, as r_{WSN} increases, RATs with low serving rates reach their capacity limits successively, due to the decrease of the number of operable RATs, the difference on the traffic allocation results of the two algorithms reduces continuously, so the gap between the total power consumptions of the two algorithms gradually decreases.

5. Conclusion

In this paper, an energy efficient traffic allocation scheme with transmission delay and buffer size constraints is proposed to improve the multi-homed WSN gateway's parallel data transmission. Simulation results demonstrate that the optimal traffic can be efficiently allocated for gateway with different parameters, and significant power savings are achieved.

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