

Research Article

Energy-Efficient Distributed Packet Scheduling Optimization Strategy in Cooperative Vehicle Infrastructure Systems

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In the cooperative vehicle infrastructure system (CVIS), due to the limitation of deployment conditions, some roadside units (RSUs) need to use renewable energy to supply power and transmit the fused sensor network's data to the backbone network through the passing vehicles. Aiming at the problem of energy consumption and time delay guarantee of multiple self-powered RSUs in the CVIS, a distributed packet scheduling optimization strategy for energy-delay trade-off in self-powered RSUs is proposed. The strategy can minimize the system energy consumption by constraining the packet queue length of the self-powered RSUs. A dynamic optimization model of distributed packet adaptive scheduling for multiple self-powered RSUs is established based on the Lyapunov optimization theory. Based on the knapsack algorithm, the analytical algorithm of the optimization model is proposed. The simulation results show that the packet scheduling strategy can reduce the energy consumption and delay of the system by satisfying the upper limit of the packet queue length.

1. Introduction

1.1. Motivation. The highway has the characteristics of long distance, small traffic density, relatively stable vehicle route, and moving speed, which is an important scene for the research and application of Internet of Vehicles [1, 2]. In the cooperative vehicle infrastructure system (CVIS), some highway roadside units (RSUs) deployed in remote mountainous areas, grassland forest belts, and Gobi Desert cannot directly access the system backbone network and power supply grid. In order to ensure the continuous operation of the equipment and real-time communication of data acquisition, it is necessary to maintain the power supply of renewable energy acquisition such as solar energy and wind energy through energy harvesting [3]. Data transmission is completed in the way of "store-carry-forward" through passing vehicles within its wireless coverage [4–6]. These RSUs not only are important network access equipment to provide information services for vehicles on highways but also serve as gateway nodes of sensor networks for the surrounding

environmental monitoring (traffic conditions, natural disasters, and animal activity information) and undertake the function of transmitting monitoring data to roadside units connected with the Internet [7].

In the above scenario, the utilization efficiency of external energy harvesting and the guarantee of monitoring data transmission efficiency are the most important issues when dealing with the distributed packet scheduling optimization of each self-powered RSUs in the CVIS. The monitoring data collected by the RSUs through the wireless sensor network needs to be sent to the RSUs connected to the Internet through the passing vehicles' relay. In order to ensure the timeliness of monitoring data, it is necessary to ensure the stability and efficiency of data transmission. Because the highway section is relatively long, it is assumed that under the condition of constant speed of vehicles, the fast vehicles will surpass the slow ones in the process of driving. Therefore, when the speed of vehicles reaching the coverage area of roadside units is slow, the RSUs should choose to send fewer packets to the vehicles or continue to wait until the

faster vehicles arrive and then send the packets to the vehicles for relaying transmission. For faster vehicles, the packets should be transferred to the vehicle as much as possible to reduce the queue length of RSUs' packet buffer. In this way, the system can reduce the waste of excess energy caused by transferring packets to slower vehicles. When the amount of RSU's data collection per unit time is fixed, the reduction of RSU's packet queue length reflects the improvement of transmission efficiency and the reduction of packet transmission delay [8]. Therefore, the main problem of this paper is to minimize the energy consumption of RSUs under the condition of low queuing delay and find the best trade-off point between energy consumption and delay.

1.2. Related Works. As mentioned in references [9, 10], the high-speed mobility of vehicles and the imbalance of vehicle distribution make the topology of vehicular networks change frequently. In reference [9], the vehicular sensing network-aided smart city model was constructed and its application in public service and urban flow management was evaluated. Then, the information source selection algorithm of the complex network and the sharing mechanism of urban information based on reinforcement learning were considered and a series of open challenges is also complemented. In reference [10], the weighted undirected graph model of Internet of Vehicles (IoV) sensing networks was established and the real taxi GPS dataset was used to verify its time invariant complex characteristics. In addition, the authors proposed an IOV-assisted local traffic information collection architecture, a sink node selection scheme for information influx, and an optimal traffic information transmission scheme. In order to improve the network access opportunities of vehicles, RSUs are deployed along the road. However, in some remote areas, the RSUs cannot be connected to the power system, so they can only operate by the way of external energy harvesting. According to the data of the U.S. Department of Transportation, it is estimated that 40% of the RSUs on highways will use energy harvesting to realize the self-powered supply through solar energy or wind energy harvesting equipment [11] and make corresponding scheduling according to the communication conditions and energy storage status of the system, so as to improve the system on the premise of ensuring the service life of RSUs' batteries. The energy efficiency can improve the performance of the CVIS.

Atallah et al. summarizes the application of renewable energy and energy harvesting technology in the field of Internet of Vehicles. By discussing the feasibility of introducing energy harvesting technology into the application of Internet of Vehicles, this paper puts forward the open research problems and directions to be solved in this field [3]. In reference [12], RSUs with self-powered function was designed to optimize the service capacity of the RSU under multiple time scales and the conditions for the system energy to reach the balance of supply and demand were studied. Ku et al. studied self-powered RSUs that can provide edge computing for Internet of Vehicles. Aiming at the energy consumption minimization problem of RSUs and space-time energy balance problem, a control algorithm combining energy consumption and service performance balance is proposed to mini-

mize QoS loss under the constraint of task delay [13]. Patra and Murthy proposed a decision-making method combining RSU deployment and dormant scheduling for self-powered RSUs with solar energy as the main energy collection source. The decision-making method combined with free flow vehicles and their speed distribution transformed the problem of RSUs' deployment interval optimization into work-sleep scheduling of RSUs to achieve the function of energy saving [14]. Nikookaran et al. studied the problem of RSUs' deployment to minimize the sum of capital and operation costs. In the literature, historical vehicle traffic tracks and a group of alternative deployment locations were sampled on highways to calculate the minimum deployment cost of RSUs. The study suggested that under specific conditions, more solar energy self-powered RSUs should be deployed on highways [15]. Khezriyan et al. studied the energy efficient downlink traffic scheduling optimization of multiple self-powered RSUs working together. By balancing the load energy consumption of each RSU, the energy consumption of the whole RSU system was balanced, which played a role in reducing consumption and increasing efficiency [16]. Atallah et al. studied the periodic charging self-powered RSUs based on reinforcement learning. Through the energy-saving adaptive scheduling protocol, the downstream traffic scheduling of RSU was optimized to maximize the number of service requests satisfied by rechargeable batteries of RSU in a discharge cycle [17]. Atoui et al. studied the downlink communication scheduling problem of self-powered RSUs. According to the energy state of the RSUs, the power was adjusted and the vehicles with different distances were selected to provide services and the number of service vehicles was maximized [18]. In reference [19], aiming at the energy efficiency problem of RSUs, under the condition that the energy of vehicles is not constrained, a scheduling method combining RSUs and relaying transmission of passing vehicles with multihop data forwarding is proposed, so as to reduce the energy consumption of RSUs. Hammad et al. studied the energy-saving scheduling problem of RSUs with variable bit rate transmission between RSUs and vehicles, obtained the lower limit of energy consumption to meet the demand of different vehicles' service volume, and designed the optimal offline variable bit rate slot scheduling algorithm of RSUs [20]. In reference [21–23], Ali et al. describes the "Green Vehicular Ad hoc Network (GVA-NET)" project, which is aimed at realizing the self-powered RSUs with reasonable cost, reliability, safety, and easy installation. At the equipment level, the project designs RSU's architecture for different fault events to ensure robustness. At the system level, the project designs a RSU system with strong sustainability, safety, reliability, and scalability.

1.3. Problem Statement and Novel Contributions. From the summary and analysis of the relevant research, it can be seen that at this stage, the main research topic based on the self-powered RSUs focuses on solving the problem of ensuring the data transmission accessibility of the RSU under the energy constraint, while the performance of the data communication network composed of all RSUs and packet-carrying vehicles on the whole road is less considered. In this paper,

we research the network performance requirements of minimizing the energy consumption of the self-powered RSUs and optimizing the service in the communication scenario between RSUs based on multigroup vehicles with relay under the background of the CVIS. In view of the trade-off between energy consumption and delay, the system dynamically adjusts the vehicles' speed selection range and the number of packets to be sent according to RSUs' packet queue length, which can reduce the transmission delay and energy consumption of self-powered RSUs. Specifically, according to the queue length of RSUs and the speed of vehicles passing by, the packet scheduling decision is made. Through the establishment of the optimization model, the optimization problem is analyzed and the optimal strategy is solved. The optimization problem is transformed by the Lyapunov function and analyzed through the structure of the optimal solution.

2. System Model

The environment monitoring data transmission scenario of the self-powered RSUs using passing vehicles' relaying in the in the CVIS studied in this paper is shown in Figure 1. N RSUs : $RSU_1, \dots, RSU_n, \dots, RSU_N$ are deployed on specific sections of the highway. Each RSU cannot be connected to the power grid and the Internet, so it is necessary to realize self-powered supply through energy harvesting technology to ensure the continuous work of the system. All vehicles passing through the coverage of RSUs can be used as mobile sinks to carry out data packet transmission and forward the packets to the RSU connected to the backbone network, so as to realize the data communication between isolated self-powered RSUs and environment monitoring data center.

2.1. Packet Scheduling Model of Self-Powered RSUs. The distributed packet scheduling model between the self-powered RSUs and the passing vehicles is shown in Figure 2. On this road section, there are N self-powered RSUs, harvesting renewable energy from the outside and storing them in their energy queue. Since the goal of this paper is to minimize energy consumption, the system needs to ensure that the energy is sufficient and will not be exhausted. The environmental monitoring data is stored in the data cache of RSUs, waiting to be sent in the form of packet queuing.

In order to describe the working process of the system conveniently, we set it as a discrete time system. In a certain time slot, if no vehicle passes through the RSU, the data packets of the RSU will be queued in its cache. If there are vehicles arriving at the RSU in the slot, the vehicle speed status $V_n[t]$ and packet queue status $Q_n[t]$ will be combined according to the packet scheduling strategy to determine whether to send packets to the vehicle and the duration of sending packets $\xi_n[t]$, so as to control the energy consumption and delay of the system. Finally, the packet-carrying vehicle will forward the data to the destination RSU connected with the Internet and then transmit the packet to the environment monitoring data center.

2.2. Vehicles' Speed State Model. Under the condition of free flow speed, the arrival time of vehicles obeys Poisson distribution with parameter μ and the time interval T between two vehicles arriving at RSU_n successively obeys negative exponential distribution. Its probability density function is $f(t) = \mu e^{-\mu t}$, $t > 0$ and the probability distribution function is $F(t) = P(T \leq t) = 1 - e^{-\mu t}$, $t > 0$. If the system time slot length is expressed by τ , then the probability that at least one vehicle will arrive in τ is as follows:

$$P_a = P(T \leq \tau) = 1 - e^{-\mu\tau}, \quad \tau > 0. \quad (1)$$

Defining t as the slot number, $t = \{0, 1 \dots T\}$ and $v_n[t]$ ($v[t] \geq 0$) is the speed status of the vehicle arriving at RSU_n in the slot t . In particular, $v_n[t] = 0$ means that no vehicle passes through RSU_n in time slot t .

It is assumed that the vehicle speed remains unchanged during the driving between RSUs and the vehicle speed is independently and identically distributed for each time slot. In the free flow velocity model, the probability density function of vehicle speed v follows the Gaussian distribution of mean value \bar{V} and standard deviation σ . It is shown as follows:

$$f(v)^* = \frac{1}{\sigma\sqrt{2\pi}} e^{[-(v-\bar{V}/\sigma\sqrt{2})^2]}. \quad (2)$$

Because of $v \in [V_{\min}, V_{\max}]$, the truncated probability density function of vehicle speed distribution can be expressed as follows:

$$f(v) = \frac{2f(v)^*}{\operatorname{erf}\left(\frac{V_{\max} - \bar{V}/\sigma\sqrt{2}}{\sigma\sqrt{2}}\right) - \operatorname{erf}\left(\frac{V_{\min} - \bar{V}/\sigma\sqrt{2}}{\sigma\sqrt{2}}\right)}. \quad (3)$$

2.3. Packet Scheduling Model. In the application scenario described in this paper, the speed of passing vehicles directly affects the packet scheduling time between RSU and vehicles, and the packet cache queue directly affects the work efficiency of the system. Therefore, the energy-delay trade-off distributed optimization strategy of packet scheduling proposed in this paper needs to start from two aspects: packet cache queue length and vehicle speed.

According to the above, the system should be modeled as a discrete time system and the slot length is t' . However, in the in the CVIS of the highway, the vehicle can only establish communication connection with RSU within whose coverage. When the vehicle drives out of the coverage of RSU_n , the communication will be disconnected. Until the vehicle enters the coverage of the next RSU, the vehicle can reestablish the connection with the RSU. Therefore, there are two communication states of on/off between vehicles and RSUs, which represent the working state and offline state between vehicles and RSUs.

Therefore, it is necessary to redefine the time slot length of the system as shown in Figure 3. The vehicles' arrival obeys the Poisson distribution with parameter μ . Therefore, it is assumed that the probability of establishing wireless

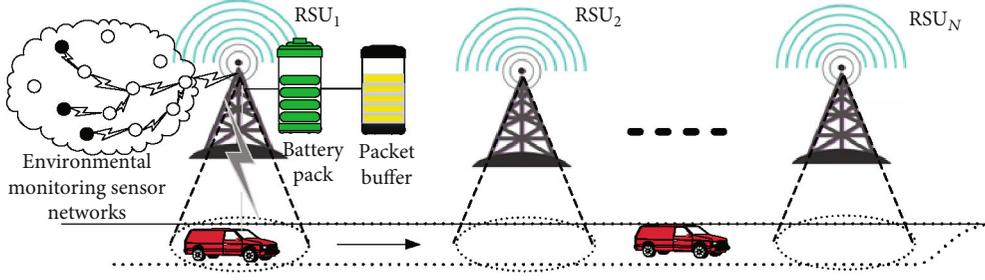


FIGURE 1: Schematic diagram of monitoring data transmission scene of self-powered RSUs.

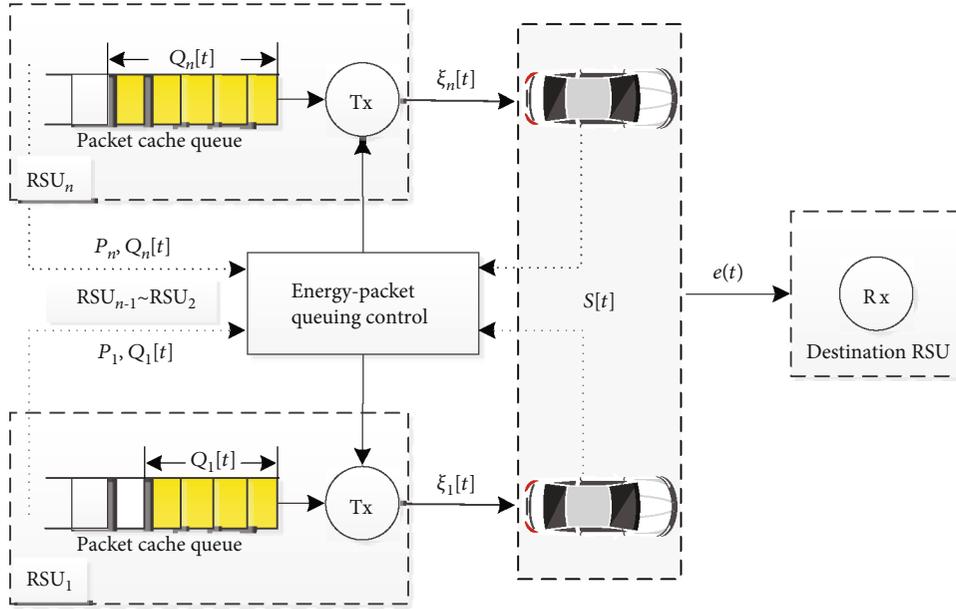


FIGURE 2: Data packet scheduling process model between self-powered RSUs and passing vehicles.

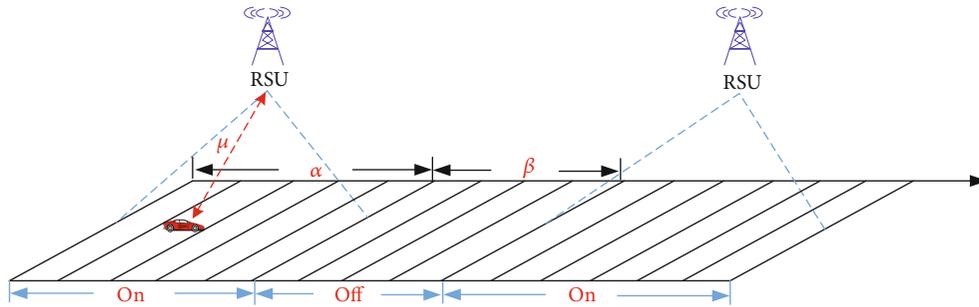


FIGURE 3: Interrupted Bernoulli process of the CVIS application scenario.

communication connection between the vehicles and RSU_n follows the interrupted Bernoulli process (IBP) with parameter (μ, α, β) . Among them, in the whole process of vehicles' relaying, the time occupied by the working state and offline state obeys the geometric distribution and the time of the two modes accounts for α and β of the total time, respec-

tively. Therefore, the discrete slot length τ in the on/off mode is redefined as follows:

$$\tau = \frac{t' \alpha}{\alpha + \beta}. \quad (4)$$

Because the number of vehicles under the coverage of RSUs is one of the important parameters to calculate the energy consumption of the system, it is necessary to establish a simple free flow model of traffic. By analyzing the vehicle distribution characteristics of the model, the number of vehicles in each time slot within the coverage of RSU $S[t]$ can be obtained.

The length of the road section considered in this paper is defined as L . According to the previous description, the average speed of vehicles under the speed limit of the highway is \bar{V} , while in the simple traffic free flow model, the default vehicle speed remains unchanged. Therefore, the cumulative distribution function of the vehicle's dwell time on this road section is as follows [24]:

$$\begin{aligned} F_r(\Delta t) &= 1 - F\left(\frac{L}{\Delta t}\right) \\ &= 1 - \frac{1 + \operatorname{erf}\left(\left(\frac{L}{\Delta t} - \bar{V}\right)/\sigma\sqrt{2}\right)}{\operatorname{erf}\left(\left(V_{\max} - \bar{V}\right)/\sigma\sqrt{2}\right) - \operatorname{erf}\left(\left(V_{\min} - \bar{V}\right)/\sigma\sqrt{2}\right)}, \end{aligned} \quad (5)$$

where $F(L/\Delta t)$ is the probability distribution function corresponding to equation (3). According to $F_r(\Delta t)$, the probability $P_n(t)$ of the number of vehicles $S[t] = n$ covered by RSU in time slot t can be deduced.

Since the arrival of vehicles obeys the Poisson distribution with parameter μ , the probability of k vehicles on this road section in the time interval of $(0, t)$ is expressed as follows:

$$a_k(t) = \frac{(\mu t)^k e^{-\mu t}}{k!}. \quad (6)$$

In equation (5), in slot t , the probability that any vehicle on the road section has arrived in slot t_i is $1 - F_r(t - t_i)$. Since the arrival of vehicles follows Poisson distribution, the distribution of vehicle arrival time with k vehicles arriving within the time interval of $(0, t)$ is equivalent to the uniform distribution of k points in the range of $(0, t)$. Therefore, the probability $P_k(t)$ of the existence of any k vehicles on the road section within time slot t is as follows:

$$P_k(t) = \int_0^t [1 - F_r(t - t_i)] \frac{dt_i}{t} = \frac{1}{t} \int_0^t [1 - F_r(t_i)] dt_i. \quad (7)$$

Therefore, the probability of opposite events of this event is as follows:

$$1 - P_k(t) = \frac{1}{t} \int_0^t F_r(t_i) dt_i. \quad (8)$$

Since the probability of an event with n vehicle running on the road section obeys binomial distribution under the condition that k vehicles arrive at the section within the time interval of $(0, t)$, the probability of the event can be deduced

from equations (7) and (8).

$$P_{n|k}(t) = \begin{cases} C_k^n [P_k(t)]^n [1 - P_k(t)]^{k-n}, & n \leq k, \\ 0, & n > k. \end{cases} \quad (9)$$

It is known that the probability of establishing communication connection between the vehicle and RSU $_n$ follows the IBP with parameter (μ, α, β) . The probability of k vehicles in the coverage of RSU in the t th slot can be deduced by synthesizing equations (6) and (9).

$$\begin{aligned} P(S[t] = k) &= \frac{\alpha}{\alpha + \beta} \sum_{k=n}^{\infty} C_k^n [P_k(t)]^n [1 - P_k(t)]^{k-n} \cdot \frac{(\mu t)^k e^{-\mu t}}{k!} \\ &= \frac{\alpha [\mu t \cdot P_k(t)]^n e^{-\mu t \cdot P_k(t)}}{(\alpha + \beta) n!}. \end{aligned} \quad (10)$$

In order to ensure the low delay of the packet forwarding, effectively reduce the energy consumption of the system and the self-powered RSUs needs to determine the duration of sending packets $\xi_n[t]$ to the vehicles according to the different speed states. If the speed of the passing vehicle is faster, the corresponding RSU $_n$ packet transmission time $\xi_n[t]$ of RSU $_n$ should be larger; conversely, if the speed of the passing vehicle is slow, RSU $_n$ should reduce the packet transmission time accordingly.

Firstly, we defined the packet transmission duration vector as $\xi[t] = \{\xi_1[t], \dots, \xi_n[t]\}$ and the number of packets transmitted by RSU $_n$ in unit time as R_n . Therefore, the number of packets transmitted by RSU $_n$ in time slot t is known as $D_n[t] = R_n \xi_n[t]$. Since the number of queued packets $Q_n[t]$ in the packet queue is limited in time slot t , the relationship between the number of packets queued and packets forwarded should be met as follows:

$$Q_n[t] \geq R_n \xi_n[t], \quad \forall n \in N. \quad (11)$$

Secondly, the speed status of passing vehicles directly affects the duration of packet forwarding $\xi_n[t]$. The faster the speed is, the longer the packet transmission duration is, and the duration should not exceed the slot length τ . Therefore, $\xi_n[t]$ needs to satisfy the following relationship:

$$\xi_n[t] = \begin{cases} \tau P\{\xi_n[t] = \tau | v_n[t] = m, A_n[t] = a, Q_n[t-1] = q\}, & 1 \leq m \leq M, \\ 0, & m = M + 1, \end{cases} \quad (12)$$

where $a = \{0, 1\}$, $0 \leq q \leq Q$. According to equations (11) and (12), the following relationship is obtained:

$$0 \leq \xi_n[t] \leq T_n[t], \quad \forall n \in N, \quad (13)$$

where $T_n[t] = \min\{(Q_n[t])/R_n, \tau\}$.

Finally, considering the packet forwarding states of all RSUs in the CVIS, the overall packet forwarding duration

$\xi_n[t]$ of the system should meet the following conditions:

$$\sum_{n=1}^i \xi_n[t] \leq S[t]\tau, \quad 1 \leq i \leq N. \quad (14)$$

2.4. Packet Queue Model of RSUs. Let $Q_n[t+1]$ denote the queue length of RSU_{*n*}'s packet cache in time slot $t+1$, and its state update expression is as follows:

$$Q_n[t+1] = \max \{Q_n[t] - D_n[t], 0\} + A_n[t]. \quad (15)$$

Because the packet queue length in RSU directly represents the efficiency of the system, the packet queue length of RSU is at a low level while reducing the transmission delay of the system. Therefore, in order to ensure the low delay of the system, it is necessary to set an upper bound value ε of the packet queue length to control the average queue length q_n of RSU. Therefore, the expression of the average packet queue length is as follows:

$$q_n = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} E\{Q_n[t]\} < \varepsilon, \quad \exists \varepsilon \in \mathfrak{R}^+. \quad (16)$$

2.5. Energy Consumption Model of the CVIS. Under the condition that the packet transmission power P_n of each RSU_{*n*} is known, the duration $\xi_n[t]$ of each RSU sending packets to passing vehicles in each time slot can be deduced. Thus, the energy consumption of each RSU due to packet transmission in time slot t is obtained. The expression of total energy consumption $e(t)$ of packet transmission in slot t in the whole CVIS is as follows:

$$e(t) = \sum_{n=1}^i P_n \xi_n[t], \quad 1 \leq i \leq N. \quad (17)$$

However, the number of vehicles passing through RSU and its speed state are dynamic. Therefore, it is more scientific to analyze the average energy consumption of the CVIS under a long-term operation. The expression of long-term average energy consumption of the system is as follows:

$$e = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} E\{e(t)\}. \quad (18)$$

3. Optimization Problem

From the discussion in the previous section, keeping the packet queue length of the system at a low state reflects the efficiency of the CVIS. Therefore, the packet scheduling optimization strategy proposed in this paper needs to control the packet transmission time of RSUs by the speed of the relaying vehicles.

The optimization goal is to minimize the total energy consumption of the CVIS, reduce the packet backlog as much as possible, and improve the packet transmission efficiency while reducing the queuing delay of the system. However, due to the stochasticity of the speed status of each vehicle

within the coverage of self-powered RSUs, if the system only waits for the fastest vehicle for packet transmission, although the energy consumption will be minimized, many packets will be overstocked, which directly reduces the work efficiency of the system. Therefore, there is a trade-off relationship between the energy consumption and the queue length of RSUs' packet cache. The optimization problem proposed in this paper coordinates the relationship between the energy and the delay and solves the trade-off between energy consumption and work efficiency of the CVIS. The optimization model is as follows:

$$\begin{aligned} \min_{\xi(t)} e &= \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} E\{e(t)\}, \\ \text{s.t.} &\begin{cases} 0 \leq \xi_n[t] \leq T_n[t], & 1 \leq n \leq N, \\ \sum_{n=1}^i \xi_n[t] \leq S[t] \cdot \tau, & 0 < i < N, \\ q_n = \lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=0}^{T-1} E\{Q_n[t]\} < \varepsilon, & \exists \varepsilon \in \mathfrak{R}^+. \end{cases} \end{aligned} \quad (19)$$

Due to the stochasticity of packet's arrival state and vehicles' speed in optimization problem (19), it is difficult to predict and analyze each state of the system through offline data statistics. In this scenario, the state space is huge and the online optimization scheme of optimization problem (19) has high computational complexity, so it is necessary to transform the problem (19) accordingly to reduce its computational complexity.

3.1. Lyapunov Optimization and Model Transformation. In this paper, we can use the Lyapunov optimization theory to transform the model, reduce the computational complexity of the model, so as to reflect the trade-off relationship between energy and packet queuing in a more intuitive way, and simplify the constraints.

Firstly, the vector matrix $\boldsymbol{\theta}(\mathbf{t})$ of each RSU_{*n*} packet queue length state $Q_n[t]$ is defined and the Lyapunov function is defined by $\boldsymbol{\theta}(\mathbf{t})$ as follows:

$$L(\boldsymbol{\theta}(\mathbf{t})) = \frac{1}{2} \sum_{n=1}^N Q_n^2[t]. \quad (20)$$

Therefore, the packet queuing state in each RSU is transformed into the form of equation (20). If the value of $L(\boldsymbol{\theta}(\mathbf{t}))$ is large, it indicates that at least one RSU has a large packet backlog; if the value of $L(\boldsymbol{\theta}(\mathbf{t}))$ is small, the packet backlog in each RSU is small. Therefore, reducing the value of $L(\boldsymbol{\theta}(\mathbf{t}))$ can directly reduce the overall packet queue length of the system. The Lyapunov drift $\Delta(\boldsymbol{\theta}(\mathbf{t}))$ can be obtained as follows:

$$\Delta(\boldsymbol{\theta}(\mathbf{t})) = E\{L(\boldsymbol{\theta}(\mathbf{t}+1)) - L(\boldsymbol{\theta}(\mathbf{t})) \mid \boldsymbol{\theta}(\mathbf{t})\}. \quad (21)$$

Since the system optimization problem should reflect the trade-off relationship between energy consumption and

packet queue length, energy should be added as a drift component in equation (21), so the redefined Lyapunov drift is expressed as follows:

$$\Delta(\mathbf{\theta}(t)) + VE\{e(t) | \mathbf{\theta}(t)\}, \quad (22)$$

where $V > 0$. As a parameter to coordinate the trade-off between the packet queue length and the energy consumption, the larger the value of V , the greater the weight of energy consumption in the Lyapunov drift parameter, the greater the impact on the system drift. Therefore, the system can be optimized by adjusting the value of V . The upper bound of Lyapunov is deduced to optimize the system.

According to the theorem, there is $\{\max[(a-b), 0]\}^2 \leq a^2 + b^2 - 2ab$ for $\forall a, b \geq 0$, so equation (15) can be transformed into the following expression:

$$Q_n[t+1]^2 \leq Q_n[t]^2 + A_n[t]^2 + D_n[t]^2 - 2Q_n[t]D_n[t] + 2 \max\{Q_n[t] - D_n[t], 0\}. \quad (23)$$

Since the size relationship between the queue length of RSU_n 's packets $Q_n[t]$ and the number of packets that can be sent $D_n[t]$ is uncertain, let $D_n[t]'$ denote the number of packets actually sent by RSU_n to passing vehicles in slot t as follows:

$$D_n[t]' = \begin{cases} D_n[t], & Q_n[t] \geq D_n[t], \\ Q_n[t], & \text{else.} \end{cases} \quad (24)$$

From equation (24), it can be concluded that

$$\max\{Q_n[t] - D_n[t], 0\} = Q_n[t] - D_n[t]'. \quad (25)$$

Using equations (23) and (25), the following relationship can be derived:

$$Q_n[t+1]^2 - Q_n[t]^2 \leq A_n[t]^2 + D_n[t]^2 + 2Q_n[t](A_n[t] - D_n[t]') - 2A_n[t]D_n[t]'. \quad (26)$$

Since $2A_n[t]D_n[t]' \geq 0$, the term does not affect the inequality of equation (26) and the inequality can be simplified by omitting this term. Therefore, inequality (25) can be transformed into the following expression:

$$\frac{1}{2}(Q_n[t+1]^2 - Q_n[t]^2) \leq \frac{1}{2}(A_n[t]^2 + D_n[t]^2) + Q_n[t](A_n[t] - D_n[t]'). \quad (27)$$

According to the relationship between equations (20), (21), and (27), we can get that the packet queue length of all RSUs in the system satisfies the following relationship:

$$\Delta(\mathbf{\theta}(t)) \leq \frac{1}{2} \sum_{n=1}^N E\{A_n[t]^2 + D_n[t]^2 | \mathbf{\theta}(t)\} + \sum_{n=1}^N Q_n[t] E\{A_n[t] - D_n[t] | \mathbf{\theta}(t)\}. \quad (28)$$

Let A_n^{\max} be the maximum value of $A_n[t]$ and R_n^{\max} the maximum value of R_n . Therefore, the right terms in equation (28) satisfy the following relation:

$$D_n[t] = R_n \xi_n[t] \leq R_n^{\max}, \quad (29)$$

$$\sum_{n=1}^N E\{A_n[t]^2 + D_n[t]^2 | \mathbf{\theta}(t)\} \leq \sum_{n=1}^N [(A_n^{\max})^2 + (R_n^{\max})^2]. \quad (30)$$

Let the parameter $C = (1/2)N[(A_n^{\max})^2 + (R_n^{\max})^2]$ and bring it into equation (28). The Lyapunov drift function described in equation (22) satisfies the following inequality relationship:

$$\Delta(\mathbf{\theta}(t)) + VE\{e(t) | \mathbf{\theta}(t)\} \leq C + \sum_{n=1}^N Q_n[t] E\{A_n[t] - D_n[t] | \mathbf{\theta}(t)\} + VE\{P_n \xi_n[t] | \mathbf{\theta}(t)\}. \quad (31)$$

The right part of inequality (31) is the upper bound of the Lyapunov drift function. By minimizing the upper bound, we can adjust the packet transmission duration $\xi_n[t]$ to obtain the optimal critical point of the optimization model. Therefore, the optimization model of the system is further transformed into the following expressions:

$$\min_{\xi_n[t]} \left\{ C + \sum_{n=1}^N Q_n[t] \{A_n[t] - R_n[t] \xi_n[t]\} + V \sum_{n=1}^N P_n \xi_n[t] \right\}, \quad (32)$$

where C and $A_n[t]$ are constants in unit time, which do not affect the system optimization results, so they can be ignored, so equation (29) can be simplified as follows:

$$\min_{\xi_n[t]} \sum_{n=1}^N \{VP_n - Q_n[t]R_n\} \xi_n[t]. \quad (33)$$

Let $\sigma_n[t] = Q_n[t]R_n - VP_n$, and bring it into equation (33) to get the final system optimization model:

$$\begin{aligned} & \max_{\xi_n[t]} \sum_{n=1}^N \sigma_n[t] \xi_n[t], \\ & \text{s.t.} \begin{cases} 0 \leq \xi_n[t] \leq T_n[t], & 1 \leq n \leq N, \\ \sum_{n=1}^N \xi_n[t] \leq S[t] \bullet \tau. \end{cases} \end{aligned} \quad (34)$$

In this paper, the proposed distributed energy-delay trade-off packet scheduling optimization strategy based on the Lyapunov optimization theory only needs to observe the backlog of all queues (packets queue and energy queue) and make corresponding decisions on the status of RSUs and passing vehicles. Therefore, the complexity of the algorithm is linear with the number of RSUs N , which is easy to realize.

TABLE 1: Simulation parameters.

Parameter	Symbol	Value	Unit
Length of expressway	L	10	Kilometer
Number of RSUs _s	N	10	/
Coverage radius of RSUs	R	250	Meter
Speed limit	$[V_{\min}, V_{\max}]$	[16.67, 33.33]	Meter/second
Speed expectation	\bar{V}	25	Meter/second
Speed standard deviation	σ	5.56	/
Vehicle arrival rate	μ	0.55	Vehicles/second
Slot length	t'	1	Second
Loop count	t	1500	/

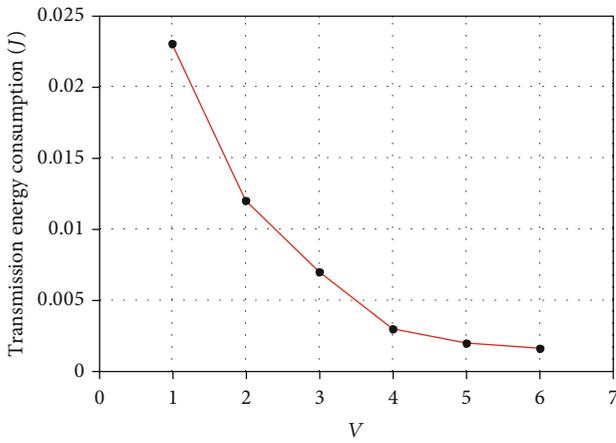


FIGURE 4: Trend of energy consumption changing with weight.

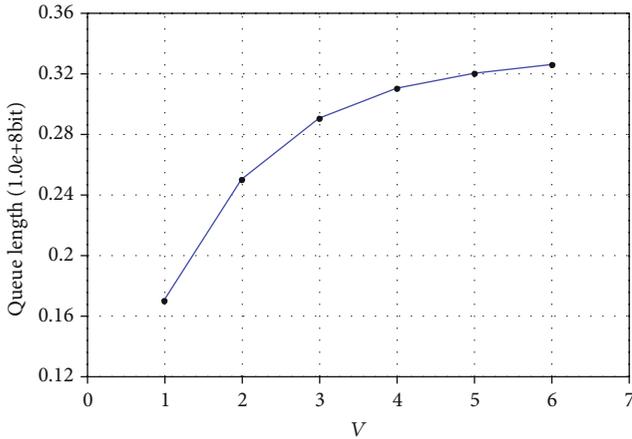


FIGURE 5: Trend of packet queue length changing with weight.

3.2. Analytical Algorithm of Optimization Problem. It can be seen from the model derived in the previous section that the optimization process of the system model can be analogized to maximize the value of the system in the limited

resource space. The constraint of the optimization model is the resource space, and the output value of the model is the embodiment of the system value. Therefore, the model can be transformed into a knapsack problem to solve [25].

The parameter $\sigma_n[t]$ of the system optimization model represents the system value. First, the system needs to sort the values of $\sigma_n[t]$ in a descending order. Secondly, the ordered $\sigma_n[t]$ is put into the limited resource space in order, that is, “backpack.” The key of the knapsack problem analysis is to find the break point of the process. Therefore, through the known interruption conditions of knapsack problem, the following is found:

- (i) The remaining resource space is empty
- (ii) The value of the “items” put into the “knapsack” is negative

Once the optimal break point of the knapsack problem is obtained, the optimal packet transmission duration $\xi_n^*[t]$ of the system can be deduced.

In order to obtain the optimal break point, Y is defined as the interruption index of the knapsack problem and $Y = \min \{\gamma_1, \gamma_2\}$, where γ_1, γ_2 satisfies the following relationship:

$$\begin{cases} \gamma_1 = \operatorname{argmin}_n \sum_{m=1}^n T_m[t] > S[t] \cdot \tau, \\ \gamma_2 = \operatorname{argmax}_n \sigma_n[t] \geq 0. \end{cases} \quad (35)$$

Therefore, the optimal packet transmission duration $\xi_n^*[t]$ is expressed as follows:

$$\xi_n^*(t) = \begin{cases} T_n[t], & n < Y, \\ \min \left\{ S[t] \tau - \sum_{n=1}^{Y-1} T_n[t], T_Y[t] \right\}, & n = Y, \\ 0, & \text{else.} \end{cases} \quad (36)$$

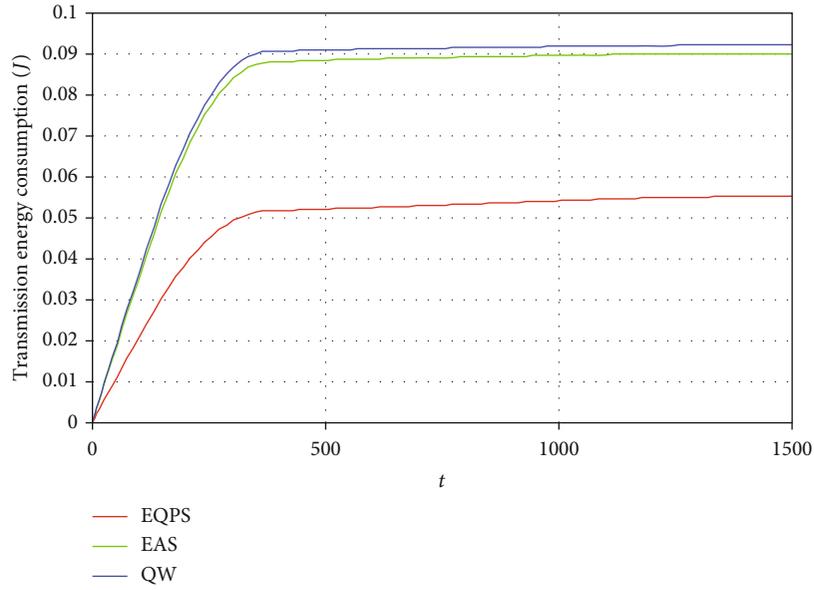


FIGURE 6: Comparison of system energy consumption simulation under different strategies.

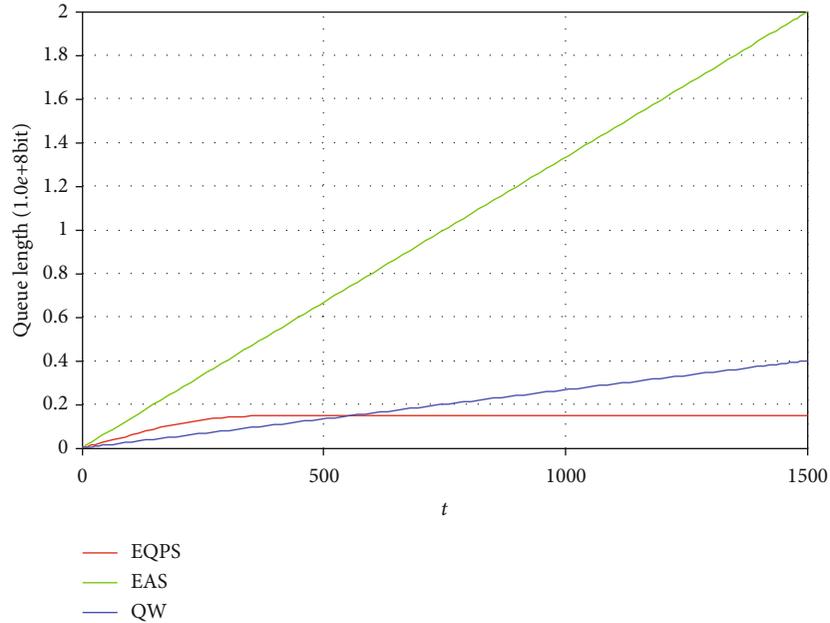


FIGURE 7: Comparison of packet queue length simulation under different strategies.

4. Simulation and Analysis

Aiming at the energy-efficient distributed packet scheduling optimization strategy (EQPS) proposed in this chapter, the following two parts of simulation experiments are carried out by using the simulation software MATLAB:

- (i) According to the system optimization model, the trend of system energy consumption and packet queuing with weight coefficient is drawn
- (ii) Under the same simulation parameters, this strategy model and the two commonly used baseline models

are compared and analyzed in terms of energy consumption and packet queuing

The basic parameters of simulation are as shown in Table 1:

In this scenario, the packet arrival rate and transmission power of RSU are uniformly distributed: $A_n[t] \sim U[0, 2000]$ bits/s, $P_n \sim U[10, 200]$ mW, so the packet transmission rate of RSU is $R_n \in [1330, 1760]$ bits/s.

The two baseline models are equal allocation strategy (EAS) and queue-weighted strategy (QW). Among them, the EAS means that the system allocates the equal packet transmission duration to all passing vehicles connected with

the RSUs. The QW means that the system determines the weight of the duration of packet transmission with vehicles according to the backlog of packets in RSU. In other words, the larger the backlog of RSU packets is, the greater the weight is, and the longer the packet transmission duration is.

The performance simulation results of EQPS proposed in this paper are shown in Figures 4 and 5, where Figure 4 shows the trend of energy consumption per time slot with the increase of weight V . The simulation results show that the overall energy consumption of the system decreases with the increase of weight V . The reason is that with the increase of weight, the impact of energy consumption on system performance increases, so the system will adaptively reduce energy consumption to balance the overall performance of the system. Similarly, Figure 5 shows the changing trend of the queue length with the weight V increasing. The length of system packet queue increases with the increase of weight V . As the weight V increases, the impact of packet queuing on system performance is relatively reduced. Therefore, while the energy consumption of the system is reduced, the queue length of the whole packet is increased, which shows that the system can balance the system performance adaptively and optimize the whole system.

Under the condition that the weight of the EQPS is set to 2, the comparison results between the EQPS and the two baseline models are shown in Figures 6 and 7. Figure 6 shows the energy consumption comparison of the system, and Figure 7 shows the comparison of the packet queue length. The simulation results show that the long-term system energy consumption and long-term packet queue length of EQPS are the lowest, because EQPS can adaptively coordinate the packet transmission duration from the vehicle speed state and packet queue length, so as to improve the system efficiency. However, the EAS strategy cannot optimize the packet transmission delay according to the vehicle speed and packet queue length. The QW only optimizes the system from the perspective of packet queue length, ignoring the impact of vehicle speed on packet transmission delay. Therefore, the system performance of these two strategies is lower than that of EQPS.

5. Conclusions

In this paper, we study the packet scheduling problem of self-powered RSUs through passing vehicles' relaying under the background of Internet of Vehicles. In order to minimize the energy consumption of packet transmission from all self-powered RSUs to passing vehicles and improve the packet transmission efficiency of the system. In this paper, a distributed packet scheduling optimization strategy for energy-delay trade-off in self-powered RSUs is proposed. The strategy makes packet scheduling decisions according to the queue length of self-powered RSUs and the speed of passing vehicles. Taking the minimization of system energy consumption as the optimization objective, the energy-delay trade-off model is transformed and solved by using the Lyapunov optimization theory and knapsack problem's optimization algorithm with the main constraint of packet queue length of self-powered RSUs. According to the optimal

solution of the above optimization algorithm, the optimal packet scheduling strategy is obtained. Simulation results show that the packet scheduling strategy proposed in this paper can effectively reduce the energy consumption and improve the packet transmission efficiency of the whole self-powered RSU system under the packet queue length constraint.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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