Power Allocation With Energy Efficiency Optimization in Cellular D2D-Based V2X Communication Network

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***Abstract*—In vehicle-to-everything (V2X) communication network, cellular device-to-device (D2D) communication can not only improve data rate and spectral utilization but also reduce the traffic load and power consumption. However, cellular D2D-based V2X technology has also a potential deficiency to meet various requirements of V2X communication, particularly in energy efficiency (EE). Power allocation provides an important approach to optimize the EE. In this paper, a new approach for power allocation with EE optimization (EEO) is proposed in cellular D2D-based V2X communication network. The mathematical framework of the new approach is formulated and proved and an algorithm is also proposed. Numerical simulation results are provided to demonstrate the feasibility of the proposed algorithm and the superiority over existing well-known algorithms.**

***Index Terms*—V2X communication, device-to-device (D2D), power allocation, energy efficiency (EE), energy harvesting (EH).**

I. Introduction

VEHICLE-TO-EVERYTHING (V2X) communication has attracted considerable attention in the recent years [1]–[3]. On the one hand, the exponential growth communication puts high pressure on cellular networks to meet the growing demand of mobile data, resulting in an increasingly severe overload problem [4]–[6]. On the other hand, the performance for V2X communication was analyzed that it is not always availed in cellular vehicular systems [7], particularly in terms of reliability [8]. Therefore, there is a strong desire for finding better solutions to support V2X communication.

Device-to-device (D2D) is a promising technology to improve reliability by supporting two closely located users reusing uplink or downlink resources of cellular users (CUs) for direct communication [9]–[11]. Besides high reliability, D2D communication also takes several advantages in terms of spectral utilization, traffic load and power consumption [12]–[14]. Therefore, D2D communication has been incorporating into V2X communication networks [15]. Furthermore, cellular networks assisted with D2D communication will provide an efficient and reliable V2X communication, which can meet V2X communication requirements due to several intrinsic advantages (i.e., fast link adaptation and dynamic user scheduling, reliable support and energy-efficient (EE) V2X users) [16]–[18].

Some related work has considered the EE optimization (EEO) problem for cellular D2D-based V2X communication. In [19], joint resource allocation and power control for EE in cellular D2D-based V2X communication were investigated, where the original non-convex optimization problem in fractional form was transformed into an equivalent optimization problem. In [20], power control with channel allocation was proposed to optimize the EE of cellular D2D-based V2X communication. To address the non-convexity EEO problem, the original problem was divided into two subproblems and an iterative algorithm was designed to solve it. In [21], an EE power control scheme for cellular D2D-based V2X communication was proposed, where multiple D2D pairs reused one cellular user resource. Taken data rate and transmit power into account, the EEO problem was formulated as a non-concave problem and the corresponding two-loop iterative algorithm was presented to solve it. However, as all the aforementioned schemes seldom take into account the interference problem between CUs and D2D, directly utilizing such optimal algorithms to V2X communication is not the best choice. Fortunately, power allocation can provide a way to mitigate interference, and thus optimize EE [22]–[25].

In this paper, a power allocation approach for EEO in cellular D2D-based V2X communication network is proposed, where information transmission is usually categorized into two types: vehicle-to-infrastructure (V2I) communications and vehicle-to-vehicle (V2V) communications. The D2D-based V2V users are denoted as V-UEs [26] and the cell-based V2I users are denoted as C-UEs. In practice, when vehicles pairs are working in a close proximity, and each vehicle is also connected to cellular vehicular network, where the energy is a major bottleneck in the operation [23]. An emerging solution to this impeding problem is the exploitation of energy harvesting (EH) at the vehicles [2], [11], [14]. Against this

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background, we consider a cellular network simultaneously supporting multiple EH aided D2D links that rely on reusing the downlink cellular resources of multiple C-UEs. We formulate our resource allocation design as an EEO problem for cellular D2D-based V2X communication links. This objective is achieved by jointly optimizing the V-UEs resource reuse and the power allocation of D2D links, whilst satisfying the quality-of-service (QoS) constraints of the C-UEs and the EH constraints of the D2D links. The optimization and analysis of EH aided D2D communication underlaying cellular networks for radio resource and power allocation at D2D links is a relatively unexplored research area.

The main contributions of this paper are summarized as follows:

- We aim to optimize the EE problem under multiple constraint conditions, which include the SINR threshold, the total power constraint, and EH target. In [27], a power allocation strategy for the EH-aided D2D communication underlaying cellular network is investigated, which proves that EH can boost the system performance. Here, EH can be implemented by existing vehicle devices and can be used as a power replenishment method to improve EE. This is a very interesting constraint condition that we find the solution for the EEO problem instead of increasing the complexity of solving the problem. However, few previous work has considered such a constraint [11], [19], [21], [24].
- The EEO problem under multiple constraint conditions is simplified into power allocation problem by exploiting Lagrangian dual method, the corresponding mathematical analysis is proved. Note that we utilize clever transformation of inequality and facilitate power allocation to reduce the complexity of EEO problem.
- Due to the existence of multiple constraints with respect to power allocation, it is very difficult to solve the problem directly. Therefore, we propose a three-loop iterative algorithm. Compared with other two-loop iterative algorithms, numerical simulation results are provided to demonstrate the feasibility of the proposed algorithm and the superiority over existing well-known algorithms. Moreover, we design a boundary constraint scheme (BCS) which can strictly guarantee the feasible solution satisfies the constraints.

The remainder of this paper is organized as follows. Section II describes the system model. Section III states the EEO problem formulation. Section IV proposes a Lagrangian coupled with the Dinkelbach method to solve EEO problem. Section V provides numerical simulation results and discussions, followed by conclusions in Section VI.

II. System Model

We consider the cross roads congestion scenarios in the city vehicular network. In our system model, high-density vehicles are randomly and irregularly distributed on the cross roads. Due to traffic congestion, energy consumption in vehicular network has been proved that the total vehicles' fuel consumption can increase up to 120% [28]. In addition, transportation

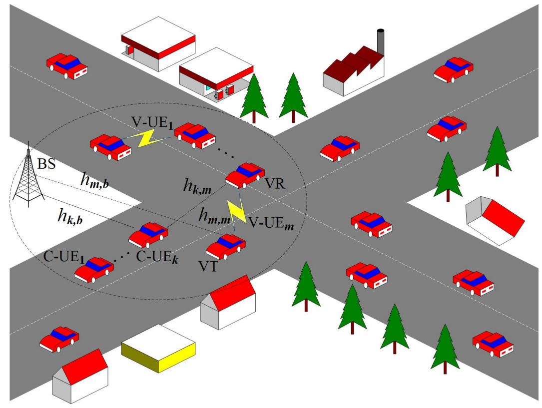

Fig. 1. System model of cellular D2D-based V2X communication.

vehicles that run on petroleum cause CO_2 emissions. EH can relieve the energy consumption burden and avoid high energy consumption of modern transportation systems that causes air pollution and greenhouse gas emission. Apart from energy availability, resource allocation in the D2D communication underlaying cellular vehicular network also becomes challenging when frequency reuse is allowed. This demand for the interference management-based resource allocation scheme in order to ensure that the performance of the cellular network is not degraded and the overall system performance is enhanced.

The cellular D2D-based V2X communication network is shown as Fig. 1. Here, the vehicles real-time localized information can be obtained through map matching, and its position error range is able to meet the application requirements of the vehicles communication [29]. Although the proposed system model focuses on V2X communications, the vehicle speed is very low or even negligible in large-scale traffic jams. In this case, the system model depends solely on the slowly varying large-scale channel parameters and only needs to be updated every few hundred milliseconds, thus significantly reducing the signaling overheads and providing feedback information within a very short interval of time than if direct applying traditional resource allocation schemes in vehicular networks. Without loss of generality, we consider the single microcell scenario, where a base station (BS) is a circular coverage area with radius R, each cell comprises K C-UEs, M V-UE transmitters (also simplified VT), and M V-UE receivers (also simplified VR). Each C-UE is pre-allocated a unique (orthogonal) channel so as to mitigate the inter-CU interference. Meanwhile, each D2D is allocated to reuse one and only one sub-channel. In addition, each pair of D2D is allowed to communicate in conventional D2D manner. The received signals at the V-UE receiver and the BS are respectively given by

$$y_m^d \triangleq \sqrt{p_m^d d_{m,m}^{-\alpha}} h_{m,m} s_m + \sqrt{p_k^c d_{k,m}^{-\alpha}} h_{k,m} s_k + \sigma^2, \quad (1)$$

$$y_k^c \triangleq \sqrt{p_k^c d_{k,b}^{-\alpha}} h_{k,b} s_k + \sqrt{p_m^d d_{m,b}^{-\alpha}} h_{m,b} s_m + \sigma^2, \quad (2)$$

where p_m^d, p_k^c denote the transmission power of the mth V-UE and the kth C-UE, respectively. $d_{m,m}$, $d_{k,m}$, $d_{k,b}$ and $d_{m,b}$ denote the distances over $m \to m$, $k \to m$, $k \to b$ and

$m \to b$ links, respectively. $h_{m,m}$, $h_{k,m}$, $h_{k,b}$ and $h_{m,b}$ denote the small-scale fading components over $m \to m$, $k \to m$, $k \to b$ and $m \to b$ links, respectively. α is the path-loss exponent, $\rho_{k,m}$ denotes the resource reuse variable for V-UE links, s_m and s_k denote the transmitted signal, respectively and σ^2 denotes the noise power.

Due to vehicular mobility, the channel state informations (CSIs) used in the V-UEs are presently substantially different from the actual channels during data transmission [30]. In other words, the CSIs used are outdated. We assume that such CSIs is obtained through channel estimation [31]. It has been verified in [32] that the first-order autoregressive (AR1) model provides a sufficiently accurate model for outdated CSI. Thus, we model $h_{k,m}$ as

$$h_{k,m} = \xi_{k,m}\tilde{h}_{k,m} + \sqrt{1-\xi_{k,m}^2}\varsigma_{k,m}, \tag{3}$$

where $\tilde{h}_{k,m}$ denotes the estimate of $h_{k,m}$ and $\left|\tilde{h}_{k,m}\right|^2$ is exponentially distributed with unit mean [33]. $\xi_{k,m} \in [0,1]$ represents the correlation coefficient over $k \to m$ link, and $\varsigma_{k,m}$ stands for the channel gain and follows a complex Gaussian distribution $\varsigma_{k,m} \sim CN\left(0,\sigma^2\right)$.

Some of the relevant theoretical and simulation studies have shown that V2V link transmissions in the traffic congestion scenarios can be modeled as Rayleigh channel fading [34]. The received SINRs at the BS for the kth C-UE and at the mth V-UE can be respectively expressed as

$$SINR_k \triangleq \frac{p_k^c h_{k,b}^2 d_{k,b}^{-\alpha}}{\rho_{k,m} p_m^d h_{m,b}^2 d_{m,b}^{-\alpha} + \sigma^2}, \tag{4}$$

$$SINR_m \triangleq \frac{p_m^d d_{m,m}^{-\alpha}\xi_{m,m}^2\tilde{h}_{m,m}^2 + p_m^d d_{m,m}^{-\alpha}(1-\xi_{m,m}^2)\varsigma_{m,m}^2}{\rho_{k,m} p_k^c(\xi_{k,m}^2\tilde{h}_{k,m}^2 + (1-\xi_{k,m}^2))d_{k,m}^{-\alpha}\varsigma_{k,m}^2 + \sigma^2}, \tag{5}$$

where we denote the product terms as $H_{k,b} = h_{k,b}^2 d_{k,b}^{-\alpha}$, $H_{m,b} = h_{m,b}^2 d_{m,b}^{-\alpha}$, $H_{m,m} = h_{m,m}^2 d_{m,m}^{-\alpha}$ and $H_{k,m} = h_{k,m}^2 d_{k,m}^{-\alpha}$, respectively. Then, (4) and (5) can be simplified as

$$SINR_k \triangleq \frac{p_k^c H_{k,b}}{\rho_{k,m} p_m^d H_{m,b} + \sigma^2}, \tag{6}$$

$$SINR_m \triangleq \frac{p_m^d H_{m,m}}{\rho_{k,m} p_k^c H_{k,m} + \sigma^2}. \tag{7}$$

The data rates of the kth C-UE link and the mth V-UE link can be respectively calculated as

$$R_{Ck} = \log_2(1 + SINR_k), \tag{8}$$

$$R_{Dm} = \log_2(1 + SINR_m). \tag{9}$$

Now we consider power consumption. We assume that EH of in-vehicle equipments come from radio frequency (RF) since RF energy transfer does not require the installation of any costly components such as solar panels and wind turbines [35], i.e., $E_m = \varepsilon_m \rho_{k,m}\left(p_m^d g_m + \sigma^2\right)$, $\varepsilon_m \in (0,1]$ denotes the energy conversion efficiency, g_m denotes RF beamforming signal which obtained by [36]. We take the harvested power into power consumption, and thus the power consumption of the mth V-UE link is expressed as

$$P_{Dm} = \frac{2}{M}p_m^0 + \eta p_m^d - E_m, \tag{10}$$

where $\frac{2}{M}p_m^0$ denotes the fixed circuit power of both the transmitter and the receiver of the mth V-UE link, η is a factor accounting for the transmit amplifier efficiency and E_m denotes the harvested power of the mth V-UE link.

III. Problem Formulation

In this section, we are ready to formulate the problem. To accurately characterize the energy consumption, we follow a different approach. We consider the network to be able to serve sessions that have different QoS requirements. According to the system model in Sec. II, the goal of this paper is to jointly design the resource reuse variable $\rho_{k,m}$ and the power allocation p_m^d to maximize the EE of all V-UE links. The EE is defined as the ratio between the sum rate and the power consumption. In order to realize a continuous information transfer, each V-UE requires its SINR and its harvest power no smaller than a given threshold, denoted by γ_m and e_m ($\forall m$), respectively. For notational convenience, we define $E_m \triangleq E_m\left(p_m^d, \rho_{k,m}\right)$, $P_{Dm} \triangleq P_{Dm}\left(p_m^d, \rho_{k,m}\right)$, and $R_{Dm} \triangleq R_{Dm}\left(p_m^d, \rho_{k,m}\right)$. Mathematically, the formulated problem is given by

$$\max_{\{p_m^d, \rho_{k,m}\}} \text{EE} = \max \frac{\sum_{m=1}^{M} R_{Dm}\left(p_m^d, \rho_{k,m}\right)}{\sum_{m=1}^{M} P_{Dm}\left(p_m^d, \rho_{k,m}\right)}, \tag{11}$$

$$\text{s.t. } SINR_m \geq \gamma_m, \quad \forall m, \tag{11a}$$

$$E_m \geq e_m, \quad \forall m, \tag{11b}$$

$$0 \leqslant p_m^d \leqslant p_{total}, \tag{11c}$$

$$\rho_{k,m} \in \{0,1\}, \tag{11d}$$

where (11a) and (11b) denote the SINR threshold and EH target, respectively. (11c) denotes the total power constraint. p_{total} denotes the maximum allowed transmission power that is the sum of each vehicle transmission power, and (11d) is described the resource reuse variable constraint.

Substituting E_m, (7) and (10) into (11), then (11) can be rewritten as the EEO problem in the following

$$\max \frac{\sum_{m=1}^{M} R_{Dm}\left(p_m^d, \rho_{k,m}\right)}{\eta\sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m\left(p_m^d, \rho_{k,m}\right)}, \tag{12}$$

$$\text{s.t. } \frac{p_m^d H_{m,m}}{\rho_{k,m} p_k^c H_{k,m} + \sigma^2} \geq \gamma_m, \quad \forall m, \tag{12a}$$

$$\varepsilon_m \rho_{k,m}\left(p_m^d g_m + \sigma^2\right) \geq e_m, \quad \forall m, \tag{12b}$$

$$0 \leqslant p_m^d \leqslant p_{total}, \tag{12c}$$

$$\rho_{k,m} \in \{0,1\}. \tag{12d}$$

IV. Lagrangian and Dinkelbach Method for Solving EEO Problem

A. Lagrangian Dual Method to Simplify the EEO Problem

We use the notations

$$w_1(\rho_{k,m}) = \frac{\gamma_m(\rho_{k,m} p_k^c H_{k,m} + \sigma^2)}{H_{m,m}},$$
$$w_2(\rho_{k,m}) = \frac{1}{g_m}\left(\frac{e_m}{\varepsilon_m \rho_{k,m}} - \sigma^2\right). \quad (13)$$

Obviously, $p_m^d \geq w_1(\rho_{k,m})$, $p_m^d \geq w_2(\rho_{k,m})$. Thus p_m^d only needs to satisfy $\min p_m^d \geq \max(w_1(\rho_{k,m}), w_2(\rho_{k,m}))$. Then, the remaining task is to solve $\min p_m^d$. Using (12c), problem (12) is shown to be feasible if and only if

$$\min p_m^d \leqslant p_{total}, \quad (14)$$
$$\text{s.t. } p_m^d \geq \max(w_1(\rho_{k,m}), w_2(\rho_{k,m})), \quad (14a)$$
$$\rho_{k,m} \in \{0,1\}, \quad (14b)$$

when $w_1(\rho_{k,m}) = w_2(\rho_{k,m})$, we can be easily obtained $\min p_m^d$ by solving a quadratic equation [33], [37].

In fact, problem (12) is a non-convex fractional programming with multiple constraints, which is difficult to directly solve. It is observed that, without the total power constraint, the constraint set of problem (12) is separable for users $m = 1, 2, \ldots, M$. In the case, we take the total power constraint into the objective function so that it can make the problem more tractable. This motivates reformulation of problem (12) to the following equivalent easier to solve problem.

$$\max \frac{\sum_{m=1}^{M} R_{Dm}(p_m^d, \rho_{k,m})}{\eta \sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m(p_m^d, \rho_{k,m})}, \quad 15)$$
$$\text{s.t. } \frac{p_m^d H_{m,m}}{\rho_{k,m} p_k^c H_{k,m} + \sigma^2} \geq \gamma_m, \quad \forall m, \quad (15a)$$
$$\varepsilon_m \rho_{k,m}\left(p_m^d g_m + \sigma^2\right) \geq e_m, \quad \forall m, \quad (15b)$$
$$\frac{\sum_{m=1}^{M} p_m^d - p_{total}}{\eta \sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m(p_m^d, \rho_{k,m})} \leq 0, \quad (15c)$$
$$\rho_{k,m} \in \{0,1\}. \quad (15d)$$

By the above analysis, therefore, we combine (15) with the constraint (15c) and define as follows.

$$L\left(p_m^d, \rho_{k,m}, \lambda\right) = \frac{\sum_{m=1}^{M} R_{Dm}(p_m^d, \rho_{k,m})}{\eta \sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m(p_m^d, \rho_{k,m})} - \lambda \frac{\sum_{m=1}^{M} p_m^d - p_{total}}{\eta \sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m(p_m^d, \rho_{k,m})}. \quad (16)$$

In (16), the right second term of the equation is not equal to 0. In the case, we must avoid that a large Lagrangian multiplier λ is adjusted to obtain an infinity result. Therefore, we define

$$\theta_p\left(p_m^d, \rho_{k,m}\right) = \min L\left(p_m^d, \rho_{k,m}, \lambda\right). \quad (17)$$

If

$$\frac{\sum_{m=1}^{M} p_m^d - p_{total}}{\eta \sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m(p_m^d, \rho_{k,m})} > 0, \quad (18)$$

we will always adjust λ to make EE become a negative infinity. In fact, (15c) is satisfied, i.e., $\theta_p(p_m^d, \rho_{k,m}) = \text{EE}$. In this case, we can obtain

$$\theta_p(p_m^d, \rho_{k,m}) = \begin{cases} \text{EE}, & \text{if } p_m^d, \rho_{k,m} \text{ satisfy original consraints} \\ \infty, & \text{otherwise} \end{cases} \quad (19)$$

Thus, the original problem is transformed into solving $\max \theta_p(p_m^d, \rho_{k,m})$, i.e., $\max \theta_p(p_m^d, \rho_{k,m}) = \max \min L(p_m^d, \rho_{k,m}, \lambda)$. For many parameters and λ with inequality constraints in our direct solution, we could consider its Lagrangian dual problem:

$$\theta_D(\lambda) = \max_{\{p_m^d, \rho_{k,m}\}} L\left(p_m^d, \rho_{k,m}, \lambda\right), \quad (20)$$
$$\text{s.t. } \frac{p_m^d H_{m,m}}{\rho_{k,m} p_k^c H_{k,m} + \sigma^2} \geq \gamma_m, \quad \forall m, \quad (20a)$$
$$\varepsilon_m \rho_{k,m}\left(p_m^d g_m + \sigma^2\right) \geq e_m, \quad \forall m, \quad (20b)$$
$$\rho_{k,m} \in \{0,1\}. \quad (20c)$$

where $\theta_D(\lambda)$ converts the problem to find the maximum value of Lagrangian function for $p_m^d, \rho_{k,m}$. Considering λ as a fixed value and denoting $p_m^d(\lambda)$, $\rho_{k,m}(\lambda)$ as the solution of p_m^d, $\rho_{k,m}$ for different λ, we can find the minimum value of dual function [36] as :

$$\min \theta_D(\lambda), \quad (21)$$

Let λ^* be the optimal dual variable. In [35], it can be shown that if p_m^d satisfied the total power constraint and that $\lambda^*\left(\sum_{m=1}^{M} p_m^d(\lambda^*) - p_{total}\right) = 0$. Therefore, $\{p_m^d(\lambda^*), \rho_{k,m}(\lambda^*)\}$ is an optimal solution to problem (15). Hence, to find λ^*, we utilize the bisection method [38]. Now, we start to solve the remaining dual problem (20).

B. A Modified Dinkelbach Algorithm for Simplified EEO Problem

Problem (20) is in non-convex fractional programming form, and the denominator contains the required variables. Finding the partial derivative for such a form will only increase the complexity of solving the problem. In the case, a modified Dinkelbach algorithm is designed to solve the simplified EEO problem. The algorithm can be used to both remove the denominator of problem (20) and convert the original non-convex optimization problem from fractional form into a subtraction form, and thus the simplified EEO problem is easier to solve. According to above analysis, we combine similar items in polynomial (16) and convert them into the following subtraction formula

$$\max_{(p_m^d,\rho_{k,m})\in \mathrm{V}} \sum_{m=1}^{M} R_{Dm}\left(p_m^d,\rho_{k,m}\right)-\lambda\left(\sum_{m=1}^{M} p_m^d - p_{total}\right) - \beta\left[\eta\sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m\left(p_m^d,\rho_{k,m}\right)\right], \quad (22)$$

where V is the solution set which satisfies restrictions (20a) (20b) (20c), β is a parameter added to make the fractional programming into a subtraction form. The solutions set V can be defined as follows.

$$\mathrm{V} \triangleq \left\{\left(p_m^d,\rho_{k,m}\right) \middle| \frac{p_m^d H_{m,m}}{\rho_{k,m} p_k^c H_{k,m}+\sigma^2} \geq \gamma_m, \; \varepsilon_m \rho_{k,m}\left(p_m^d g_m+\sigma^2\right) \geq e_m, \rho_{k,m}\in\{0,1\}\right\}. \quad (23)$$

Supposed that $\left(\bar{p}_m^d,\bar{\rho}_{k,m}\right)$ is the optimal solution of original problem (11), with $\beta=\beta^*$ given by

$$\beta^* \triangleq \frac{\sum\limits_{m=1}^{M} R_{Dm}\left(\bar{p}_m^d,\bar{\rho}_{k,m}\right)-\lambda^*\left(\sum\limits_{m=1}^{M} \bar{p}_m^d - p_{total}\right)}{\eta\sum\limits_{m=1}^{M} \bar{p}_m^d + 2p_m^0 - \sum\limits_{m=1}^{M} E_m\left(\bar{p}_m^d,\bar{\rho}_{k,m}\right)}. \quad (24)$$

Clearly, β^* is the optimal EE. The modified Dinkelbach method is an iterative algorithm that generates a sequence of values that converge to the optimal EE monotonically [35]. Generally, the corresponding algorithm could be considered as a two-loop algorithm, where the inner-loop uses the Dinkelbach method while the outer-loop adopts the bisection method. We design the modified Dinkelbach algorithm as Algorithm 1. In the algorithm 1, the proposed method for finding the optimal power allocation and the resource reuse of the D2D links under the QoS constraints of the C-UEs and the EH constraints of the D2D links.

Algorithm 1 Modified Dinkelbach Algorithm

Initialize feasible p_m^d, $\rho_{k,m}$, λ_1, λ_2, $\lambda^{(1)} \leftarrow 0$, initialize the maximum value $\beta^{(0)}=\beta^0$, $\beta^{(1)}=\beta^1$, the iteration index $i \leftarrow 1$, convergence index $\Delta \leftarrow 10^{-4}$, maximum number of iterations $N_{\max}^i \leftarrow 10$.
Find λ_2 such that $p_m^d(\lambda_2) \leq p_{total}$
Repeat
$\lambda^{(i)} \leftarrow \frac{\lambda_1+\lambda_2}{2}$
while $\left|\beta^{(i)}-\beta^{(i-1)}\right| \leq \Delta$ **and** $i \leq N_{\max}^i$ **do**
  a) Solve problem (20),
  b) Update the maximum value of $i-1$-th $\beta^{(i-1)} \leftarrow \beta^{(i)}$,
  c) Update the iteration index $i \leftarrow i+1$,
  d) Calculate the corresponding maximum value of i-th $\beta^{(i)} = \frac{\sum_{m=1}^{M} R_{Dm}(p_m^d,\rho_{k,m})-\lambda\left(\sum_{m=1}^{M} p_m^d - p_{total}\right)}{\eta\sum_{m=1}^{M} p_m^d+2p_m^0-\sum_{m=1}^{M} E_m\left(p_m^d,\rho_{k,m}\right)}$.
end while
if $p_m^d(\lambda) \leq p_{total}$ **then**
  $\lambda_2 \leftarrow \lambda^{(i)}$
else $\lambda_1 \leftarrow \lambda^{(i)}$
end if
Until $\left|\lambda^{(i)}-\lambda^{(i-1)}\right| \leq \Delta$
Output β^*

C. The BCS for the Problem (22)

It can be seen that problem (22) is separable. That is, problem (22) can be decomposed into M subproblems with the mth $(m=1,2,\ldots,M)$ subproblem given by

$$\max_{(p_m^d,\rho_{k,m})\in \mathrm{V}} R_{Dm}\left(p_m^d,\rho_{k,m}\right)-(\lambda+\beta\eta)\,p_m^d + E_m\left(p_m^d,\rho_{k,m}\right), \quad (25)$$

$$\text{s.t. } p_m^d \geq \max\left(w_1\left(\rho_{k,m}\right), w_2\left(\rho_{k,m}\right)\right), \quad (25a)$$

$$0 \leq p_m^d \leq p_{total}, \quad (25b)$$

$$\rho_{k,m}\in\{0,1\}. \quad (25c)$$

Define

$$\Phi_m\left(\rho_{k,m}\right) \triangleq R_{Dm}\left(p_m^d(\rho_{k,m}),\rho_{k,m}\right)-(\lambda+\beta\eta)\,p_m^d(\rho_{k,m}) + E_m\left(p_m^d(\rho_{k,m}),\rho_{k,m}\right), \quad (26)$$

problem (25) is equivalent to the problem (27)

$$\max_{\rho_{k,m}\in\{0,1\}} \Phi_m\left(\rho_{k,m}\right) \quad \text{s.t. } p_{total} \geq p_m^d \geq \max\left(w_1\left(\rho_{k,m}\right), w_2\left(\rho_{k,m}\right)\right). \quad (27)$$

Supposing that $\rho_{k,m}$ is fixed, the convex problem (27) is easy to solve the solution p_m^d. Taking the first-order derivative of (27), we find the stationary point $\tilde{p}_m^d$ of the objective function (26) as

$$\tilde{p}_m^d = \frac{1}{(\lambda+\beta\eta)-g_m\varepsilon_m\rho_{k,m}} - \frac{\rho_{k,m}p_k^c H_{k,m}+\sigma^2}{H_{m,m}}. \quad (28)$$

For univariate problem (27), we can obtain its optimal value either on the constraint boundary or at the stationary point $\tilde{p}_m^d$ according to their relative magnitudes of $\tilde{p}_m^d$, p_{total}, $w_1\left(\rho_{k,m}\right)$ and $w_2\left(\rho_{k,m}\right)$. In the case, the optimal solution p_m^d is given by

$$\begin{aligned}
&1)\text{ If } \max\left(w_1\left(\rho_{k,m}\right), w_2\left(\rho_{k,m}\right)\right) \leq p_{total} \leq \tilde{p}_m^d,\\
&p_m^d = p_{total},\\
&2)\text{ If } \max\left(w_2\left(\rho_{k,m}\right), \tilde{p}_m^d\right) \leq w_1\left(\rho_{k,m}\right) \leq p_{total},\\
&p_m^d = w_1\left(\rho_{k,m}\right),\\
&3)\text{ If } \max\left(w_1\left(\rho_{k,m}\right), \tilde{p}_m^d\right) \leq w_2\left(\rho_{k,m}\right) \leq p_{total},\\
&p_m^d = w_2\left(\rho_{k,m}\right),\\
&4)\text{ If } \max\left(w_1\left(\rho_{k,m}\right), w_2\left(\rho_{k,m}\right)\right) \leq \tilde{p}_m^d \leq p_{total},\\
&p_m^d = \tilde{p}_m^d,
\end{aligned} \quad (29)$$

where (29) is called BCS. By combining Algorithm 1 and the above analysis, we proposed a three-loop iteration algorithm (Algorithm 2) to solve the EEO problem under the BCS.

Algorithm 2 Three-Loop Iteration Algorithm

Initialize feasible p_m^d, $\rho_{k,m}$, $\lambda_1 \leftarrow 0$, $\lambda_2 \leftarrow 0$, $\lambda^{(1)} \leftarrow 0$, m, M, initialize the maximum value $\beta^{(0)} = \beta^0$, $\beta^{(1)} = \beta^1$, the iteration index $i \leftarrow 1$, convergence index $\Delta \leftarrow 10^{-4}$, maximum number of iterations $N_{\max}^i \leftarrow 20$.
Find λ_2 such that $p_m^d(\lambda_2) \le p_{total}$
Repeat
$\lambda^{(i)} \leftarrow \frac{\lambda_1+\lambda_2}{2}$
while $\left|\beta^{(i)} - \beta^{(i-1)}\right| \le \Delta$ **and** $i \le N_{\max}^i$ **do**
  a) Solve problem (20),
  b) Update the maximum value of $i-1$-th $\beta^{(i-1)} \leftarrow \beta^{(i)}$,
  c) Update the iteration index $i \leftarrow i+1$,
  d) Calculate the corresponding maximum value of i-th
$$\beta^{(i)} = \frac{\sum_{m=1}^{M} R_{Dm}\left(p_m^d, \rho_{k,m}\right) - \lambda\left(\sum_{m=1}^{M} p_m^d - p_{total}\right)}{\eta \sum_{m=1}^{M} p_m^d + 2p_m^0 - \sum_{m=1}^{M} E_m\left(p_m^d, \rho_{k,m}\right)}.$$
  for $m = 1 : M$ **do**
    Update p_m^d, $\rho_{k,m}$ by solving problem (27)
  end for
end while
if $p_m^d\left(\lambda^{(i)}\right) \le p_{total}$ **then**
  $\lambda_2 \leftarrow \lambda^{(i)}$
else $\lambda_1 \leftarrow \lambda^{(i)}$
end if
Until $\left|\lambda^{(i)} - \lambda^{(i-1)}\right| \le \Delta$
Output p_m^d, $\rho_{k,m}$, β^*

Note that the complexity of Algorithm 2 is $\mathrm{O}\left(M^3\right)$. Compared to the algorithm for EEO problem in [35] of complexity $\mathrm{O}(M!)$, it means that the proposed algorithm is better in terms of the complexity.

According to (29), we first separately check the four cases of BCS and then keep the best $\rho_{k,m}$ to obtain the problem (27) solution. From (26), $p_m^d\left(\rho_{k,m}\right)$ is differentiable, and thus the best optimal solution $\rho_{k,m}$ is a stationary point of the objective function $\Phi_m\left(\rho_{k,m}\right)$ [40]. Now, we address the four results separately and particularly examine the corresponding first-order difference equals to 0. Here, the first-order condition can be converted into a polynomial function for which it is easy to find a stationary point [35].

1) For $p_m^d = p_{total}$, we will have

$$\Phi_m\left(\rho_{k,m}\right) = \log_2\left(1 + \frac{p_{total} H_{m,m}}{\rho_{k,m} p_k^c H_{k,m} + \sigma^2}\right) - (\lambda + \beta\eta)\, p_{total} + \varepsilon_m \rho_{k,m}\left(p_{total} g_m + \sigma^2\right). \tag{30}$$

Taking the derivative of $\Phi_m\left(\rho_{k,m}\right)$ with respect to $\rho_{k,m}$, we obtain

$$\frac{d\Phi_m\left(\rho_{k,m}\right)}{d\rho_{k,m}} = \frac{1}{\rho_{k,m} p_k^c H_{k,m} + \sigma^2 + p_{total} H_{m,m}} \times \frac{-p_{total} H_{m,m} p_k^c H_{k,m}}{\rho_{k,m} p_k^c H_{k,m} + \sigma^2} - \varepsilon_m\left(p_{total} g_m + \sigma^2\right) = 0, \tag{31}$$

where the equation for $\rho_{k,m}$ can be expressed by a quadratic equation. Therefore, the general formula is given by

$$a_1\rho_{k,m}^2 + b_1\rho_{k,m} + c_1 = 0. \tag{32}$$

And then, we use a sigmoid function mapping method to obtain a probability p representing $\rho_{k,m} = 1$. The general formula of the sigmoid function [41] is given as follows

$$sig\left(\rho_{k,m}\right) = \frac{1}{1 + \exp\left(-\rho_{k,m}\right)}. \tag{33}$$

Similar to 1), we explain other cases as follows.

2) For $p_m^d = w_1\left(\rho_{k,m}\right)$, the equation for $\rho_{k,m}$ can be expressed by a quadratic equation. Therefore, the general formula is given by

$$a_2\rho_{k,m}^2 + b_2\rho_{k,m} + c_2 = 0. \tag{34}$$

And then, the sigmoid function is calculated.

3) For $p_m^d = w_2\left(\rho_{k,m}\right)$, the equation for $\rho_{k,m}$ can be expressed by a quintic equation. Therefore, the general formula is written as

$$a_3\rho_{k,m}^5 + b_3\rho_{k,m}^4 + c_3\rho_{k,m}^3 + d_3\rho_{k,m}^2 + e_3\rho_{k,m} + f_3 = 0. \tag{35}$$

And then, the sigmoid function is calculated.

4) For $p_m^d = \tilde{p}_m^d$, the equation for $\rho_{k,m}$ can be expressed by a sextic equation. Therefore, the general formula is given by

$$a_4\rho_{k,m}^6 + b_4\rho_{k,m}^5 + c_4\rho_{k,m}^4 + d_4\rho_{k,m}^3 + e_4\rho_{k,m}^2 + f_4\rho_{k,m} + g_4 = 0. \tag{36}$$

And then, the sigmoid function is calculated.

V. Numerical Simulation Results and Discussions

In this section, the performance of the proposed EEO algorithm is evaluated. Here, the vehicles' locations follow a Poisson distribution [42]. We randomly choose K C-UEs and M V-UEs among vehicles, and each V-UE is always paired between neighboring vehicles. The following parameter values are used in all simulations unless stated otherwise [27], [35]: the coverage of the BS is $200m$, path loss index is set $\alpha = 4$, the maximum communication distance between V-UE is $25m$, the maximum transmission powers is set $p_{total} = 1W$, the fixed circuit power of V-UE link is $p_m^0 = 0.25W$, the transmit amplifier efficiency is $\eta = 5$, the noise power is equal to $10^{-8}W$ for every link, $\varepsilon_m = 0.65$, and $g_m = 3.9 \times 10^{-5}$. Moreover, we examine the simulation of the average EE performance over 100,000 random channels, and the value of Δ is equal to 10^{-4}.

Fig. 2 illustrates the convergence of the Algorithm 1. It can be observed that the Algorithm 1 can always converge very quickly within only several iterations. As expected, Algorithm 2 converges very quickly, as shown in Fig. 3. We verify the validity of the proposed algorithms. Note that we set $p_{total} = p_m^0 = 0.25W$ and increase appropriately to verify simply the convergence of the proposed algorithm.

Fig. 4 illustrates the EE for the four schemes, where $d_{k,m} = 80m$, $\gamma_m = 10dB$, $e_m = 10^{-5.5}W$. The four schemes are

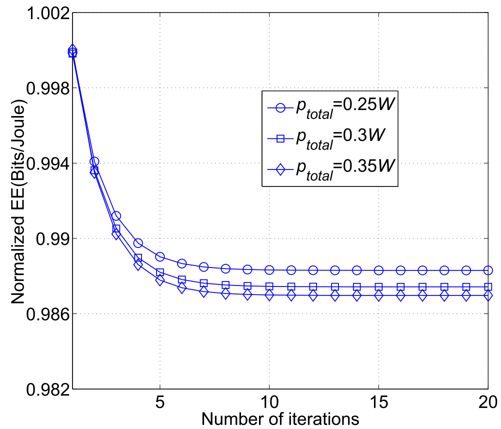

Fig. 2. The convergence of Algorithm 1.

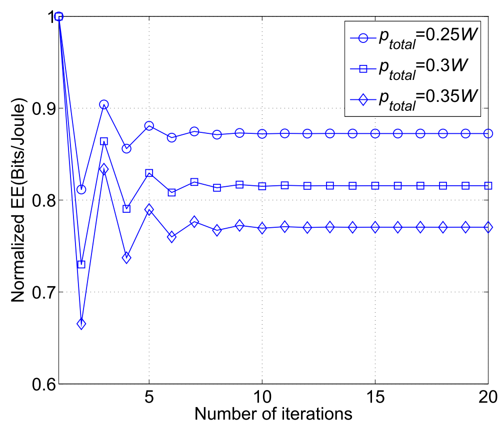

Fig. 3. The convergence of Algorithm 2.

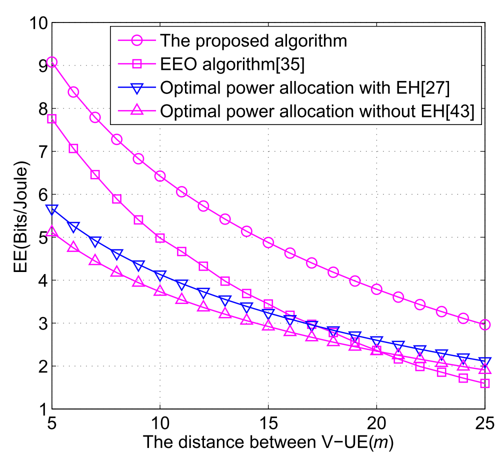

Fig. 4. EE versus the distance between V-UE compared with other algorithms.

the proposed scheme, EEO algorithm [35], optimal power allocation with EH [27], and optimal power allocation without EH [43], respectively. Among the four schemes, the proposed scheme has the largest EE regardless of the variance of the distance between V-UE. Compared to [43], the proposed scheme contains EH target constraint, which can guarantee the most power replenishment to increase EE. Compared to [27], the proposed scheme not only achieves the power allocation through the BCS but also further optimizes the EE.

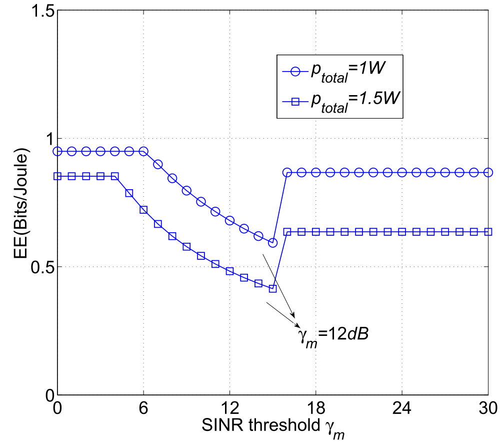

Fig. 5. EE versus SINR threshold γ_m for different p_{total}.

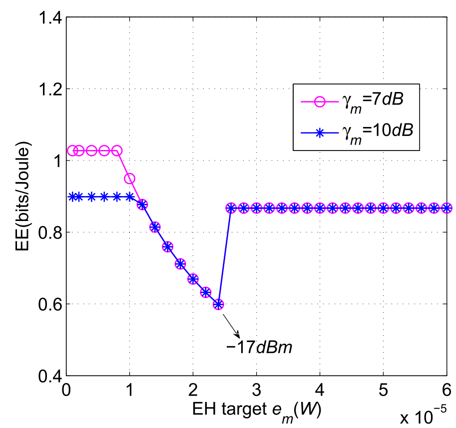

Fig. 6. EE versus EH target e_m for different γ_m.

Compared to [35], the proposed scheme is superior to the EEO algorithm in terms of EE and complexity. For each of the four schemes, the EE decreases as the distance between V-UE increases. The reason is that the path-loss increases with the distance between V-UE. As a conclusion, the distance has influence on the four schemes' performance. As expected, the EEO of proposed algorithm outperforms previous algorithms under the same conditions.

Fig. 5 illustrates the EE versus SINR threshold γ_m for different p_{total}, where $d_{m,m} = 20m$, $d_{k,m} = 40m$. We can find that there exists a critical point beyond which the EE no longer decreases with increasing γ_m, and it shows that γ_m influences the optimal EE. When γ_m is too little, the second case of the BCS is eliminated. Moreover, we observe that the EE decreases as γ_m is gradually increased, due to the limitation of the power of the V-UE. When γ_m is too large, the power does not increase indefinitely due to total power constraint, and thus the EE will not change. In this case, we can get the maximum γ_m of the BCS as $12dB$.

Fig. 6 illustrates the EE versus EH target e_m for different γ_m. We observe that there also exists a critical point beyond which the EE no longer decreases with increasing e_m. We can get the maximum EH target under BCS as $-17dBm$. Moreover, we can also observe a key point from which γ_m does not affect the value of EE, because the EH target starts to play a leading role in the BCS.

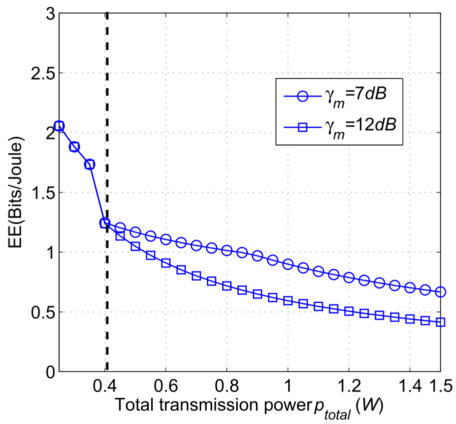

Fig. 7. EE versus total transmission power p_{total} for different γ_m.

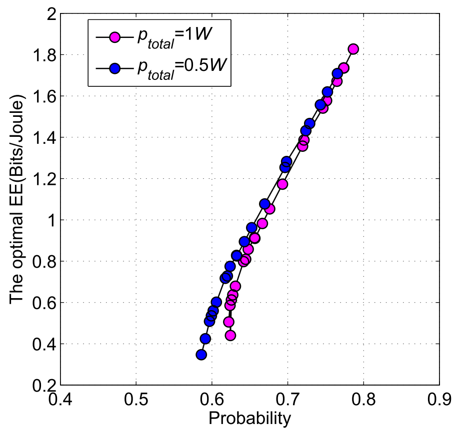

Fig. 8. The optimal EE versus probability of the resource reuse $\rho_{k,m} = 1$.

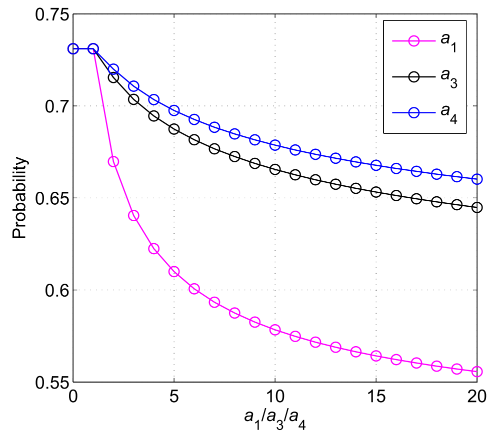

Fig. 9. Probability of the resource reuse $\rho_{k,m} = 1$ versus $a_1/a_3/a_4$.

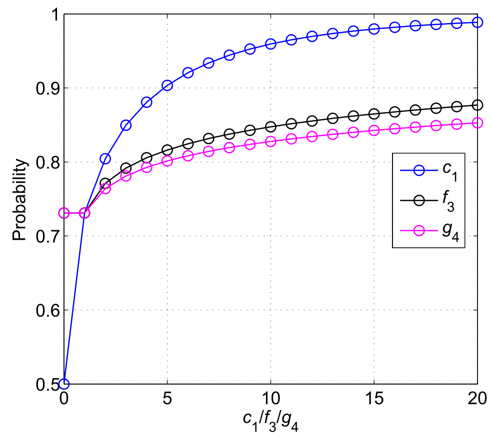

Fig. 10. Probability of the resource reuse $\rho_{k,m} = 1$ versus $c_1/f_3/g_4$.

Fig. 7 illustrates the EE versus total transmission power p_{total} for different γ_m. When p_{total} is too little, the BCS is not established. However, the total power constraint still works. As expected, the EE has the same values for different γ_m. When p_{total} increases, the BCS has effect on the EE, we observe that the EE decreases as p_{total} increases for different γ_m. Moreover, it can be seen that the EE decreases with the increasing γ_m under the same p_{total}. The reason is the increasing transmission power for SINR requirement.

Fig. 8 illustrates the optimal EE versus the probability p of the resource reuse $\rho_{k,m} = 1$ for different p_{total}. We assume a random V-UE to reuse uplink resources of C-UEs, where $K = 22$, $\gamma_m = 0$, $\sigma^2 = 10^{-6}$. It can be seen that the probabilities are all mapped to $0.5 \sim 0.8$, and the EE value increases as the probability p rises. Moreover, we can clearly find that the EE values at probability $p \in [0.7, 0.8]$ are greater than that of $p \in [0.5, 0.7]$. Here, we can set $\rho_{k,m}$ equal to 1 if the probability p is greater than 0.7, where the V-UE can reuse uplink resource of C-UE. Otherwise, $\rho_{k,m}$ is equal to 0, which indicates that the V-UE will not reuse uplink resource of C-UE. At this point, the best resource reuse and the optimal EE can be obtained. The feasibility and superiority of the proposed algorithm is demonstrated.

Fig. 9 illustrates the coefficient of the highest-order term effects on the probability p, the probability p gradually decreases with the increase of the coefficient of the highest-order term. In the case, we can reduce the probability p by increasing the coefficient of the highest-order term. Fig. 10 illustrates the effects of the constant term and the coefficient of the fourth power term on the probability p, respectively. In the case, we can obtain the probability p by adjusting the corresponding coefficients.

VI. Conclusion

In this paper, we have formulated the EEO problem while guaranteeing multiple constraints with respect to V-UEs. Since the EEO problem is a non-convex problem, Lagrangian coupled with the Dinkelbach method has been used to address it. We have firstly utilized Lagrangian dual method to simplify the EEO problem under multiple constraint conditions. And then, a modified Dinkelbach algorithm has been devised to solve the simplified EEO problem. Finally, we have proposed a three-loop iterative algorithm and examined the effects of the BCS on the involved quantities. Numerical simulation results show that the proposed algorithm can obtain the optimal EE for different distance between V-UE users. Compared with other schemes, the EEO of proposed algorithm outperforms previous algorithms under the same conditions. We have also obtained the maximum SINR threshold and EH target for different BCS. Furthermore, a sigmoid function method is utilized to obtain a feasible solution for resource reuse problem, which is very convenient to be used in practical vehicular communication networks.

APPENDIX

In section IV, we have derived the corresponding general formula for the four cases of BCS. Here, we will show the specific coefficients of each formula. 1) The coefficient for each item is as follows

$$\begin{aligned}
a_1 &= p_k^{c2} H_{k,m}^2 \varepsilon_m \left(p_{total} g_m + \sigma^2\right),\\
b_1 &= \varepsilon_m p_k^c H_{k,m} \left(p_{total} g_m + \sigma^2\right)\left(2\sigma^2 + p_{total} H_{m,m}\right),\\
c_1 &= \sigma^2 \varepsilon_m \left(p_{total} g_m + \sigma^2\right)\left(\sigma^2 + p_{total} H_{m,m}\right)\\
&\quad - p_{total} H_{m,m} p_k^c H_{k,m}.
\end{aligned}$$

2) The coefficient for each item is as follows

$$\begin{aligned}
a_2 &= -\varepsilon_m p_k^c H_{k,m} (1+\gamma_m)(1+g_m),\\
b_2 &= p_k^c H_{k,m}\\
&\quad \times (1+\gamma_m)\left(\sigma^2 \varepsilon_m \gamma_m + \sigma^2 \varepsilon_m H_{m,m} + \lambda + \beta\eta + \varepsilon_m g_m\right)\\
&\quad - \sigma^2 \varepsilon_m (1+g_m)(1+\gamma_m) + \gamma_m^2 p_k^{c2} H_{k,m}^2,\\
c_2 &= \sigma^2 (1+\gamma_m)\\
&\quad \times \left(\sigma^2 \varepsilon_m \gamma_m + \sigma^2 \varepsilon_m H_{m,m} + \lambda + \beta\eta + \varepsilon_m g_m\right)\\
&\quad + \sigma^2 \gamma_m^2 p_k^c H_{k,m}.
\end{aligned}$$

3) The coefficient for each item is as follows

$$\begin{aligned}
a_3 &= -2 g_m^2 \varepsilon_m^2 p_k^{c2} H_{k,m}^2,\\
b_3 &= Y g_m \varepsilon_m p_k^{c2} H_{k,m}^2 + g_m \varepsilon_m^2 \sigma^2 H_{m,m} p_k^c H_{k,m}\\
&\quad + 4 g_m^2 \varepsilon_m^2 p_k^c H_{k,m}\left(p_k^c H_{k,m} - \sigma^2\right),\\
c_3 &= 2Y g_m \varepsilon_m p_k^c H_{k,m}\left(-p_k^c H_{k,m} + \sigma^2\right)\\
&\quad - 2 g_m \varepsilon_m U - \sigma^2 g_m \varepsilon_m \left(2 p_k^c H_{k,m} - \sigma^2\right)\\
&\quad - g_m \varepsilon_m^2 4\sigma^2 H_{m,m} p_k^c H_{k,m},\\
d_3 &= Y\left[p_k^c H_{k,m} U - \sigma^2 g_m \varepsilon_m \left(2 p_k^c H_{k,m} - \sigma^2\right)\right]\\
&\quad - 2 g_m \varepsilon_m \left[p_k^c H_{k,m} V + \sigma^2 U\right]\\
&\quad + g_m \varepsilon_m \left[5 \varepsilon_m \sigma^2 H_{m,m} p_k^c H_{k,m} - X\right],\\
e_3 &= Y\left(p_k^c H_{k,m} V + \sigma^2 U\right) - 2 g_m \varepsilon_m \sigma^2 V\\
&\quad - 2 g_m \varepsilon_m \left(\varepsilon_m \sigma^2 H_{m,m} p_k^c H_{k,m} - X\right),\\
f_3 &= \sigma^2 Y V - g_m \varepsilon_m X.
\end{aligned}$$

In addition,

$$\begin{aligned}
Y &= e_m (\lambda + \beta\eta + 2 g_m \varepsilon_m),\\
U &= g_m \varepsilon_m p_k^c H_{k,m} - g_m \varepsilon_m 2\sigma^2 + \sigma^2 \varepsilon_m H_{m,m} - e_m H_{m,m},\\
V &= g_m \varepsilon_m \sigma^2 + e_m H_{m,m} - \sigma^2 \varepsilon_m H_{m,m},\\
X &= e_m H_{m,m} \sigma^2 + e_m H_{m,m} p_k^c H_{k,m} - \varepsilon_m \sigma^2 H_{m,m} p_k^c H_{k,m}.
\end{aligned}$$

4) The coefficient for each item is as follows

$$\begin{aligned}
a_4 &= B E g_m^3 \varepsilon_m^3 p_k^c H_{k,m} - p_k^{c2} H_{k,m}^2 g_m^3 \varepsilon_m^3 E,\\
b_4 &= \left[p_k^c H_{k,m}\left(3AB g_m^2 \varepsilon_m^2 + C g_m^3 \varepsilon_m^3\right) + B g_m^3 \varepsilon_m^3 \sigma^2\right] E\\
&\quad - B g_m^3 \varepsilon_m^3 p_k^c H_{k,m} F + p_k^{c2} H_{k,m}^2 g_m^3 \varepsilon_m^3 F\\
&\quad - \left(p_k^{c2} H_{k,m}^2 3A g_m^2 \varepsilon_m^2 + 2 p_k^c H_{k,m} g_m^3 \varepsilon_m^3 \sigma^2\right) E,\\
c_4 &= -H_{m,m} E p_k^c H_{k,m} g_m^2 \varepsilon_m^2 - g_m^2 \varepsilon_m^2 p_k^c H_{k,m} D\\
&\quad + p_k^c H_{k,m}\left(3AB g_m \varepsilon_m + 3AC g_m^2 \varepsilon_m^2\right) E\\
&\quad + \left(3AB g_m^2 \varepsilon_m^2 + C g_m^3 \varepsilon_m^3\right)\sigma^2 E\\
&\quad - p_k^c H_{k,m}\left(3AB g_m^2 \varepsilon_m^2 + C g_m^3 \varepsilon_m^3\right) F\\
&\quad - B g_m^3 \varepsilon_m^3 \sigma^2 F + g_m^3 \varepsilon_m^3 B p_k^c H_{k,m}\\
&\quad + D p_k^{c2} H_{k,m}^2 g_m^2 \varepsilon_m^2 + p_k^{c2} H_{k,m}^2 3A g_m^2 \varepsilon_m^2 F\\
&\quad + 2 p_k^c H_{k,m} g_m^3 \varepsilon_m^3 \sigma^2 F - p_k^{c2} H_{k,m}^2 3A^2 g_m \varepsilon_m E\\
&\quad + \left(6A p_k^c H_{k,m} g_m^2 \varepsilon_m^2 \sigma^2 + \sigma^4 g_m^3 \varepsilon_m^3\right) E\\
&\quad - p_k^{c2} H_{k,m}^2 g_m^3 \varepsilon_m^3,\\
d_4 &= H_{m,m} F p_k^c H_{k,m} g_m^2 \varepsilon_m^2\\
&\quad - H_{m,m} E\left(p_k^c H_{k,m} 2A g_m \varepsilon_m + g_m^2 \varepsilon_m^2 \sigma^2\right)\\
&\quad - D\left[\left(2AB g_m \varepsilon_m + C g_m^2 \varepsilon_m^2\right) p_k^c H_{k,m} + g_m^2 \varepsilon_m^2 \sigma^2\right]\\
&\quad + p_k^c H_{k,m}\left(BA^3 + 3CA^2 g_m \varepsilon_m\right) E\\
&\quad + \left(3BA^2 g_m \varepsilon_m + 3AC g_m^2 \varepsilon_m^2\right)\sigma^2 E\\
&\quad - p_k^c H_{k,m}\left(3BA^2 g_m \varepsilon_m + 3AC g_m^2 \varepsilon_m^2\right) F\\
&\quad - \left(3AB g_m^2 \varepsilon_m^2 + C g_m^3 \varepsilon_m^3\right)\sigma^2 F\\
&\quad + g_m^2 \varepsilon_m^2 p_k^c H_{k,m} (AB + C g_m \varepsilon_m)\\
&\quad + g_m^2 \varepsilon_m^2 B g_m \varepsilon_m \left(\sigma^2 - p_k^c H_{k,m}\right)\\
&\quad + p_k^{c2} H_{k,m}^2 2A g_m \varepsilon_m D + p_k^c H_{k,m} 2A g_m^2 \varepsilon_m^2 \sigma^2 D\\
&\quad + p_k^{c2} H_{k,m}^2 3A^2 g_m \varepsilon_m F\\
&\quad + \left(+6A p_k^c H_{k,m} g_m^2 \varepsilon_m^2 \sigma^2 + \sigma^4 g_m^3 \varepsilon_m^3\right) F\\
&\quad - 6 p_k^c H_{k,m} \sigma^2 A^2 g_m \varepsilon_m E\\
&\quad - \left(p_k^{c2} H_{k,m}^2 A^3 + \sigma^4 3A g_m^2 \varepsilon_m^2\right) E\\
&\quad + g_m^2 \varepsilon_m^2 \left(p_k^{c2} H_{k,m}^2 g_m \varepsilon_m - p_k^{c2} H_{k,m}^2 A\right)\\
&\quad - 2A p_k^c H_{k,m} g_m \varepsilon_m \sigma^2 g_m^2 \varepsilon_m^2\\
&\quad + g_m^3 \varepsilon_m^3 H_{m,m}\left(B\sigma^2 + C p_k^c H_{k,m}\right),\\
g_4 &= H_{m,m} D\sigma^2 A + H_{m,m} F\sigma^2 A^2 + H_{m,m} g_m^2 \varepsilon_m^2 \sigma^2\\
&\quad - CA^2\sigma^2 D + CA^3\sigma^2 F + CA\sigma^2\\
&\quad + D\sigma^4 A^2 + \sigma^4 A^3 F + g_m^2 \varepsilon_m^2 \sigma^4 A\\
&\quad - A H_{m,m}\left(g_m \varepsilon_m \sigma^2 + p_k^c H_{k,m}\right)\\
&\quad - A^3 H_{m,m}\left(B\sigma^2 + C p_k^c H_{k,m}\right).
\end{aligned}$$

$$
\begin{aligned}
e_4 = {} & p_k^c H_{k,m} g_m \varepsilon_m H_{m,m} D \\
& + H_{m,m} F \left(p_k^c H_{k,m} 2A g_m \varepsilon_m + g_m^2 \varepsilon_m^2 \sigma^2 \right) \\
& - H_{m,m} E \left(p_k^c H_{k,m} A^2 + 2A g_m \varepsilon_m \sigma^2 \right) \\
& - H_{m,m} g_m^2 \varepsilon_m^2 p_k^c H_{k,m} \\
& - \left(B A^2 + 2AC g_m \varepsilon_m \right) p_k^c H_{k,m} D \\
& - \left(2AB g_m \varepsilon_m + C g_m^2 \varepsilon_m^2 \right) \sigma^2 D \\
& + \left[C A^3 p_k^c H_{k,m} + \left(B A^3 + 3 C A^2 g_m \varepsilon_m \right) \sigma^2 \right] E \\
& - p_k^c H_{k,m} \left(B A^3 + 3 C A^2 g_m \varepsilon_m \right) F \\
& - \left(B 3 A^2 + 2AC \right) g_m^2 \varepsilon_m^2 \sigma^2 F \\
& + g_m^2 \varepsilon_m^2 \left(AB + C g_m \varepsilon_m \right) \left(\sigma^2 - p_k^c H_{k,m} \right) \\
& + g_m^2 \varepsilon_m^2 \left(C A p_k^c H_{k,m} - B g_m \varepsilon_m \sigma^2 \right) \\
& + 4 p_k^c H_{k,m} \sigma^2 A g_m \varepsilon_m D \\
& + D \left(p_k^{c2} H_{k,m}^2 A^2 + \sigma^4 g_m^2 \varepsilon_m^2 \right) \\
& + 6 A^2 p_k^c H_{k,m} \sigma^2 g_m \varepsilon_m F \\
& + \left(p_k^{c2} H_{k,m}^2 A^3 + 3 A \sigma^4 g_m^2 \varepsilon_m^2 \right) F \\
& - \left(2 p_k^c H_{k,m} \sigma^2 A^3 + \sigma^4 3 A^2 g_m \varepsilon_m \right) E \\
& + 2 p_k^c H_{k,m} \sigma^2 g_m^3 \varepsilon_m^3 + g_m^2 \varepsilon_m^2 H_{m,m} p_k^c H_{k,m} \\
& + g_m^2 \varepsilon_m^2 \left(p_k^{c2} H_{k,m}^2 A - g_m \varepsilon_m \sigma^4 \right) \\
& + A g_m^2 \varepsilon_m^2 H_{m,m} \left(B \sigma^2 + C p_k^c H_{k,m} \right) \\
& + g_m^2 \varepsilon_m^2 H_{m,m} 2A \left(B \sigma^2 + C p_k^c H_{k,m} \right),
\end{aligned}
$$

$$
\begin{aligned}
f_4 = {} & H_{m,m} D \left(p_k^c H_{k,m} A + g_m \varepsilon_m \sigma^2 \right) \\
& + H_{m,m} F \left(p_k^c H_{k,m} A^2 + 2A g_m \varepsilon_m \sigma^2 \right) \\
& - H_{m,m} E \sigma^2 A^2 + H_{m,m} g_m^2 \varepsilon_m^2 \left(p_k^c H_{k,m} - \sigma^2 \right) \\
& - \left[p_k^c H_{k,m} C A^2 + \left(B A^2 + 2AC g_m \varepsilon_m \right) \sigma^2 \right] D \\
& + C A^3 \sigma^2 E - C A^3 p_k^c H_{k,m} F \\
& + \left(B A^3 + 3 C A^2 g_m \varepsilon_m \right) \sigma^2 F \\
& - \left[C A \sigma^2 - C A p_k^c H_{k,m} - \left(AB + C g_m \varepsilon_m \right) \sigma^2 \right] \\
& + D \left(2 p_k^c H_{k,m} \sigma^2 A^2 + \sigma^4 2 A g_m \varepsilon_m \right) \\
& + \left(2 p_k^c H_{k,m} \sigma^2 A^3 + \sigma^4 3 A^2 g_m \varepsilon_m \right) F \\
& + g_m^2 \varepsilon_m^2 \left(2 p_k^c H_{k,m} \sigma^2 A + g_m \varepsilon_m \sigma^4 \right) \\
& - \sigma^4 A^3 E - \sigma^4 A g_m^2 \varepsilon_m^2 \\
& + A g_m \varepsilon_m H_{m,m} \left[2A \left(B \sigma^2 + C p_k^c H_{k,m} \right) + p_k^c H_{k,m} \right] \\
& + g_m \varepsilon_m H_{m,m} \left(g_m \varepsilon_m \sigma^2 + p_k^c H_{k,m} \right) \\
& + g_m \varepsilon_m H_{m,m} A^2 \left(B \sigma^2 + C p_k^c H_{k,m} \right),
\end{aligned}
$$

In addition,

$$
\begin{aligned}
A &= \lambda + \beta\eta - g_m \varepsilon_m, \\
B &= p_k^c H_{k,m} / H_{m,m}, \\
C &= \sigma^2 / H_{m,m}, \\
D &= \lambda + \beta\eta + g_m \varepsilon_m, \\
E &= \left(\lambda + \beta\eta + g_m \varepsilon_m \right) B + g_m \varepsilon_m = DB + g_m \varepsilon_m, \\
F &= \varepsilon_m \sigma^2 - C \left(\lambda + \beta\eta + g_m \varepsilon_m \right) + g_m \varepsilon_m \\
&= \varepsilon_m \sigma^2 - CD + g_m \varepsilon_m.
\end{aligned}
$$

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