Dynamic Unicast-Multicast Scheduling for Age-Optimal Information Dissemination in Vehicular Networks

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Abstract—This paper investigates the problem of minimizing the age-of-information (AoI) and transmit power consumption in a vehicular network, where a roadside unit (RSU) provides timely updates about a set of physical processes to vehicles. Each vehicle is interested in maintaining the freshness of its information status about one or more physical processes. A framework is proposed to optimize the decisions to unicast, multicast, broadcast, or not transmit updates to vehicles as well as power allocations to minimize the AoI and the RSU’s power consumption over a time horizon. The formulated problem is a mixed-integer nonlinear programming problem (MINLP), thus a global optimal solution is difficult to achieve. In this context, we first develop an ant colony optimization (ACO) solution which provides near-optimal performance and thus serves as an efficient benchmark. Then, for real-time implementation, we develop a deep reinforcement learning (DRL) framework that captures the vehicles’ demands and channel conditions in the state space and assigns processes to vehicles through dynamic unicast-multicast scheduling actions. Complexity analysis of the proposed algorithms is presented. Simulation results depict interesting trade-offs between AoI and power consumption as a function of the network parameters.

Index Terms—Age-of-information (AoI), ant colony optimization (ACO), deep reinforcement learning (DRL), unicast and multicast transmission, vehicular networks.

I. INTRODUCTION

With the increasing diversity of vehicular applications that require real-time information updates, such as blind spot/lane change and forward collision warnings, vehicular communications over the upcoming 6G mobile networks become time-critical, and thus, fresh updates are of high importance [1]. While the conventional communication latency and throughput are effective metrics to evaluate the performance of the vehicular communication networks, these metrics do not capture the information freshness which is critical to obtain the real-time knowledge about the location, orientation, and speed of the vehicles. To this end, the age-of-information (AoI) is emerging as a useful metric to quantify the freshness of the information while taking into account the transmission latency, update generation time, and inter-update time interval. Specifically, AoI is defined as the elapsed time between the received information at the destination and the time when it was generated at the source [2]. It should be noted that the inter-update time —which is a scheduling parameter— is a crucial parameter in the AoI [2], and thus optimizing AoI is totally different from optimizing other metrics such as the throughput and latency.

Moreover, the dramatic upsurge in the number of vehicles requires the roadside infrastructures—such as roadside units (RSUs)—to serve more vehicles simultaneously and support their time-critical update requirements. In this context, unicast and multicast transmissions are typically considered to transmit independent data messages of interest for a user and a group of users, respectively. For instance, in [3], the authors considered maximizing the spectral efficiency by optimizing the downlink training and transmit power allocations. However, the unicast-multicast transmissions are predefined such that a user is either a unicast or belongs to a group of the multicast groups. Another predefined unicast-multicast transmission scenario was considered in [4], in which each user receives a private message and a common message is broadcasted to all users. The authors maximized the desired effective channel gain by designing the unicast power allocation and multicast beamformers. In [5], the energy efficiency was maximized while considering a predefined unicast-multicast scenario with simultaneous wireless information and power transfer.

None of the aforementioned research works considered optimizing a unicast, multicast, broadcast transmission scheduling, while minimizing AoI. Note that the consideration of minimizing a time-dependent metric, such as AoI necessitates a dynamic transmission scheduling over the time horizon. This paper develops a dynamic transmission scheduling and power allocation framework, in which at each time slot a vehicle receives either unicast, multicast, or broadcast message from the RSU with optimized power allocations. The main contributions of this paper are summarized as follows:

- We consider minimizing both the AoI at the vehicles and the RSU’s power expenditure, while optimizing the unicast-multicast scheduling decisions and their corresponding power allocations. The two objectives are coupled in a conflicting manner, due to the transmit power allocations. Therefore, we formulate a multi-objective optimization problem for the two conflicting objectives.
- We develop a metaheuristic solution based on the ant colony optimization (ACO) to solve the optimization problem, which provides a near-optimal solution.
- A computationally efficient solution for the real-time implementation purposes is also developed using deep reinforcement learning (DRL) model, which captures the
vehicles’ demands and the channel conditions in the state space and assigns processes to vehicles through dynamic unicast-multicast scheduling actions.

- Complexity analysis of the proposed algorithms is presented. Simulation results demonstrate interesting trade-offs between AoI and power consumption as a function of system parameters.

The remainder of this paper is organized as follows. Section II presents the system model. The performance metrics and problem formulation are discussed in Section III. Section IV presents the AC0 and DRL solutions. Section V illustrates simulation results and Section VI concludes the paper.

II. SYSTEM MODEL AND ASSUMPTIONS

The considered system consists of a set $\mathcal{V} = \{v_i\}_{i=1}^{V}$ of $V$ vehicles supported by an RSU that disseminates timely status updates to the vehicles. The RSU is equipped with a uniform linear array of $N$ antennas. A multi-modal data dissemination scenario is considered, in which the RSU is capable of providing timely status updates about a set $\mathcal{F} = \{f_i\}_{i=1}^{F}$ of $F$ physical processes. The payload size of an update is $L$ bits. Each vehicle is interested in maintaining freshness of its information status about a subset of processes $\mathcal{R}_i \subseteq \mathcal{F}$. To represent the information demands of the vehicles, we define $\mathbf{R} = [r_{il}]_{V \times F}$ such that

$$r_{il} = \begin{cases} 1, & \text{if vehicle } i \text{ is interested in process } l, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The time is divided into $T$ time slots each of duration $\delta$. Let $\psi_0 = \{x_0, y_0\}$ be the coordinates of the RSU and $\psi_i = \{x_i(t), y_i(t)\}$ be the coordinates of vehicle $i$ at time slot $t$. The angle of vehicle $i$ relative to the RSU at time slot $t$ can be expressed as $\phi_i(t) = \arccos \frac{x_i(t) - x_0}{\ell_i(t)}$, where $\ell_i(t) = \|\psi_i(t) - \psi_0\|$ is the distance between the vehicle $i$ and the RSU. Let us define the process-vehicle assignment decision variable $\eta_i(t) = [\eta_{il}(t)]_{V \times F}$, such that

$$\eta_{il}(t) = \begin{cases} 1, & \text{if the update of } f_l \text{ is assigned to } v_i \text{ at time slot } t, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

It is worth noting that $\sum_{i=1}^{V} \eta_{il}(t) = 1$ implies that the update of $f_l$ is unicasted to a single vehicle with $\eta_{il}(t) = 1$, $\sum_{i=1}^{V} \eta_{il}(t) = V'$ implies that the update of $f_l$ is multicasted to a group of vehicles with $\eta_{il}(t) = 1$. Finally, $\sum_{i=1}^{V} \eta_{il}(t) = V$ implies that the update message of $f_l$ is broadcasted to all vehicles and $\sum_{i=1}^{V} \eta_{il}(t) = 0$ implies that the information of process $f_l$ is not transmitted to any vehicle at time slot $t$. The communication channel between the RSU and vehicle $i$ at time slot $t$ is modeled as follows:

$$h_i(t) = \sqrt{\frac{c_0}{4 \pi f_c \ell_i(t)}} \mathbf{a}^H(\phi_i(t)) e^{j2\pi \ell_i(t)}, \quad (2)$$

where $f_c$ is the carrier frequency, $c_0$ is the speed of light, $H$ denotes the Hermitian transpose of $\mathbf{a}$, and $\ell_i(t)$ is the Doppler shift due to the movement of vehicle $i$ expressed as $\ell_i(t) = \frac{c_i f_c \cos \phi_i(t)}{c_0}$, where $c_i$ is the speed of vehicle $i$ [6]. Assuming a uniform linear antenna array at the RSU, the transmit array steering vector $\mathbf{a}(\phi_i(t)) = \mathbb{C}^{N \times 1}$ (with $\phi_i(t)$ as the azimuth angle between the RSU and vehicle $i$ at time slot $t$) can be expressed as follows:

$$\mathbf{a}(\phi_i(t)) = [1, e^{j \pi \sin \phi_i(t)}, e^{j2\pi \sin \phi_i(t)}, \ldots, e^{j(N-1)\pi \sin \phi_i(t)}], \quad (3)$$

where $j = \sqrt{-1}$ and the antenna spacing is $\lambda/2$ with $\lambda$ as the carrier wavelength.

III. PERFORMANCE METRICS AND PROBLEM STATEMENT

A. Decoding Error Probability

To guarantee the vehicles’ quality-of-service (QoS) requirements, the decoding error probability of each message should be less than a tolerable decoding error. The decoding error probability can be expressed as [7] follows:

$$\varepsilon_i(\gamma_i(t)) = \Phi \left( \frac{\delta_2 \omega_i}{\Gamma_i(t)} \left[ \ln \left( 1 + \gamma_i(t) \right) - \frac{L}{2} \ln 2 \right] \right), \quad (4)$$

where $\Phi(q) \triangleq \frac{1}{\sqrt{2\pi}} \int_q^\infty \exp(-\frac{u^2}{2}) du$, $\Gamma_i(t) \triangleq 1 - \frac{1}{(1+\gamma_i(t))^2}$ is the channel dispersion, $\gamma_i(t)$ is the signal-to-interference plus-noise ratio (SINR) at vehicle $i$ at time slot $t$, $\omega$ is the bandwidth of the channel, and $\delta_2 \triangleq \delta - \delta_1$ is the information transmission time, with $\delta_1$ as the dedicated time to acquire the vehicles’ angular parameters (i.e., location and speed).

B. SINR Model with MRT Beamforming

The maximum ratio transmission (MRT) beamforming scheme is considered, in which the asymptotically optimal beamformer vector for the vehicles that assigned the same update message is a linear combination of channels of these vehicles [8], [3]. Consequently, for a given $\eta_i(t)$, the linear combination of the channel vectors of vehicles that receive a message about $f_i$ is expressed as $\sum_{i=1}^{V} \eta_i h_i(t)$, let $\mathbf{p}(t) = [p_1(t), \ldots, p_N(t)]$ be the power allocation decision with $p_i(t)$ as the allocated power to transmit message update of $f_i$. For a given process-vehicle assignment $\eta_i(t)$ and power allocation decision $\mathbf{p}(t)$, the MRT beamforming vector of message $f_i$ (the beamforming vector of the group of vehicles that receive an update about $f_i$) is expressed as follows:

$$w_i(\eta_i(t), \mathbf{p}(t)) = \sum_{i=1}^{V} \eta_i \frac{\sqrt{p_i(t)}}{\sqrt{N \chi_i(t) \xi_i(t)}}, \quad (5)$$

where $\chi_i(t) = \frac{c_0}{4 \pi f_c \ell_i(t)} e^{-j2\pi \ell_i(t)}$ is the large-scale channel attenuation of vehicle $i$ and $\xi_i(t)$ is a normalization factor [3], [9]. The SINR at vehicle $i$ can thus be expressed as follows:

$$\gamma_i(t)(\eta_i(t), \mathbf{p}(t)) = \frac{|h_i(t)^H w_i(t)(\eta_i(t), \mathbf{p}(t))|^2}{\sum_{m=1}^{F} |h_i(t)^H w_m(t)(\eta(t), \mathbf{p}(t))|^2 + \sigma^2}. \quad (6)$$

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C. Age of Information

The instantaneous AoI of the physical process \( f_i \) at vehicle \( i \) evolves according to

\[
\Delta_{it}^{(t)}(\eta^{(t)}, p^{(t)}) = \begin{cases} 
\delta, & \text{if } \eta_{it}^{(t)} = 1 \text{ and } \epsilon_i(\gamma_i^{(t)}(\eta^{(t)}, p^{(t)})) \leq \varepsilon_i^{\max}, \\
\Delta_{it}^{(t-1)} + \delta, & \text{otherwise}, 
\end{cases}
\]

where \( \varepsilon_i^{\max} \) is the maximum allowed error probability at vehicle \( i \). The time-average AoI of \( f_i \) at vehicle \( i \) over \( T \) time slots is \( \bar{\Delta}_{it}(\eta^{(t)}, p^{(t)}) = \frac{1}{T} \sum_{t=1}^{T} \Delta_{it}^{(t)}(\eta^{(t)}, p^{(t)}) \). Consequently, the total time-average AoI can be expressed as follows:

\[
\bar{\Delta}(\eta^{(t)}, p^{(t)}) = \sum_{i=1}^{V} \sum_{l=1}^{F} \bar{\Delta}_{il}(\eta^{(t)}, p^{(t)})
= \frac{1}{T} \sum_{i=1}^{V} \sum_{l=1}^{F} \sum_{t=1}^{T} r_{il} \Delta_{it}^{(t)}(\eta^{(t)}, p^{(t)}).
\]

Note that the maximum value of \( \bar{\Delta}_{il} \) is \( \delta(T + 1)/2 \), which corresponds to the case of no update about \( f_i \) is received at vehicle \( i \) over the \( T \) time slots. Thus, the maximum value (upper bound) of the total time-average AoI \( \bar{\Delta}^{\max} \) can be expressed as:

\[
\bar{\Delta}^{\max} = \frac{\delta(T + 1)}{2} \sum_{i=1}^{V} \sum_{l=1}^{F} r_{il},
\]

which corresponds to the case of no update is received by any vehicle during the \( T \) time slots. The minimum value (lower bound) of the total time-average AoI \( \bar{\Delta}^{\min} \) corresponds the case of updating each vehicle in each time slot. Keeping in mind that a vehicle \( i \) is interested in \( | R_i | = \sum_{l=1}^{F} r_{il} \) processes and the best option is to alternate the updates between the \( | R_i | \) processes, \( \bar{\Delta}^{\min} \) can be expressed as:

\[
\bar{\Delta}^{\min} = \sum_{i=1}^{V} \frac{\delta}{T} \left[ \frac{| R_i |}{2} \right] - \sum_{r=1}^{| R_i | - 1} \frac{r(r + 1)}{2}.
\]

D. Significance of Process-Vehicle Assignment and Power Allocation - A Toy Example

Let us consider \( V = 5 \) vehicles, where each vehicle is interested in a subset of \( F = \{ f_1, f_2, f_3, f_4 \} \) processes with demands as illustrated in Fig. 1. The associated information demand matrix \( R \) can be represented as follows:

\[
R = [r_{il}]_{5 \times 4} = \begin{bmatrix}
1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
1 & 1 & 1 & 0 \\
1 & 1 & 0 & 0
\end{bmatrix} \begin{bmatrix}
v_1 \\
v_2 \\
v_3 \\
v_4 \\
v_5
\end{bmatrix}.
\]

Let us assume that the observation interval is \( T = 7 \) time slots and other parameters are as listed in Table I. According to (9) and (10), the maximum and minimum time-average AoI at the vehicles can be computed \( \bar{\Delta}^{\max} = 308/7 = 44s \) and \( \bar{\Delta}^{\min} = 108/7 \approx 15.4s \), respectively. Let us assume that the RSU assigns the processes to vehicles and allocates the power at random, the time-average AoI will vary around 210/7 \( \approx 30s \) and the power consumption will be around 0.5W. By examining all possible process-vehicle assignment and power allocation decisions with objective of minimizing both AoI and power consumption, the time-average AoI can be reduced to 214/7 \( \approx 17s \) while the time-average consumed power is 0.18W if the following decisions are performed. At \( t = 1 \) no message is transmitted. At \( t = 2 \), an update about \( f_1 \) is broadcasted to all vehicles. At \( t = 3 \), an update about \( f_3 \) is unicasted to \( v_2 \) and updates about \( f_4 \) and \( f_2 \) are multicasted to \( \{ v_1, v_3 \} \) and \( \{ v_4, v_5 \} \), respectively, and so on. The question is how to select optimal scheduling and power allocation decisions at each time slot for arbitrary number of physical processes and vehicles with different demands. This motivates the problem formulation in the following.

E. Problem Formulation

We consider minimizing the time-average AoI of each process at the vehicles as well as the time-average power consumption at RSU. Keeping in mind the trade-off between these two objectives and the fact that they have different units, ranges, and orders of magnitude, they should be normalized such that they have similar ranges [10]. Consequently, we define a multi-objective weighted sum utility function as:

\[
O(\eta^{(t)}, p^{(t)}) = \frac{\bar{\Delta}(\eta^{(t)}, p^{(t)}) - \bar{\Delta}^{\min}}{\bar{\Delta}^{\max} - \bar{\Delta}^{\min}} + (1 - \zeta) \frac{p^{(t)} - \bar{p}^{\min}}{\bar{p}^{\max} - \bar{p}^{\min}},
\]

where the time-average power consumption can be given as \( \bar{p}^{(t)} = \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{V} p_{il}^{(t)} \). Let \( 0 < \zeta \leq 1 \) is a relative weight to give preference to minimize the AoI or the power, \( \bar{\Delta}^{\max} \) and \( \bar{\Delta}^{\min} \) are the maximum and minimum total time-average AoI as expressed in (9) and (10), respectively, \( \bar{p}^{\max} \) is the maximum transmission power of the RSU, and \( \bar{p}^{\min} = 0 \). The optimization problem is thus formulated as follows:
\begin{align}
P_1 \min_{\eta^{(t)}, p^{(t)}} & \quad O(\eta^{(t)}, p^{(t)}) \tag{13a} \\
\text{s.t.} & \quad \sum_{l=1}^{F} p_l^{(t)} \leq P_{\text{max}}, \tag{13b} \\
& \quad \sum_{l=1}^{F} \eta_{il}^{(t)} \leq 1, \forall v_i \in V, \tag{13c} \\
& \quad \eta_{il}^{(t)} r_{il} = \eta_{il}^{(t)}, \forall 1 \leq i \leq V, 1 \leq l \leq F, \tag{13d} \\
& \quad p_l^{(t)} \geq 0, \forall f_l \in \mathcal{F}, \tag{13e} \\
& \quad \eta_{il}^{(t)} \in \{0,1\}, \forall v_i \in V, f_l \in \mathcal{F}. \tag{13f}
\end{align}

Constraint (13b) guarantees that the allocated power is less than the maximum transmission power of the RSU. Constraint (13c) guarantees that at most one process is assigned to each vehicle at each time slot. Keeping in mind that \( R \) and \( \eta^{(t)} \) are binary variables, (13d) guarantees that if a vehicle \( i \) is not interested in process \( l \) (i.e., \( r_{il} = 0 \)) then process \( l \) will not be assigned to vehicle \( i \) (i.e., \( \eta_{il}^{(t)} \) should be 0).

The optimization problem in (13) is a mixed-integer non-linear programming (MINLP) problem, where the discontinuity in the objective function comes from (8), the non-linearity comes from (6), and the integer constraint arises from (14f).

**IV. PROPOSED AGE-OPTIMAL SOLUTIONS**

First, it is important to note that from (7), the AoI of process \( f_l \) at vehicle \( i \) can be minimized if both \( \eta_{il}^{(t)} = 1 \) and \( \xi_i(\gamma_i^{(t)}(\eta^{(t)}, p^{(t)})) \leq \varepsilon^{\text{max}} \). To ensure that \( \xi_i(\gamma_i^{(t)}(\eta^{(t)}, p^{(t)})) \leq \varepsilon^{\text{max}} \), we denote \( \gamma_i \) be the SINR at vehicle \( i \) that ensures \( \xi_i(\gamma_i) = \varepsilon^{\text{max}} \) which can be found by solving (4) numerically. Then, from (4) and (6), the AoI of the process \( f_l \) at vehicle \( v_i \) can be minimized if both \( \eta_{il}^{(t)} = 1 \) and the following inequality are satisfied, i.e.,

\[ \frac{\sum_{m \neq l} p_m^{(t)} | h_{il}^{(t)} w_m^{(t)}(\eta^{(t)})|^2}{\sum_{m} p_m^{(t)} | h_{il}^{(t)} w_m^{(t)}(\eta^{(t)})|^2 + \sigma^2} \geq \gamma_i. \tag{14} \]

Consequently, a solution for the optimization problem in (13) can be obtained by solving the following optimization problem:

\[ \begin{align*}
P_2 \min_{\eta^{(t)}, p^{(t)}} & \quad O(\eta^{(t)}, p^{(t)}) \\
\text{s.t.} & \quad (13c),(13d), \text{ and } (13f),
\end{align*} \]

where \( p^{(t)} = [p_{\eta_i}^{(t)}, \cdots, p_{\eta_i}^{(t)}] \) is the solution of the following linear programming problem:

\[ \begin{align*}
\mathbf{p}^{(t)} = \min_{\mathbf{p}} & \quad \sum_{l=1}^{F} p_l^{(t)} \\
\text{s.t.} & \quad \sum_{l=1}^{F} \eta_{il}^{(t)} | h_{il}^{(t)} w_l^{(t)}(\eta^{(t)})|^2 \geq \eta_{il}^{(t)} \gamma_i, \forall f_l, v_i, \tag{16a} \\
& \quad \sum_{m \neq l} p_m^{(t)} | h_{il}^{(t)} w_m^{(t)}(\eta^{(t)})|^2 + \sigma^2 \tag{13b} \\
& \quad \text{and } (13e)
\end{align*} \]

It is worth noting that for a given \( \eta^{(t)} \), constraint (16a) guarantees that the allocated power minimizes the AoI. If (16) is infeasible for a given \( \eta^{(t)} \), then \( \eta^{(t)} \) does not minimize the objective function and will be discarded. The strategy of the following ACO and DRL solution approaches can be summarized as follows. Search for an optimized \( \eta^{(t)} \) by exploring its search space and for each candidate \( \eta^{(t)} \) find the corresponding best power allocation by solving (16). The fitness of a candidate \( \eta^{(t)} \) is reflected by its ability to minimize the objective function with a feasible power allocation.

**A. Ant Colony Optimization (ACO)**

The optimization problem in (15) can be solved by enumerating all the feasible decisions. Such exhaustive search approach is computationally inefficient, which motivates designing a metaheuristic solution based on the ACO for rapid discovery of good solutions and guarantee convergence [11, Ch.4.3]. In the proposed ACO algorithm, a colony of \( A \) ants collaborate to solve \( P_1 \). Each ant \( a \) in \( A \) travels a tour of \( T \) steps. In each step, it assigns a process to each vehicle. The probability that ant \( a \) assigns process \( f_l \) to vehicle \( v_i \) and the probability it does not assign a process to vehicle \( v_i \) at time \( t \) are obtained as:

\[ \tilde{\pi}_{il}^{(t)} = \frac{(\tilde{\pi}_{il}^{(t)})^{1+\bar{\pi}_{il}^{(t)}}}{1 + \sum_{l=1}^{F} (\tilde{\pi}_{il}^{(t)})^{1+\bar{\pi}_{il}^{(t)}}}, \quad \bar{\pi}_{il}^{(t)} = 1 - \sum_{l=1}^{F} \tilde{\pi}_{il}^{(t)}, \tag{17} \]

respectively, where \( \bar{\pi}_{ir}^{(t)} \) is the trail pheromone and \( \tilde{\pi}_{il}^{(t)} \) is the attractiveness of assigning process \( f_l \) to vehicle \( v_i \). The latter is set to be

\[ \tilde{\pi}_{il}^{(t)} = \frac{r_{il}^{(t)} \Delta^{(t)}_{il}}{t}, \tag{18} \]

to give higher attractiveness to assigning the process with high AoI and of interest to \( v_i \). The parameters \( \epsilon_1 \) and \( \epsilon_2 \) control the influence of the pheromone and attractiveness, respectively. At each step, ant \( a \) obtains \( \eta^{(t,a)} \) based on (17) and obtain the power allocation \( p^{(t,a)} \) by solving (16). Only ants that obtain the highest and second-highest \( O(\eta^{(t,a)}, p^{(t,a)}) \) \( \forall a \in A \) deposit their pheromone [12]. The pheromone is updated as follows:

\[ \tilde{\pi}_{il}^{(t)} \leftarrow (1 - \kappa) \tilde{\pi}_{il}^{(t)} + \delta^{(t,a)}_{il} \Delta^{(t,a)}, \tag{19} \]

where \( \kappa \) is the pheromone evaporation coefficient and \( \Delta^{(t,a)} \) is the deposit pheromone, which is expressed as

\[ \Delta^{(t,a)} = \begin{cases} 
\exp[-O(\eta^{(t,a)}, p^{(t,a)})], & \text{if } \sum_{l=1}^{F} p_l^{(t,a)} \leq P_{\text{max}}, \\
0, & \text{otherwise}
\end{cases}, \tag{20} \]

The ACO algorithm is illustrated in Algorithm 1 which iterates until the improvement in the best solution of the whole colony is less than a threshold \( \epsilon_0 \) or a maximum number of colonies \( I \) has been generated.
Algorithm 1 ACO algorithm for age-optimum dynamic transmission.

1: Input $R$, $h^{(t)}$, $\kappa$, $I$, $A$, $\epsilon_0$;
2: $O^* \leftarrow \infty$; $O_p \leftarrow 0$;
3: while $I \geq 1$ and $|O^* - O_p| \geq \epsilon_0$ do
4: $O_t \leftarrow \infty$; $O_2 \leftarrow \infty$; $I = I - 1$; $O_p = O^*$;
5: for $a = 1$ to $A$ do
6: for $t = 1$ to $T$ do
7: Obtain $\eta^{(t,a)}$ using (17); Obtain $p^{(t,a)}$ by solving (16);
8: end for
9: Evaluate $O(\eta^{(t,a)}, p^{(t,a)})$ using (12);
10: if $O^* > O(\eta^{(t,a)}, p^{(t,a)})$, $O^* = O(\eta^{(t,a)}, p^{(t,a)})$; end if;
11: if $O_1 > O(\eta^{(t,a)}, p^{(t,a)})$, $a_1 = a$;
12: else if $O_2 > O(\eta^{(t,a)}, p^{(t,a)})$, $a_2 = a$; end if
13: end for
14: Deposit pheromone of $a_1$ and $a_2$ using (19);
15: end while
16: Return $O^*$.

B. DRL-Based Solution Approach

In this section, we aim to design a real-time solution approach for the optimization problem in (13). In this context, we develop a DRL model that involves the definition of the environment state space $s^t \in \mathcal{S}$, the action space $\mu^t \in \mathcal{A}$, and the immediate reward function $\rho^t$.

- The state of the environment at time slot $t$ is given by

$$s^t = \{x_{i}^{(t)}, \{r_{11} \Delta_{11}^{(t)}, r_{12} \Delta_{12}^{(t)}, \cdots, r_{iF} \Delta_{i}^{(t)}\}\}_{i=1}^{V},$$

which captures the channel state and the AoI of the processes of interest for the $V$ vehicles.

- The action at time slot $t$ is defined as $\mu^t = [\mu^{(t)}_i]_{V \times 1}$, which is a vector of integers $\mu^{(t)}_i \in \{0 \cup R_i\}$, such that

$$\mu^{(t)}_i = \begin{cases} l, & \text{if } v_i \text{ is assigned to } v_{i}, \\ 0, & \text{otherwise} \end{cases}.$$  

It is worth noting that $\mu^{(t)}$ is an equivalent representation to $\eta^{(t)}$ with a dimension of $V \times 1$ instead of $V \times F$.

- The immediate reward at time slot $t$ is expressed as

$$\rho^{(t)} = \Delta_{t} (\eta^{(t)}, p^{(t)}) - \Delta_{t}^{\min} + (1 - \zeta) \frac{p^{(t)}}{p^{\max}} \frac{\bar{p}^{(t)}}{p^{\min}},$$

where $p^{(t)} = \frac{1}{t} \sum_{t'=1}^{t} p^{(t')}$, $\Delta_{t} (\eta^{(t)}, p^{(t)})$, $\Delta_{t}^{\max}$, and $\Delta_{t}^{\min}$ are obtained by replacing $T$ by $t$ in (8), (9), and (10), respectively. The reward is set to $\log(p^{(t)} + \nu)$, where $\nu$ is a very small number that introduced to avoid infinite reward.

The DRL training algorithm is illustrated in Algorithm 2. It is worth mentioning that the trained DRL agent estimates an action $\mu^{(t)}$ for a given state, the corresponding $\eta^{(t)}$ is utilized to find the power allocation in (16) and evaluate the objective function in (13a).

C. Complexity Analysis

Keeping in mind that a process-vehicle assignment decision $\eta^{(t)}$ can be represented by a vector $\mu^{(t)} = [\mu^{(t)}_i]_{1 \times V}$, the search space of (15) over the $T$ time slots is $O((F + 1)^{VT})$. The worst-case computational complexity of evaluating the objective function in (12) is $O(V F T^2)$ operations and solving (16) requires $O((V + F)^2.5)$ operations. Consequently, the computational complexity of the exhaustive search is $O(V^{3.5} T^2 F^V)$. An ant agent performs $O(V F)$ operations to find a process-vehicle assignment decision, $O((V + F)^2)$ operations to allocate the power, and $O(V F T^2)$ operations to evaluate (12). Consequently, the worst-case computational complexity of the ACO is $O((V F)^{1.5} T^3 A I)$, where $A$ is the number of ants in the colony and $I$ is the maximum number of colonies. Considering a scenario of $V = 5$ vehicles and $F = 4$ processes, the average execution time of the exhaustive search, ACO, and DRL solution approaches is 1.8 s, 0.2 s, and 0.01 s, respectively. Average execution time using MATLAB on an Intel(R) Core(TM) i7-3770 CPU machine working at a clock frequency of 3.4 GHz and 16 GB of RAM.

V. SIMULATION RESULTS AND DISCUSSIONS

This section introduces simulation results to evaluate the proposed framework and compare its performance with the random solution approach, in which the process-vehicle assignment and power allocations decisions are selected at random. Unless otherwise stated, the considered numerical values of the system parameters and solution approaches are listed in Table I.

| Parameter | Value       | Parameter | Value       | Parameter | Value       |
|-----------|-------------|-----------|-------------|-----------|-------------|
| $F$       | 0.1 byte    | $\epsilon$ | 10/10/10   | $\nu$     | 0.1         |
| $V$       | 10          | $\mu$     | 10 Mbit/s  | $\gamma$  | 0.1         |
| $T$       | 50          | $\kappa$  | 500         | $\tau$    | 1           |
| $\alpha$  | 0.1         | $\eta$    | 1/1/1/1     | $\lambda$ | 0.05        |
| $\beta$   | 10          | $\nu$     | 0.01        | $\omega$  | 0.001       |

TABLE I: Simulation Parameters.
Figure 2 illustrates the objective function versus the relative weight \( \zeta \) for the proposed framework obtained using the exhaustive search, ACO, and DRL solution approaches as well as the random approach. It is seen that the ACO and DRL approaches achieve performance close to that of the exhaustive search approach and the random approach provides the worst performance in comparison with the proposed framework with the three solution approaches.

To get more insight into this result, Fig. 3 shows the average normalized AoI and power consumption versus the relative weight \( \zeta \) for the random solution and the proposed framework using the ACO and DRL solutions. The curves of the exhaustive search follow a similar trend to that of the ACO and are omitted to make Fig. 3 less crowded. It is noticed that the proposed framework provides a good trade-off between AoI and power expenditure as for low values of \( \zeta \) it minimizes the power expenditure and as \( \zeta \) increases it minimizes the AoI.

That is not the case for the random solution, in which both the AoI and power expenditure are not function of the relative weight and the power consumption is higher than that of the proposed framework.

Figure 4 depicts the average normalized AoI and power expenditure of the random solution and the proposed framework using the ACO solution versus the number of process of interest per vehicle \( |\mathcal{R}_i| \). It is clear that the AoI increases as the vehicles’ demand increases in both random solution and proposed framework, with less AoI in the proposed framework. On the other hand, the power expenditure in the proposed framework is decreased as the vehicles’ demand increases. This is attributed to the fact that for a fixed set of processes, as the number of process of interest per vehicle increases the demand of the vehicles becomes more similar which enables the proposed framework to transmit the same update to more vehicles, which reduces the interference, and thus reduces the power expenditure.

VI. CONCLUSION

This paper has proposed a dynamically unicast, multicast, and broadcast transmission framework to minimize both AoI and power consumption in vehicular networks. To solve the formulated mixed integer optimization problem, two solution approaches have been developed, namely a metaheuristic solution based on ACO and less computational complex in real-time evaluation solution based on DRL approach. Simulation results have illustrated that the proposed framework minimizes both the AoI and power consumption and provides a good trade-off between them. Results also have showed that ACO and DRL solution approaches provide close to the optimal solution, which is obtained through exhaustive search.

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REFERENCES

[1] Noor-A-Rahim et al., “6G for vehicle-to-everything (v2x) communications: Enabling technologies, challenges, and opportunities,” Proc. IEEE, vol. 110, no. 6, pp. 712–734, 2022.
[2] S. Kaul, R. Yates, and M. Gutierrez, “Real-time status: How often should one update?” in Proc. IEEE INFOCOM, 2012, pp. 2731–2735.
[3] M. Sadeghi et al., “Joint unicast and multi-group multicast transmission in massive MIMO systems,” IEEE Trans. Wirel. Commun., vol. 17, no. 10, pp. 6375–6388, 2018.
[4] J. Wang, H. Xu, B. Zhu, L. Fan, and A. Zhou, “Hybrid beamforming design for mmWave joint unicast and multicast transmission,” IEEE Commun. Lett., vol. 22, no. 10, pp. 2012–2015, 2018.
[5] W. Hao, G. Sun, F. Zhou, D. Mi, J. Shi, P. Xiao, and V. M. Leung, “Energy-efficient hybrid precoding design for integrated multicast–unicast millimeter wave communications with SWIPT,” IEEE Trans. Veh. Technol., vol. 68, no. 11, pp. 10956–10968, 2019.
[6] W. Yuan, Z. Wei, S. Li, J. Yuan, and D. W. K. Ng, “Integrated sensing and communication-assisted orthogonal time frequency space transmission for vehicular networks,” IEEE J. Sel. Top. Signal Process., vol. 15, no. 6, pp. 1515–1528, 2021.
[7] C. She, C. Sun, Z. Gu, Y. Li, C. Yang, H. V. Poor, and B. Vucetic, “A tutorial on ultra reliable and low-latency communications in 6G: Integrating domain knowledge into deep learning,” Proc. IEEE, vol. 109, no. 3, pp. 204–246, 2021.
[8] M. Sadeghi and C. Yuen, “Multi-cell multi-group massive MIMO multicasting: An asymptotic analysis,” in Proc. IEEE Global Communications Conference (GLOBECOM), 2015, pp. 1–6.
[9] M. Sadeghi, E. Björnson, E. G. Larsson, C. Yuen, and T. L. Marzetta, “Max–min fair transmit precoding for multi-group multicasting in massive MIMO,” IEEE Trans. Wirel. Commun., vol. 17, no. 2, pp. 1358–1373, 2018.
[10] R. T. Marler and J. S. Arora, “Survey of multi-objective optimization methods for engineering,” Structural and multidisciplinary optimization, vol. 26, no. 6, pp. 369–395, 2004.
[11] M. Dorigo and T. Stützle, Ant Colony Optimization, 1st ed. A Bradford Book, Cambridge, MA, U.S.A., 2004.
[12] K. Doerner et al., “Pareto ant colony optimization: A metaheuristic approach to multiobjective portfolio selection,” Annals of Operations Research, vol. 131, no. 1-4, pp. 79–99, Oct. 2004.