A Dynamic Transmission Design via Deep Multi-task Learning for Supporting Multiple Applications in Vehicular Networks

Zhixing He, Mengyu Ma, Chao Wang(✉), and Fuqiang Liu

Department of Information and Commnication Engineering, Tongji University, Shanghai 201804, China
{1830275,mengyu_ma,chaowang,liufuqiang}@tongji.edu.cn

Abstract. We study a cross-layer transmission design problem for vehicular communication networks. Two source-destination links are considered to share the same spectrum resource. Each link intends to send two types of messages to support different delay-sensitive applications. The whole system operates in a dynamic environment in which the small-scale channel fading may change rapidly. Therefore, the sources need to vary their transmission strategies accordingly to efficiently use the available resources while keeping the performance requirements satisfactory. Conventional transmission design via mathematical tools in general demands an iterative computation process and results in high complexity unsuitable for rapid decision-making. In this paper, we propose tackling such a problem by first transforming the transmission design problem into a joint classification-regression problem, and then applying deep multi-task learning (MTL) to solve it. Through simulation results, we show that our method can achieve the similar performance as the transmission design found by mathematical optimizations, with a much faster inference process. The advantages would become even more notable when the network size increases and the environment becomes more complex.

Keywords: Cross-layer transmission design · Vehicular communication · Multi-task learning

1 Introduction

Improving road safety, alleviating traffic congestion, and reducing energy consumption have become the major concerns in the development of modern road transportation systems. Allowing high-quality communications among the elements on the road (including vehicles, roadside infrastructure, pedestrians, etc.) serves as one of the key technologies for establishing an intelligent transportation system (ITS) [1]. It can enable a rich amount of sensing, computing, storage and communication resources to be shared to enhance the capability of each

H. Gao et al. (Eds.): ChinaCom 2021, LNICST 433, pp. 306–321, 2022.
https://doi.org/10.1007/978-3-030-99200-2_24

individual [2]. However, transmission design in vehicular communication networks can be much more challenging than those in conventional cellular and WiFi networks [3]. First, vehicular communication often needs to support multiple safety-related applications, which have different quality of service (QoS) requirements. Second, the available spectrum resource is normally limited and may be shared by multiple links. Hence inter-user interference has to be taken into account, if efficient channel usage is desired. Finally, due to the rapid movement of vehicles, the channel fading changes dynamically. Continuous and rapid transmission decision-making should be conducted accordingly.

Efficient transmission design in wireless networks through power control to balance the desired performance of each link and mutual interference between links has been studied extensively in the past decade [4–6]. The optimization target can be very different, ranging from minimized energy consumption to maximized throughput, depending on the application demand. For instance, the amount of information that can be successfully delivered by one joule of energy (also termed energy efficiency, EE) has attracted recent attentions due to its fractional nature, practical meaning, and difficulties in solving the problem. For a multi-user interference channel, reference [5] proposes a quadratic transform technique for tackling the multiple-ratio concave-convex fractional problem for EE. Reference [6] also studies a successive pseudoconvex approximation framework to maximize the EE.

But these works may not be naturally applicable in vehicular communication networks because of a number of reasons. First, they consider only a single type of message between each source-destination link. In addition, transmission design is carried out based on information theory and considers only the channel state information (CSI) in the physical (PHY) layer. By this means, the queue state information (QSI) in the MAC layer is ignored such that message transmission delay cannot be properly taken into consideration in a dynamic environment [7]. To handle these issues, our earlier work [8] investigates a two-user vehicular communication network in which each link desires to deliver two types of different messages, representing periodic heart-beat status messages and random sensing messages respectively. Applying the Lyapunov optimization theory, sequential power control in a dynamic environment is transformed into a new optimization problem that can be solved greedily. It is shown that the EE can be notably improved by the proposed method compared with conventional approaches.

Nevertheless, the computation complexity of the above method is high since it applies an iterative process to identify the solution of the power control problem, and also exhaustively searches the best decision for determining which message should be transmitted. This hinders the method's operation in an online fashion. There is a need for an efficient and dynamic transmission design strategy for supporting multiple applications in vehicular communication networks.

In the past few years, using machine learning (ML) tools to solve complex optimization and decision-making problems in wireless systems has drawn a large amount of research interests. For example, reference [9] shows that the beamforming design in a multiple-input multiple-output (MIMO) system can be formulated as a multi-class classification problem, and thus be solved efficiently

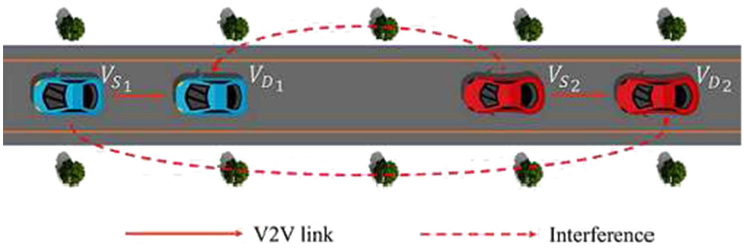

Fig. 1. System model

using ML algorithms without significant performance loss. References [10–12] prove that the power control problem and user scheduling problem can respectively be treated as regression and classification problems. Therefore, after being properly trained by datasets generated using time- and computation-demanding mathematical tools, ML models, especially deep learning models, can rapidly carry out the inference process and reach near-optimal solutions for unseen data. Advanced ML schemes, e.g. convolution neural networks [13] and ensemble learning [14], are applied to solve complex power control problems recently as well.

In this paper, we borrow the above ideas to solve the aforementioned dynamic transmission design problem. Specifically, we consider a vehicular communication system that consists of two source-destination links sharing the same spectrum resource. Each link intends to deliver two types of messages with different QoS requirements: The periodic heart-beat messages should be transmitted immediately with high reliability, while the sensor messages should be sent with limited delay. Targeting maximized EE, we first transform the non-convex fractional optimization problem with time average constraints into a series of solvable mixed integer optimization problems. Further, we apply a deep multi-task learning (MTL) network trained by data generated using mathematical optimization tools, and with loss function properly designed to balance individual learning tasks. Numerical results show that the proposed MTL-aided dynamic transmission design can achieve the similar performance as that found by mathematical optimizations, but with limited computational complexity.

The remainder of the paper is organized as follows. In Sect. 2, we present the system model, transmission design problem formulation, and the conventional solution. In Sect. 3, we develop the MTL-aided transmission design and elaborate the training process. Section 4 illustrates numerical performance assessments of the proposed method. Finally, Sect. 5 concludes the paper.

2 System Model and Transmission Design Problem

We consider a multi-user vehicular communication network, in which two pairs of information source and destination vehicles, denoted by V_{S_i} and V_{D_i} for $\forall i \in \{1, 2\}$, share the same spectrum resource, as shown in Fig. 1. Their operations can be coordinated by the serving roadside infrastructure. Each source V_{S_i} desires to send two types of delay-limited messages, which have different characteristics and

QoS requirements to support different road safety applications, to V_{D_i}. Messages generation and transmission are assumed to conduct in discretized unit time slots. Thus, V_{S_i} executes its transmission operation at the beginning of each time interval $[t, t+1)$, for $t \in \{1, 2, \dots\}$.

The first type of messages, termed *type-1 messages*, represent heartbeat messages and arrive in V_{S_i} periodically with a constant data rate r_i bits/slot. They normally carry real-time status of V_{S_i}. Hence they should be transmitted immediately. To guarantee V_{D_i} to attain a proper knowledge of the status of V_{S_i}, the successful transmission ratio should be sufficiently large. We use a binary indicator $\phi_i[t]$ to denote whether, at time slot t, V_{D_i} receives the message. The QoS requirement of the type-1 message can hence be expressed as

$$\bar{\phi_i} = \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \phi_i[t] \geq \phi_{i,\min}, \tag{1}$$

where $\phi_{i,\min}$ is the minimum threshold value for the ith link (e.g. 70%).

The second type of messages, termed *type-2 messages*, represent messages that randomly arrive in V_{S_i}. Such messages can be those that support environment sensing or on-board infotainment applications. Let $a_i[t]$ (in bits) denote the generated data volume (within time interval $[t, t+1)$), which, without loss of generality, is assumed to follow a stationary random process with expectation λ_i bits/slot. Different from type-1 messages, type-2 messages can normally tolerate certain delay. Hence, the data unable to delivery are temporarily stored in the source queue of V_{S_i} (denoted by $\mathbb{Q}_i$). Use $Q_i[t]$ and $b_i[t]$ to respectively denote the amounts of data stored in and leave $\mathbb{Q}_i$, at the beginning of time interval $[t, t+1)$. For some initial value $Q_i[1]$, the queue state $Q_i[t+1] = \max\{Q_i[t]-b_i[t], 0\}+a_i[t]$. To avoid the queuing delay to become unlimitedly large, we set the QoS requirement of the type-2 messages to be

$$\lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} b_i[t] \geq \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} a_i[t] = \lambda_i. \tag{2}$$

This implies the queues being stable [15].

The message transmissions are conducted in a block-fading environment. The fading coefficient between V_{S_j} and V_{D_i} at time interval $[t, t+1)$ is denoted by $h_{ij}[t]$, which accounts for both the large-scale and small-scale fading phenomenon. We assume that the knowledge of $h_{ij}[t]$ is causally available at all terminals (through, e.g., channel training coordinated by the serving infrastructure). $|h_{ij}|^2$ denotes the channel power gains correspondingly. Use $p_i[t]$ (chosen from domain $[p_{i,\min}, p_{i,\max}]$) and $R_i[t]$ to denote the transmit power and data rate of V_{S_i} at time interval $[t, t+1)$. Encoding using unit-power capacity-achieving Gaussian random codes leads to

$$R_i[t] \leq B\log_2\left(1 + \frac{|h_{ii}[t]|^2\, p_i[t]}{|h_{ij}[t]|^2\, p_j[t] + N_0}\right), \quad \forall i \in \{1, 2\}, \tag{3}$$

where B is the bandwidth and N_0 is the noise power.

We consider a dynamic vehicular communication environment such that the small-scale fading coefficients change independently across time slots. Therefore, a corresponding dynamic transmission design is expected to efficiently deliver the messages while keeping the QoS requirements satisfactory. In what follows, the transmission efficiency is evaluated by energy efficiency, i.e., the amount of information transmitted by one joule of energy consumption. Mathematically, it is defined as the ratio of the average of long-term aggregate data to the average of the corresponding long-term total energy consumption:

$$\bar{\eta} = \frac{\bar{R}}{\bar{P}} = \frac{\bar{R}_1 + \bar{R}_2}{\bar{p}_1 + \bar{p}_2}, \tag{4}$$

where the individual average transmission rate $\bar{R}_i = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} R_i[t]$, and the individual average power consumption $\bar{p}_i = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} P_i[t] = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} p_i[t] + p_{\mathrm{c},i}$, and $p_{\mathrm{c},i}$ is the constant circuit power of V_{S_i} [16].

In addition to controlling power $p_i[t]$, due to the requirement of supporting multiple applications, each source has an additional action to choose encoding which message, denoted mathematically by a binary indicator $\psi_i[t]$. Specifically, $\psi_i[t] = 0$ represents the case that V_{S_j} chooses excluding a type-1 message in its transmitted signal. As a result, all power consumption is used to satisfy the QoS requirement of the type-2 messages, i.e., emptying the queue $\mathbb{Q}_i$ with $b_i[t] = R_i[t]$. On the other hand, choosing $\psi_i[t] = 1$ means that V_{S_j} intends to send both types of messages. By this means, $b_i[t] = R_i[t] - r_i$ and the remaining r_i bits are allocated to the type-1 message. Note that in this case, V_{S_j} needs to use sufficient power to guarantee $R_i[t] \geq r_i$.

In summary, the dynamic transmission design in the considered vehicular communication network aims to, based on the knowledge of CSI in the PHY layer (i.e., channel fading coefficients) and QSI in the MAC layer (i.e., queue lengths), solve the following stochastic optimization problem:

$$\text{maximize}: \ \bar{\eta} = \frac{\bar{R}_1 + \bar{R}_2}{\bar{p}_1 + \bar{p}_2} \tag{5}$$

$$\text{s.t.}: \ \text{C1: } \bar{\phi}_i \geq \phi_{i,\min}, \quad \forall i \in \{1,2\}, \tag{6}$$

$$\text{C2: } \mathbb{Q}_i \text{ is stable}, \quad \forall i \in \{1,2\}, \tag{7}$$

$$\text{C3: } p_{i,\min} \leq p_i[t] \leq p_{i,\max}, \quad \forall i \in \{1,2\}. \tag{8}$$

$$\text{C4: } \ \psi_i[t] \in \{0,1\}, \ \forall i \in \{1,2\}. \tag{9}$$

The above problem is hard to solve exactly, since the objective function and constraints have time average operations. One can reach a suboptimal solution with the aid of Lyapunov optimization theory [8,15]. We define $\mathbf{p}^* = [p_1[1], p_2[1], p_1[2], p_2[2], \cdots]$ as the optimal power allocation vector. The optimal power allocation achieves the optimal EE $\bar{\eta}_{opt}$ if and only if $\max((\bar{R}_1 + \bar{R}_2) - \bar{\eta}_{opt}(\bar{p}_1 + \bar{p}_2)) = 0$ [17]. Thus, we can first transform the objective function at the beginning of time interval $[t, t+1)$ into the form:

$$\text{maximize}: \ (R_1[t] + R_2[t]) - \bar{\eta}_{opt}\,(p_1[t] + p_{\mathrm{c},1} + p_2[t] + p_{\mathrm{c},2}) \tag{10}$$
$$\text{s.t.:} \ \text{C1, C2, C3, C4.}$$

Since $\bar{\eta}_{opt}$ is unknown, we define $\eta[t]$ as the objective function achieved so far:

$$\eta[t] = \frac{\sum_{\tau=1}^{t-1} (R_1[\tau] + R_2[\tau])}{\sum_{\tau=1}^{t-1} (p_1[\tau] + p_{c,1} + p_2[\tau] + p_{c,2})}. \tag{11}$$

We next replace $\bar{\eta}_{opt}$ in (10) by $\eta[t]$ and eliminate the constant part $p_{c,1}$ and $p_{c,2}$. Then problem (10) is cast as

$$\begin{aligned} \text{maximize}: \ & (R_1[t] + R_2[t]) - \eta[t](p_1[t] + p_2[t]) \\ \text{s.t.:} \ & \text{C1, C2, C3, C4.} \end{aligned} \tag{12}$$

It is shown in [8,15] that the transformation is effective for solving the original problem (5), since the time average operation (over future transmission strategies) in the objective function is avoided.

Furthermore, we can transform the constraint C1 into an equivalent queue stability constraint [15], by defining a virtual queue for each source-destination pair $\mathbb{Y}_i, \forall i \in \{1, 2\}$. Use $Y_i[t]$ to represent the queue length of $\mathbb{Y}_i$ at the beginning of time interval $[t, t+1)$. For a certain initial value $Y_i[1]$, the virtual queue updates according to the following formula:

$$Y_i[t+1] = \max\{Y_i[t] - \phi_i[t], 0\} + \phi_{i,\min}, \quad \forall i \in \{1, 2\}. \tag{13}$$

Demanding the stability of the virtual queue eliminates the time average operation of the constraint C1 since it implies $\lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \phi_i[t] = \bar{\phi}_i \geq \phi_{i,\min}$.

Based on the Lyapunov optimization theory, the constrains that the queues $\mathbb{Y}_1$, $\mathbb{Y}_2$, $\mathbb{Q}_1$, and $\mathbb{Q}_2$ are stable can be described by a Lyapunov drift-plus-penalty, and then transformed to a cost function in the objective function. In addition, finding a lower bound of the changing part of the drift-plus-penalty, the original transmission design problem (5) is transformed into a mixed integer optimization problem at each time interval $[t, t+1)$ as follows [8]:

$$\begin{aligned} \text{maximize}: \ & V \sum_{i=1}^{2} (R_i[t] - \eta[t]p_i[t]) + 2 \sum_{i=1}^{2} (u_i Q_i[t] b_i[t] + v_i Y_i[t] \phi_i[t]) \\ \text{s.t.:} \ & \text{C3 and C4,} \end{aligned} \tag{14}$$

where the parameter V can be tuned to trade off energy efficiency and queue lengths (both actual source queues $\mathbb{Q}_i$ and virtual queues $\mathbb{Y}_i$), and u_i and v_i are the weighting parameters of $Q_i[t]$ and $Y_i[t]$ controlling the power assignment between the two types of messages. All time average operations are eliminated.

Now, by individually considering each of the four encoding options in the constraint C4, the above optimization problem has only the constraint C3. Although it is not a convex optimization problem, it can be solved by the concave convex procedure algorithm [18]. By comparing the solutions corresponding to the four encoding options and using the one with the best performance, a sub-optimal solution to the original problem (5) is found. Through extensive simulations, it is shown in [8] that such a dynamic transmission design achieves better performance than a number of conventional methods. However, the concave convex procedure algorithm demands an iterative searching process to reach the solution. Taking enumerating the encoding actions also into account, at the beginning of each time interval, a complex computation is demanded to determine the dynamic transmission design strategy. This may prevent the strategy to be conducted in an online fashion. In what follows, we propose applying the deep MTL technique to tackle this problem.

3 Deep Multi-task Learning-Aided Transmission Design

To solve the dynamic transmission design problem for the considered vehicular communication network, we follow the idea presented in [12] and transform the solution of the optimization problem (14) at each time slot into a mapping problem, from the network CSI (taken as the form of channel power gains $|h_{ij}[t]|^2$), QSI (queue lengths $Q_i[t]$ and $Y_i[t]$), and achievable performance so far (energy efficiency $\eta[t]$), to the optimal encoding actions and transmission powers of both links. Specifically, let $\mathcal{F}$ denote the function that describes the mapping relationship. For fixed transmission requirement parameters $\phi_{1,\min}$, $\phi_{2,\min}$, $p_{1,\min}$, $p_{2,\min}$, $p_{1,\max}$, $p_{2,\max}$, and optimization weighting parameters u_1, u_2 v_1, v_2, V, the function $\mathcal{F}$ can be written as

$$\begin{aligned}\mathcal{F}:\ &\Big\{|h_{11}[t]|^2, |h_{12}[t]|^2, |h_{21}[t]|^2, |h_{22}[t]|^2, Q_1[t], Q_2[t], Y_1[t], Y_2[t], \eta[t]\Big\}\\ &\quad\mapsto\ \Big\{p_1^*[t], p_2^*[t], \psi_1^*[t], \psi_2^*[t]\Big\},\ \forall t\in\{1,2,\cdots\},\end{aligned}\tag{15}$$

where the set $\{p_1^*[t], p_2^*[t], \psi_1^*[t], \psi_2^*[t]\}$ denotes the solution to problem (14).

If one knows the function $\mathcal{F}$, then making the dynamic transmission design decision is straightforward. However, the general form of function $\mathcal{F}$ is clearly unknown. On the other hand, for each possible realization of the input set $\{|h_{11}[t]|^2, |h_{12}[t]|^2, |h_{21}[t]|^2, |h_{22}[t]|^2, Q_1[t], Q_2[t], Y_1[t], Y_2[t], \eta[t]\}$, the associated output set $\{p_1^*[t], p_2^*[t], \psi_1^*[t], \psi_2^*[t]\}$ can be derived by the concave convex procedure algorithm, as explained above. But the computation process can be very time-consuming. Therefore, we considering integrating the advantages of the two approaches, by training a deep neural network (DNN), with data coming from mathematical derivations, to approximate $\mathcal{F}$. As long as the approximation is sufficiently accurate, inference using the DNN can guarantee a rapid and good decision-making process. Nevertheless, the mapping function presented in (15) is different from those considered in conventional works (e.g., [12]), since the problem (14) is a mixed integer optimization problem. The function output contains both quantitative (i.e., $p_1^*[t], p_2^*[t]$) and categorical (i.e., $\psi_1^*[t], \psi_2^*[t]$) values. The learning problem cannot be simply modeled as a regression or classification problem. To handle this issue, we propose applying the MTL technique to train the DNN and establish the approximate function.

MTL is a branch in ML that aims to exploit useful information contained in multiple related tasks to improve the generalization performance of all the tasks, [19]. DNN with hard parameter sharing is one of the frequently used structures in MTL networks [20]. As show in Fig. 2, there are two parts of hidden layers

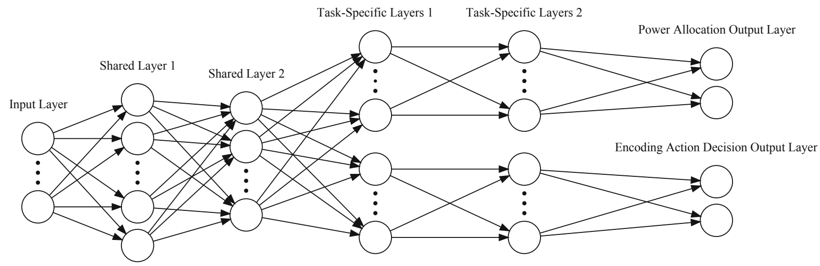

Fig. 2. Network structure with hard parameter sharing

between the input layer and the output layer, namely share layers and task-specific layers. The shared layers are used to learn the common information of different tasks. The task-specific layers are used to integrate information from the shared layers, learn the individual inherent characteristics, and output the specific form of each task. The network structure can be considered as a variant of a fully connected network. Having two different types of hidden layers simultaneously obtains input-output mapping of multiple tasks, and may also lead to a better generalization performance of each individual task [20].

For conventional regression and classification problems, one can use loss functions such as mean square errors (MSE) and cross entropy (CE) to respectively evaluate the difference between prediction and desired output results, to train DNNs. But in general it is difficult to find a single unified loss function for an MTL network. One apparent way is to add up all the losses with pre-defined weights, i.e.,

$$\mathcal{L}_{\text{total}} = \sum_i \omega_i \mathcal{L}_i, \tag{16}$$

where $\mathcal{L}_i$ and ω_i are the loss and weight parameters of the ith task, respectively.

However, the inference performance of such learning models are often strongly dependent on whether the weights are determined properly. Tuning these weight parameters manually, via e.g., grid search, is a difficult task. For practical applications, having a loss function that automatically finds the weights for different tasks are much more attractive. For this reason, reference [21] proposes a multi-task loss function based on maximizing the Gaussian likelihood with task-dependent uncertainty. Next we introduce how to transform the considered optimization problem into individual tasks and define the corresponding loss function.

In our vehicular communication network, the allocated power of each V2V link at each time slot is a real value between $p_{i,\min}$ and $p_{i,\max}$. We regard both links' powers at each time slot as a two-dimensional vector. The mapping from inputs to output with real values (i.e., from $|h_{11}[t]|^2, |h_{12}[t]|^2, |h_{21}[t]|^2, |h_{22}[t]|^2, Q_1[t], Q_2[t], Y_1[t], Y_2[t], \eta[t]$ to power assignments $p_1^*[t], p_2^*[t]$) is formulated as a regression problem. However, $p_1^*[t], p_2^*[t]$ can be chosen from a wide region (e.g., in our experiments in Sect. 4, the powers frequently change between 10^{-5} W to 10^{-1} W). Directly using them in the loss function may cause model training to mainly consider the impact of large power values, while small values, especially when the channel qualities of the desired links are good, are actually more important in achieving high energy efficiency. Therefore, we follow [10] and conduct a feature transformation process that takes the logarithm operation to transmit powers (values close to zero are set to 10^{-30}). The output vector of the power control regression problem in our MTL network is thus formed by $\log p_1^*[t]$ and $\log p_2^*[t]$. Due to similar reasons, the same feature transformation is carried out for the channel power gains, i.e. $\log\left(|h_{ij}[t]|^2\right)$ are actually used.

To define a loss function that can be used for training the MTL network, we follow [21] and consider the task-dependent uncertainty between the model output (denoted as $f_r^W(x)$, with x and W respectively being the input and network parameters of the MTL network) and desired output (denoted as y_r) of the regression task. Assume that $y_r - f_r^W(x)$ follows a zero-mean Gaussian distribution, i.e.,

$$y_r - f_r^W(x) \sim \mathrm{N}(0, \sigma_r^2), \tag{17}$$

where the standard deviation σ_r represents observation noise level. For the maximum likelihood estimation, we can obtain the log likelihood [21]:

$$\log \Pr\left\{y_r | f_r^W(x), \sigma_r\right\} = \log \Pr\left\{y_r - f_r^W(x) | \sigma_r\right\} \propto -\left(\frac{1}{2\sigma_r^2}\mathcal{L}_{\mathrm{MSE}}(W) + \log \sigma_r\right), \tag{18}$$

where $\mathcal{L}_{\mathrm{MSE}}(W) = \left\|y_r - f_r^W(x)\right\|^2$ is the regression output MSE.

In addition, the condition C4 in (14) represents the encoding actions in the considered network. This determines whether type-1 messages should be transmitted. Since $\psi_1^*[t]$ and $\psi_2^*[t]$ are binary indicators, seeking the optimal mapping from inputs $|h_{11}[t]|^2, |h_{12}[t]|^2, |h_{21}[t]|^2, |h_{22}[t]|^2,\ Q_1[t], Q_2[t], Y_1[t], Y_2[t], \eta[t]$ to them can be formulated as a classification problem. One simple way of the formulation is to treat it as a multi-class classification problem. For instance, in the considered 2-link network, the number of classes (all possible encoding actions at each time slot) is four. But as the network size becomes large, such a number increases exponentially. To avoid this issue, we deem the encoding action of each link as a single binary classification problem. This still fits in the MTL framework and leads to only a linear increase of decision space as the network size increases.

Let the MTL network have two classification output neurons, each applying the Sigmoid function to represent the probability that the input leads to the associated category. Again, following [21], assume that the likelihood of the output of the ith transmission link equals a scaled softmax function with scalar $\sigma_{c,i}$:

$$\Pr(y_{c,i} | f_{c,i}^W(x), \sigma_{c,i}) = \mathrm{Softmax}\left(\frac{1}{\sigma_{c,i}^2} f_{c,i}^W(x)\right), i \in \{1, 2\}, \tag{19}$$

where $f_{c,i}^W(x)$ and $y_{c,i}$ respectively denote the model output and actual value (encoding action derived using mathematical optimization) of the ith link. The log likelihood of multiple classification tasks can be simplified as

$$\log \Pr \left\{ y_c | f_c^W(x), \sigma_c \right\} = \log \prod_{i=1}^{2} \Pr\{y_{c,i} | f_{c,i}^W(x), \sigma_{c,i}\}$$
$$\approx - \sum_{i=1}^{2} \frac{1}{\sigma_{c,i}^2} \mathcal{L}_{\mathrm{CE}}(y_{c,i}, f_{c,i}^W(x)) - \sum_{i=1}^{2} \log \sigma_{c,i}, \quad (20)$$

where $\mathcal{L}_{\mathrm{CE}}(y_{c,i}, f_{c,i}^W(x))$ denotes the ith classification output CE, and y_c and $f_c^W(x)$ denotes the vector representation of all desired outputs and all model outputs respectively. In our work, the two V2V links have the similar message transmission demands. To simplify the model training process, we set $\sigma_{c,1} = \sigma_{c,2} = \sigma_c$. Thus, the above log likelihood can be written as

$$\log \Pr \left\{ y_c | f_c^W(x), \sigma_c \right\} \approx -2 \left(\frac{1}{2\sigma_c^2} \sum_{i=1}^{2} \mathcal{L}_{\mathrm{CE}} \left(y_{c,i}, f_{c,i}^W(x) \right) + \log \sigma_c \right)$$
$$\propto - \left(\frac{1}{\sigma_c^2} \mathcal{L}_{\mathrm{BCE}}(W) + \log \sigma_c \right), \quad (21)$$

where $\mathcal{L}_{\mathrm{BCE}}(W) = \frac{1}{2} \sum_{i=1}^{2} \mathcal{L}_{\mathrm{CE}}(y_{c,i}, f_{c,i}^W(x))$.

To facilitate training one MTL network for making concurrent decisions of both encoding actions and power assignment, we formulate a single loss function as the negative sum of the above two log likelihood functions, i.e.,

$$\mathcal{L}_{\mathrm{total}}(W, \sigma_r, \sigma_c) = \frac{1}{2\sigma_r^2} \mathcal{L}_{\mathrm{MSE}}(W) + \frac{1}{\sigma_c^2} \mathcal{L}_{\mathrm{BCE}}(W) + \log \sigma_r + \log \sigma_c. \quad (22)$$

Minimizing $\mathcal{L}_{\mathrm{total}}(W, \sigma_r, \sigma_c)$ allows simultaneously increasing the performance of both the regression and classification tasks. The tradeoff between the impacts of the two tasks is determined by the uncertain weights $\frac{1}{2\sigma_r^2}$ and $\frac{1}{\sigma_c^2}$, as well as the term $\log \sigma_r + \log \sigma_c$, in which σ_r and σ_c are determined, together with W, in the training process as model parameters.

However, in (22), small values of σ_r and σ_c may cause the terms $\log \sigma_r$ and $\log \sigma_c$ to dominate the loss function and thus improperly influence the training performance. Following [22], we can slightly revise the loss function to mitigate the issue:

$$\mathcal{L}_{\mathrm{total}}(W, \sigma_r, \sigma_c) = \frac{1}{2\sigma_r^2} \mathcal{L}_{\mathrm{MSE}}(W) + \frac{1}{\sigma_c^2} \mathcal{L}_{\mathrm{BCE}}(W) + \log(1 + \sigma_r^2) + \log(1 + \sigma_c^2). \quad (23)$$

In what follows, we term the MTL model using loss function (22) as MTL with simple uncertainty weights, and that using (23) as MTL with revised uncertainty weights. The latter is mainly adopted for conducting the dynamic transmission design in the considered vehicular communication networks.

To establish an MTL-based transmission decision-making solution, we can design a deep MTL network structure as Fig. 2. The input layer contains 9 neurons, taking $\log |h_{11}[t]|^2$, $\log |h_{12}[t]|^2$, $\log |h_{21}[t]|^2$, $\log |h_{22}[t]|^2$, $Q_1[t]$, $Q_2[t]$, $Y_1[t]$, $Y_2[t]$, $\eta[t]$ at each time slot as inputs. Through shared layers, the network can learn the common representation from the inputs, and then is separated into two branches. The power allocation task-specific layers and output layer transform the common representation into two positive real values, denoting the log transformation of the allocated powers of the two links. The encoding action task-specific layers and output layer transform the common representation into two real values bounded between 0 and 1. They represent the probabilities whether the V2V links choose to send type-1 messages (when an output value is greater than 0.5) or not. All the training data can be generated using the mathematical optimization method described in Sect. 2. The network parameters together with $\log \sigma_r$ and $\log \sigma_c$ are trained using the loss function (23). Although the training procedure is time and computation consuming, the inference process is much faster than the mathematical optimization and hence suitable for rapid online decision making. In next section, we demonstrate the performance of the proposed dynamic transmission design method.

4 Numerical Results

Consider a V2V communication network with two pairs of vehicles. Each source intends to send type-1 messages with data rate $r_i = 7$ bits/Hz/slot and reliability requirement $\Phi_{i,\min} = 70\%$, for $\forall i \in \{1, 2\}$. The type-2 messages are generated from a Poisson process with average rate $\lambda_i = 3$ bits/Hz/slot $\forall i \in \{1, 2\}$. The source transmission powers are bounded below $p_{i,\max} = 0.1$ W and above $p_{i,\min} = 0$ W. At each time slot, the circuit power of each source is set to be $p_{\mathrm{c},i} = 10^{-3}$ W. The large-scale fading is considered to be path loss following model $PL_{ij} = 103.4 + 24.2 \log_{10}(d_{ij})$ dB with distance d_{ij} [23]. The small-scale fading is assumed to be Rayleigh. The data transmissions are operated in a spectral channel with bandwidth $B = 1$ MHz. The noise power spectral density is -174 dbm/Hz. The weighting parameters in the optimization objective are set to $u_i = 10$ and $v_i = 80$ for $i \in \{1, 2\}$.

In order to establish a sufficiently large dataset to train our MTL model, we apply the optimization algorithm described in Sect. 2 to generate 1000 blocks of transmission data. The distance between each source and its desired destination is 30 m. The distances for the V_{S_1}-V_{D_2} and the V_{S_2}-V_{D_1} interference links are 430 m and 460 m. For each block, the transmission between every source-destination pair contains a total of $T = 200$ time slots. We generate random small-scale fading coefficients and type-2 arrival data volume for each slot. The initial queue status $Q_i[1]$ and $Y_i[1]$ are sampled from an exponential distribution with parameter 80. The above process creates 200000 useful data samples, 180000 out of which are used as training set, and the remaining 20000 are used as test set.

The MTL network structure is shown in Fig. 2. There are 4 hidden layers, each containing 16 neurons. The first two are shared layers and the latter two are task-specific layers. ReLU is used as the activation function for hidden layers and the regression output layer, and Sigmoid is used for the classification output layer. We take the logarithmic transformation of the channel power gains

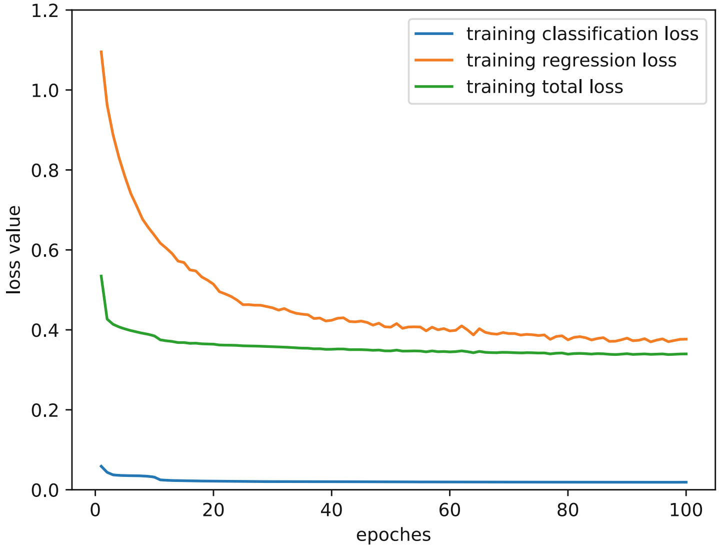

Fig. 3. Learning curves

(i.e., $|h_{ij}[t]|^2$) before sending them to the MTL network. The same is also conducted for the output power values (i.e., $p_1^*[t]$ and $p_2^*[t]$). By this means, failure of training can be notably reduced.

Figure 3 displays the learning curves of the MTL network with revised uncertainty weights for the case $V = 60$. In the experiments, the mini-batch size is chosen to be 10 (each epoch has 18000 mini-batches), and the learning rate is 0.001. From the figure we can see that loss values (for both the classification and regression problems, as well as the total loss) reduce as the training proceeds, and eventually converge to fixed values. The proposed MTL network thus can learn the patterns contained in the training data.

In addition to the revised uncertainty weights (23), we also conduct training of MTL networks (using the same network structure) with equal weights (i.e., setting as 1) and the simple uncertainty weight (22). Their training and test results (regarding classification and regression performance) are shown in Table 1. Clearly, MTL with the revised uncertainty weights performs better than the other two. Treating the encoding action selection and power control problems as independent classification and regression problems can also lead to two individual single-task models (one for encoding action selection and one for power control) that can be integrated to determine transmission decisions (termed Single-task in Table 1). This method has the similar classification accuracy as our MTL model, but with much worse performance in the regression problem (power control). Actually, the transmission power control and encoding action selection problems are strongly interrelated. Ignoring such a fact can cause serious problems in transmission decision-making. In Table 1, we also display the ratio of successful transmissions in the training and test experiments.

Table 1. Comparison of different models

Weights	Regression loss		Classification accuracy		Successful transmission	
	Training	Test	Training	Test	Training	Test
Single-task	0.45	0.58	94.16%	93.34%	82.60%	80.20%
Equal weights	0.40	0.56	78.39%	78.15%	72.68%	71.81%
Simple uncertainty weights	0.38	0.53	92.87%	92.50%	87.92%	87.73%
Revised uncertainty weights	0.36	0.49	93.84%	93.23%	89.53%	89.16%

Ideally, if a source chooses to send a type-1 message at time slot t, it should allocate sufficient power to guarantee $R_i[t] \geq r_i$. Otherwise, transmission failure would occur and the energy consumption is wasted. In Table 1, it is seen that the Single-task model achieves less successful transmissions compared with our MTL model (with revised uncertainty weights). Having a high classification accuracy alone may not be sufficient for making good transmission decisions. The advantages of the proposed method may be even more notable when the system model becomes more complex (e.g. with more source-destination links and heterogeneous QoS requirements).

Finally, we compare our MTL-aided transmission design scheme with three conventional solutions. The first considers only CSI to make transmission decisions. Since the QSI is not taken into consideration, both sources intend to transmit their messages with a fixed data rate of $R_i[t] = 10 + \theta$ bits/Hz/slot using the minimum power at each time slot. In such a fixed rate (FR) transmission, both messages are always transmitted and the parameter θ is chosen to counterbalance the impact of channel outage and keep queue length stable. Similar to our proposed method, the remaining two methods take into account both CSI and QSI. One of them orthogonalizes the message delivery processes of the two links and is termed orthogonal transmission (OT). In this case, the maximum transmission data rate between V_{S_i} and V_{D_i} within time interval $[t, t+1)$ is $R_i[t] = \frac{B}{2} \log \left(1 + \frac{2p_i[t]|h_{ii}[t]|^2}{N_0}\right)$ bits/slot. Inter-user interference is avoided with the cost of inefficient channel usage. The other method is the one that is described in Sect. 2. This method is termed Lyapunov optimization (LO) scheme and the concave convex procedure algorithm is applied to solve the optimization problem (5). In fact, this is also the method that we use to generate our training data.

For all the four schemes, we adjust the weighting factors so that the achievable QoS results of both types of messages are almost the same. Figure 4 illustrates the energy efficiency, the optimization objective in (5), for changing choices of V (for our MTL-aided design). It is seen that as V increases, the achievable energy efficiency of the OT, LO, and MTL schemes become larger, since more attentions have been placed to enhancing the energy efficiency, as expected. Because the spectrum resources are divided into 2 parts, the OT method needs larger powers to ensure the message QoS requirements, which leads to lower energy efficiency. The FR scheme intends to minimize the whole power consumption. However, a low power usage does not always mean a high energy efficiency. Thus,

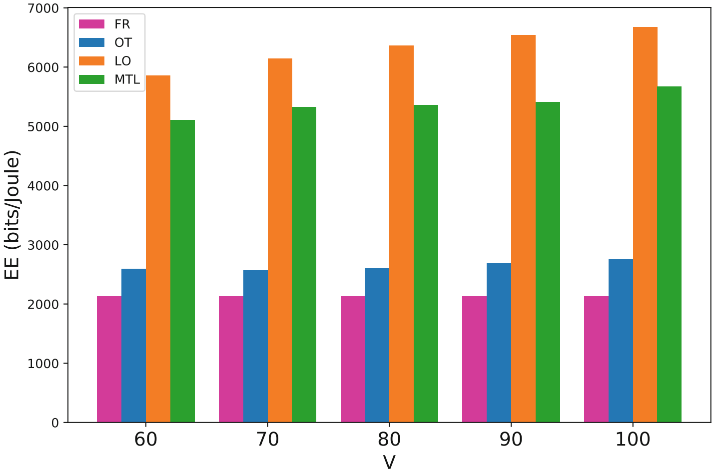

Fig. 4. Energy efficiency comparison

our MTL-aided design outperforms the FR and OT schemes. Finally, although our method does not perform as well as the LO scheme, the former demands much more computation time than the latter. Implementing the LO scheme on a PC with Inter Core i7-6800K CPU consumes around 10 hours for completing the transmission design of the 100 test transmission blocks (each consisting of 200 time slots). But the time consumption for the MTL-aided scheme (i.e., the inference process) is around only 30 s. The advantages of the proposed method can be clearly seen and are again expected to be even more significant in more complex systems.

5 Conclusion

We have investigated the potential of applying ML to facilitate dynamic cross-layer transmission design in vehicular communication networks. The system considered in this paper consists of two source-destination links. Each link desires to communicate information with the maximum energy efficiency to potentially support multiple applications, in a changing fading environment. Conventionally, to solve the formulated mixed integer optimization problem at each time slot, a time-consuming derivation procedure is needed. We have proposed transforming the optimization problem into a joint classification-regression problem, and then applying deep MTL to solve it. Simulation results have shown that our method can achieve similar performance as the mathematical optimization solution with a much faster decision-making process. The advantages are expected to be even more significant in more complex networks.

Acknowledgement. This work was supported in part by the National Natural Science Foundation of China (61771343), the National Key Research and Development Program of China (2018YFE0125400), and the EU H2020 Programme under Marie Curie IF (752979). We are also grateful for the support of the Sino-German Center of Intelligent Systems, Tongji University.

References

1. Garcia-Roger, D., González, E., Martín-Sacristán, D., Monserrat, J.: V2X support in 3GPP specifications: from 4G to 5G and beyond. IEEE Access **8**, 190946–190963 (2020)
2. Boban, M., Kousaridas, A., Manolakis, K., Eichinger, J., Xu, W.: Connected roads of the future: use cases, requirements, and design considerations for vehicle-to-everything communications. IEEE Veh. Technol. Mag. **13**(3), 110–123 (2018)
3. Dar, K., Bakhouya, M., Gaber, J., Wack, M., Lorenz, P.: Wireless communication technologies for ITS applications. IEEE Commun. Mag. **48**(5), 156–162 (2010)
4. Kha, H., Tuan, H., Nguyen, H.: Fast global optimal power allocation in wireless networks by local D.C. programming. IEEE Trans. Wirel. Commun. **11**(2), 510–515 (2011)
5. Shen, K., Yu, W.: Fractional programming for communication systems-part I: power control and beamforming. IEEE Trans. Signal Process. **66**(10), 2616–2630 (2018)
6. Yang, Y., Pesavento, M.: A unified successive pseudoconvex approximation framework. IEEE Trans. Signal Process. **65**(13), 3313–3328 (2017)
7. Cui, Y., Lau, V., Wang, R., Huang, H., Zhang, S.: A survey on delay-aware resource control for wireless systems-large deviation theory, stochastic Lyapunov drift, and distributed stochastic learning. IEEE Trans. Inf. Theory **58**(3), 1677–1701 (2012)
8. Lan, D., Wang, C., Wang, P., Liu, F., Min, G.: Transmission design for energy-efficient vehicular networks with multiple delay-limited applications. In: 2019 IEEE Global Communications Conference (GLOBECOM), pp. 1–6. IEEE (2019)
9. Joung, J.: Machine learning-based antenna selection in wireless communications. IEEE Commun. Lett. **20**(11), 2241–2244 (2016)
10. Matthiesen, B., Zappone, A., Besser, K.L., Jorswieck, E., Debbah, M.: A globally optimal energy-efficient power control framework and its efficient implementation in wireless interference networks. IEEE Trans. Signal Process. **68**, 3887–3902 (2020)
11. Zappone, A., Di Renzo, M., Debbah, M.: Wireless networks design in the era of deep learning: model-based, AI-based, or both? IEEE Trans. Commun. **67**(10), 7331–7376 (2019)
12. Zappone, A., Sanguinetti, L., Debbah, M.: User association and load balancing for massive MIMO through deep learning. In: 2018 Asilomar Conference on Signals, Systems, and Computers, pp. 1262–1266. IEEE (2018)
13. Lee, W., Kim, M., Cho, D.: Deep power control: transmit power control scheme based on convolutional neural network. IEEE Commun. Lett. **22**(6), 1276–1279 (2018)
14. Liang, F., Shen, C., Yu, W., Wu, F.: Towards optimal power control via ensembling deep neural networks. IEEE Trans. Commun. **68**(3), 1760–1776 (2019)
15. Neely, M.J.: Stochastic Network Optimization with Application to Communication and Queueing Systems. Morgan & Claypool Publishers (2010)

16. Li, Y., Sheng, M., Shi, Y., Ma, X., Jiao, W.: Energy efficiency and delay tradeoff for time-varying and interference-free wireless networks. IEEE Trans. Wirel. Commun. **13**(11), 5921–5931 (2014)
17. Dinkelbach, W.: On nonlinear fractional programming. Manage. Sci. **13**(7), 492–498 (1967)
18. Yuille, A., Rangarajan, A.: The concave-convex procedure. Neural Comput. **15**(4), 915–936 (2003)
19. Zhang, Y., Yang, Q.: A survey on multi-task learning. IEEE Trans. Knowl. Data Eng. 1 (2021, early access). https://ieeexplore.ieee.org/abstract/document/9392366
20. Ruder, S.: An overview of multi-task learning in deep neural networks. arXiv preprint arXiv:1706.05098 (2017)
21. Kendall, A., Gal, Y., Cipolla, R.: Multi-task learning using uncertainty to weigh losses for scene geometry and semantics. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 7482–7491 (2018)
22. Liebel, L., Körner, M.: Auxiliary tasks in multi-task learning. arXiv preprint arXiv:1805.06334 (2018)
23. Access, E.U.T.R.: Further advancements for E-UTRA physical layer aspects (release 9), 3GPP (2010)