Real-Time Scheduling for Wireless Networks with Random Deadlines

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***Abstract*—The use of wireless communications in industrial environments is motivated by the flexibility that wireless networks provide and their cost-efficient setup and maintenance. Various wireless technologies have been introduced to satisfy the strict industrial requirements. Time division multiple access (TDMA) protocols have been widely exploited in various wireless technologies due to the ease of implementation and packets collision avoidance. In this work, we consider the problem of scheduling multiple flows over a wireless network in industrial environments. These flows represent the data coming from the sensors to the controller and the control commands going to the actuators from the controllers. These flows are characterized by random strict deadlines for each packet in a flow following a given probability distribution. Moreover, the schedule is built over a frame of transmissions with the objective of minimizing the total number of packets missing their deadlines. We obtain the optimal scheduling scheme by formulating and solving an unobservable Markov decision problem (UMDP). Then, we obtain a sub-optimal scheduling scheme which has a near-optimal performance for a wide range of system parameters. Finally, we evaluate these scheduling schemes numerically to study the effects of various system parameters on the performance.**

I. Introduction

Various networking protocols have been introduced to meet the requirements of the industrial enviornments and improve control capabilities. Typically, wired networks have been employed based on structured cabling which is defined as cabling infrastructure that consists of a number of standardized smaller elements. Lately, industrial wireless technologies have been recognized as attractive alternatives to their wired counterparts due to increased networking flexibility, and lower setup and maintenance costs. These wireless technologies include WirelessHART and ISA 100.11a. Various advantages and disadvantages of these technologies have been considered in the literature [1], [2].

The main challenge facing deployment of wireless networks in industrial environments is the lack of reliability of such networks. The nature of wireless channel leads to considerable bit errors and hence packets can be lost or delayed past their intended delivery deadlines. Due to the importance of timing, strict deadlines are commonly enforced for data packets in industrial environments. To achieve these reliability goals, time division multiple access (TDMA)-based medium access control (MAC) protocols are used to eliminate the possibility of intra-network interference and to increase the likelihood that packets would meet their deadline requirements.

One of the major approaches to enhance wireless network reliability is scheduling which ensures that only one network node transmits at any given time. In addition, scheduling makes it possible to introduce redundancy by transmitting the same information packet over several time slots to increase the chance of the packet reaching its destination correctly and before its deadline. Many survey papers have been written on scheduling in wireless sensor networks (WSN). The work in [3] describes the network parameters that affect TDMA scheduling and considers various performance measures including latency, synchronization time, and energy consumption, and the communication patterns supported by various algorithms. Moreover, heuristic scheduling algorithms have been surveyed in [4]. The scheduling algorithms that use guaranteed time slot (GTS) in IEEE 802.15.4-based networks have been compared in [5].

In this work, we consider the TDMA-based scheduling problem for multiple real-time flows with strict deadlines. The goal of the schedule is to minimize the total number of packets missing their deadlines. The schedule is built at the beginning of a frame to reduce the computational complexity of decision making at every time slot. It is then updated at the beginning of every new frame. The routing protocol is assumed to be known. Therefore, the route for any flow from a certain source to a certain destination is predetermined before the scheduling problem is solved. The data flows carry either sensing data or control commands. Hence, the packet generation process and the deadlines are not assumed to be periodic. Instead, they are assumed to have a stochastic nature with known probability density functions.

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Sensing data flows are typically periodic, but there are also event-based signals that are aperiodic. The same is true for control commands. This has motivated the consideration of data flows with random deadlines in this paper. The problem of scheduling flows with random deadline has been considered in the literature [6]-[9]. In [6], a multi-class queueing network is considered where the customers arrive in the network with random deadlines. Each class has its own deadline probability distribution. In [7], the problem of online packet scheduling is considered in a multi-hop wired network, where each packet has a weight indicating the importance of being delivered by the deadline and the cumulative weights of packets delivered before their deadlines are maximized using admission control and scheduling. In [8], a packet scheduling algorithm is proposed to optimize the performance in the case of having both real-time and best effort flows concurrently. The traffic characteristics of the flows are considered to be stochastic. The randomness of deadlines in these works, namely [6]-[8], may arise from the initial queueing delays and the randomnes of data processing. In [9], the problem of providing timeliness guarantees for multi-hop messages is considered, where the effective deadlines of messages are determined by how long the data is valid/operative and by what time it is needed at the destination. The validity of the data depends on the underlying physical processes and hence can be random and the time it is needed at the destination is determined by the criticality of the data and the time it takes to process the data. In this paper, we solve the scheduling problem for frame-based transmissions in a multi-hop network with random deadlines where each wireless link has a certain packet transmission success probability.

The problem of minimizing the number of packets missing their deadlines is formulated as an unobservable Markov decision problem (UMDP), which is a special case of partially observable Markov decision problems (POMDPs) [10]. The system state is not observable as we compute the schedule at the beginning of the frame. The system state is defined by the numbers of remaining time slots before the deadlines and the numbers of remaining hops till the destinations. The complexity of the obtained algorithm using the solution of the UMDP has motivated finding a sub-optimal solution for the problem through modifying the commonly used earliest deadline first (EDF) algorithm to consider the randomness in deadlines.

The rest of this paper is organized as follows. The system model is presented in Section II. The optimal scheduling problem is formulated and solved in Section III. The sub-optimal scheduling is discussed in Section IV. In Section V, numerical results are presented. Finally, Section VI presents the concluding remarks.

II. System Model

Consider a set of M wireless flows $\mathcal{F} = \{F_1, F_2, ...F_M\}$ to be scheduled over a single frequency band. The route for F_m is denoted by ϕ_m. The length of ϕ_m, denoted by h^*_m, is the total number of hops a packet in F_m has to go through before it gets to its destination. A new packet arrives in F_m when the deadline for the preceding packet in the same flow expires. The schedule for the network flows is calculated every hyper-period T, which consists of a fixed number of time slots. In the case of an industrial environment with field devices that generate packets in a periodic manner and the packet generation period is a multiple of the duration of a time slot, the hyper-period is commonly defined in the literature as the least common multiple of the packet generation periods of the field devices [11].

This paper does not consider the possibility of spatial frequency reuse. Therefore, at most one node in the network transmits in each time slot. This assumption is inline with how WirelessHART and ISA100.11a are used. The wireless channel between a node i and a node j, representing a single hop in the route of F_m, is modeled as a binary erasure channel that is independent of the packet generation process. The quality of this channel is represented by the probability $\rho_{i,j}$ of successful transmission of a packet, called (packet) success probability. The success probability is determined by the channel impulse response for the physical channel between nodes i and j as well as the wireless communications system's physical parameters such as transmission power, modulation scheme, coding scheme, and targeted bit-error rate. Even though the scheduling algorithms developed in this paper can handle the possibility of having different success probabilities for the channels between different pairs of nodes, we assume that $\rho_{i,j} = \rho$, for all (i,j), for the sake of simplicity.

Each packet in F_m has a deadline that is modeled by a positive discrete random variable D_m with probability mass function $f_m(.)$. The discrete random variable D_m takes positive integer values denoted by $d_m \in \mathcal{B}_m$ where $\mathcal{B}_m$ is the space of the random deadlines and it can be be any subset of $\{h^*_m, h^*_m + 1, \ldots, D^*_m\}$, where D^*_m can be infinite. The mean and variance of D_m are denoted by μ_m and σ^2_m, respectively. We consider data transmission with strict deadlines, such that each packet in F_m is discarded if it has not reached its intended destination prior to its deadline. Regardless of whether a packet in F_m succeeds or fails to reach its destination by its deadline, the next packet in this flow is generated and released at this deadline.

The network manager is responsible for generating schedules for the field devices deployed in an industrial environment. The schedule for each hyper-period is generated just before the beginning of that hyper-period. In this work, due to the randomness of flow deadlines, we define the hyper-period as the least common multiple of the nearest integer numbers of time slots to the average deadlines of all the flows.

We derive an algorithm for finding the optimal scheduling policy to be administrated by the network manager. This algorithm is obtained by solving the UMDP formulated in Section III.B to obtain a schedule for the next hyper-period. We also introduce a sub-optimal scheduling strategy to reduce the computational complexity of the scheduling process. The sub-optimal algorithm exploits the statistical characteristics of the flows to obtain near-optimal performance.

III. Optimal Scheduling Strategy

In this section, we start by defining the system parameters such as the states, the transition probabilities, and the cost function for the optimization problem to be solved. Then, the UMDP is formulated employing these parameters to introduce the framework for obtaining the optimal scheduling strategy.

A. System Definition

The state of F_m at the beginning of a given time slot is denoted by $S_m = (t_m, h_m)$, where t_m is the number of remaining time slots before the deadline and h_m is the number of remaining hops on the route before reaching the destination. The whole system state which is denoted by $S = (S_1, S_2, ..., S_M)$. In general, if a packet from F_m is scheduled for transmission in a given time slot, S_m will transition to $(t_m - 1, h_m - 1)$ or $(t_m - 1, h_m)$ depending on whether the packet transmission succeeds or fails, respectively. The value of t_m is always greater than zero because a new packet arrival occurs as soon as the previous packet deadline is reached. Hence, t_m changes directly from 1 to the the value d_m of the random deadline D_m for the next packet in F_m. The number of remaining hops h_m takes the value 0 when a packet is successfully received at its destination and moves directly from any value to h_m^* when the packet misses its deadline. The state $S_m = (1, 1)$ is a special state for any m, because one would think the next state if a packet from F_m is scheduled for transmission in a given time slot is (d_m, h_m^*) with d_m representing the value for D_m for the next packet in F_m, regardless of whether the packet transmission succeeds or fails. However, this poses a challenge for computing the total number of missed packets in the network, because such a transition would not distinguish between packet transmission success and failure. We solve this problem by letting the state of the flow transition to the auxiliary state $(d_m, h_m^* + 1)$ if the packet transmission succeeds and to the state (d_m, h_m^*) if it fails. The transitions from $(d_m, h_m^* + 1)$ will be to the states $(d_m - 1, h_m^* - 1)$ and $(d_m - 1, h_m^*)$ depending on whether the packet transmission succeeds or fails, respectively. Various cases are described later during the discussion of state transition probabilities.

The action to be chosen at any time slot is denoted by $A \in \{1, 2, ...M\}$, and it determines which of the flows will be served in this time slot.

The conditional transition probability of the system describes the transition from the state S to the state $\tilde{S}$ given that an action A is chosen. It is denoted by $P(\tilde{S}|S, A)$. The value of this conditional probability is calculated as a function of the conditional probabilities of individual flows as follows

$$P(\tilde{S}|S, A) = \prod_{m=1}^{M} P(\tilde{S}_m|S_m, A), \tag{1}$$

where $P(\tilde{S}_m|S_m, A)$ is the conditional transition probability of S_m given that the action A is chosen. In the following, we provide expressions for these conditional transition probabilities for all the flows given that action $A = n$ is chosen. First, we express the conditional transition probability of S_n given that F_n is scheduled to be served in the current time slot.

$$P\left(\tilde{S}_n|S_n, A = n\right) = \begin{cases} \rho, & (C_1) \text{ or } (C_2), \\ \rho f_n(d_n), & (C_3), \\ 1-\rho, & (C_4), (C_5), \text{ or } (C_6), \\ (1-\rho) f_n(d_n), & (C_7), \\ 1, & (C_8) \text{ or } (C_9), \\ f_n(d_n), & (C_{10}) \text{ or } (C_{11}), \end{cases} \tag{2}$$

where, the conditions are defined as follows:

$$(C_1): \tilde{S}_n = (t_n - 1, h_n - 1), S_n = (t_n, h_n), \quad \min(h_n^*, t_n) \geq \quad h_n > 0, t_n > 1,$$

$$(C_2): \tilde{S}_n = (t_n - 1, h_n^* - 1), S_n = (t_n, h_n^* + 1), t_n \geq h_n^*,$$

$$(C_3): \tilde{S}_n = (d_n, h_n^* + 1), S_n = (1, 1), d_n \in \mathcal{B}_n,$$

$$(C_4): \tilde{S}_n = (t_n - 1, h_n), S_n = (t_n, h_n), t_n > h_n > 0,$$

$$(C_5): \tilde{S}_n = (h_n - 1, h_n^*), S_n = (h_n, h_n), h_n > 1,$$

$(C_6): \tilde{S}_n = (t_n - 1, h_n^*), S_n = (t_n, h_n^* + 1), t_n \geq h_n^*,$

$(C_7): \tilde{S}_n = (d_n, h_n^*), S_n = (1, 1), d_n \in \mathcal{B}_n,$

$(C_8): \tilde{S}_n = (t_n - 1, h_n^*), S_n = (t_n, h_n^*), 1 < t_n < h_n^*,$

$(C_9): \tilde{S}_n = (t_n - 1, 0), S_n = (t_n, 0), 1 < t_n \leq D_n^* - h_n^*,$

$(C_{10}): \tilde{S}_n = (d_n, h_n^*), S_n = (1, 0), d_n \in \mathcal{B}_n,$

$(C_{11}): \tilde{S}_n = (d_n, h_n^*), S_n = (1, h_n^*), h_n^* > 1, d_n \in \mathcal{B}_n.$

(C_1) represents the successful transmission of the packet to the following node on the route while the deadline has not been reached yet, and hence the number of remaining hops is decremented by 1. (C_2) represents the successful transmission of a packet at its first transmission from the source when the previous packet was successfully transmitted to the destination at the last time slot before the deadline. (C_3) represents the successful transmission of the packet to its destination at the last time slot before the deadline, and hence the new deadline is a random number following the distribution of $f_n(*)$ and the remaining number of hops is set to h_n^*+1 to indicate successful reception. These three conditions cover all the cases where a packet is successfully transmitted from one network node to another.

Similarly, the conditions for transition probabilities in the cases where the packet transmission fails are as follows. (C_4) represents the case where the transmitted packet has not been successfully received by the following node on the route while the deadline has not been reached yet. (C_5) represents the case where the packet transmission fails resulting in the deadline to be missed because the number of remaining hops is larger than the number of time slots left until the deadline. (C_6) represents the case where the first transmission of the packet from the source fails when the previous packet was successfully transmitted to the destination at the last time slot before the deadline.

Moreover, (C_7) represents the case where the transmission fails and the packet does not make the last hop to the destination and misses its deadline, and hence the new deadline is a random number following the distribution of $f_n(*)$ and the remaining number of hops is set to h_n^* to indicate failed transmission at the previous time slot for this flow.

Next we discuss the cases where no transmission is made when the flow is chosen because either the packet has already missed its deadline (C_8) or been received at the destination before the deadline (C_9).

Furthermore, the conditions (C_{10}) and (C_{11}) represent the cases in which no transmission occurs at the last time slot before the deadline and hence the remaining number of time slots resets to the new random deadline following the distribution of $f_n(*)$. While in the (C_{10}) case the packet has been received at the destination before the deadline, in the (C_{11}) case it has not. Fig. 1 shows the state transitions and the respective probabilities for S_n when the action $A = n$ is chosen.

In general, if a packet from F_n is scheduled for transmission in a given time slot, $S_m = (t_m, h_m)$ for $m \neq n$, will transition to $(t_m - 1, h_m)$ with probability 1. We now provide the complete set of conditional transition probabilities for S_m when F_n for $n \neq m$ is scheduled to be served in the current time slot.

$$P\left(\tilde{S}_m | S_m, A = n\right)|_{\{m \neq n\}} = \begin{cases} 1, & (C_{12}), (C_{13}), (C_{14}) \text{ or } (C_{15}), \\ f_m(d_m), & (C_{16}), \end{cases} \quad (3)$$

where, the conditions are defined as follows:

$(C_{12}): \tilde{S}_m = (t_m - 1, h_m), S_m = (t_m, h_m), t_m > h_m > 0,$

$(C_{13}): \tilde{S}_m = (h_m - 1, h_m^*), S_m = (h_m, h_m), h_m > 1,$

$(C_{14}): \tilde{S}_m = (t_m - 1, 0), S_m = (t_m, 0), t_m > 1,$

$(C_{15}): \tilde{S}_m = (t_m - 1, h_m^*), S_m = (t_m, h_m^*), 1 < t_m < h_m^*,$

$(C_{16}): \tilde{S}_m = (d_m, h_m^*), S_m = (1, h_m), d_m \in \mathcal{B}_m,$

where (C_{12}), (C_{13}), (C_{14}), and (C_{15}) represent the case in which $t_m > 1$. (C_{12}) represents the case in which the packet in F_m has a remaining number of hops $h_m < t_m$, and hence the packet will continue to be in the network after the current time slot. (C_{13}) represents the case where the packet in F_m has a remaining number of hops $h_m = t_m$, and hence the packet will miss its deadline as a result of not being scheduled for transmission in the current time slot. While (C_{14}) represents the case where the packet in F_m has already successfully arrived at the destination before its deadline. (C_{15}) represents the case where the packet has already missed its deadline.

Finally, (C_{16}) represents the cases where the packet in F_m had already been delivered to its destination, the packet had already missed its deadline, or the packet will miss its deadline as a result of not being scheduled for transmission in this time

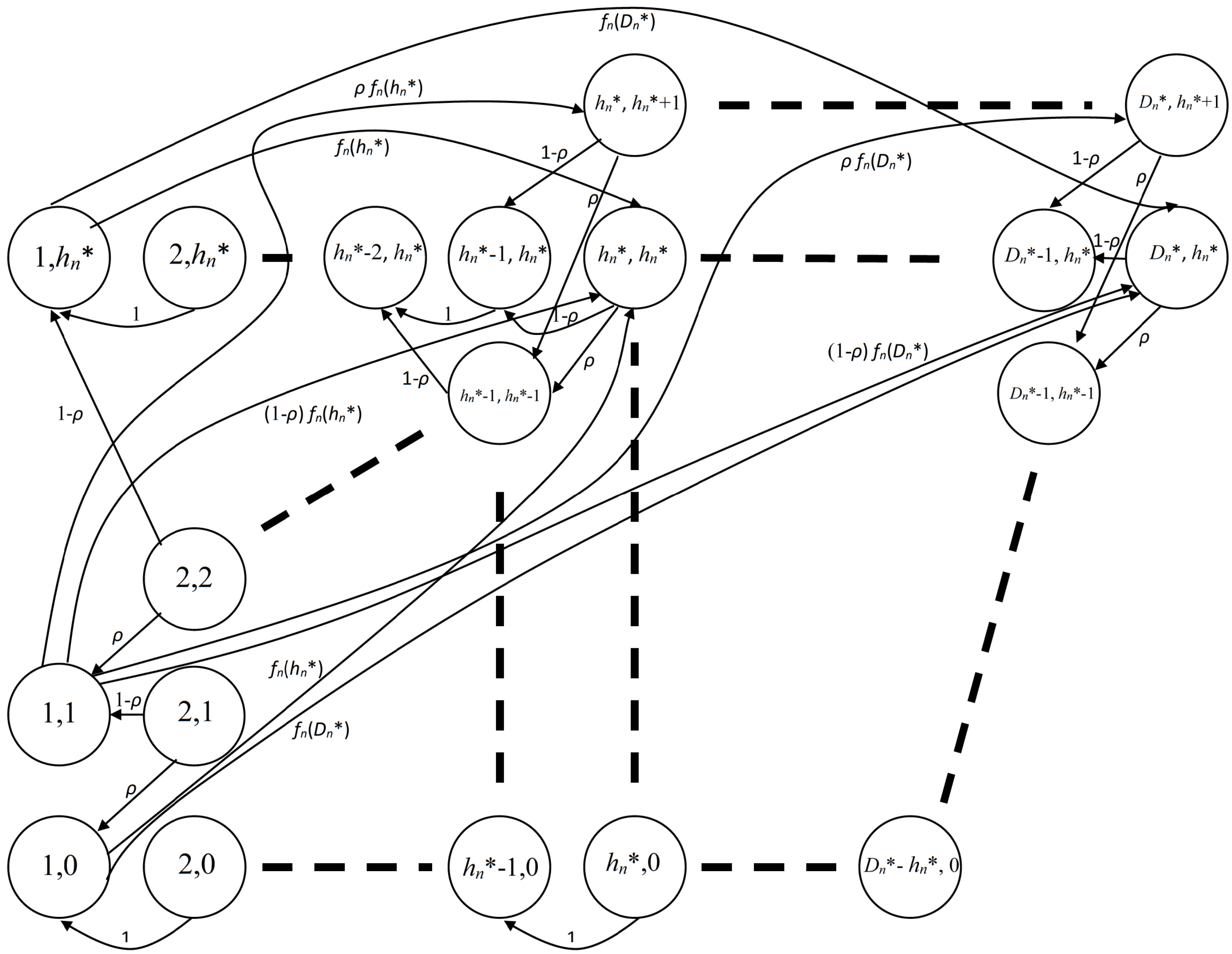

Fig. 1. The Markov chain transitions of the nth flow when $A = n$ is chosen.

slot. In all these cases, a random deadline for a new packet from F_m will be selected following the distribution $f_m(*)$, and the remaining number of hops is set to h_m^*. Fig. 2 shows the state transitions and the respective probabilities for S_m when the action $A = n$, with $n \neq m$, is chosen.

The optimal scheduling strategy is determined by minimizing the total system cost over all possible schedules. The system incurs a cost of one for each packet that misses its deadline for being delivered to its destination. Suppose a packet from F_n, for some $n \in \{1, 2, \ldots, M\}$, is selected for transmission at time slot $t \in \{1, 2, \ldots, T\}$. The system incurs a cost of one in time slot t if F_n is in state (h_n, h_n), for $h_n = 1, 2, \ldots, h_n^*$, and the packet transmission fails. In addition, for each $m \in \{1, 2, \ldots, M\} - \{n\}$, the system incurs a cost of one in time slot t if F_m is in state (h_m, h_m), for $h_m = 1, 2, \ldots, h_m^*$. The transition cost of the system for F_m is denoted by $\gamma\left(\tilde{S}_m | S_m, A = n\right)$, where m and n can take any values in $\{1, 2, \ldots, M\}$. It is given by:

$$\gamma\left(\tilde{S}_m | S_m, A = n\right) = \begin{cases} 1, & (C_{17}) \text{ or } (C_{18}), \\ 0, & \text{Otherwise.} \end{cases} \quad (4)$$

where, the conditions are defined as follows:

$$(C_{17}) : \tilde{S}_m = (h_m - 1, h_m^*), S_m = (h_m, h_m), h_m > 1,$$

$$(C_{18}) : \tilde{S}_m = (d_m, h_m^*), S_m = (1, 1), d_m \in \mathcal{B}_m.$$

The total number of packets that miss their deadlines in time slot $t \in \{1, 2, \ldots, T\}$ is given by:

$$\gamma\left(\tilde{S} | S, A\right) = \sum_{m=1}^{M} \gamma\left(\tilde{S}_m | S_m, A\right), \quad \forall \tilde{S}, S \in \mathcal{S}, A \in \mathcal{A}. \quad (5)$$

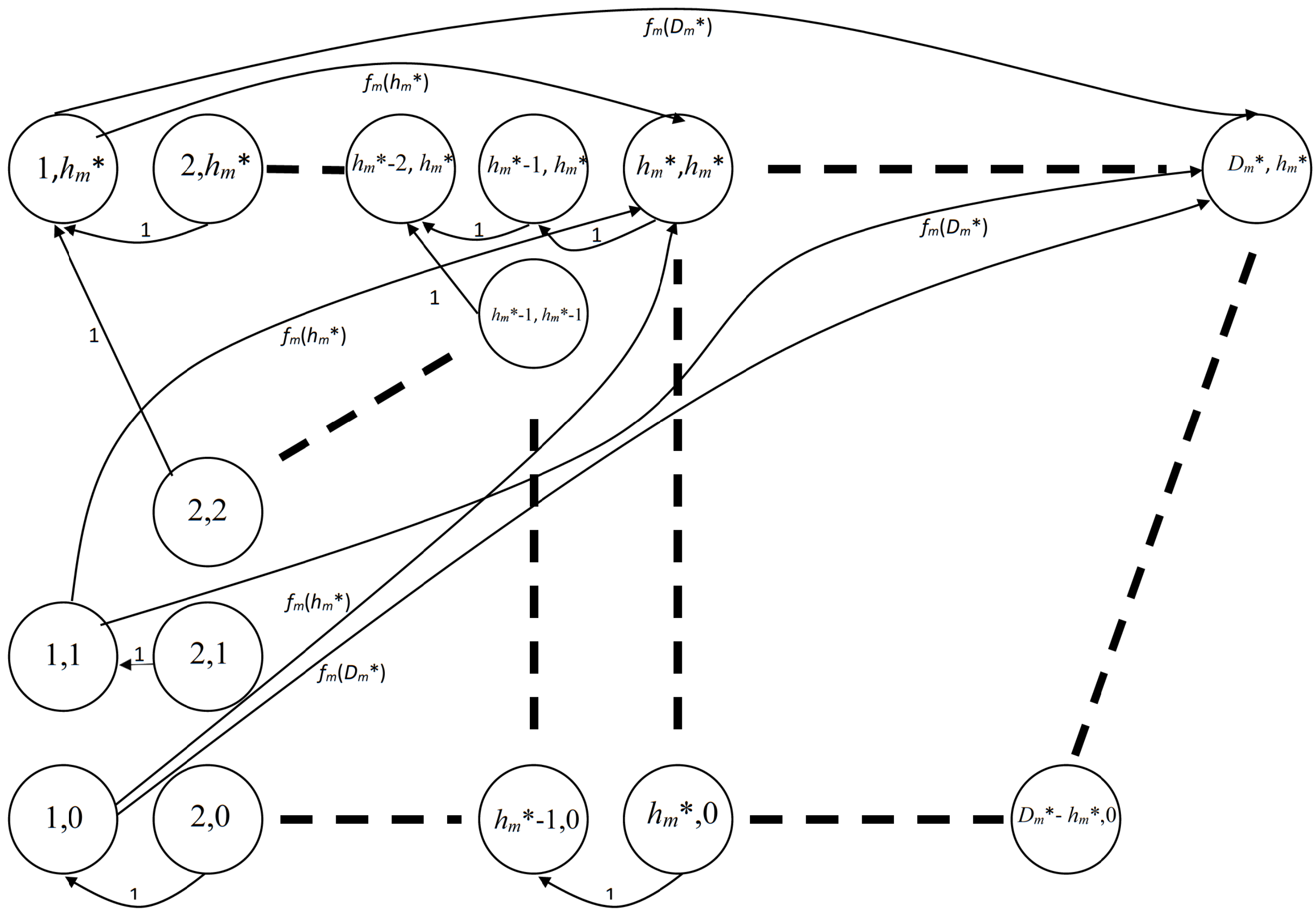

Fig. 2. The Markov chain transitions of the mth flow when $A = n$ is chosen while $n \neq m$.

B. Problem Formulation

In this subsection, we obtain the UMDP formulation for the optimal scheduling problem where the system evolves in a Markovian fashion depending on the chosen scheduling actions at every time slot. Moreover, the schedule is computed at the beginning of the hyper-period and the system state is not observed during the hyper-period. Thus, the problem is considered to be a finite horizon UMDP. The components of the UMDP are defined as follows:

1) The state space, which is denoted by $\mathcal{S}$, contains all the system states S defined in Section III.A.
2) The actions space, which is denoted by $\mathcal{A}$, is defined to be the set of the flows indices $\{1, 2, \ldots, M\}$. The action taken at the beginning of time slot $t \in \{1, 2, \ldots, T\}$ is the flow from which a packet is scheduled for transmission during that time slot.
3) The transition probabilities between system states have been defined in Section III.A.
4) The expected cost is the total number of packets missing their deadlines in time slot t as a result if taking the action $A = n$, as given by Equation (5).

In [12], the author shows that there exists a stationary policy which is optimal for solving POMDP with the average reward/cost criterion under two conditions: 1) the immediate rewards are non-negative; and 2) the Markov chain which represents the system progress is irreducible and ergodic. In our problem, the Markov chain with the network states is irreducible and ergodic. Thus, both conditions are satisfied and the UMDP is a special case of the POMDP.

We define the belief vector P as a probability mass function (pmf) on the set of all system states $\mathcal{S}$, where P_S denotes the probability of a particular system state. The value of this belief vector at the end of a time slot $t \in \{1, 2, \ldots, T\}$ is denoted by $P^{(t)}$. This is the pmf for the set of system states at the end of time slot t. The initial value of this belief vector, denoted by $P^{(0)}$, is assumed to be known through the knowledge of the network state at the beginning of the hyper-period. Moreover, we denote the action taken at a time slot t by $A^{(t)}$, where a packet from the selected flow is transmitted in time slot t. The complete sequence of actions over the hyper-period is the schedule, which is denoted by $A_{\text{sch}} = \left(A^{(1)}, A^{(2)}, \dots, A^{(T)}\right)$. In UMDP, the belief update equation for a given time slot depends on the action taken in that time slot only as no information about the state is observed. Hence, the value of the belief vector is updated over time for a given selected action $A^{(t)}$ using the transition probabilities as follows

$$P_{\tilde{S}}^{(t)}|_{A^{(t)}} = P_S^{(t-1)} P(\tilde{S}|S, A^{(t)}), \forall \tilde{S}, S \in \mathcal{S}, A^{(t)} \in \mathcal{A}, \quad (6)$$

where the values of the belief vectors is calculated for all $t \in \{1, 2, \dots, T\}$ and for all $A^{(t)} \in \mathcal{A}$. We denote the set of all the obtained belief vectors at the time $t \in \{1, 2, \dots, T\}$ by $\mathcal{P}^{(t)}$.

As the whole schedule A_{sch} is computed and fixed at the beginning of the hyper-period and the network is not observed during the hyper-period, the optimal schedule, denoted by A^*_{sch}, can be evaluated directly by solving over the complete sequence of actions as follows

$$A^*_{\text{sch}} = \underset{\left(A^{(1)}, A^{(2)}, \dots, A^{(T)}\right) \in \mathcal{A}^T}{\operatorname{argmin}} \sum_{t=1}^{T} \sum_{\tilde{S}} \sum_{S} P_S^{(t-1)} \cdot \gamma(\tilde{S}|S, A^{(t)}) P(\tilde{S}|S, A^{(t)}). \quad (7)$$

This is a very high-dimensional optimization problem depending on the hyper-period length. As a result, we will use POMDP-solving sequential techniques in order to efficiently solve the formulated problem.

In order to evaluate the optimal strategy, a backward tracing is performed over the objective function where the initial value at the last time slot of the hyper-period is evaluated as follows

$$V_{A^{(T)}}^{(T)}(P^{(T-1)}) = \sum_{\tilde{S}} \sum_{S} P_S^{(T-1)} \gamma(\tilde{S}|S, A^{(T)}) P(\tilde{S}|S, A^{(T)}), \quad \forall A^{(T)} \in \mathcal{A}, P^{(T-1)} \in \mathcal{P}^{(T-1)}. \quad (8)$$

Then, the objective is evaluated using backward tracing by adding the minimum cost for all future time slots to the immediate cost at the current time slot. The recursive relation for calculating the cost function is expressed as follows

$$V_{A^{(t)}}^{(t)}(P^{(t-1)}) = \sum_{\tilde{S}} \sum_{S} P_S^{(t-1)} \gamma(\tilde{S}|S, A^{(t)}) P(\tilde{S}|S, A^{(t)}) + \min_{A^{(t+1)} \in \mathcal{A}} V_{A^{(t+1)}}^{(t+1)}(P^{(t)}), \quad \forall A^{(t)} \in \mathcal{A}, t \in 1, 2, \dots, T-1, P^{(t-1)} \in \mathcal{P}^{(t-1)}. \quad (9)$$

The optimal action at time slot t is evaluated using the obtained objective functions and belief vector at the edge of the time slot t as follows

$$A^{*(t)}(P^{(t-1)}) = \arg \min_{A^{(t)} \in \mathcal{A}} V_{A^{(t)}}^{(t)}(P^{(t-1)}), \forall P^{(t-1)} \in \mathcal{P}^{(t-1)}. \quad (10)$$

The above recursive equations can be solved sequentially as follows: i) Solve Equation (6) for all $t \in \{1, 2, \dots, T\}$ and for all $A^{(t)} \in \mathcal{A}$, ii) evaluate Equation (8), iii) solve the optimization problem (10) at the time slot corresponding to the last evaluated objective function, iv) evaluate Equation (9) for the preceding time slot, and v) go back to item iii) except when $t = 1$. After running this described algorithm, the optimal schedule can be expressed as follows

$$A^*_{\text{sch}} = \left(A^{*(1)}(P^{(0)}), A^{*(2)}(P^{(1)}|_{A^{*(1)}}), \dots, A^{*(T)}(P^{(T-1)}|_{A^{*(T-1)}})\right). \quad (11)$$

In this paper, the formulated UMDP is then solved using one of POMDP solving techniques used by the solver in [13] to obtain the optimal schedule of the system in a computationally efficient way compared to implementing the backward tracing algorithm directly.

IV. A Sub-Optimal Scheduling Policy

In the case of periodic flows with deterministic deadlines, various scheduling strategies have been considered [14]. A common real-time scheduling policy that has been found to be effective for industrial environments is the earliest deadline first (EDF) strategy [15]. It has been shown in [11] that it outperforms fixed priority scheduling, where the priorities of flows are fixed over time and do not depend on the deadlines, while delivering competitive acceptance ratios to the optimal dynamic priority scheduling policies, where the priorities depend on the network status and can change with time, at lower computational cost. Moreover, EDF has been used in [11] for obtaining schedules over a hyper-period in industrial environments.

In this work, we propose an extension to the EDF strategy to work in the case of random deadlines. The proposed strategy results in a sub-optimal schedule for a whole hyper-period of the discussed network. We denote the proposed strategy by earliest average deadline first (EADF). The computational complexity of EADF is much smaller than that of the optimal scheduling scheme. In this strategy, we take into account the averages of the flow deadlines to choose the transmitting flow at a time slot. At any time slot, the flow with the earliest expected deadline is chosen for transmission. Algorithm 1 illustrates the proposed technique as follows

Algorithm 1 EADF Scheduling Strategy

Initialization: $T, M, \mu_m \forall m$;
Initialization: $S^{(0)}$;
for $t = 1 : T-1$ **do**
  Evaluate: $A^{*(t)} = \arg\min_m t_m^{(t-1)}$;
  for $m = 1 : M$ **do**
    if $t_m^{(t-1)} > 1$ **then**
      Update: $t_m^{(t)} = t_m^{(t-1)} - 1$;
    else
      Update: $t_m^{(t)} = \text{round}(\mu_m)$;
    end if
  end for
end for
Output: $A^*_{\text{sch}} = \left(A^{*(1)}, A^{*(2)}, \ldots, A^{*(T)}\right)$;

V. Numerical Results

In the following, we assess the performance of the proposed scheduling algorithms when packets with random deadlines are considered. The minimized objective function is the total number of packets that have missed their deadlines. We will compare the performance of the optimal strategy, the EADF strategy, and the basic round robin benchmark in which flows are scheduled over time in equal portions and in circular order without prioritizing any of the flows [16]. We will refer to these three strategies, respectively, as 'Optimal', 'EADF', and 'Round Robin'. In these simulations, we have used the POMDP solver in [13] to obtain the optimal scheduling strategy. In all the following results, the deadlines are following a uniform distribution over the range $[\max(\mu_m - 1, h_m^*), \mu_m + 1]$.

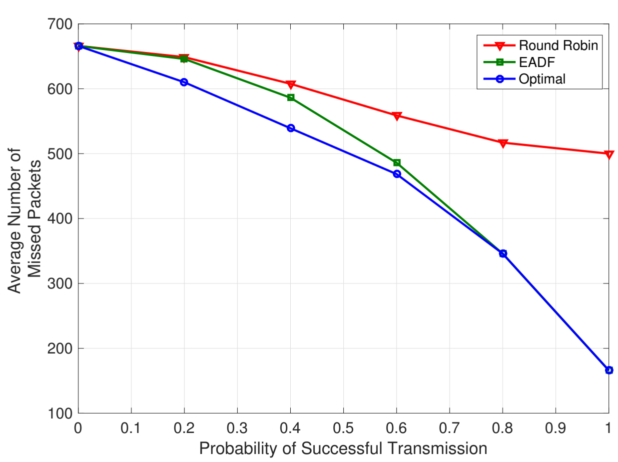

Fig. 3. The total number of missed packets against the channel quality for various scheduling strategies.

In Fig. 3, we consider the case of two flows with $h_1^* = h_2^* = 2$, $\mu_1 = 2$, $\mu_2 = 6$, and $T = 1000$. We have chosen a long hyper-period to capture the effect of randomness on the performance. We show the performance as a function of success probability in transmitting a packet. The improvement in the performance of the optimal policy over the round robin policy is higher in the case of better channels. EADF's performance is identical to the optimal policy for success probability larger than 0.8 and only slightly worse for low to moderate values of success probability. The EADF strategy actions depend on the number of remaining time slots to the deadline and not the remaining number of hops. As a result in the case of poor channels, the EADF does not prioritize flows with lower remaining number of hops to improve packet delivery for the flows.

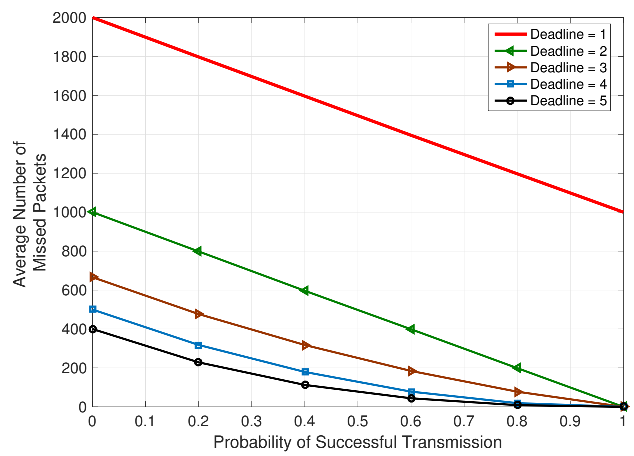

Fig. 4. The total number of missed packets against the channel quality for various average deadline values.

In Fig. 4, we consider the case of 2 symmetric flows with a single hop between the respective sources and destinations. We show the system performance for different values of the same average deadline for both flows. As the average deadline increases, the improvement in the performance decreases. Also, this improvement is larger for poorer channel conditions. This shows the importance of having good scheduling schemes for poor conditions due to the necessity to optimize system parameters for improved performance.

In Fig. 5, we consider two flows with $h_1^* = 1$ and $h_2^* = 3$ and a common average deadline μ. We compare the performance of the optimal, EADF and round robin policies for two values of μ, namely 3 and 5. At $\mu = 3$, the performance of the optimal policy almost coincides with that of the round robin strategy at $\rho = 1$ because, on average at every 3 time slots, a packet arrives at each of the flows, $h_1^* = 1$, and $h_2^* = 3$. As a result, only one packet from these two flows can be delivered before its deadline in almost all of the cases and hence both algorithms have very similar total number of packets missing

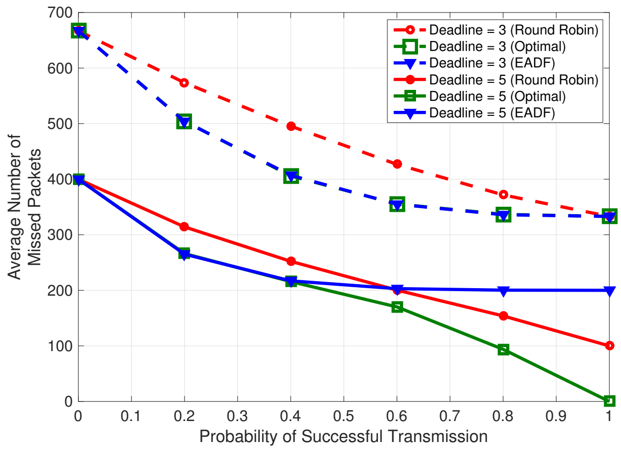

Fig. 5. The total number of missed packets against the channel quality for various average deadline values and verious scheduling strategies.

their deadlines. Moreover, the EADF performance coincides withe optimal for the whole range of ρ. At $\mu = 5$, the optimal strategy achieves better performance because both flows can be scheduled within five time slots successfully, and hence an efficient scheduling scheme improves the performance significantly. Moreover, the EADF has a poor performance at the high values of ρ because it does not consider channel quality during the schedule calculation and hence it does not benefit from the good channel quality while it has optimal performance on the poor channel quality cases.

VI. Conclusions

In this work, we have modeled the scheduling problem for a system with M flows with random deadlines as a UMDP. The investigation of the case of flows with random deadlines has been motivated by scenarios in industrial environments where data flows carry sensing and control decision data. The solution of the UMDP is the optimal scheduling strategy which determines the sequence of chosen flows for transmission over the hyper-period. We also obtained a sub-optimal EADF strategy to lower the complexity of the scheduling process. Numerical results suggest the use of the optimal policy in situations where the channel quality is good and the average deadlines for the flows are large compared to the lengths of the routes of various flows. Also, it is beneficial to use the optimal scheduling policy for tighter deadlines when the channel quality is poor.

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