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A Co-design Distributed Bayesian Approach for Decision and Scheduling of WNCS

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Abstract: This paper deals with the problem of co-design of Wireless Networked Control systems (WNCS). The integration of the Wireless Network (WN) in the control loop influences the Quality of Control (QoC) of the system in terms of the Quality of Service (QoS) of the WN. We present a co-design approach for WNCS based on distributed Bayesian Network (BN) and we illustrate it with Khepera III robot. The proposed BN is constructed from the robot experimental data. This approach allows to make decisions to ensure a good QoC for the robot and also ensure that the QoS is always sufficient to maintain a good QoC. Keeping a sufficient QoS depends on the scheduling method used and therefore the proposed approach aims also to determine the proper scheduling method to keep the system's performance. Finally a comparison is performed with the classical time-triggered scheduling. The results obtained with BN scheduling are better in terms of QoS and QoC for WNCS.

Keywords: Wireless Networked Control Systems, Co-design, Bayesian Network, Scheduling, Decision-making, Mobile robot.

1. INTRODUCTION

Wireless Networked Control Systems (WNCS) are distributed systems in which the information between the node controller and node system are exchanged via a wireless communication network. Compared with traditionally known controlled systems, the Quality of control (QoC) in the WNCS depends mainly on the Quality of Service (QoS) of the used Wireless Network (WN). Using a WN to interconnect different nodes of a distributed system brings many benefits. One of the advantages of WNCS is to reduce complexity in terms of installation. The weight and the limited space of WNCS may be one of the criteria for selecting such systems. The simplicity of maintenance also proves a great advantage for these systems. These benefits can also increase system flexibility. Therefore, the WNCS have found applications in various fields such as mobile sensor networks [Leonard et al., 2007], robotics and mobile robotics [Arzen et al., 2007, Cremean et al., 2006], Unmanned Aerial Vehicles UAV [Berbra et al., 2009] etc. . However, the integration of the WN in the control loop introduces some difficult problems to solve.

Traditionally known Controlled Systems are based on the assumption that all transmitted information is received without loss and delay, which means that the link between the various components of the system is considered as "perfect". However, in Networked Control Systems (NCS), the network either wired or wireless is "imperfect", and the modeling and analysis of such NCS are more complex

[Hespanha et al., 2007]. The network influence on the QoC of the system can be due to sampling, delay, packets loss and the rate of the WN.

A lot of works have been done recently on these topics. According to various aspects of the analysis and design of the NCS, existing works can be broadly divided into four categories: stability analysis [Hespanha et al., 2007, Liu et al., 2008, Xiaomei et al., 2008], state estimation [Giorgiev and Tilbury, 2006, Sinopoli et al., 2004], control synthesis [Varsakelis and Zhang, 2008, Guo and Li, 2010, Fu and Dai, 2009] and co-design of control and communication [Aubrun et al., 2010, Branicky et al., 2002, 2003].

Co-design approach is a new research domain. In such approach, problems due to the network such as delays, packet loss and jitter (QoS) are considered simultaneously with the control problems such as stability and performance of the controller (QoC). Generally, NCS has to be assigned to a schedule of transmission for each transmission entity (sensor, controller) based on a scheduling algorithm. Usually, the control system design and network scheduling are studied separately. This separation allowed the automatic community to focus on this particular field without taking into account the scheduling. But with the growing use of NCS, the need to address simultaneously the problem of scheduling and control encouraged the researchers to work on a so-called problem of co-design (adapt the network to the dynamic needs of the control and vice-versa) Fig.1. Therefore, understanding the impact of scheduling on the stability and performance of the control

has become crucial. Indeed, recent years have allowed the automatic community to study the communication network [Branicky et al., 2002, Cervin and Eker, 2005, Branicky et al., 2003]. All these works are focused on NCS and less works have been done till now on WNCS. This paper proposes a novel approach of Co-design of WNCS.

The causality between the different parameters of the WN and the QoS and the QoC permits to use the graph theory to model the system. The probability theory can also be used according to the stochastic aspect of WN. Hence, we propose in this paper to use Bayesian Network (BN) [Pearl, 1988], [Naim et al., 2004] to model the QoS and the QoC of the WNCS as it brings graph theory and probability theory together. BN is used in this paper to schedule the information and to make on-line decision to avoid both degradation of the QoS and the QoC. The reconfiguration of the WN is required to fulfill the need of control in the case of degradation of the QoC. The adaptation of control is required too in the case of the degradation of the QoS of the WN.

To illustrate our proposals, the communication architecture for two mobile robots moving with obstacle avoidance strategy in a 2D space with fixed control station is considered. According to the information delivered by the proposed BN, the reconfiguration of both the communication architecture (Dynamic priority) and the strategy of control is possible by using different methods of tasks scheduling.

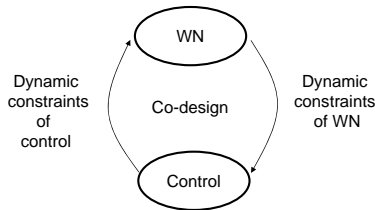


Fig. 1. Co-design problem

The paper is organized as follows. Section 2 presents the co-design problem and describes the proposed BN approach. The qualitative and the quantitative approach to model the proposed distributed BN using the experimental results are presented. The decision and scheduling approach using distributed BN are discussed in section 3. Section 4 demonstrates the effectiveness of the approach using simulated results for two robots and two scenario are studied and compared. Section 5 gives conclusion and some perspectives.

2. CO-DESIGN PROBLEM

Distributed systems generally incorporate communication resources (such as networks and wireless networks) to connect their different subsystems. This category of systems requires appropriate scheduling taking into account stochastic phenomena and decision to ensure the reconfiguration of the communication resource to maintain an acceptable QoC for the system, and also to ensure the adaptation of the control strategy to maintain a good QoS of the network. To solve this co-design problem, we need also to locate on-line the source of degradation of the QoC

and QoS. We propose Bayesian networks to come through these tasks and to achieve scheduling and decision making of the system.

The system considered in this paper is KHEPERA III mobile robot. The modeling methodology of the robot and the strategy of communication of two robots is presented in [Mechraoui et al., 2010, 2009]. For this robot, two missions are described (reach a target and avoid obstacles).

2.1 Definition of Bayesian network

Formally, BNs are directed acyclic graphs whose nodes represent random variables in the Bayesian meaning: they may be observable quantities, latent variables, unknown parameters or hypotheses. Edges represent causal relationships; nodes which are not connected represent variables which are conditionally independent from each other. Each node is associated with a probability function that takes as input a particular set of values for the node's parent variables and gives the probability of the variable represented by the node. Efficient algorithms exist that perform *inference* and *learning* (structure and parameter) in BN (see [Naim et al., 2004] for more details).

Many definition of BN exist in the literature. For what follows, let $G = (V, E)$ be a directed acyclic graph, and let $x = (x_v)_{v \in V}$ be a set of random variables indexed by V . x is a BN with respect to G if its joint probability density function can be written as a product of the individual density function, conditional on their parent variables:

$$p(x) = \prod_{v \in V} p(x_v | x_{pa(v)}) \quad (1)$$

Where $pa(v)$ is the set of parents of v .

2.2 Distributed Bayesian Networks

The modeling of a system using Bayesian networks (BN) takes two important steps: qualitative approach and quantitative approach. The first consists of determining the structure of the BN (i.e. causal relationships between nodes), the second consists of finding for each node X , the probability conditional distribution upon X 's parents. In the simplest case, a BN can be specified by an expert and is then used to perform inference. In other applications defining the network is too complex for humans. In this case, the structure and the parameters of the local distributions must be learned from data (see [Naim et al., 2004] for more details). However, in distributed systems, nodes might not be physically connected. In our application, which consists of controlling a group of robots via a WN, the idea of distributing the BN comes out from the fact that some of the nodes are aboard the robots, some are in the control station. In addition to that, the complexity of a BN render impossible embedding all of it in a robot, due to memory and energy consumption constraints [Mechraoui et al., 2009]. That led us to imagine a distribution strategy that can handle those constraints, and simplify as possible the complexity of the BN.

For our application, the structural modeling can be done, based on graph theory, by analyzing influence between the nodes. On the other hand, the quantitative approach will be performed by parameter learning of the BN, due to it's

relative complexity, using BayesiaLab.

Table 1. Signification of different nodes of the BN

Nodes	Signification
QoC	Quality of Control
QoS	Quality of Service
R	State of the robot
PL	Packet loss
RSSI	Request Signal Strength Indicator
Δ_t	Delay
Obst	Obstacle
D	Distance between the station and the robot
Col	Collision
N	Number of communicating nodes
M	Mission

Qualitative approach The QoC is mainly influenced by three parameters: the network's QoS, the mission the robot M and the state of the robot R . Referring to [Hespanha et al., 2007] and [Li and Wang, 2008], the QoS is influenced by the delay Δ_t between transmission and reception, and by the rate of packet loss PL . The signal strength represented by the Request Signal Strength Indicator ($RSSI$) influences the packet loss. The $RSSI$ is affected directly by the distance D and obstacles $Obst$ between the robot and the control station. The delay Δ_t is influenced by the probability of collisions Col between sources (robots or other applications) sending information via the network. The node Col is affected by the number N of robots communicating with the control station (see Fig.2, Tab.2 and Tab.1).

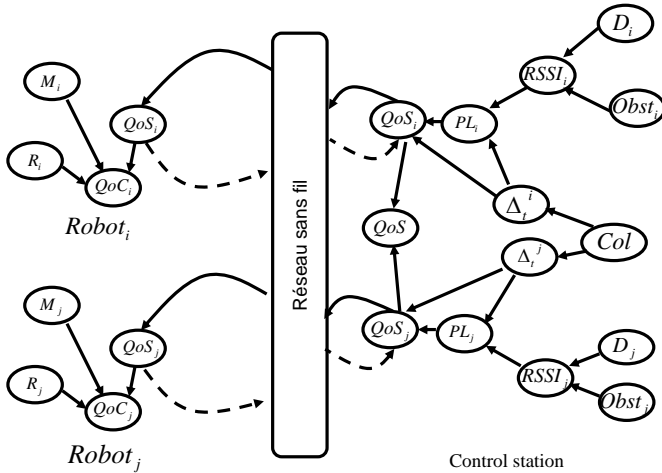


Fig. 2. Distributed Bayesian network

Quantitative approach Here we're looking for finding the probability distributions based on available data from a real robot. Two simple methods will be described here to perform this task. When all the variables are observable the simplest method is the *statistical estimation* which consists of estimating the probability of an event by the frequency of appearance of this event in a database constructed from series of tests on the real system. The estimator is then given by:

$$\hat{P}(X_i = x_k | pa(X_i) = x_j) = \hat{\theta}_{i,j,k}^{LH} = \frac{N_{i,j,k}}{\sum_k N_{i,j,k}} \quad (2)$$

Table 2. Node modes of BN

Nodes	Modes
QoC	Good, Degraded, Bad
QoS	Good, Degraded, Bad
R	Good, Degraded, Faulty
PL	$0\% \leq PL < 24\%$, $24\% \leq PL < 46\%$, $46\% \leq PL < 74\%$, $74\% \leq PL < 100\%$
RSSI	$(\leq -48, > -40, -48 < RSSI \leq -40)dBm$
Δ_t	$\Delta_t < T_{threshold}, T_{threshold} \leq \Delta_t < T_s, \Delta_t \geq T_s$
Obst	Yes, No
D	$D < D_1, D_1 \leq D < D_2, D \geq D_2$
Col	yes, No
N	Number of nodes
M	Reach target, Obstacle avoidance

Where $N_{i,j,k}$ is the number of events in database for which the variable X_i is in the state x_k and its parents are in the configuration x_j . The statistical learning is chosen here over other methods for its simplicity. Database is constructed from series of tests on the real system and was obtained based on two criteria for such systems (robot unicycle and a WN). These criteria are proposed to quantify the QoS and the QoC.

As stated above, the QoS is particularly influenced by packet loss and also the delay. To construct the database, we need to quantify the QoS for this system, and then qualify by ranges of values to define the modes (or states) of QoS. For this, we propose the following criterion:

$$QoS = \max\left(\frac{(1 - PL) * (nT_s - \Delta_t)}{nT_s}, 0\right) \quad (3)$$

PL is the probability of packet loss, it is defined by tests on the real system. Δ_T is the delay between the sensor and the controller. T_s is the sampling period. n is a constant that characterizes the maximum number of lost samples that can be tolerated in which the system works perfectly. the QoC is influenced mainly by three parameters, namely QoS, the state of the robot and the system's mission. This leads us to propose the following criterion:

$$QoC = QoS * \kappa_j * \varrho_i \quad (4)$$

κ_j is a variable that depends on the state j of the robot such that $j \in \{\text{Good, degraded or bad}\}$ and $\kappa_{good} > \kappa_{deg} > \kappa_{bad}$, in our case we took: $\kappa_{good} = 1, \kappa_{deg} = 0.5$ and $\kappa_{bad} = 0$. ϱ_i is a variable that depends on the mission i of the robot ($i \in \{\text{obstacle, target}\}$) as $\varrho_{obstacle} < \varrho_{target}$ ($\varrho_{target} = 1$ and $\varrho_{obstacle} = 0.5$). Fig.3 shows the variation of the QoC depending on the QoS in two different cases ("Reach a target" and "Avoid obstacle"). We note that the robot needs more QoS in the case of obstacle avoidance. The decreasing of the QoS is caused by the number of nodes that communicates.

3. DISTRIBUTED BAYESIAN NETWORK FOR SCHEDULING AND DECISION

After proposing a distributed BN model Fig.2 and performing parameter learning (using BayesiaLab) to define the probability distribution for every node, this BN is used for scheduling, and also making on-line decision to maintain an acceptable QoC and/or QoS. However, to perform this task, the BN needs information and knowledge about the robot's QoC. A criterion designed to evaluate on-line QoC is used (Algorithm 1). This algorithm gives the

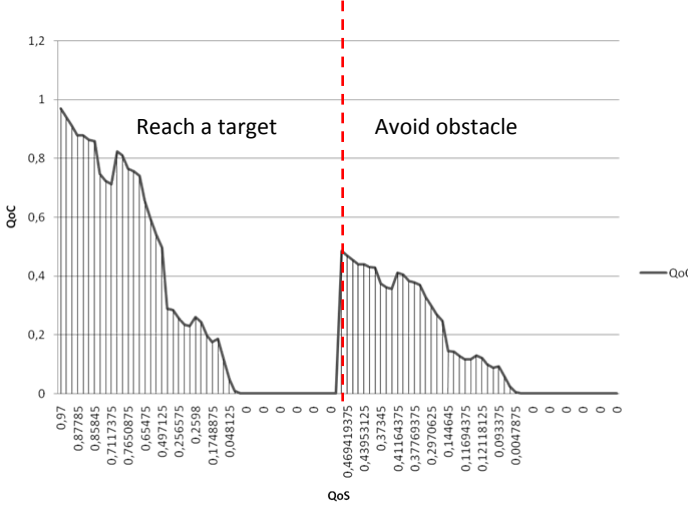


Fig. 3. QoC depending on QoS with two missions: reach a target and avoid obstacle

evidence concerning the QoC of the robot. If the distance (d) between the robot and the station increases, the QoC is considered as bad. Now, if the distance decreases, we verify the orientation error ($\tilde{\theta}$). If the orientation error decreases, then the QoC is good, else the QoC is degraded.

Algorithm 1 Scheduling using QoC criterion

```

if  $d = 0$  and  $\dot{d} = 0$  then
   $QoC = \text{good}$  and  $\text{sensor} \leftrightarrow \text{controller}$ 
else if  $\dot{d} < 0$  then

  if  $\dot{\tilde{\theta}}(k) \geq 0$  and  $\dot{\tilde{\theta}}(k-1) \geq 0$  then
     $QoC = \text{degraded}$  and  $\text{sensor} \leftrightarrow \text{controller}$ 
  else
     $QoC = \text{good}$  and  $\text{sensor} \leftrightarrow \text{controller}$ 
  end if
else
   $QoC = \text{bad}$  and  $\text{sensor} \leftrightarrow \text{controller}$ 
end if

```

d : distance between the robot and the target, $\tilde{\theta}$: orientation error.

\leftrightarrow : communication, \leftrightarrow : stop communication.

Using information about all the measured variables, the BN provides a probabilistic estimation of the QoC and the QoS. Based on this estimation, the robot can make decision to change the scheduling strategy. The objective is to keep the better possible QoC for each robot and the better possible network's QoS.

According to the state of the QoC of the robot (delivered by Algorithm 1) and the state of the QoS (delivered by the BN knowing the state of the QoC), the system changes the scheduling strategy. Thus, with probability delivered by the BN (Algorithm 2) and Algorithm 1, the values of the conditional probability $P(QoS|QoC, D, Col, M)$ triggers the sensor task. With only Algorithm 1, the state of the QoC triggers the sensor task of each robot.

Algorithm 2 Scheduling using BN

```

 $P_1 = P(QoS = \text{good} | QoC, D, Col, M)$ 
 $P_2 = P(QoS = \text{degraded} | QoC, D, Col, M)$ 
 $P_3 = P(QoS = \text{bad} | QoC, D, Col, M)$ 
if  $(P_1 > P_2)$  and  $(P_1 > P_3)$  then
   $\text{sensor} \leftrightarrow \text{controller}$ 
else
  Execute Algorithm 1
end if

```

4. RESULTS

To verify the efficiency of the proposed BN to schedule and to make decision, two scenarios are presented. In each scenario, the BN and Algorithm 1 are tested and compared with the system without the proposed approach. The use of Algorithm 1 without BN to schedule is also compared with the other strategies (see Table 3).

To perform the comparison, five criteria are considered.

- (1) The first criterion (Eq. 5) is the Use Request Factor (URF) which represents the frame rate requested to the MAC layer [Juanole and Mouney, 2005]. It influences directly the QoS.

$$URF = \sum_{i=1}^N \frac{\xi_i}{\Gamma * T_s^i} \quad (5)$$

ξ_i is the length of the frame of task i . Γ is the throughput of the WN. N is the number of tasks.

- (2) The second criterion concerns also the rate of packet loss. It is calculated as follow:

$$\Phi = \frac{P_r}{P_s} \quad (6)$$

P_s is the number of packets sent and P_r the number of received packets.

- (3) The third criterion concerns the QoC. It is the Integral of the Absolute Error (IAE) (see Eq.7).

$$IAE = \sum_{k=0}^p \epsilon_x(k)^2 + \epsilon_y(k)^2 \quad (7)$$

ϵ_x and ϵ_y are errors between the reference trajectories (at 0% of network load) and other trajectory (depending on the network load rate) with respect to X - axis and Y - axis respectively computed with p points representing each trajectory.

- (4) The fourth criterion is the fact that the robot reaches the target or not.
- (5) The last criterion is the collision between the obstacle and the robot.

4.1 Scenario 1

In the first scenario, we suppose that the two robots communicate with one control station. The initial position of the robot 1 is $(x_0, y_0, \theta_0) = (0, 0, 0)$ and the position of the target is $(x_d, y_d) = (1, 1)$. The two robots are always within the coverage area of the station. Hence, the probability $P(D < D_{Threshold}) = 1$ for each robot.

To limit the resource of the WN and to study the network limits, the throughput is set to 8000bits/s. With this throughput and the sensor tasks of $R1$ and $R2$ and the

controller tasks, the $URF = 64\%$ in the case of non application of the proposed methods of scheduling (BN and Algorithm1). In this case, the robot reaches the target but it cannot avoid the obstacle. When Algorithm 1 is applied to control the sending of sensor measurements to controllers, it provides the current state of the QoC to the robot. Taking into account this state, a boolean signal for scheduling is generated; "0" starts the communication and "1" stops it. We note that after applying Algorithm 1, URF decreases from 64% to 34%, the QoS becomes good but the IAE increases from 0.13 to 0.89 for Robot 1 and 0.42 to 1.36 for Robot 2 (see Table 3). However, despite the increasing value of IAE, the application of this algorithm has slightly influenced the trajectory and the two robots reach their targets (see Fig. 4) and avoid the obstacle. However, applying the scheduling based on the results of BN, we notice that we have the same performance as with Algorithm 1 except that the IAE drops to zero. This can be explained by the fact that the BN has taken into account the state of the QoS and as it is sufficient to send periodic measurements, the two sensor tasks remain time-triggered. We can conclude that the proposed method is efficient because it takes into account both the QoS and the QoC to make decision and scheduling.

4.2 Scenario 2

In this scenario, the same situation as in first scenario is kept but the throughput of the WN is set to 3000bits/s , which means that $URF = 170\%$ in the case of non application of the proposed methods of scheduling. The IAE is increased from 0 to 90 and thus the robot cannot reach the target (Fig. 4) and cannot avoid the obstacle (see Table 3). Now Algorithm 1 is applied to control the sensor task flow. The IAE is decreased from 170% to 82%. Packet losses are increased but still reasonable. In fact, the robot can reach a target (see Fig. 4) but it cannot avoid the obstacle. Fig. 5 shows the delay with and without the proposed approach. It is clear that the delay with BN is less than the delay without BN. Using results provided from the BN, and with the same scenario, the robot can reach its target (see Fig. 4) and avoid the obstacle. This scenario shows that, the proposed approach is efficient and solves the co-design problem.

5. CONCLUSION

In this paper, a novel distributed BN based approach has been proposed to model the QoS and the QoC of WNCS. This model combines all parameters or variables that influence the Quality of Service of the WN and the Quality of Control of the robot. The BN is designed using statistical learning of experimental data acquired from Khepera III robot. The use of the BN is justified by the stochastic behavior of the WN. The main objective of the BN is to make decisions and to control the sensor task flow. According to the situation, the scheduling strategy is applied to guarantee a good QoC of the robot and also to keep a sufficient QoS to send the critical information. The proposed model achieves the desired objectives in terms of scheduling and decision-making. In this paper, the communication architecture for two mobile robots

Table 3. Comparison between the classical approach and the proposed one

		Scenario1	Scenario2	
\overline{BN} $\overline{Algo1}$	URF		64%	170%
	Φ	R1	0%	91%
		R2	0%	96%
		S	0%	91%
	IAE	R1	0.13	66.35
		R2	0.42	49.97
	Reach target		Yes	No
	Collision		Yes	Yes
\overline{BN} $Algo1$	URF		34%	82%
	Φ	R1	0%	32%
		R2	0%	33%
		S	0%	64%
	IAE	R1	0.89	1.31
		R2	1.36	1.76
	Reach target		Yes	Yes
	Collision		No	Yes
BN $Algo1$	URF		64%	79%
	Φ	R1	0%	33%
		R2	0%	30%
		S	0%	56%
	IAE	R1	0.21	0.87
		R2	0.59	1.02
	Reach target		Yes	Yes
	Collision		No	No

Table 4. Signification of the used abbreviations

Abbreviation	Signification
R1	Robot number 1
R2	Robot number 2
S	Control Station
Φ	Packet loss rate
IAE	Integral of the Absolute Error
\overline{BN}	Without BN Approach
$\overline{Algo1}$	Without Algorithm 1
BN	With BN approach
$Algo1$	With Algorithm 1

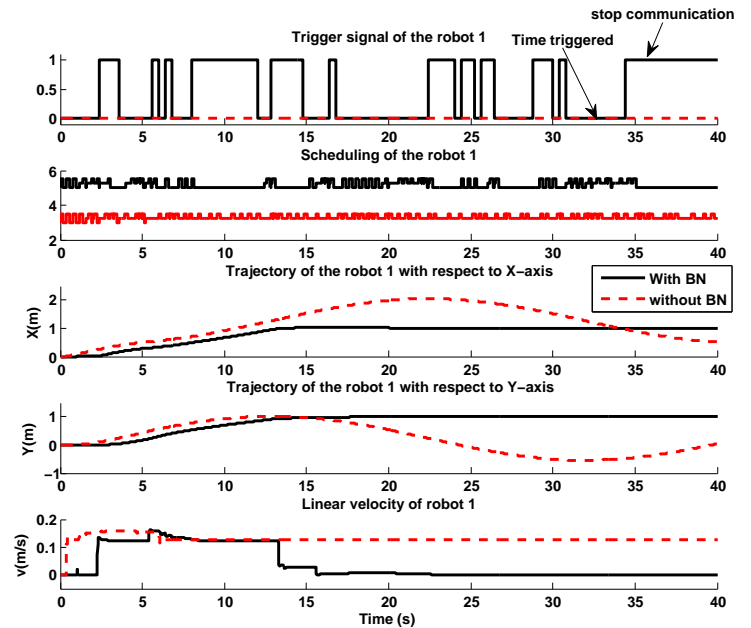


Fig. 4. Comparison between the trajectory of Robot1 with and without BN

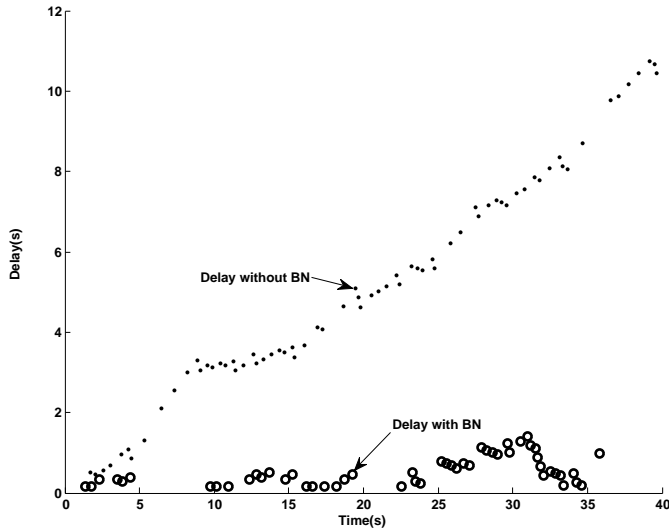


Fig. 5. Comparison between the delay of the sensor task of Robot1 with and without BN

moving in a 2D space with fixed control station has been considered as an illustrative example. According to the information delivered by the proposed BN, the strategy of controlling the sensor flow is applied. It aims to keep a good QoC in when the robot has to reach a target and avoid obstacle and also to ensure a sufficient QoS. Finally a comparison of the proposed BN scheduling with the classical time-triggered scheduling is performed and the results obtained with BN scheduling are better in terms of QoS and QoC for WNCS.

In the future work, the degradation of the QoC and the QoS of WNCS can be avoided by adding some dynamic nodes in two time slices. The probability of the QoC and the QoS in time slice $t+1$ knowing their states in time slice t can help predict the degradation of the QoC.

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