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# Optimal distributed resource allocation in a wireless sensor network for control systems*

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**Abstract:** Wireless technology is applied increasingly in networked control systems. A new form of wireless network called wireless sensor network can bring control systems some advantages, such as flexibility and feasibility of network deployment at low costs, while it also raises some new challenges. First, the communication resources shared by all the control loops are limited. Second, the wireless and multi-hop character of sensor network makes the resources scheduling more difficult. Thus, how to effectively allocate the limited communication resources for those control loops is an important problem. In this paper, this problem is formulated as an optimal sampling frequency assignment problem, where the objective function is to maximize the utility of control systems, subject to channel capacity constraints. Then an iterative distributed algorithm based on local buffer information is proposed. Finally, the simulation results show that the proposed algorithm can effectively allocate the limited communication resource in a distributed way. It can achieve the optimal quality of the control system and adapt to the network load changes.

**Key words:** Wireless sensor networks (WSN), Distributed resource allocation, Control systems, Optimization

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## INTRODUCTION

With the rapid development of wireless communication technology, the combination of wireless communication and control systems becomes a new trend of networked control systems. Among the kinds of wireless technologies, wireless sensor network (WSN) has attracted a lot of interest and visibility due to its huge application space. WSN is a kind of wireless ad-hoc network which connects embedded sensors, actuators, and processors and in which each node consists of a wireless communication device (Stankovic *et al*., 2003; Akyildiz and Kasimoglu, 2004). It allows rapid deployment, flexible installation, fully mobile operation and prevents cable wear and tear problem. WSN will play an increasingly important role in constructing complex industry control systems.

Introducing WSN into control systems (Fig.1) will raise some new challenges. First, the limited communication resources of WSN are shared by all the control tasks. Second, this kind of network is generally a wireless and multi-hop network, which means that the wireless communication resources are decentralized but strongly coupled. Third, the sensor node has limited computation capability. These challenges make it harder to efficiently allocate communication resources to those control loops.

For the above wireless resource allocation problem, we set up a nonlinear optimization model, where the objective is to maximize the performance of control systems, subject to the node channel capacity. We solve it by the barrier function method in nonlinear optimization theory (Bazaraa and Shetty, 1979; Bersekas, 1995). Our main contribution is that the

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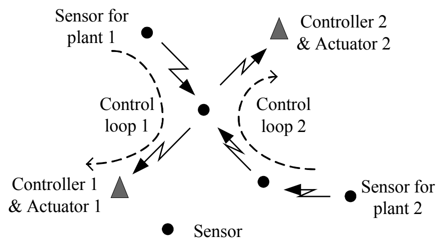


**Fig.1 A wireless sensor network for control systems**

node buffer information is used to construct a barrier function, which can greatly lower the complexity of the optimal computation. Additionally, inspired by Kunniyur and Srikant (2003), we maintain that our algorithm is convergent. Finally we give a distributed iterative algorithm, which can be easily realized by the sensor nodes.

## RELATED WORK

The idea of using nonlinear optimization in the context of network system has been explored in wired networks, ad-hoc networks and sensor networks. In wired network area, Kelly *et al*.(1998) presented an overall optimization framework for proportionally fair rate control problem, and prove that the controller can converge to the unique solution of the penalty function form of the nonlinear program. For such a problem, some researchers use duality theory (Low and Lapsley, 1999), or game theory (Yaiche *et al*., 2000). Others use barrier function method (or penalty-based approach). Instead of the abstract penalty price definition in (Kelly *et al*., 1998), Kunniyur and Srikant (2003) used end-to-end measurable losses as the penalty function. Alpcan and Basar (2003) adopted queuing delay to represent the penalty function. Dong *et al*.(2004) used explicit congestion notification as the feedback penalty information. Compared with them, our work uses buffer storage cost as the penalty function.

In wireless multi-hop networks, based on the idea in wired networks (Kelly *et al*., 1998; Low and Lapsley, 1999), researchers present several distributed rate control methods (Qiu and Marbach, 2003; Xue *et al*., 2003; Yi and Shakkottai, 2004). These works need to know either the capacity of node or the capacity of the wireless link, which are not fixed quantity and hard to acquire in CSMA-based networks. Besides, their penalty definitions are similar to those of (Kelly *et al*., 1998) which are comparable with ours. Liu *et al*.(2003) also presented a distributed optimization framework, but their discussion was for a CDMA sensor network. For CSMA-based network, some other researchers use centralized computation at sink node to control the source rate. Some of them (Karenos *et al*., 2005; Zhou and Lyu, 2005) collected network status described by some simple tags to be the basis of rate adjusting, while other researchers (Chen and Sha, 2004) used the mathematical model of system which is too complicated to compute. Different from them, we discuss an explicit rate control problem and propose a distributed algorithm.

## PROBLEM FORMULATION

Consider a WSN serving control systems, as shown in Fig.1, where the controllers are set on the actuator nodes. In this system, each node has a transmitter, a receiver, and a finite buffer, and wishes to communicate with other nodes, possibly by multi-hop routing. We assume that nodes cannot transmit and receive at the same time, and that every transmission is intended for a single node. The Mac protocol adopts CSMA/CA channel access scheme.

In the above system, there is a tradeoff with the sensors' sampling frequencies. Worst case frequencies will lead to a low quality of control (QoC) of the control system, while too high frequencies will result in network congestion, accompanied by large delay and high drop ratio. This also degrades the QoC of the control system. Therefore, proper sensor frequencies and data transmission rates should be set. This problem is then formulated as a constrained nonlinear optimization problem P, where the objective is to maximize the performance of control systems, subject to the node channel capacity.

To present the problem clearly, the following notations are defined first:

$s$: the session ID. Each session means a periodic sampling task for a control system.

$M$: the total number of sessions in the system.

$f_s$: the sampling frequency of session $s$.

$x_s$: the flow rate of the data of session $s$ in the network.

$C_n^{\text{channel}}$: the channel capacity of node $n$. It should be stressed that this variable is topology-dependent.

Then the problem is as follows:

$$\text{P}:\ \min\ \sum_{s=1}^{M}\omega_s U_s(f_s)=\sum_{s=1}^{M}\omega_s\alpha_s \mathrm{e}^{-\beta_s f_s}, \tag{1}$$

$$\text{s.t.:}\ \boldsymbol{f}\le\boldsymbol{x}, \tag{2}$$

$$\boldsymbol{Ax}\le\boldsymbol{C}^{\text{channel}}, \tag{3}$$

$$\boldsymbol{f}^{\min}\le\boldsymbol{f}\le\boldsymbol{f}^{\max}, \tag{4}$$

In Eq.(1), $\omega_s$ is the weight of the control loop, $U_s(f_s)$ is a control performance index (Sanfridson, 2000), derived by Seto *et al*.(1996). In this paper, this objective function is assumed to be decreasing, strictly convex, and continuously differentiable function of $f_s$ over the range $[f_s^{\min}, f_s^{\max}]$. In $U_s(f_s)$, parameter $\alpha_s$ is the magnitude coefficient, $\beta_s$ is the decay rate. In most control systems, this control performance index can describe the relationship between the QoC and the sampling frequency in a discrete digital control system. The smaller the index is, the better is the QoC.

In Eqs.(2)~(4), the symbols in bold font represent the vector of the corresponding variables. The constraint in Eq.(2) means each session flow should be transmitted at a rate larger than or equal to the sensor's sampling frequency, or the sensor data would jam at source nodes.

In Eq.(3), $\boldsymbol{C}^{\text{channel}}$ is a vector of node channel capacity $C_n^{\text{channel}}$, $\boldsymbol{A}$ is a node burden matrix, where $A_{ij}$=2, if node $i$ is a router of session $j$, node $i$ needs to use the wireless channel twice to receive and transmit a packet; $A_{ij}$=1, if node $i$ is the source/destination of session $j$, node $i$ only needs to use the channel once to transmit/receive a packet; otherwise, $A_{ij}$=0. Eq.(3) means the total communication tasks of a sensor node should not exceed its wireless channel capability.

Eq.(4) defines the feasible set scope, i.e., each sensor node has a maximum and a minimum sampling frequency.

## ITERATIVE DISTRIBUTED ALGORITHM BASED ON LOCAL BUFFER INFORMATION

### Transform of the constrained optimization problem

According to barrier function methods, we transform the constrained nonlinear programming problem P to another form with penalty:

$$\text{Q:}\ \min Q(f)=\sum_{s=1}^{M}\omega_s U_s(f_s)+\sum_{s=1}^{M}\xi_s B_s,$$

where $f_s\in[f_s^{\min}, f_s^{\max}]$, $\xi_s>0$, $B_s$ is a penalty to a session $s$, it is some function of the transmitted rates of the concerned users. It should be noted that the minimization of the problem Q approximates arbitrarily closely to the primal problem P when $\xi_s\to0$.

For the convenience of presentation, some notations are listed in advance:

$R(s)$: the route of session $s$, i.e., the set of those nodes by which the session $s$ passes.

$S(n)$: the set of sessions flowing through node $n$.

$r_n$: the utilization ratio of the node $n$'s buffer.

$D_n(x_s)$: the number of packets of the session $s$ in the buffer of node $n$ when this session flow rate is $x_s$.

$C_n^{\text{b}}$: the buffer capacity of node $n$.

To be complete, there have to be some descriptions about Q:

(1) Without losing rationality, we take $f_s$ as its upper bound in constraint (2), i.e., $f_s$=$x_s$.

(2) The penalty function $B_s$ of a session is the sum of the cost $B_{sn}$ at router $n$. It is of the form:

$$B_s=\sum_{n\in R(s)}B_{sn}=\sum_{n\in R(s)}\int_0^{\sum_{s\in S(n)}x_s} g_{sn}(x_s)\mathrm{d}x_s, \tag{5}$$

where $g_{sn}(x_s)$ is a function concerned with all the flows passing through node $n$, and $B_s$ is a function of all the flows passing by all the routers of session $s$. In the network, $x_s$ impacts the queue length of router's buffer. From the fluid model point of view, during the time interval $\Delta t$, the queue length $L_n$ at node $n$ and the aggregate flow rate have the following relationship (Alpcan and Basar, 2003):

$$\frac{\partial L_n}{\partial t}=\begin{cases}\min(0,X), & L_n=C_n^{\text{b}},\\ X, & 0<L_n<C_n^{\text{b}},\\ \max(0,X), & L_n=0,\end{cases} \tag{6}$$

where $X=\sum_{s\in S(n)}x_s-C_n^{\text{channel}}$.

Therefore, we can reasonably define the penalty function as storage cost, as follows:

$$B_s=\sum_{n\in R(s)}B_{sn}=\sum_{n\in R(s)}(1-L_n/C_n^{\mathrm{b}})^{-w}$$
$$=\sum_{n\in R(s)}(1-r_n)^{-w}=\sum_{n\in R(s)}\left(1-\sum_{s\in S(n)}D_n(x_s)\Big/C_n^{\mathrm{b}}\right)^{-w}, \quad (7)$$

where $w\geq 1$. From Eqs.(6) and (7), it is easy to deduce that $B_s$ is a convex function of $x_s$ over its feasible region. Here, $B_s$ can be interpreted as the total routing storage cost of session $s$ to network.

(3) Function $g_{sn}(x_s)$ can be interpreted as the cost-per-unit flow. From Eqs.(5) and (7), we can deduce:

$$g_{sn}(x_s)=\frac{\partial B_{sn}}{\partial f_s}=\frac{\partial B_{sn}}{\partial x_s}=\frac{w}{C_n^{\mathrm{b}}}\cdot\left(\frac{1}{1-r_n}\right)^{w+1}\cdot\frac{\mathrm{d}D_n(x_s)}{\mathrm{d}x_s}.$$

(4) The problem Q can be rewritten as below:

$$\min Q(f)=\sum_{s=1}^{M}\omega_s U_s(f_s)+\sum_{s=1}^{M}\xi_s\sum_{n\in R(s)}\int_0^{\sum_{s\in S(n)}x_s}g_{sn}(x_s)\mathrm{d}x_s. \quad (8)$$

Now, the problem Q can be viewed as trying to minimize the index with a lower storage cost.

**Frequency control algorithm**

To problem Q, the frequency control algorithm is then given as follows:

$$\dot{f}_s=-k_s\left(-\omega_s\alpha_s\beta_s\mathrm{e}^{-\beta_s f_s}+\xi_s\cdot\sum_{n\in R(s)}g_{sn}(x_s)\right)$$
$$=k_s\left(h_s(f_s)-\xi_s\cdot\sum_{n\in R(s)}g_{sn}(x_s)\right). \quad (9)$$

We now show that the above algorithm can converge to a stable point.

**Proposition 1** $Q(f)$ in Eq.(8) is a strictly convex Lyapunov function for the system described by Eq.(9). The unique value $x$ minimizing $Q(f)$ is a stable point of the system, to which all trajectories converge.

**Proof** Our representation of $Q(f)$ in Eq.(8) and the frequency control scheme in Eq.(9) is analogous to that in (Kelly *et al*., 1998), the proof can follow along the lines of the proof in (Kelly *et al*., 1998), we skip the details.

**Iterative solution of the optimization problem**

From Eq.(9), the iterative form of the optimization problem is then given as:

$$f_s(i+1)=\underset{f_s^{\min}\leq f\leq f_s^{\max}}{\arg\min}\left\{f_s(i)+k_s\left(h_s(i)-\xi_s\cdot\sum_{n\in R(s)}g_{sn}(i)\right)\right\}, \quad (10)$$

where

$$h_s(i)=h_s(f_s(i))=\omega_s\alpha_s\beta_s\mathrm{e}^{-\beta_s f_s(i)},$$
$$g_{sn}(i)=g_{sn}(x_s(i))=\sum_{n\in R(s)}\frac{w}{C_n^{\mathrm{b}}}\left(\frac{1}{1-r_n}\right)^{w+1}\left.\frac{\mathrm{d}D_n(x_s)}{\mathrm{d}x_s}\right|_{x_s=x_s(i)}. \quad (11)$$

To Eq.(11), transform $\mathrm{d}D_n(x_s)/\mathrm{d}x|_{x_s=x_s(i)}$ to its difference form, i.e., $\{D_n[x_s(i)]-D_n[x_s(i-1)]\}/[x_s(i)-x_s(i-1)]$. Define $x_s(i)=I_n^s(i)/T$, where $I_n^s(i)$ is the packet amount of session $s$ flowing into node $n$ during the $i$th iteration interval $T$. Then,

$$g_{sn}(i)=\frac{wT}{C_n^{\mathrm{b}}}\left(\frac{1}{1-r_n}\right)^{w+1}\frac{D_n[x_s(i)]-D_n[x_s(i-1)]}{I_n^s(i)-I_n^s(i-1)}. \quad (12)$$

To the above iteration algorithm, a termination criterion is adopted: if $||f_s(i+1)-f_s(i)||<\varepsilon$ is satisfied, then the iteration procedure stops, where $\varepsilon$ is a sufficiently small real number. $||\boldsymbol{v}||_n$ is the $n$th-norm of vector $\boldsymbol{v}=[v_1, v_2, \ldots, v_k]$.

In addition, to the variables in Eq.(10), some comments should be given:

(1) $g_{sn}(i)$ defined in Eq.(12) is only concerned with the local information of node $n$, like $C_n$, $r_n$, $D_n(x_s)$, $I_n^s$, etc. Thus, $g_{sn}(i)$ can be computed by node $n$ locally.

(2) In Eq.(10), all the variables are only concerned with the source sensor node except the $\sum_{n\in R(s)}g_{sn}(i)$. Therefore, if the source node could get this value, the iterative computation process can be accomplished at each source node in a distributed way.

**Distributed realization of IDALBI**

The main idea of the distributed realization is firstly to design a price accumulating packet (PAP), which can collect and accumulate the individual prices $g_{sn}(i)$ at the router nodes, and send $\sum_{n\in R(s)} g_{sn}(i)$ to the source node of session $s$ during the $i$th iteration. Thus each source node can adjust its sampling frequency by an iterative and distributed way according to Eq.(10).

The structure of PAP includes four parts: the common header of packet, the PAP flag, the session ID and the price data, where the common header of packet includes basic information on a packet, like the source node ID, the destination node ID and packet ID, etc., the price data field ships the accumulated value of $g_{sn}(i)$.

Based on the idea of PAP packet, the IDALBI algorithm can be realized by a distributed way. The realization has three local parts:

(1) Destination node procedure

At each iteration time, the destination puts zero into the price field of PAP, then sends it with the highest priority to the source nodes along the route of the session.

(2) Router node procedure

Upon reception of the PAP, the node needs to: (i) count its buffer to get $r_n$, $D_n(x_s)$ and $I_n^s$, which should be saved for the next iteration; (ii) compute its $g_{sn}(i)$ value according to Eq.(12); (iii) add the result into the price data in PAP; (iv) pass forward this PAP.

(3) Source node procedure

At the reception of a PAP, the source node gets the total price $\sum_{n\in R(s)} g_{sn}(i)$. Then it updates its sampling frequency according to Eq.(10) and the termination criterion.

## PERFORMANCE EVALUATION

### System settings

In this subsection, we evaluate the performance of the IDALBI algorithm using the ns-2.28 (Ns-2, http://www.isi.edu/nanam/ns). The network structure used in simulation is depicted in Fig.2, where each sensor needs to send its data to the corresponding controller. The MAC layer adopts CSMA/CA channel access scheme. The other network settings are as follows: a packet length is set as 120 bytes, the data transmission rate of wireless channel is assumed to be 1000 kbps. The buffer capacity of a node is set as 100 packets.

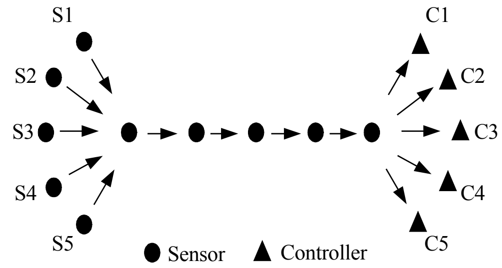


**Fig.2 System structure for simulation**

In these control loops, the parameters in the performance index are: $\omega_s$=[1, 2, 3, 4, 5], $\alpha_s$=[0.98, 0.98, 0.98, 0.98, 0.98], $\beta_s$=[1.00, 0.71, 0.58, 0.50, 0.45]. The frequency scopes of these sensors are all in 2~40 Hz.

### Validation of convergency and uniqueness

Two experiments were run to validate the convergency and uniqueness of the IDALBI algorithm, the results are shown in Fig.3 and Fig.4. In the first situation, the network runs from an initial frequency of 10 Hz. The result (see Fig.3) shows that these five curves can gradually converge to a stable state [7.30, 11.10, 13.43, 15.44, 17.10]. During this procedure, the object value of $Q(f)$ decreases from 0.048 (at 44 s) to 0.020 (at 332 s), and finally reaches a minimum value of 0.018 (at 580 s), i.e., those control systems get their optimal QoCs.

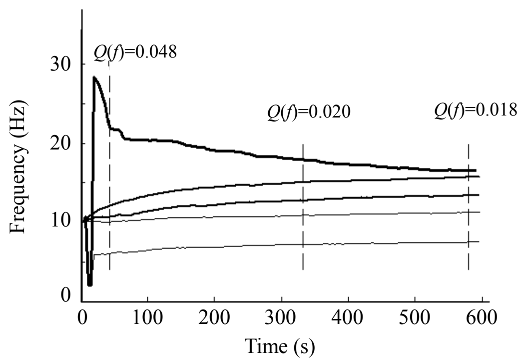


**Fig.3 Sampling frequency frequency updating of five sensors ($k_s$=25, $\xi_s$=0.08). The five curves from top to bottom refer to Sensors 5, 4, 3, 2, 1 respectively**

In Fig.4, only two nodes' results are given in order to make the figure clear. The first group with dotted lines are the results with initial frequency of 40 Hz, the other group with solid lines are the results from the randomly selected frequencies. The results depict: (1) IDALBI can quickly eliminate the network congestion caused by those high sampling frequencies; (2) the results of IDALBI from different initial values can converge to a unique value.

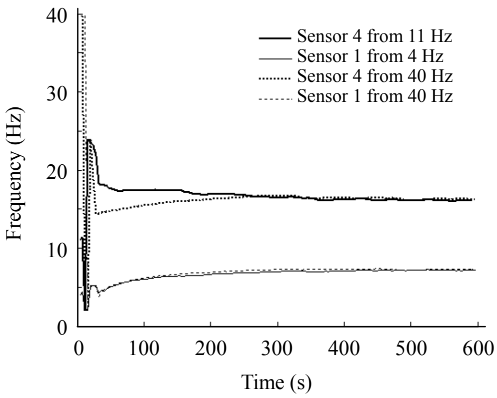


**Fig.4 Sampling frequency updating of sensors starting from different initial values ($k_s$=25, $\xi_s$=0.08)**

### Adaptability evaluation

In a WSN, network load would change because the node may be mobile or new-coming or energy-exhausted. Hence, whether an algorithm can adapt to such changes is important in WSN.

In this experiment, we change the network load by adding a new session into the running network at 400 s. As Fig.5 shows, the four curves gradually converge before 400 s, while the new session breaks the coming balance, these five sessions begin to reallocate the resources, and reach a new balance state soon. It is shown that the IDALBI algorithm can adapt to the change of network load.

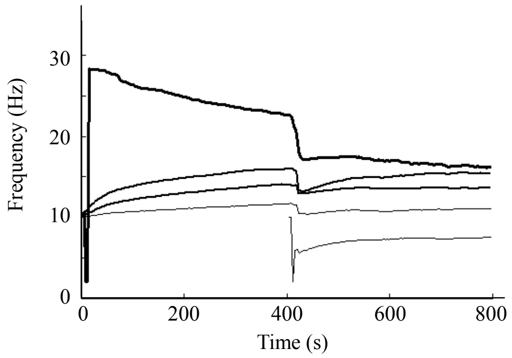


**Fig.5 Sampling frequency updating when a new session arrives ($k_s$=30, $\xi_s$=0.5). The five curves from top to bottom refer to Sensors 5, 4, 3, 2, 1 respectively**

### Effectiveness of parameters

In the IDALBI algorithm, $\xi_s$ and $k_s$ are two important parameters influencing the convergence effect of the algorithm, as shown in Fig.6 and Fig.7.

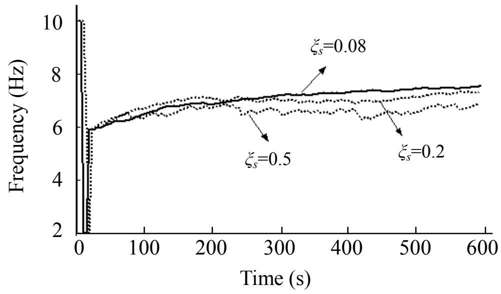


**Fig.6 Sampling frequency updating of Sensor 1 at different $\xi_s$'s**

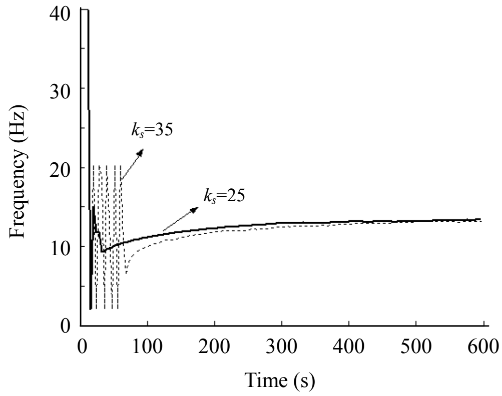


**Fig.7 Sampling frequency updating of Sensor 2 at different $k_s$'s**

Fig.6 shows that $\xi_s$ influences the convergence effect and convergence value. In Fig.6, when $\xi_s$ increases from 0.08 to 0.50, the optimal frequency value becomes smaller, while the jitter becomes larger. This is firstly because a larger value of $\xi_s$ results in a larger objective value $Q(f)$. In the feasible area, $Q(f)$ is a decreasing function of $f$. Therefore, the larger $\xi_s$ is, the smaller $f$ would be acquired. In addition, when $\xi_s$ increases, Eq.(10) will be more sensitive to the variation of $\xi_s$, which will lead to a larger jitter of the frequency, as shown in Fig.6.

Fig.7 shows that $k_s$ only influences the vibration of the curves at the beginning. This is because the gradient of $Q(f)$ is large at first, so that a larger $k_s$ plays a larger role in the system, which is easier to make the results vibrate. However, when time passing by, the gradient of $Q(f)$ decreases to a very small value, then the difference of $k_s$ decreases and nearly vanishes at last. As shown in Fig.7, the two curves almost overlap.

## CONCLUSION

In wireless sensor networks, communication resources have two features: highly decentralized and strongly coupled, which make the resource allocation more difficult. Through observing that the resource allocation has impact on buffer information, we skillfully introduce the buffer information at nodes to solve the problem. Two advantages are: (1) strongly coupled resource representation is avoided, which decreases the degree of difficulty of the problem; (2) each node only needs to care for its buffer change information, which makes the computation simple and local. Such feature is suitable for wireless sensor networks.

Based on the above idea, we design a buffer-based iterative distributed algorithm in a wireless sensor network serving control systems. The objective is to maximize the QoC of control systems under the limited communication bandwidth. The simulation results showed that this algorithm can effectively allocate communication resources, and find the optimal running point of the system automatically. Moreover, it has a good adaptability to the change of network load.

Finally we believe that distributed resource allocation in wireless sensor networks is a new challenging field of research, and that the optimization theory can provide a useful model to design an adaptive and optimized system strategy in such dynamic, decentralized networks.

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