Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

WIRELESS SENSOR NETWORK BASED CONTROL SYSTEM CONCIDERING COMMUNICATION COST

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Abstract: This paper is discussed on some new control methodologies for wireless sensor network based control system, minimizing communication energy consumption. Some control problems with communication cost saving are defined. Then, a heuristic control method based on the Model Predictive Control strategy with a receding horizon cost function including control performance and communication cost is proposed. For a state feedback control problem, a sufficient condition to keep stability of the closed loop system is obtained. Some numerical examples are also illustrated.

1. INTRODUCTION

Recently, wireless sensor network technology has been developed rapidly, and various applications to control system fields have been examined and discussed in these years, such as (Liu, X. and A. Goldsmith 2004). One of the benefits of wireless sensor network is flexibility for developing a new sensor system in plants, factories, and buildings with easy instrumentation and low construction costs. Nevertheless, application of wireless sensor network is sometimes restricted in viewpoints of energy consumption related to battery life, or wireless energy supply problem.

In this paper a wireless network based control system is discussed with consideration of the “communication cost” as energy consumption, in order to maximize the battery life of each wireless node, which corresponds to reduction of communication frequency or control period.

Many control problems with communication network environment had been discussed and investigated recent years. They are discussed mainly robust control problems under unknown communication delay, packet losses and congestion, which are caused by communication network status (B. A. Sadjadi 2003). Where the communication period is supposed to be "uncontrollable" in these problems.

In this paper, the control system optimization problem with wireless network system is discussed based on optimization of control action and sampling period simultaneously (Iino, Yutaka, 2007), (Iino, Y. and M. Fujita, 2007). The most essential feature, which is different from general networked control problems, is that the “sampling period” corresponds to the communication frequency is supposed to be "controllable" and it is incorporated to the control problem as a new independent manipulation variable. It is possible because the wireless network protocols are supposed to be locally adjustable between each wireless node. Thus, the motivation of this research is to propose and solve the problems peculiar to wireless network based sensing and control system, and to challenges to establish a new systematic theory in this field.

The remained sections are organized as follows. In section 2, general wireless networked control problem is defined and some control strategies for the communication cost saving are discussed. Then, some heuristic control schemes are proposed in section 3, which is based on the optimization of a cost function including control performance and communication cost. Then two types of optimization problems are defined, which correspond to state estimation problem and state feedback control problem. In section 4, stability of the control system is considered. In section 5, numerical examples are illustrated. Lastly in section 6, these discussions are summarized and concluded.

2. BASIC FORMULATIONS OF WIRELESS NETWORKED SENSING & CONTROL SYSTEM

2.1 Definition of Wireless Networked Sensing and Control System

In general, the sensor network means multiple sensor nodes. Though, to investigate properties of closed loop control system, hereafter we focus on a SISO closed loop system for simplicity without loss of generality. A general configuration of a wireless networked closed loop control system is illustrated in Fig.1, which is composed of a process, a wireless sensor node, two functions of wireless controller nodes, namely a state estimator and a control calculator, and a wireless actuator node. The sensor node and the actuator node are supposed to be connected directly to the process. These components are basic elements in a general closed loop control system. Thus, three types of wireless communication paths I, II, III are possible, and corresponding three types of wireless networked control problems are defined as follows.

Type I: Wireless sensor networked control problem.
Type II: Wireless estimator networked control problem.
Type III: Wireless actuator networked control problem.

Type I is just the sensor network problem, while Type III is the controller node problem. Type II may be rather meaningless because usually state estimation and control calculation are executed in the same processor.

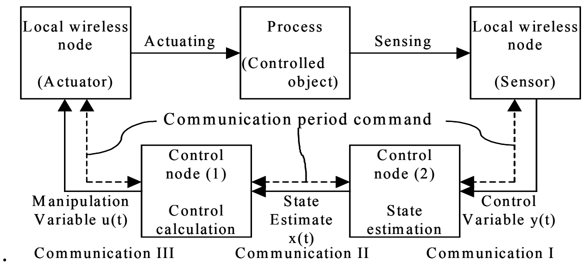


Fig. 1. General configuration of wireless network based closed loop control system

In wireless network application including wireless sensor network, energy saving problem considering battery life is one of the important issue in practical point of view. Many energy saving strategies are investigated such as (Fischione, C. et al. 2006), where trade-off between power of wireless nodes and communication outage probability is discussed. Another effective strategy of energy saving is the sleep control of wireless nodes. Then two types of wireless network protocol for sleep control are defined as follows.

Type A: A priori time scheduled sleep control; Before going to sleep mode in the wireless network, next awake time is scheduled a priori.

Type B: Event triggered sleep control; Once switched to sleep mode, sleeping is continued until any event is triggered.

The latter strategy is the event-triggered control, which is investigated such as (Lemmon, M. et al. 2007) where state conditioned event trigger logic is proposed which assure bounded L1 norm from disturbance. In this paper we consider Type A wireless network protocol because our aim is to optimize, in some sense, trade-off between control performance and wireless energy consumption. In Fig.1, communication period command, in broken line arrow, controls the sleep mode of each wireless node.

2.2 General Configurations of Sensor Network based Control Systems

First, a simple and heuristic control system configuration is proposed here as shown in Fig. 2 to illustrate the key concept of wireless sensor network based control system proposed in this paper. Control error signal $e(t)=r(t)-y(t)$ is observed, and the control period as well as the control parameters are adjusted in each control period, according to a gain and control period scheduling table as shown in Fig.2. Then the communication period for each wireless module, namely the sampling period corresponding to sensor module and the holding period corresponding to actuator module is supervised with the designated control period. In Fig.2, we can also suppose an extended holder to generate manipulation signal autonomously between control periods. Though, a simple zero-order holder is considered in this paper for the simplicity of discussion.

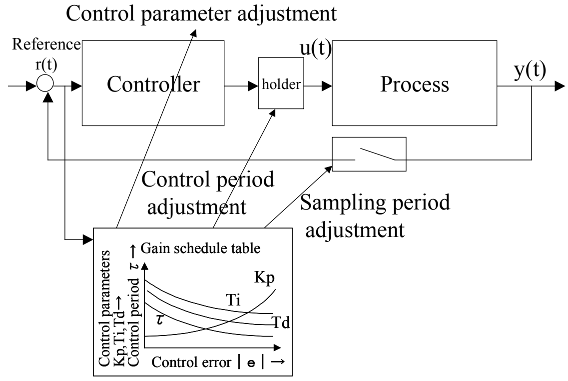


Fig. 2. Control error based sampling period & gain scheduling method

Here a supervisory function for control period adjustment is incorporated to the control system. Strictly speaking, which node should have the supervisory function is an important problem in viewpoint of instrumentation. Though, it is not essential for performance of the control system, so we do not discuss this matter anymore.

Next example shown in Fig.3 is the generalized configuration of the wireless sensor network based control system. Where,

(a) A supervisory function for control period adjustment is incorporated to the control system,

(b) Process states are estimated by state observer and predicted future behaviours of process responses,

(c) Based on the predicted behaviours, control performance in future is predicted and evaluated,

(d) The supervisory function for control period adjustment determines a new control period for next control action at each control period, as the trade-off between control performance and wireless communication energy consumption.

(e) Each wireless module, namely the sensor module and the actuator module is supervised respectively by the supervisory function for control period adjustment, and adjusted the communication period according to the newly determined control period.

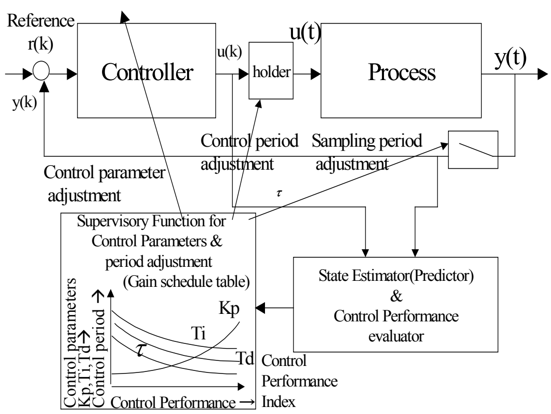


Fig. 3. Supervisory function for wireless sensor based control system

3. FORMULATION WITH MODEL PREDICTIVE CONTROL

3.1 Conventional MPC formulation

Here after a Model Predictive Control scheme (Maciejowski, J. M., 2002) is introduced because the problem is inherently a nonlinear optimization problem, and it cannot be analytically formulated. The Model Predictive Control scheme is quite generalized concept of real-time optimization for control. Notation of process and predictor is as follows. First, the process is supposed to be a discrete time LTI system,

$$\tilde{x}(k+1) = \tilde{A}\tilde{x}(k) + \tilde{B}u(k)$$
$$y(k) = \tilde{C}\tilde{x}(k) \tag{1}$$

The state space model is augmented with integral factor for zero off-set tracking as follows.

$$x(k+1) = Ax(k) + B\Delta u(k)$$
$$y(k) = Cx(k) \tag{2}$$

where,

$$A = \begin{bmatrix} \tilde{A} & \tilde{B} \\ 0 & I \end{bmatrix}, \quad B = \begin{bmatrix} \tilde{B} \\ I \end{bmatrix}$$
$$C = \begin{bmatrix} \tilde{C} & 0 \end{bmatrix}, \quad x(k) = \begin{bmatrix} \tilde{x}(k) \\ u(k-1) \end{bmatrix}$$

and

$$\Delta u(k) = u(k) - u(k-1) \tag{3}$$

Then from 1 to Np steps predictor is formulated as follows, in general MPC formulation manner.

$$\begin{bmatrix} y(k+1) \\ \cdots \\ y(k+Np) \end{bmatrix} = G \begin{bmatrix} \Delta u(k) \\ \cdots \\ \Delta u(k+Nu-1) \end{bmatrix} + Fx(k)$$
$$\Rightarrow \quad Y(k) = G\Delta U(k) + Fx(k) \tag{4}$$

where

$$G = \begin{bmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & 0 \cdots 0 \\ \cdots & \cdots & & \\ CA^{Np-1}B \cdots CB \end{bmatrix} \quad \text{and} \quad F = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{Np} \end{bmatrix} \tag{5}$$

Future reference vector is denoted as follows,

$$Y^*(k) = [y^*(k+1), \cdots, y^*(k+Np)]^T \tag{6}$$

and a quadratic objective function

$$J = \sum_{i=1}^{Np} (y^*(k+i) - y(k+i))^2 + \lambda \sum_{j=1}^{Nu} \Delta u(k+i-1)^2 \tag{7}$$

is minimized. General linear control law is given as follows.

$$\Delta U(k) = [G^T G]^{-1} G^T (Y^*(k) - Fx(k))$$
$$u(k) = u(k-1) + \Delta u(k) \tag{8}$$

Also the general quadratic objective function

$$J = \sum_{i=1}^{Np} \{x^T(k+i)Qx(k+i) + \Delta u^T(k-1+i)R\Delta u(k-1+i)\} \tag{9}$$

where Nu=Np is applicable. Furthermore, some linear constraint conditions such as, upper and lower limit for control variable y(t), manipulation variable u(t) and their increments as follows.

$$y\min(k+i) \le y(k+i) \le y\max(k+i),$$
$$\Delta y\min(k+i) \le \Delta y(k+i) \le \Delta y\max(k+i), \tag{10}$$
$$u\min(k+j-1) \le u(k+j-1) \le u\max(k+j-1),$$
$$\Delta u\min(k+j-1) \le \Delta u(k+j-1) \le \Delta u\max(k+j-1),$$
$$i = 1, \cdots, Np, \quad j = 1, \cdots Nu$$

Then the quadratic objective function (7) or (9) subject to (10) is minimized with QP: quadratic programming optimization.

Hereafter, the wireless sensor and actuator based control scheme based on the Model Predictive Control formulations are considered.

3.2 Wireless actuator based MPC strategy

First, Type III problem defined in section 2 with Fig.1, where only wireless actuator network is incorporated to the closed loop system, is considered. Suppose the state vector of the process is perfectly observable, and the wireless network based control problem is only affected by control period. So an optimization problem considering both control performance and communication energy is defined. Some additional parameters and variables are introduced as follows,

Cc: communication energy cost,

$\mu_C(i)$: i-th ahead communication switching variable where,

$\mu_C(i) = 1$ means communication execution, as well as

$\mu_C(i) = 0$ means communication suspension.

$$M_C = [\mu_C(1), \mu_C(2), \cdots, \mu_C(Nu)]^T \tag{11}$$

is a vector composed of the communication switching variables $\mu_C(i)$. Then the communication energy in the receding horizon is defined as

$$J_{Com} = C_C sum\{M_C\} \tag{12}$$

Optimization problem with these integer variables is generally defined as a Mixed Integer Programming (MIP).

Then 3 types of trade-off optimization problems are defined as follows.

A1: Control performance optimization with communication energy constraint; Control performance index (7) or (9) is minimized subject to the constrained conditions (10) and the communication energy constraint,

$$J_{Com} \le C1 \tag{13}$$

A2: Communication energy optimization with control performance constraint; Communication energy Eq.(12) is minimized subject to the control performance constrained conditions (10) and (14).

$$J = \sum_{i=1}^{Np} (y^*(k+i) - y(k+i))^2 + \lambda \sum_{j=1}^{Nu} \mu_C(j) \Delta u(k+j-1)^2 \le C2 \tag{14}$$

A3: Control performance and communication energy optimization; Control performance index (7) or (9) and communication energy Eq.(12) are combined as

$$J_c = J + J_{com}$$
$$= \sum_{i=1}^{Np} (y^*(k+i) - y(k+i))^2$$
$$+ \lambda \sum_{j=1}^{Nu} \mu_c(j)\, \Delta u(k+j-1)^2 + C_C \sum_{j=1}^{Nu} \mu_C(j) \tag{15}$$

and it is minimized subject to the constraint conditions (10).
In these 3 types of optimization problems, the integer variables $\mu_C(i)$ as communication switching variables are incorporated, and it leads to some kinds of Mixed Integer Programming (MIP) optimizations. Solving the MIP problem at each control period, the optimal manipulation sequence

$$[\mu_C(1)\ \Delta u(k),\ \mu_C(2)\ \Delta u(k+1),\cdots,\mu_C(Nu)\ \Delta u(Nu-1)] \tag{16}$$

is obtained. The first term $\Delta u(k+i-1)$ such that $\mu_C(i)=1$ is selected and send from the control node to the actuator node in Fig.1, to generate manipulation variable

$$u(k+i) = u(k-j) + \Delta u(k+i-1) \tag{17}$$

where u(k-j) is the last time manipulation variable send to the actuator node in the last time communication. The control variable u(k) is assumed to be hold until a new control variable is received at the actuator node.
Additionally some constraint conditions such as,

$$\sum_{i=1}^{Nu} \mu_C(i) \quad \geq \quad N_C \tag{18}$$

can be also considered, which means to require at least NC times of wireless communication in future control horizon [k, …, k+Nu-1] to ensure minimum feedback control actions.
These optimization problems automatically minimize or restrict the communication energy consumption and it leads to realize long battery life in wireless communication nodes.

3.3 Wireless observation based MPC strategy

Second, Type I problem defined in section 2 with Fig.1, where only wireless sensor network is incorporated to the closed loop system, is considered. In this case the control performance is affected by accuracy of state estimation. So an optimization problem considering both state estimation accuracy and communication energy is defined as a performance index and is also formulated as a MIP optimization problem. Introduce communication cost Co and the integer variables $\mu_O(i)$ that are similar to (11),

$$\mathrm{M}_O = [\mu_O(1), \mu_O(2), \cdots, \mu_O(Nu)]^T \tag{19}$$

Then the communication energy in receding horizon is denoted as

$$J_{Com} = C_O sum\{M_O\} \tag{20}$$

Optimization problem with these integer variables is generally defined as a Mixed Integer Programming (MIP) as well as the former problem. Consider,

$$\min J_o = \sum_{i=1}^{Np} \|\hat{x}(k+i) - x(k+i)\|_S^2 + C_O \sum_{i=1}^{Np} \mu_O(i) \tag{21}$$

s.t.

$$\begin{aligned} \hat{x}(k+i+1) &= A\ \hat{x}(k+i) + B\ u(k+i) \\ &+ \mu_O(i) K_{k+i} (y(k+i) - \hat{y}(k+i)) \\ \hat{y}(k+i) &= C\ \hat{x}(k+i) \\ &(i = 1, \cdots, Np) \end{aligned} \tag{22}$$

where Eq.(22) is a state observer. Then the error system is,

$$\Delta x(k+i) = \hat{x}(k+i) - x(k+i) \tag{23}$$

$$\Delta x(k+i+1) = (A - \mu_{O\,i} K_{k+i} C) \Delta x(k+i) \tag{24}$$

So, the objective function (21) is modified to

$$\min J_o = \sum_{i=1}^{Np} \|\Delta x(k+i)\|_S^2 + C_O \sum_{i=1}^{Np} \mu_O(i) \tag{25}$$

subject to (24), which is a MIP optimization problem. Unfortunately we cannot obtain future true state vector x(k), this optimization problem is not executable. An possible approximated manner is estimating the expected state error $\Delta x(k+i)$ from past observations, and optimize (25) in stochastic sense. It needs more investigation as future work.

4. CONSIDERATION ON STABILITY

Here a sufficient condition for stability for Type I problem is given bellow. Suppose the process is (1), (2) and (3). Let's consider the proposed control law (15) and generalize it to state space formulation,

$$\begin{aligned} \min_{\Delta u, \mu} J = \sum_{i=1}^{Np} \{ & x^T(k+i) Q x(k+i) + \Delta u^T(k-1+i) R \Delta u(k-1+i) \\ & + C_C \mu_C(i) \} \end{aligned} \tag{26}$$

then following results are obtained.

Proposition: Suppose dim{x}=n and (A,B) is controllable. Then the proposed control is controllable in control horizon [1 to Np] which means $\forall x(k)$ can be moved to origin in Np steps, x(k+Np)=0, if and only if

$$sum\{\mathrm{M}_C\} = \sum_{i=1}^{Np} \mu_C(i) \geq n \tag{27}$$

Proof:

$$x(k+Np) = A^{Np} x(k) + \left[\mu_{C\,1} A^{Np-1} B\ \mu_{C\,2} A^{Np-2} B \cdots \mu_{C\,Np} B\right] \times \begin{bmatrix} \Delta u(k) \\ \cdots \\ \Delta u(k+Np-1) \end{bmatrix} \tag{28}$$

so at least n factors in the matrix

$$Mcont = \left[\mu_{C\,1} A^{Np-1} B\ \mu_{C\,2} A^{Np-2} B \cdots \mu_{C\,Np} B\right] \tag{29}$$

if (27) is valid, then at least n columns in Mcont is not zero, so that rank{Mcont} = n because $A^m B$ (m>=n) can be transferred to combination of [B, AB, …, $A^{n-1}B$] with Cayley-Hamilton's Theorem.

Theorem 1: (Main result) Suppose the process (1),(2),(3), where (A,B) is controllable and state vector x is measurable, controlled by optimal control with minimizing (15), under the terminal constraint condition,

$$x(k+Np) = 0 \tag{31}$$

Then closed loop system is asymptotically stable.

Proof: Suppose a function V(k),

$$\begin{aligned} V(k) = \min_{\Delta u, \mu} [\sum_{i=1}^{Np} \{ & x^T(k+i) Q x(k+i) \\ & + \mu_C(k+i) \Delta u^T(k-1+i) R \Delta u(k-1+i) + C_c \mu_C(k+i) \}] \end{aligned} \tag{32}$$

then

$$\begin{aligned} V(k+1) = \min_{\Delta u, \mu} [\sum_{i=1}^{Np} \{ & x^T(k+1+i) Q x(k+1+i) \\ & + \mu_C(k+i+1) \Delta u^T(k+i) R \Delta u(k+i) + C_c \mu_C(k+i+1) \}] \end{aligned}$$

$$
\begin{aligned}
&= \min_{\Delta u,\mu}[\sum_{i=1}^{Np}\{x^T(k+i)Qx(k+i) \\
&\quad + \mu_C(k+i)\Delta u^T(k-1+i)R\Delta u(k-1+i) + C_c\mu_C(k+i)\} \\
&- \{x^T(k+1)Qx(k+1) + \mu_C(k+1)\Delta u^T(k)R\Delta u(k)\} \\
&+ \{x^T(k+1+Np)Qx(k+1+Np) \\
&\quad + \mu_C(k+Np+1)\Delta u^T(k+Np)R\Delta u(k+Np)\} \\
&\quad\quad - C_c\mu_C(k+1) + C_c\mu_C(k+Np+1)] \\
&\le V(k) - \{x^T(k+1)Qx(k+1) + \mu_C(k+1)\Delta u^T(k)R\Delta u(k)\} \\
&+ \min_{\Delta u,\mu}\{x^T(k+1+Np)Qx(k+1+Np) \\
&\quad + \mu_C(k+Np+1)\Delta u^T(k+Np)R\Delta u(k+Np)\} \\
&\quad\quad + C_c\{\mu_C(k+Np+1) - \mu_C(k+1)\} \\
&< V(k) + \min_{\Delta u,\mu}\{x^T(k+1+Np)Qx(k+1+Np) \\
&\quad + \mu_C(k+Np+1)\Delta u^T(k+Np)R\Delta u(k+Np)\} \\
&\quad\quad + C_c\{\mu_C(k+Np+1) - \mu_C(k+1)\}
\end{aligned} \tag{33}
$$

Where the terminal condition, x(Np)=0 is achieved so that,

$$
x(Np+i)=0, \quad \Delta u(k+Np-1+i)=0 \qquad \textit{for} \quad i=1,\cdots,\infty \tag{34}
$$

and it means

$$
\min_{\Delta u,\mu}\{x^T(k+1+Np)Qx(k+1+Np) + \mu_C(k+Np+1)\Delta u^T(k+Np)R\Delta u(k+Np)\} = 0 \tag{35}
$$

From constraint (18), if $\mu_c(k+1)=1$ then $\sum_{i=2}^{Np}\mu_C(k+i)\ge N_c - 1$ so $\mu_c(k+Np+1)=1$ must be 1 to keep (18).

On the contrary, if $\mu_C(k+1)=0$ then $\sum_{i=2}^{Np}\mu_C(k+i)\ge N_c$ so $\mu_C(k+Np+1)$ may be 0 to keep (18), and as $\Delta u(k+Np)=0$, $\mu_C(k+Np+1)$ must be 0 with minimization of (26) as the control law. So, $\mu_C(k+Np+1)-\mu_C(k+1)$=0 is always valid.

Then some of the last terms of (33) vanishes and V(k+1) < V(k) is valid at anytime is a Lyapnov function. It means the control system is asymptotically stable.

Q.E.D.

5. NUMERICAL EXAMPLES

Some numerical examples for the proposed sensor network based control system with model predictive control formulation are illustrated bellow. Controlled object is

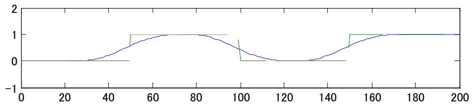
$$
G(s) = \frac{1}{1+20s+100s^2}e^{-2s} \tag{36}
$$

and basic sampling period is 2.0sec. Prediction horizon [L, Np] is [3, 30], control horizon is 5, and weighting coefficients in the objective function is,

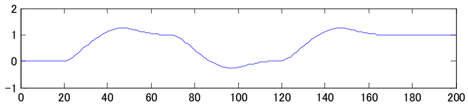
weight for input change $\lambda = 1.0$,
weight for communication cost ,Cc = 0.0, 1.0, 3.0,
standard deviations of observation noise Nstd = 0, 0.5, 1.0,
amplitude of stepwise disturbance Damp = 0,0.1,0.3,
and reference is stepwise change with amplitude 1.0.
Simulation conditions are summarized in Table 1.

Table 1. Simulation Conditions

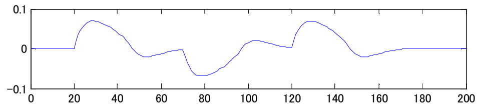
Case No.	Cc	Nstd	Damp
1	0.0	0.0	0.0
2	1.0	0.0	0.0
3	3.0	0.0	0.0
4	1.0	0.5	0.0
5	1.0	0.0	0.1
6	1.0	0.0	0.3



(a) Reference r(k) vs. Output y(k)

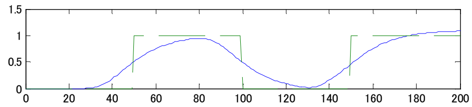


(b) Input u(k)

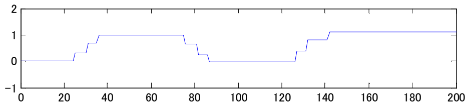


(c) Communication actions $\Delta u(k)$

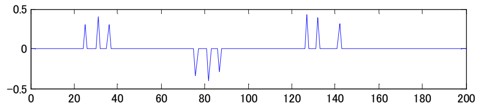
Fig.4.1. Case1: Conventional Model Predictive Control.



(a) Reference r(k) vs. Output y(k)

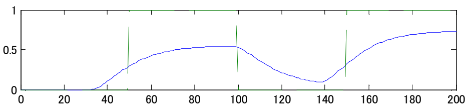


(b) Input u(k)

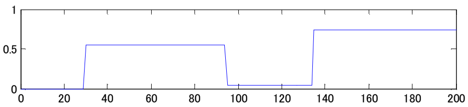


(c) Communication actions $\Delta u(k)$

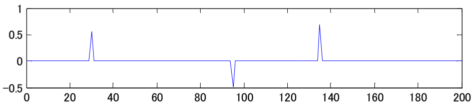
Fig.4.2. Case2: Proposed Control with Cc=1.0.



(a) Reference r(k) vs. Output y(k)

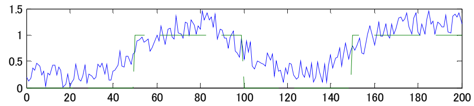


(b) Input u(k)

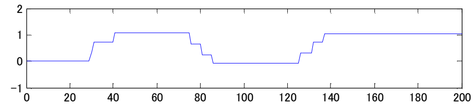


(c) Communication actions $\Delta u(k)$

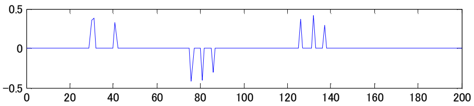
Fig.4.3. Case3: Proposed Control with Cc=3.0.



(a) Reference r(k) vs. Output y(k)

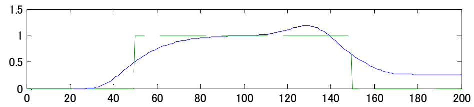


(b) Input u(k)

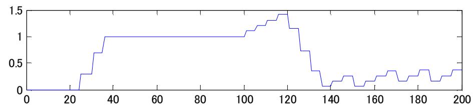


(c) Communication actions $\Delta u(k)$

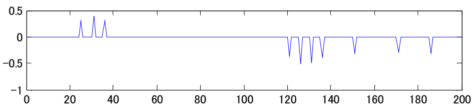
Fig.4.4. Case4: Proposed Control with Cc=1.0 & Nstd=0.5.



(a) Reference r(k) vs. Output y(k)

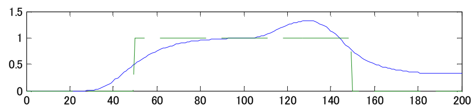


(b) Input u(k)

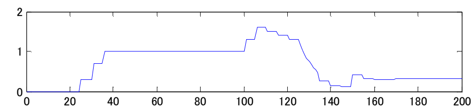


(c) Communication actions $\Delta u(k)$

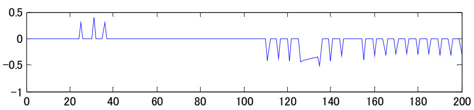
Fig.4.5. Case5: Proposed Control with Cc=1.0 & Damp=0.1.



(a) Reference r(k) vs. Output y(k)



(b) Input u(k)



(c) Communication actions $\Delta u(k)$

Fig.4.6. Case6: Proposed Control with Cc=1.0 & Damp=0.3.

Fig.4.1 to 4.6 are the simulation results case 1 to 6. Case1 is conventional MPC. Case 2 and 3 are the proposed control method with communication cost Ccj = 0.3 and 1.0 respectively. As Ccj goes larger, communication action is restricted and the control performance is deteriorated. Case 4 where the output y(k) is corrupted by observation noise with standard deviation Nstd = 0.5. It shows that even if there exist the observation noise, the proposed method works well. Case 5 and 6 are the cases with stepwise disturbances at control input with amplitudes Damp=0.1 and 0.3. As amplitude Damp goes lager the communication frequency increase to keep control performance after the control system is disturbed by the disturbance.

6. CONCLUSION

This paper discussed wireless sensor network based control system considering communication energy saving. A heuristic optimization algorithm considering trade off between control performance and communication cost corresponding to control period is proposed. Father research is expected on subjects of

- total optimality evaluation in sense of infinite horizon,
- reduction of computational effort for optimization considering real-time calculation,
- more simple algorithm for industrial applications.

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