Predictive Control for Energy Efficiency in Wireless Cellular Networks

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***Abstract*—Coordinated multipoint (CoMP) communication is a new method that improves energy efficiency, extends cell coverage, and increases capacity in cellular networks. However, since channel state information from the involved cells is needed in CoMP systems, practical systems that employ CoMP techniques suffer from constraints imposed by the backhaul network. In this paper, we take a novel approach to study the energy efficiency issues in cooperative wireless cellular networks with CoMP communications. Specifically, to derive the base station grouping decisions for energy-efficient transmissions in CoMP, we use stochastic predictive control algorithm. Simulation results are presented to show the effectiveness of the proposed scheme.**

***Index Terms*—Energy efficiency, wireless cellular networks, predictive control**

I. Introduction

Rapidly rising energy costs and increasingly rigid environmental standards have led to an emerging trend of addressing "energy efficiency" aspect of wireless communication technologies [1, 2]. In a typical wireless cellular network, base stations account for up to more than 70 percent of the total energy consumption [3]. In addition, a base station consumes more than 90% of its peak energy even when there is little or no traffic [4]. Therefore, it is important to increase the energy efficiency of radio access networks to meet the challenges raised by the high demands of traffic and energy consumption. To improve energy efficiency of base stations, they can dynamically cooperate to provide services to mobile stations, and switch off redundant base stations if necessary.

Coordinated multipoint (CoMP) communication is a new method that helps with the dynamic base station cooperations, where signals transmitted or received by spatially separated antenna sites are jointly processed. CoMP communication is considered as a key technology for future wireless cellular networks, and is expected to be deployed in the future long term evolution-advanced (LTE-A) systems to improve the cellular network's performance [5].

In theory, CoMP communication can improve energy efficiency, extend cell coverage, and increase capacity in cellular networks. However, since channel state information from all involved cells is needed in CoMP systems, practical systems that employ CoMP techniques suffer from constraints imposed by the backhaul network, which is used to exchange channel state information from all involved cells. Backhaul networks are constrained in capacity, and introduce lost and/or outdated channel state information, which will result in performance degradation of CoMP systems [6, 7].

In this paper, we take a control-theoretical approach to study the energy efficiency issues in cooperative wireless cellular networks with CoMP communications. Specifically, to derive the optimal base station grouping decisions for energy-efficient transmissions in CoMP, we use generalized predictive control (GPC) algorithm, which is easy to implement and robust with respect to modeling errors, over and under parameterization, and sensor noise [8]. GPC algorithm has been successfully used in many applications, such as non-minimum phase systems, open-loop unstable systems, and systems with variable or unknown dead time [9]. Simulation results are presented to show the effectiveness of the proposed scheme.

The rest of this paper is organized as follows. Section II presents the system models. Section III presents the proposed control-theoretical approach. CARIMA model parameters estimation is presented in Section IV. Simulation results are presented and discussed in Section V. Finally, we conclude this study in Section VI.

II. System Models

A. Coordinated Multipoint (CoMP) Communication

In cellular networks, inter-cell interference can significantly affect system performance, especially in urban cellular systems. CoMP, originally proposed to overcome inter-cell interference, has been selected as a key technology for LTE-A [5]. There are two different kinds of base station cooperations: inter-site CoMP and intra-site CoMP. Intra-site cooperation is easier and less costly to implement. However, inter-site cooperation is needed to reduce total interferences due to the cooperation between base stations [5].

CoMP can be applied in both uplink and downlink, both of which can improve average throughput and cell edge

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throughput. For example, uplink CoMP can improve cells' average throughput around 80% and even more at the cell edge, where the throughput improvement can reach roughly threefold. The terminal does not need to be modified in order to support uplink CoMP. Nevertheless, all schemes increase the demand on backhaul and synchronization requirements, need more channel estimation effort, and produce more overhead and higher complexity [5].

Assume there is a perfect backhaul network (unlimited capacity and no packet delay/loss). There are V BSs in the CoMP cluster. These base stations can cooperate in any combination, as shown in Fig. 1, and each combination set u is an element of the cooperation set $\mathcal{U}$, whose cardinality is 2^V. For an arbitrary base station grouping decision $u \in \mathcal{U}$, the capacity $C(u)$ can be calculated as follows [10]:

$$C(u) = \log_2 \det(\mathbf{I}_{|u|} + P\mathbf{H}\mathbf{H}^{\dagger}), \quad (1)$$

where $\mathbf{I}_{|u|}$ denotes a $|u| \times |u|$ identity matrix, $|u|$ denotes the cardinality of combination set u, P denotes the transmission power, and $\mathbf{H} \in \mathbb{C}^{|u| \times |u|}$ denotes the channel matrix.

In practical CoMP systems, channel station information and CoMP decisions will be delayed or lost due to the limited capacity of backhaul networks. The performance is degraded significantly due to the imperfect channel state information caused by packet delay and losses over the backhaul network [6].

B. Energy Efficiency Measure

One common method to measure energy efficiency is to use bits per Joule [11]. For a base station grouping decision u, energy efficiency can be defined as the ratio of transmission capacity to transmission power as follows.

$$\zeta(u) = \frac{C(u)}{P + P_a}, \quad (2)$$

where $C(u)$ is defined in (1), P denotes the transmission power, and P_a denotes the additional circuit power consumption of devices during transmissions (e.g., digital-to-analog converters, filters, etc), which is independent to the data transmission power. The intuitive explanation of (2) is to transmit more data with low transmission power, which is a tradeoff between transmission rate and power consumption.

The whole system is operated in a time-slotted manner. In each time slot k, an optimal base station group decision $u^*(k)$ should be derived for energy-efficient transmissions, which can be described as follows.

$$u^*(k) = \arg\max_{u(k) \in \mathcal{U}} \zeta(u(k)). \quad (3)$$

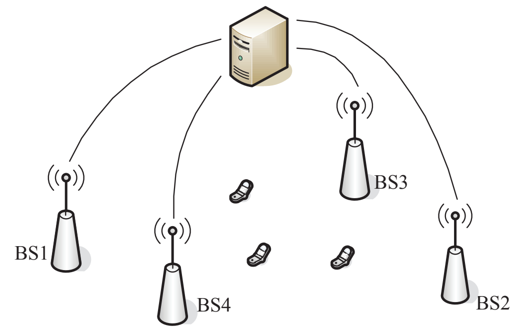

Fig. 1: A wireless cellular network with CoMP.

C. Controlled Auto-Regressive Integrated Moving Average Model for Channel Estimation

To mitigate the impact of the channel state information delay/loss, a controlled-auto-regressive-integrated-moving average (CARIMA) model in [12] is used to estimate the channel state. The CARIMA model is chosen to coincide with the prediction model used in the predictive control part (see Subsection III-A). The CARIMA model is described as follows.

$$\mathbf{A}(z^{-1})\mathbf{y}(k) = \mathbf{B}(z^{-1})\mathbf{u}(k-1) + \mathbf{C}(z^{-1})\omega(k)/\Delta, \quad (4)$$

where $\Delta = 1 - z^{-1}$, which is the differencing operator, $\mathbf{u}(k-1)$ is the input control signal in the $(k-1)$th time slot, $w(k)$ is uncorrelated stochastic sequence, $\mathbf{A}(z^{-1})$, $\mathbf{B}(z^{-1})$, $\mathbf{C}(z^{-1})$ are polynomials of backward shift operator z^{-1}.

$$\begin{aligned} \mathbf{A}(z^{-1}) &= 1 + a_1 z^{-1} + \cdots + a_{n_a} z^{-n_a}, \\ \mathbf{B}(z^{-1}) &= b_0 + b_1 z^{-1} + \cdots + b_{n_b} z^{-n_b}, \\ \mathbf{C}(z^{-1}) &= 1 + c_1 z^{-1} + \cdots + c_{n_c} z^{-n_c}. \end{aligned} \quad (5)$$

It is generally assumed that $C(z^{-1}) = 1$ so that the process disturbance model is purely auto-regressive. Thus, the model equations are

$$A\left(z^{-1}\right) y\left(k\right) = B\left(z^{-1}\right) u\left(k-1\right) + \omega\left(k\right)/\Delta. \quad (6)$$

Let the number of delayed or missing data at the controller at the kth sampling instant be τ_{dl}. Using (4), the estimated value for $y(k - \tau_{dl} + 1)$ can be determined as

$$\mathbf{\Delta A}(z^{-1})\hat{\mathbf{y}}(k - \tau_{dl} + 1) = \mathbf{B}(z^{-1})\mathbf{\Delta u}(k - \tau_{dl}). \quad (7)$$

The estimation error is $\varepsilon(k) = y(k) - \hat{y}(k)$. Using this as the correction term, the optimal output estimate is obtained as

$$\tilde{y}(k - \tau_{dl} + 1) = \hat{y}(k - \tau_{dl} + 1) + \varepsilon(k - \tau_{dl}). \quad (8)$$

Continuing the same way, the delayed output can be estimated up to the kth instant

$$\tilde{y}(k-\tau_{dl}+i)=\hat{y}(k-\tau_{dl}+i)+\varepsilon(k-\tau_{dl}), \qquad (9)$$

where $i=1,2,\cdots,\tau_{dl}$, $\hat{y}(k-\tau_{dl}+i)=\tilde{y}(k-\tau_{dl}+i-1)$ to replace the unknown values of the output at instant $(k-\tau_{dl})$.

In the current system (see Section V), $A(z^{-1})$ is of first degree and $B(z^{-1})$ is of zero degree, with $n_a=1$ and $n_b=0$, i.e.,

$$A(z^{-1})=1+a_1z^{-1}$$

$$B(z^{-1})=b_0$$

Application of (9) yields

$$\begin{aligned}\tilde{y}(k-\tau_{dl}+i) &= (1-a_1)\tilde{y}(k-\tau_{dl}+i-1)+\\ &\quad +a_1\tilde{y}(k-\tau_{dl}+i-2)+\\ &\quad +b_0\Delta u(k-\tau_{dl}+i-1)+\\ &\quad +\varepsilon(k-\tau_{dl}),\end{aligned} \qquad (10)$$

where $\tilde{y}(k-\tau_{dl}+i-1)=y(k-\tau_{dl}+i-1)$, $\tilde{y}(k-\tau_{dl}+i-2)=y(k-\tau_{dl}+i-2)$, $\Delta u(k-\tau_{dl}+1),\Delta u(k-\tau_{dl}+2),\cdots,\Delta u(k-1)$ are calculated at previous time steps by the predictive controller discussed in the next section.

III. Optimal Base Station Grouping in CoMP Based on Stochastic Predictive Control

To derive the optimal base station grouping decisions in CoMP for energy-efficient transmissions, we take a control-theoretical approach. In this section, we first present the generalized predictive control algorithm. Then, constrained coefficient matrix GPC (CCM-GPC) algorithm is presented to improve the convergence speed and reduce the computational complexity of the original GPC algorithm. Finally, the procedure for optimal base station grouping in CoMP is presented.

A. Generalized Predictive Control (GPC) Algorithm

To construct the controller that controls base station grouping decisions, a suitable linear model for the energy-efficient control process is needed. We consider the optimal base station grouping decision $u^*(k)$, defined in (3), to be the control input command, and the process output $y(k)$ to be the observed energy efficiency. We consider the CARIMA model in (4).

In order to obtain the optimal predictive solution $y(k+j)$ after the jth step, we need to introduce Diophantine equation [8]

$$\begin{gathered}1=\mathbf{E}_j(z^{-1})\mathbf{A}(z^{-1})\Delta+z^{-j}\mathbf{F}_j(z^{-1}),\\ \mathbf{E}_j(z^{-1})\mathbf{B}(z^{-1})=\mathbf{G}_j(z^{-1})+z^{-j}\mathbf{H}_j(z^{-1}),\end{gathered} \qquad (11)$$

where $j=1,\cdots,N_1$, and

$$\begin{aligned}\mathbf{E}_j &= e_0+e_1z^{-1}+\cdots+e_{j-1}z^{-j+1},\\ \mathbf{F}_j &= f_0^j+f_1^jz^{-1}+\cdots+f_{n_a}^jz^{-n_a},\\ \mathbf{G}_j &= g_0+g_1z^{-1}+\cdots+g_{j-1}z^{-j+1},\\ \mathbf{H}_j &= h_0^j+h_1^jz^{-1}+\cdots+h_{n_b-1}^jz^{-n_b+1},\end{aligned} \qquad (12)$$

The jth step predictive output value from (4) is

$$\begin{aligned}\mathbf{y}(k+j) &= \mathbf{G}_j\Delta u(k+j-1)+\mathbf{F}_j\mathbf{y}(k)+\\ &\quad \mathbf{H}_j\Delta u(k-1)+\mathbf{E}_j\omega(k+j).\end{aligned} \qquad (13)$$

Using the information given above, the predictions may be shown in closed form as

$$\mathbf{Y}=\mathbf{GU}+\mathbf{F}\mathbf{y}(k)+\mathbf{H}\Delta u(k-1)+\mathbf{E}, \qquad (14)$$

where

$$\begin{aligned}Y^T &= [y(k+N_1),\cdots y(k+N_2)]\\ U^T &= [\Delta u(k+1),\cdots,\Delta u(k+N_u)],\\ F^T &= [F_1,\cdots,F_{N_2}],\\ H^T &= [H_1,\cdots,H_{N_2}],\\ E^T &= [E_1w(k+1),\cdots,E_{N_2}w(k+N_2)],\end{aligned} \qquad (15)$$

$$G=\begin{bmatrix} g_0 & 0 & 0 & \cdots & 0\\ g_1 & g_0 & 0 & \cdots & 0\\ \vdots & \vdots & \vdots & \cdots & \vdots\\ g_{N_u-1} & g_{N_u-2} & g_{N_u-3} & \cdots & g_0\\ \vdots & \vdots & \vdots & \cdots & \vdots\\ g_{N_2-1} & g_{N_2-2} & g_{N_2-3} & \cdots & g_{N_2-N_u}\end{bmatrix},$$

where N_2 is the predictive time horizon, N_u is the control time horizon, and $E_jw(k+j)$ is the white noise. Then the optimal predictive solution in the $(k+j)$th time slot is

$$\hat{\mathbf{y}}(k+j)=\mathbf{G}_j\Delta\mathbf{u}(k+j-1)+\mathbf{F}_j\mathbf{y}(k)+\mathbf{H}_j\Delta\mathbf{u}(k-1). \qquad (16)$$

B. Constrained Coefficient Matrix GPC (CCM-GPC) Algorithm

In the original GPC algorithm [8], the convergence speed may be slow and the computational complexity may be very high. In order to improve the convergence performance and reduce the computational complexity, we use the soften output, which is spread into the soften input. This algorithm is called constrained coefficient matrix GPC (CCM-GPC). The constraint matrix is

$$\begin{aligned}Q^T &= [q_0,q_1,\cdots,q_{N_u-1}]\\ &= \left[1,1+\alpha,1+\alpha+\alpha^2,\cdots,1+\sum_{i=1}^{N_u-1}\alpha^i\right],\end{aligned} \qquad (17)$$

where α is constraint factor, $0\le\alpha\le1$. So

$$U^T=Q^T\Delta u(k+1). \qquad (18)$$

The performance index of the CCM-GPC is given as

$$\eta = E\left\{\sum_{j=N_1}^{N_2}[y(k+j)-y_r(k+j)]^2 + \sum_{j=N_1}^{N_u}\lambda(j)[\Delta u(k+j-1)]^2\right\}, \quad (19)$$

where E is mathematical expectation, y_r is the reference trajectory, N_1 and N_2 are the initial value and final value of predictive time horizon, respectively. N_u is control time horizon, and $\lambda(j)$ is control weight sequence. Then the performance index is

$$\eta = E\{[(Y-Y_r)^T(Y-Y_r)] + \lambda U^T U\} \quad (20)$$

Substitute (17) into (14), substitute(14) into (19). To obtain the optimal solution, we set $\partial\eta/\partial\mathbf{U} = 0$. Then, we obtain the optimal solution as follows.

$$\Delta u(k+1) = [(GQ)^T(GQ)+\lambda Q^T Q]^{-1}(GQ)^T \times [Y_r - Fy(k+1) - H\Delta u(k)], \quad (21)$$

$$u(k+1) = u(k) + \Delta u(k+1), \quad (22)$$

where $u(k+1)$ is the optimal base station grouping decision for the $(k+1)$th time slot in CoMP for energy-efficient transmissions.

IV. CARIMA Model Online Parameters Estimation

Since the channel state information is time-varying, the CCM-GPC controller performance may degrade when the channel parameters are varying often. We need an online model identifier to cope with such situations. The recursive least square estimate (RLSE) is an common identifying method. In this paper, we use RLSE to identify the CARIMA model parameters [13]. To do this, the CARIMA model structure can be represented in terms of its regressor vector as:

$$y(k) = \varphi^T(k)\theta(k), \quad (23)$$

where $\theta(k)$ is the vector of the model parameters, $\theta^T(k) = [a_0, b_0]$. $\varphi(k)^T$ is the regressor vector consisting of the past measured inputs and outputs, $\varphi^T(k) = [-y(k-\tau_{dl}+i-1), -y(k-\tau_{dl}+i-1), u(k-\tau_{dl}+i-1)]$. Then the parameter vector $\theta(k)$ can be updated recursively using any recursive parameter estimation method.

$$\theta(k) = \theta(k-1) + K(k-1)[y(k) - \varphi(k-j-1)\theta(k-1)], \quad (24)$$

$$K(k-1) = P(k-1)\varphi^T(k-j-1)[1 + \varphi(k-j-1)P(k-1)\varphi^T(k-j-1)]^{-1}, \quad (25)$$

where $P(k-1)$ is an output of recursion formula.

$$P(k) = P(k-1) - K(k-1)[1 + \varphi(k-j-1)P(k-1)\varphi^T(k-j-1)]K^T(k-1). \quad (26)$$

From the above equations, the corresponding gain $K(k-1)$ will then also be the same for all coefficients $\theta(k)$. In this way significant savings in the computations can be obtained. To implement the above RLSE method, we initialize θ_0 as a zero matrix, and P_0 is defined as follow.

$$P_0 = \gamma\mathbf{I}, \quad (27)$$

where γ is a large number, $0 < \gamma < \infty$, and I is the identity matrix. In this study, we set $\gamma = 10^9$.

The procedure for the optimal base station grouping in CoMP based on the CCM-GPC algorithm is as follows.

1) Obtain the channel state information that arrived in the previous time slot.

2) Update the history of system outputs by replacing previously predicted values with the actual data.

3) Estimate the missing or delayed system outputs up to the kth time slot using (10).

4) Update the reference trajectory $y_r(k)$. (A random number is used as reference trajectory here.)

5) Determine the currently required prediction horizons N_2 and control horizon N_u.

6) Calculate the latest estimated system model coefficient a_0 and b_0 using (24).

7) Calculate the capacity $C(u)$ using (1).

8) Calculate the energy efficiency $\zeta(u)$ using (2).

9) Determine the base station grouping decision for the kth time slot $u^*(k)$ using (3).

10) Determine the base station grouping decision for the $(k+1)$th time slot $u(k+1)$ using (22).

11) Set $k = k+1$ and go back to 1).

V. Simulation Results and Discussions

In this section, we use computer simulations to evaluate the performance of the proposed scheme and the influnce of packet delay and loss. For the time-varying wireless channels, we use 3GPP-SCME channel model [14], which is widely used in simulations of wireless cellular networks. We consider the dense urban scenario with users moving at the same speed. The delay caused by the backhaul network is exponentially distributed with means of 3 ms and 10 ms. We assume that there are three base stations in a CoMP cluster. These three base stations dynamically cooperate to provide services to mobile stations for energy-efficient transmissions, depending on the channel transmission information. The constraint factor $\alpha = 0.3$. We compare the energy efficiency error of the proposed scheme with packet delay and loss, which uses capacity as the base station grouping decision

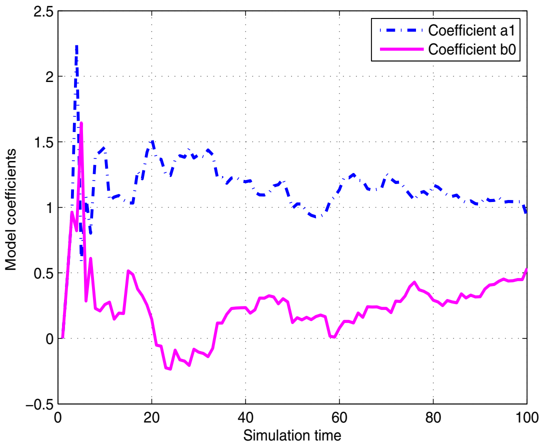

Fig. 2: The coefficients in the generalized predictive control model online parameter adaptation.

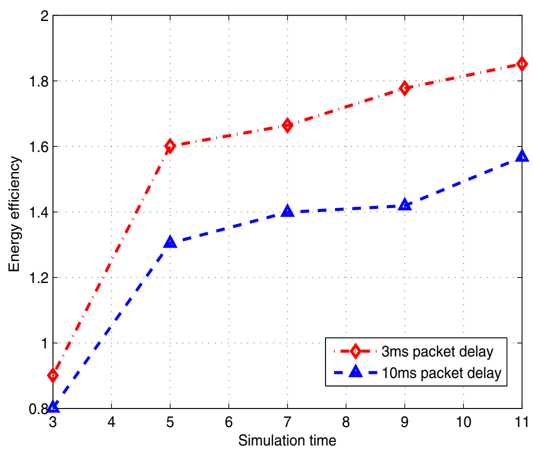

Fig. 3: Comparison of energy efficiency with different level of packet delay.

criterion, and another energy efficiency error comparison of different predictive horizon and control horizon.

Fig. 2 shows the coefficients in the GPC model algorithm of one wireless channel, a_1 and b_0, which are defined in (10). As we can see from the figure, the coefficients vary with simulation time due to the time-varying wireless channel. The recursive least square estimate (RLSE) algorithm presented in Section IV can accommodate the time-varying wireless channel conditions to make accurate model estimation. In Fig. 3, we compare the energy efficiency with different level of packet delay. We can observe from the figure that the energy efficiency becomes small when the packet delay becomes long. This is because the proposed scheme can make more accurate estimation and decision when the packet delay is shorter.

VI. Conclusions

In wireless cellular networks, it is very important to increase the energy efficiency of radio access networks to meet the challenges raised by the high demands of traffic and energy consumption. In this paper, we proposed a control-theoretical approach to study the energy efficiency issues in cooperative wireless cellular networks with coordinated multipoint (CoMP) communications. We presented a generalized predictive control (GPC) algorithm and an improved algorithm called constrained coefficient matrix GPC (CCM-GPC) to derive the optimal base station grouping decisions for efficient transmissions in CoMP. In addition, we presented CARIMA model in our control-theoretical approach to mitigate the impacts of imperfect channel state information. Simulation results have been presented to show the effectiveness of the proposed scheme.

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