SELF-TUNING ADAPTIVE ALGORITHMS IN THE POWER CONTROL OF WCDMA SYSTEMS

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ABSTRACT

Power control is an essential radio resource function in WCDMA systems. It is needed to compensate the near-far effect, i.e., a strong signal overriding a weaker one at a receiver. In practical systems power control is handled so that a receiver measures the signal-to-interference ratio (SIR) and compares it to a target value. Based on this comparison, the receiver requests the transmitter to either decrease or increase its transmitter power by a fixed amount, typically 1 dB. A more sophisticated approach has been proposed in [0], where an adaptive self-tuning controller (STC) with generalized minimum variance (GMV) criterion was applied in the closed-loop power control. Simulations indicated that the proposed method outperformed the conventional bang-bang type power control algorithm proposed in [1]. However, it is not clear how to select the various polynomials included in the design of the GMV controller to maximize the controller performance. In this paper we use system identification methods for modeling the WCDMA closed-loop power control. Simulations indicated that the proposed method outperformed the conventional bang-bang type power control algorithm proposed in [1]. However, it is not clear how to select the various polynomials included in the design of the GMV controller to maximize the controller performance. In this paper we use system identification methods for modeling the WCDMA closed-loop power control. The power control process is modeled using a convenient parameterized linear structure, which can be used to tune the GMV controller performance in the design phase. The model is identified using input-output data collected from a radio network simulator by opening the power control loop of a randomly selected user. The results give significant insight to the power control process and are useful in the design of adaptive power control algorithms.

1. INTRODUCTION

Transmitter power control (TPC) is one of the important radio resource management functions that are shown to increase the capacity of cellular communication systems (see e.g. [2-4]). Power control is essential in code-division multiple access (CDMA) or wideband-CDMA (WCDMA) systems, where the users share simultaneously the same transmission medium and thus interfere with one another. Due to channel variations, the levels of several transmitters’ signals might vary considerably at the receiver if the transmitters use the same transmitter power. This is called the near-far effect. By controlling the transmitter powers, the aim is to provide sufficient signal quality for all the users. This basically means that the users must have sufficient signal-to-interference ratios (SIRs).

A conventional power control algorithm for practical applications is shown in Figure 1 for uplink. This was proposed in [1]. The SIR is measured at each receiver, and compared to a target value, which is set by a quality controller to achieve a sufficient signal quality. Based on this measurement, a command is sent to the transmitter to either increase or decrease its transmitter power by a fixed amount. We refer to this control scheme as the Bang-Bang.

A more sophisticated power control algorithm was proposed in [0]. The general idea there is to precede the relay (or comparator) in the conventional algorithm with an adaptive self-tuning controller (STC) with generalized minimum variance (GMV) criterion. However, to tune the controller to best performance, more insight is needed of the properties of the controlled system.

In this paper, we apply system identification methods to model the uplink closed-loop power control process in WCDMA systems. The idea is to collect input and output data from a radio network simulator and use them to find a linear model structure that sufficiently describes the properties of the power control process. The insight gained from this process can then be used for the design of the GMV controller to improve its performance in the power control algorithm proposed in [0].

The paper is organized as follows. In Section 2 the system model is defined. Section 3 describes the identification methods and results. In Section 4 an adaptive GMV controller is designed for the identified process model. A brief introduction to adaptive control is also given. In Section 5 the controller performance is simu-
lated in the radio network simulator. Finally, some conclusions are drawn in Section 6.

2. SYSTEM MODEL

2.1. Cellular Network Simulator and Data Collection

The data for the identification is collected from a radio network system simulator, which is described here. We consider a two-dimensional seven-cell hexagonal pattern, where the cell radius is 50 m. 200 users are uniformly distributed over the seven cells. In the beginning of the simulation, the users are assigned velocities uniformly between 0 km/h and 30 km/h and a random direction of movement. These are not changed during simulation. Ideal handovers are assumed in the sense that each user is connected to the base station with the least channel attenuation at all times. The radio link attenuation is modeled as a product of three variables: the large scale propagation loss that depends on the distance between the transmitter and the receiver, log-normal shadowing with a mean of 0 dB and standard deviation of 8 dB, and motion-induced Rayleigh-distributed multipath fading generated by Jakes' model [5]. The log-normal shadowing component has also a correlation model first proposed by Gudmundson [6]. The model is extended to two dimensions as in [7].

In the beginning of the simulation, a randomly selected user, initially connected to the central cell, is selected for observation and its velocity is set to 5 km/h. Each user except the observed user is power controlled using the power control method in [2] as illustrated in Figure 1. The users transmit at a constant data rate without voice activity.

To collect the input-output data for the system identification, the power control loop of the observed user is opened at points "IN" and "OUT" in Figure 1. The point "IN" is then connected to a pseudo-random binary signal (PRBS) generator, and the resulting SIR is measured at the base station (point "OUT" in Figure 1). In other words, the selected mobile unit receives power control commands from the PRBS generator and adjusts its transmitter power according to those commands. The generated PRBS sequence and the resulting SIR sequence (both in decibels) are then regarded as input and output, respectively, of an unknown system to be identified. Bit errors in the power control commands were not considered. The sampling rate of the simulator matches the sampling rate of the power control, which is 1.5 kHz for WCDMA.

2.2. Model of the Closed Loop Power Control

We attempt to model the closed-loop power control with a linear parameterized model of the following form:

\[ y(t) = C + g^{-k} Bu(t) + Ce(t), \]

where \( y(t) \) is the output of the model at time \( t \) (in our case, the SIR at the receiver), \( u(t) \) is the input of the model at time \( t \) (in our case, the power control command), \( \{e(t)\} \) is a sequence of white Gaussian noise samples with variance \( \sigma^2_e \), \( q^{-1} \) is the backward shift operator defined by \( q^{-1} x(t) = x(t-1) \) for an arbitrary discrete-time signal \( x(t) \), \( k \) is the delay of the system, and \( A \), \( B \) and \( C \) are polynomials in \( q \), given by

\[ A = 1 + a_1 q^{-1} + \ldots + a_n q^{-n}, \]
\[ B = b_0 + b_1 q^{-1} + \ldots + b_m q^{-m}, \]
\[ C = 1 + c_1 q^{-1} + \ldots + c_n q^{-n}. \]

If \( n_e = 0 \), this model is referred to as an autoregressive model with an exogeneous variable, denoted by ARX\((n_a, n_b, k)\). Otherwise it is referred to as an autoregressive moving average model with an exogeneous variable, denoted by ARMAX\((n_a, n_b, n_c, k)\) [8]. The model is illustrated in Figure 2. We consider only the ARX model in this paper.

3. MODEL IDENTIFICATION

The input-output data collected from the radio network simulator according to Section 2.1. is used to identify the model parameters, i.e., the coefficients of the polynomials \( A \) and \( B \). Since the system is time-varying, we use the Recursive Least Squares (RLS) algorithm with exponential forgetting to take this variation into the model.

Equation (1) with \( C = 1 \) can be cast in the form

\[ y(t) = \theta^T x(t) + e(t), \]

where

\[ e(t) \]

\[ u(t) \]

\[ y(t) \]

Figure 2. ARX model of the closed-loop power control.
Equation (5) is the familiar linear regression form, which can be used for recursive estimation of the parameter vector $\theta$. The RLS algorithm equations are

$$e(t) = y(t) - x^T(t-1)\hat{\theta}(t-1), \quad (8)$$

$$\hat{\theta}(t) = \hat{\theta}(t-1) + L(t)e(t), \quad (9)$$

$$L(t) = \frac{P(t-1)x(t-1)}{\alpha_f + x^T(t-1)P(t-1)x(t-1)}, \quad (10)$$

$$P(t) = (I - L(t)x^T(t-1))P(t-1) - \frac{1}{\alpha_f}, \quad (11)$$

where $P$ is the inverse of the covariance matrix of the parameter estimates, $L$ is the Kalman gain, $\alpha_f$ is the forgetting factor and $\hat{\theta}(k)$ is a vector containing the parameter estimates, i.e.,

$$\hat{\theta}(t) = [\hat{a}_1(t) \ldots \hat{a}_{n_a}(t) \hat{b}_0(t) \ldots \hat{b}_{n_b}(t)]^T. \quad (12)$$

### 3.1. Selection of Model Order and delay

To select the model order, i.e., the orders of the model polynomials $n_a$ and $n_b$, we ran the RLS algorithm with forgetting factor 0.99 with various values for $n_a$ and $n_b$. Figure 3 shows the variance of the residual signal $e(t)$ in various cases. The "knee-point" in the figure occurs with the configuration $(n_a, n_b) = (2,1)$, and there is practically no advantage in increasing the model order beyond this point.

The delay is already defined in the simulator, and it is assumed to be one sampling period (1/1500 seconds).

Thus our model structure will be an ARX(2,1,1) model.

### 3.2. Identification Results

Figure 4 shows the parameters that resulted from the RLS-identification of the model of the selected structure. The coefficients of the model were updated every 30th sample in order to catch the time-variation of the system and to neglect the unwanted noise components from the parameters, since the identified time-varying parameters are later to be used for controller design for the system. Figure 5 shows the time-development of the absolute values of the poles and zeros of the identified model.

**Remarks:**

- the model is unstable around time 0 ... 0.5 s and after that only marginally stable (the absolute value of one pole stays around 0.995)
- the model is minimum-phase, although the zero is relatively close to the unit circle around time 0.3 ... 0.5 s
4. CONTROLLER DESIGN

4.1. Brief History of Adaptive Control
Adaptive controllers are considered to be one special type among general nonlinear controllers. The theory behind adaptive control has its origins in early 1950s, when there was a need to design well-operating autopilots to high-performance aircraft. The fundamental problem was how to control a system, which has several operation points and which may even be continuously varying between different operation modes. The fundamental issue then is to combine closed loop identification and control – a combination which makes the problem nonlinear and extremely complex. For example, the question of stability has been, and to some extent still is, a difficult problem to deal with in adaptive control systems.

In 1960s control theory developed significantly, when state-space theory was formulated and the stability methods by Lyapunov became known in the control engineering community. Optimal control was developed in the state-space framework, and major new ideas like dynamic programming, dual control, and stochastic control were invented. Also, major advances in the identification theory were made. The basic concepts in adaptive control – model reference adaptive control and self-tuning regulator or pole-placement adaptive control were introduced.

The connections to the theory of linear quadratic control were established, which led naturally to minimum-variance control and its extensions also in the adaptive context.

In 1970s and 1980s major stability results for adaptive controllers were found. A wide amount of practical applications were reported. However, adaptive control had a reputation of being a difficult control scheme, which was often difficult to apply such that the stability and performance specifications could be proved to hold. A major drawback came, when it was noticed that many adaptation schemes could lead to unstable control because of disturbances in the process or unmodelled dynamics in the process. As the theory of robust control has been a hot topic for research in the 1990s and from here on, the new concept of robust adaptive control has been created to overcome the robustness problems. This work is still going on.

Minimum-variance control and its generalizations, moving-average control and general predictive control are methods, which have been studied extensively in the literature for different kinds of plants. Adaptive versions of these control methods are also available and their problems are well understood. Usually the problems are related to difficulties in the on-line identification of the plant in closed-loop and to the ringing effect of the control signal. No general solution to these problems exists today, and the implementation of these controllers is a combination of theoretical research and practical engineering expertise.

4.2. Generalized Minimum Variance (GMV) Controller
The GMV controller is briefly introduced here. More information can be found from [8-11].

Figure 6 illustrates the concept of feedback control. It is desired to design the controller $G_c$ in such a way that the output $y(t)$ of the system follows the reference signal $r(t)$. The original idea of minimum variance control is to design a feedback controller to minimize the variance of the output of the controlled system with the reference signal set to zero. This is referred to as the regulator problem, whereas the nonzero reference signal case is called a servo problem [8].

It is well known that pure minimum variance control is not applicable to nonminimum phase systems. The GMV approach circumvents this problem by including a penalty for the control signal $u(t)$ in the cost function. Thus, instead of minimizing the variance of $y(t)$, the following cost is minimized:

$$I_1 = E\left\{ (y(t+k)-r(t+k))^2 + Su^2(t) \right\}, \quad (13)$$

where $E\{ \}$ is the expectation operator and

$$S = s_0 + s_1 q^{-1} + \ldots + s_n q^{-n}. \quad (14)$$

The controller can be further modified to force the steady state error of $y(t)-r(t)$ to zero by addition of an integrator into the feedback loop [8]. In this case the cost function is

$$I_2 = E\left\{ (y(t+k)-r(t+k))^2 + \Delta Su^2(t) \right\}, \quad (15)$$

where $\Delta = 1-q^{-1}$.

As can be seen in (15), the GMV controller no longer minimizes the variance of the output, but instead minimizes the variance of a combination of the output, the reference signal, and the control signal. The control signal penalty $S$ is usually chosen as a constant in practice.

The GMV controller is [8],[9]
\[ Fu(t) + Gy(t) - Cr(t) = 0 \, , \]

where
\[ F = BT + SC \, , \]
and \( T \) and \( G \) are defined via the identity
\[ C = TA + q^{-k}G \, , \]
where
\[ T = 1 + t_1 q^{-1} + \ldots + t_{k-1} q^{-(k-1)} \, , \]
\[ G = g_0 + g_1 q^{-1} + \ldots + g_n q^{-n} \, , \]
\[ n_s = \max(n_s - 1, n_s - k) \, . \]

Our interest in this paper is to investigate the effect of the tuning polynomial \( S \) to the controller performance.

4.3. Performance of the GMV controller designed for the identified process

For the process model identified in Section 3.2, the GMV controller is, from (1) and (13)–(21),
\[ u(t) = \frac{a_1 y(t) + a_2 y(t-1) - b_1 u(t-1) + r(t)}{b_0 + s} \, (22) \]
for cost function \( I_1 \) and
\[ u(t) = \frac{a_1 y(t) + a_2 y(t-1) - (b_1 - s) u(t-1) + r(t)}{b_0 + s} \, (23) \]
for cost function \( I_2 \). Here we have used \( S = s \). Note that the indirect version of the adaptive GMV controller was used, instead of the direct version as in [0], where the controller parameters were directly identified.

We simulated an ARX(2,1,1) system, the parameters of which were varied according to those in Figure 4. The system parameters were estimated in real time using the RLS algorithm, and the parameter estimates were at each time fed to the GMV controller (22) or (23). The reference signal was a sawtooth wave of amplitude one, mean value -17 and 1 second period, resembling the variation of the SIR target by WCDMA outer loop power control.

Figure 7 shows the variance of \( y(t) - r(t) \) versus the tuning parameter \( s \) for the controllers (22) and (23). Subplots (b) and (d) show the results for unlimited control signal \( u(t) \). Subplots (a) and (c) show the results of the case where the control signal calculated from equations (22) and (23) were quantized by taking only its sign, thus resembling the power control method in [0]. The dashed lines correspond to the Bang-Bang control scheme, were the controller is
\[ \text{Sign} (r(t) - y(t)) \, , \]
where
\[ \text{Sign} (x) = \begin{cases} 1, & \text{if } x \geq 0 \\ -1, & \text{if } x < 0 \end{cases} \, (25) \]

As seen in Figure 7, the variance grows with the tuning parameter when the command is unlimited, as expected from (13) and (15). Since the system is minimum phase, the controller works even with \( s = 0 \). However, including the nonlinear component (Sign-function) in the GMV controller brings more ambiguity to the results. With controller (22) the tuning parameter is not affecting the results at all. With controller (23) there is still the trend of growing variance with respect to \( s \), although not so clear as with unlimited commands. Note that by selecting \( s \) properly the variance is always smaller than with the Bang-Bang controller (24).

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5. RADIO NETWORK SIMULATION RESULTS

Having observed the controller performance in a somewhat idealized linear world, we now check the performance of the designed controller in the radio network simulator described in Section 2.1. Now we let all the mobile users in the system, including the observed user, be controlled by the designed adaptive GMV controller.

Figure 8 shows the receiver SIR and SIR target for the observed user. The SIR target (in decibels) was the same sawtooth signal as the reference signal used in Section 4.3, but with a slightly different mean value (since the mean value was set in the beginning of the simulation to such a level that the radio network can still support all users). Three different controllers were used, namely the GMV controller (23) with \( s = 0.1 \), MV controller (corresponds to GMV controller with \( s = 0 \)) and the Bang-Bang controller of [1]. In all controllers, the control signal was limited to \( \pm 1 \) dB.

It is seen that the variance minimizing controllers indeed achieve smaller variance than the Bang-Bang controller. With the minimum variance controller there are
problems in the beginning (between 0 ... 0.1 seconds), which is due to the identified system being nonminimum phase. By including a small penalty for the control signal, we see that the GMV controller avoids these problems with insignificant change in the variance. The variance of SIR minus SIR target (with the first 0.15 seconds ignored) for the three cases are shown in Table 1.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Var(SIR–SIR target)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMV (s = 0.1)</td>
<td>0.8854</td>
</tr>
<tr>
<td>MV</td>
<td>0.8789</td>
</tr>
<tr>
<td>Bang-Bang</td>
<td>1.2961</td>
</tr>
</tbody>
</table>

Figure 8. Receiver SIR and SIR target for the observed user, when all users are power-controlled using (a) GMV controller, (b) MV controller and (c) Bang-Bang controller.

6. CONCLUSIONS

We investigated the properties of WCDMA power control by modeling the power control process with a linear parameterized ARX model. The model was identified recursively using signal data exported from a WCDMA network simulator. The time-varying nature of the radio network was taken into account by using RLS algorithm with exponential forgetting for the identification. Using this linear model, significant insight to the properties of the system can be observed, and one can easily design adaptive controllers to drive the system into a desired performance. We designed a GMV controller for the identified process model, and verified its performance by simulation of the linear model and by simulation in the WCDMA network simulator that was used for data collection. The WCDMA network simulations showed good correspondence to simulations with the linearized model. However, the optimal selection of the tuning parameters of the adaptive controller for this particular case (WCDMA power control) is still an open problem and is a subject for further research.

7. REFERENCES