Xerographic Printing System Performance Optimization by Toner Throughput Control

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Abstract

For two component xerographic development systems the toner concentration and the average toner residence time in the developer sump are desired to be within optimal ranges for acceptable image quality. The toner concentration and the average toner residence time are coupled such that independent ranges are not typically achievable and so a tradeoff must be managed. Also the required toner for any given job is highly variable and not known well in advance, yet significantly impacts the two aforementioned parameters. In this paper we propose and demonstrate a model predictive control design framework to optimally manage toner throughput to achieve performance objectives.

Motivation

In two component xerographic development systems the toner charge to mass ratio, i.e. the toner tribo, is regulated in part by control of the ratio of toner mass to carrier mass in the developer sump (i.e. toner concentration or TC). Failure modes associated with high tribo (poor development, poor transfer) and low tribo (background, emissions) can be avoided by controlling the TC to within a predetermined latitude window. As the development system delivers toner to the latent image on the photoreceptor, the change in TC from a desired set point is measured by a sensor and used to trigger a dispense motor which delivers new toner to the developer sump. In practice, a proportional controller often forms the basis of the TC feedback control. In addition to feedback from the TC sensor, the anticipated toner usage based on customer image content is often used as a feed forward signal to improve the transient response [1].

Toner aging is an important image quality degradation phenomena in two-component development systems [2]. Toners typically use surface additives for flowability and adhesion control. Toner functionality may degrade over time because additives get buried into the toner surface due to repeated collisions in the developer housing. Consequently, the average resident time of toner in the housing, frequently referred to simply as toner age, can often be used as a measure correlated to image quality.

Simultaneously managing the TC and toner age parameters can be complex. The toner input and output rates necessary to regulate the TC are frequently not compatible with rates necessary to regulate the toner age within acceptable limits. Also the toner output rate is a strong function of the customer image content and so is highly variable. The system is nonlinear, multivariable, and has numerous physical as well as cost constraints.

To manage the system under such complex conditions, we propose a material state control architecture that utilizes toner dispense (a material input rate) and inter document zone imaging (a material output rate) to manage both TC and toner age in an optimal sense. The design approach is based on the Model Predictive Control (MPC) methodology and is easily applied to multivariable systems with constraints on inputs and outputs. MPC can also be economically advantageous since it permits operation close to constraint boundaries. Because of the aforementioned characteristics of MPC, it is one of the few advanced control methodologies that has made a significant impact in the process control industry since the mid 1970's.

Model Predictive Control (MPC) Overview

In general an MPC formulation is applied to a dynamic system, or "plant", that is assumed linear and time invariant (the application to time varying linear systems is straight forward but does not concern us here, and extensions to some nonlinear systems have been made [3]). The inputs to the system may include unmeasured disturbances, measured disturbances, set-points (or references) and manipulated variables (actuators). Outputs may be measured or unmeasured. In addition, a measurement noise model may be combined with the outputs to improve estimates of the variable to be controlled. MPC, as the name suggests, requires a model to predict the impact that inputs and measurable disturbances will have on the outputs. The model enables one to estimate the output trace due to a set of assumed inputs over a future specified time horizon p_1. An input, or actuation sequence is computed to minimize a quadratic cost functional subject to constraints. The actuation changes are constrained to vary over a "control" horizon p_2 that is necessarily less than p_1. The sequence of control inputs that minimizes the quadratic cost functional is the solution to a convex optimization problem and solved by quadratic programming. Only the first control input computed is in fact applied, after which the process is repeated at the next sample instant with updated measurements. The challenge is to tune the controller to meet the varied objectives. Tuning is achieved mainly by varying weights in the quadratic cost functional.

In the remainder of this paper we formulate the MPC problem for developer material state control. Through this example the basic features of MPC will be illustrated. For those interested in a more in depth discussion we refer to references [4] and [5].

In the next section we discuss a dynamic sump model. Next we describe the controller design, simulate the performance under a range of conditions, and lastly present conclusions.

System Model

The dynamics of the sump are described by mass balance expressions in the form of discrete difference equations that represent the evolution of TC and toner age over time. To arrive at the expressions we first define the following variables: $k = 1,2,3,...$ represents the sampling time instances which for a constant speed printer and given sheet size can be re-parameterized by print; $m_t(k)$ is the toner mass level in the sump; m_c is the carrier mass level in the sump which is assumed to be constant; $Age(k)$ is the average toner resident time in the sump; $TC(k)$ is the percent toner concentration; and $AC(k)$ is the area coverage of the customers job and will act as a disturbance to both the $Age(k)$ and $TC(k)$ variables. In digital printing applications the future values for $AC(k)$ are known over some future time horizon. Knowledge of disturbances well in advance can be exploited by the MPC approach since output predictions over a future time horizon are required.

The system also includes two manipulated variables; $Disp(k)$ is the toner dispense rate and $AC\_act(k)$ is the additional area coverage that may be printed in the inter document zone. The actuator $AC\_act(k)$ may be necessary to remove toner from the system when the customer job's area coverage is too low to do so. Though use of $AC\_act(k)$ is occasionally necessary, it is a costly actuator and its use will be discouraged through an appropriate weighting term in the cost functional. Costs are incurred because the toner is simply cleaned from the photoreceptor and sent directly to the waste collection bottle.

Using the terminology from above, we now describe the relevant plant dynamics. A toner mass balance expression yields,

$$m_t(k+1) = m_t(k) + \alpha(Disp(k) - AC\_act(k) - AC(k)) \qquad (1)$$

α is a function of the printer developed mass per unit area and print speed. α includes the scaling terms necessary to normalize the mass input and output rates. The normalization is such that $Disp(k)$, $AC\_act(k)$, and $AC(k)$ all range from 0 to 1, where 1 corresponds to a 100% area coverage throughput rate. In practice however, the maximum of $Disp(k)$ and $AC\_act(k)$ are less than 1 because of admix and inter document zone size constraints. From equation (1) the toner mass level at the next sampling instant, $k+1$, is equal to the toner mass level at the previous sampling instant plus the toner mass dispensed at time k, minus the toner mass lost from the sump at time k due to inter page zone development and the rendering of the customer's job. Though toner enters and leaves the system continuously between sample instants k and $k+1$, we consider the toner that has entered or left the sump as having occurred at the instant k. The output to be controlled is TC which is related to toner mass by,

$$TC(k) = 100 \times \frac{m_t(k)}{m_c(k)}. \qquad (2)$$

To express the evolution of $Age(k)$ we have

$$Age(k+1) = \frac{(m_t(k) - \alpha(AC(k) + AC\_act(k)))(Age(k)+1) + \alpha Disp(k)*1}{m_t(k) + \alpha(Disp(k) - AC(k) - AC\_act(k))}. \qquad (3)$$

Equation 3 models the age progression as a weighted sum of the mass not lost during the interval k to $k+1$, which advances by one time interval, and the newly dispensed mass that has advanced by one time interval. It is assumed that none of the dispensed toner at time k is developed between times k and $k+1$. This assumption is reasonable since typically the toner dispense port is located far from the development zone to allow time for add mix. Rearranging the age expression we have,

$$Age(k+1) = \frac{1}{1 + \dfrac{Disp(k)}{\dfrac{m_t(k)}{\alpha} - AC(k) - AC\_act(k)}} Age(k) + 1. \qquad (4)$$

The age expression above can be seen to be a first order difference equation with a constant input of value 1. The pole, given by,

$$\frac{1}{1 + \dfrac{Disp(k)}{\dfrac{m_t(k)}{\alpha} - AC(k) - AC\_act(k)}} \qquad (5)$$

is generally time varying, depending at any given time on the values of the inputs and outputs. When $Disp(k) = 0$, the pole assumes a value of 1 and the expression reduces to that of an integrator, i.e. the age of the toner that remains in the housing simply increases by 1 time unit at each sampling interval. For any non zero value for dispense, $Disp(k) > 0$, the pole is necessarily < 1. For constant inputs and outputs the pole assumes a fixed value and applying the final value theorem [6] [7], the age asymptotically converges to $\frac{Disp + (\frac{m_t}{\alpha} - AC - AC\_act)}{Disp}$. For time varying inputs and outputs the age expression is non linear (actuators and states are multiplicative). Since the general implementation of MPC requires linear system models [3], [4], a linear approximation is considered.

Recall that $Disp(k)$, $AC\_act(k)$, and $AC(k)$ are constrained in the interval from 0 to 1. For typical production printers $m_t(k)$ is on the order of 75 to 150 grams, α ranges from .5 to 2, and so the ratio $\frac{Disp(k)}{\frac{m_t(k)}{\alpha} - AC(k) - AC\_act(k)}$ <<1. Since $\frac{1}{1+\beta} \cong 1-\beta$ for β <<1, it follows that,

$$Age(k+1) \approx (1 - \frac{Disp(k)}{\dfrac{m_t(k)}{\alpha} - AC(k) - AC\_act(k)}) * Age(k) + 1,$$

which can be further simplified to (6)

$$Age(k+1) \approx Age(k) - Disp(k) * \alpha \frac{\overline{Age}(k)}{\overline{m}_t(k)} + 1.$$

Because the MPC controller is required to project the toner age evolution over a horizon from k to $k + p_1$, and the MPC computation requires a linear time invariant expression for $Age(k)$, the value for age and the toner mass level are assumed fixed from k to $k + p_1$ and are set at their respective values at time k. The constant values over the horizon are indicated as $\frac{\overline{Age}(k)}{\overline{m}_t(k)}$. At the next sampling instant in which the MPC controller repeats the computation of the optimal actuator commands, the values for $\overline{Age}(k)$ and $\overline{m}_t$ are updated. $\overline{Age}(k)$ is updated via the nonlinear expression (3) that can run in the background, and $\overline{m}_t$ can be updated by expression (2) in which the TC sensor output and the assumed carrier mass m_c are substituted. For systems with carrier mass trickle the variation in m_c may need to be taken into account. In this way a linear approximation to the age expression can be used for the MPC computation, and at each new sampling instant the coefficients are updated. The result is a toner age expression approximated as a first order integrator with input $1-\alpha\frac{\overline{A}ge(k)}{\overline{m}_t(k)}Disp(k)$, i.e. the input to the integrator is 1 less an amount proportional to $Disp(k)$. Below in Figure 1 is an example of the toner age evolution computed with equation 3 and the results produced by the corresponding linear approximation for typical values of $Disp(k)$, $Age(k)$, α, and $m_t(k)$. The age projection degrades with time but at a ~100 minute level the error remains under ~10 seconds throughout the 3 minute duration.

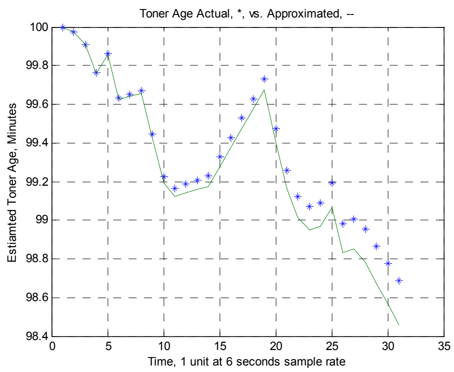

Figure 1*.Toner age, simulated actual vs. linear approximation*

Control Design

The MPC controller requires that we specify the soft or hard constraints that may exist. Soft constraints can be violated (though violation is discouraged) to ensure a feasible solution during optimization. Hard constraints cannot be violated, rather it is preferable for a machine shut down, call for service, or a non productive dead cycle to occur. The following are constraints relevant to a typical production printer and are imposed in the simulation [8].

A non zero lower limit on dispense ensures at least a continuous, although small, introduction of fresh toner entering the sump. This is beneficial in managing toner properties that degrade with age. Under low throughput conditions the TC upper limit may be reached necessitating a dead cycle and adversely impacting productivity. Furthermore, though dispense may in principle keep up with 100% area coverage rates, a smaller upper limit may be set to ensure proper admix. Under high throughput conditions a lower TC limit may be reached necessitating a dead cycle and re-tone process and again adversely impacting productivity. For the simulation we set hard constraints of $.05 \le Disp(k) \le .5$. For $AC\_act(k)$ there is an upper limit due to limited photoreceptor space between customer images. An image skip mode can be used to increase the upper limit if necessary but that is not considered here because it adversely impacts productivity. Hard constraints are set to $0 \le AC\_act(k) \le .15$. The TC latitude window is dependent on the development system characteristics. Exceeding an upper limit may result in toner emissions. Exceeding a lower limit will result in a supply limit. Because of inaccuracies in the TC sensor, a TC target is usually set between the upper and lower limits. Variation from the target is permitted but discouraged. For the simulation we choose hard constraints (soft is also an option) of $4\% \le TC(k) \le 6\%$ and a TC target of 5%. Through experimentation an acceptable upper threshold of toner age can be determined by correlating age with toner related image quality degradation. We impose a hard constraint of $Age(k) \le 100$ minutes.

Subject to the constraints outlined above the MPC controller will compute an actuator sequence that is permitted to change over the future time horizon from k to $k+p_2$ that minimizes a quadratic cost functional over the larger time horizon k to $k+p_1$. The actuator values computed are implemented at time $k+1$ after which the computation is repeated with updated measurements. The two actuators are expressed in vector notation as, $u(k+i\mid k)=[Disp(k+i\mid k), AC\_act(k+i\mid k)]$ where the integer i ranges from 1 to p_2. The notation $k+i\mid k$ signifies the determination of a value at time $k+i$ based on information available at time k. To minimize the $TC(k)$ deviation from target and penalize the use of the actuator $AC\_act(k)$, the cost functional proposed is

$$\min_{u(k+1\mid k)\ldots u(k+p_2\mid k),\varepsilon}\left\{\sum_{i=0}^{p_1-1}\left(\begin{array}{l}\omega^{TC}\left[TC(k+i+1\mid k)-TC_{SetPoint}\right]^2+\\ \omega^{AC\_act}\left[AC\_act(k+i+1\mid k)\right]^2+\rho_\varepsilon\varepsilon^2\end{array}\right)\right\} \tag{7}$$

Weights ω^{TC} and ω^{AC_act} can be time varying, but in the simulation are constant and of equal value. The slack variable ε permits soft constraints to be violated in case we are faced with an infeasible problem (eg. a large disturbance such that it is impossible to stay within the constraints). The soft constraints are modified by ε which is always ≥ 0. So for example the constraint that the TC remain between 4% and 6%, can be modified as $4\%-\varepsilon TC_{\min} < TC(k) < 6\%+\varepsilon TC_{\max}$ for some $TC_{\min}$ and $TC_{\max}$.

Simulation Results

Two scenarios are simulated using the Matlab® model predictive control toolbox MPCtool®. Many initial conditions in area coverage, TC, and age are possible. First we consider TC regulation only as illustrated in Figures 2 and 3. Due to low area coverage and a non zero minimum constraint on the dispenser the TC increases. As it approaches an upper limit of 6% the costly actuator, $AC\_act(k)$, reluctantly increases to prevent the TC from exceeding 6%. However, due to future knowledge that the job area coverage will transition to 50%, $AC\_act(k)$ is reduced in advance to save toner.

Next we consider the inclusion of age. In this scenario we are at a low area coverage (1%), high age condition. The age constraint is weighted more than that of TC. Notice that to reduce the age $Disp(k)$ quickly drives to a maximum, the costly actuator, $AC\_act(k)$ is driven up to limit the rate of increase for $TC(k)$. When $TC(k)$ reaches the 6% upper constraint $Disp(k)$ is reduced (with a soft constraint on the lower bound) and $AC\_act(k)$ slowly decreased while continuing the age reduction trend. These results are shown in Figures 4 and 5.

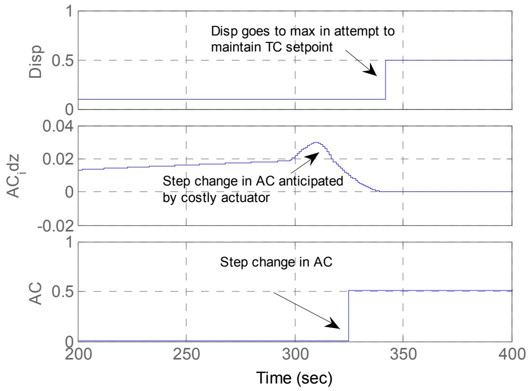

Figure 2: *Plant Inputs Disp, AC_IDZ, and Job Area Coverage*

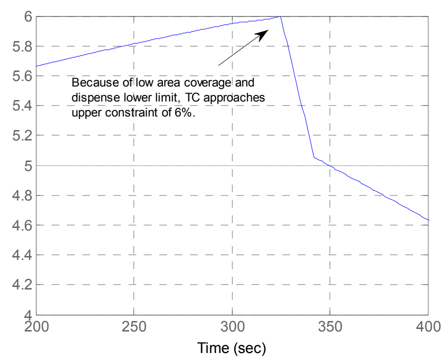

Figure 3: *Plant Output percent TC*

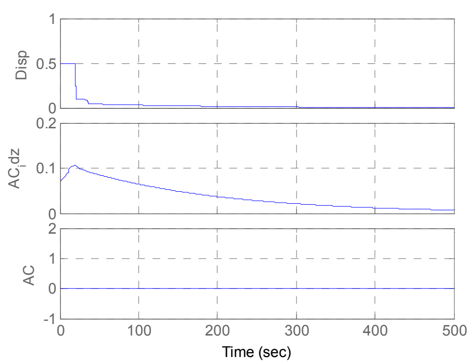

Figure 4: *Plant Inputs Dispense, AC_IDZ, and Area Coverage AC*

Conclusion

In conclusion an exploration of the suitability of the Model Predictive Control framework to the design of a xerographic toner dispense system in which toner age and TC are controlled outputs has been presented The system model for the TC and age expression was derived and constraints relevant to a typical production printer were considered. The simulations demonstrated complex yet desirable behavior. A comparison to alternative methods should involve simulation over a representative distribution of jobs.

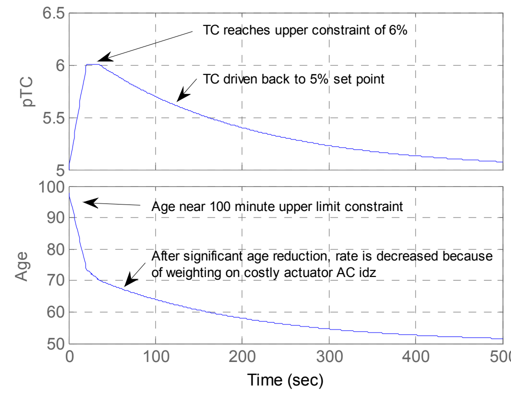

Figure 5: *Plant Outputs TC and Age vs. Time*

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Author Biography

Eric Gross received his BS in Mechanical Engineering from Rensselaer Polytechnic Institute in 1986, and was employed at the Aerospace Corporation from 1987 until 1989. He completed his PhD in Dynamic Systems and Control from the UC Berkeley in 1993 and spent 4 years on the technical staff at the Toshiba Center for Manufacturing Research in Isogo, Japan. Since joining Xerox in 1997 he has been a member of the Production Systems Group and is currently in the Xerox Innovation Group, Webster. Eric's focus is systems integration and control. He is the author of more than 20 patents related to xerographic control systems technology.

Palghat Ramesh received his BTech in Mechanical Engineering from IIT Madras, India in 1982 and PhD in Mechanical Engineering from Cornell University in 1988. Since joining Xerox in 1989, his focus has been in the areas of xerographic process modeling and simulation. He is currently a Principal Scientist with the Xerox Innovation Group. Ramesh is the author of 7 US patents and more than 40 external publications.