Automatic, In-bin Grain Drying Using Model Predictive Control

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Abstract

In-bin grain drying is a perfect tool to deal with unexpected weather on farms all over the world. The downfall of the method is that it takes a lot of personal experience and can be difficult for farmers to devote the attention needed in order to catch the best conditions for drying. This paper proposes an automatic way to control in-bin grain drying in order to reduce the manual monitoring demanded by farmers. The use of model predictive control is tested on the first layer of the drying bin to assess the practicality and performance. Using simulated results from complex equations as the real world system, an approximated model is used to design a controller which yielded great results in driving the moisture content to the reference.

Key words: Model predictive control, in-bin grain drying

1 Introduction

Many farms across the globe have grain storage bins on the property to hold the crops after they are harvested from the field. The grain bins serve as a storage area while the farmers wait for the price to peak but they are also used to condition the crops so they have the correct moisture content. The moisture content is important because the grain is sold by weight so higher moisture content returns more money but if the grain is above the moisture content limit, a penalty fee is applied. Many times farmers try to harvest as close to the limit as possible to ensure maximum gain from the crops but this can be difficult due to unforeseen weather conditions.

The criticality of this situation can be illustrated with soybean sales in the US. In the US, the grain elevator, where the grain is sold, pays per bushel based on a bushel weighing 56 pounds, no matter what the true weight is, which can increase and decrease with moisture content. Caution must be observed though because above 14%, there is adjustment for moisture and a fee for drying. So, if the soybeans are 19% moisture, they have 5% over so the weight is adjusted by 5%, plus a fee is added for drying. For a more concrete example, imagine a grain bin that could hold 24,000 bushels. If the grain loses 5% moisture content, the 24,000 bushels lose 2.8 lbs each, which means 67,200 lbs are lost overall. This divided by 56 lbs per bushel means that the equivalent of 1200 bushels are lost which, depending on the selling price, say $10 per bushel, equates to a $12,000 loss in profit, not to mention the penalty fee that is added for drying.

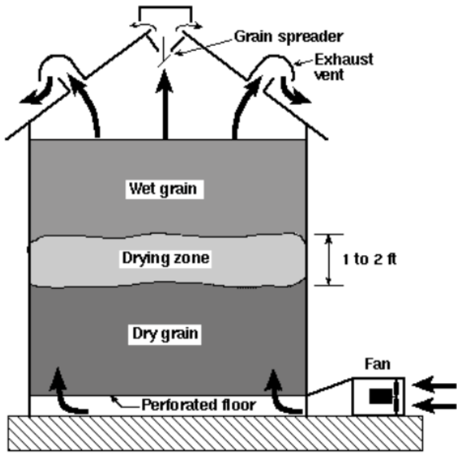

Figure 1. A schematic of the in-bin grain drying process.

To gain the maximum profit from the cultivated land, methods have been developed for farmers to condition the grain while it is stored in their bins. The moisture of the grain is a function of temperature and humidity. Grain will dry with high temperature and low humidity. It will get wetter with lower temperature and high humidity. Most large grain drying operations use a gas fired burner to raise the temperature of the air and blow it through the grain.

Air drying is a simple drying method where a large fan blows air into the bin through a perforated floor and out the exhaust vents in the roof. The perforation in the floor helps evenly distribute the air inflow so that the grain is dried more uniformly. As the air flows, a 'drying zone' is created, spanning about one to two feet, above which the grain is unconditioned. Figure 1 shows an schematic of the typical grain bin setup for natural air drying. For natural drying, the inlet air temperature is the same temperature as the outside air so there is very little to control but adding a burner to change the air temperature allows for optimal control and fast and efficient drying.

The main contribution of this paper is to propose an automatic control drying system based on Model Predictive Control (MPC). The MPC controller manipulates the input air temperature in order to maximize profit by ensuring the correct moisture grain content. Moreover, this project will help maximize efficiency while lowering the manual effort needed from the farmer since most systems are monitored and controlled manually, often by guess and check using personal experience. Also, because of the addition of a burner, the system will not be slave to the ambient weather conditions which change constantly throughout the day.

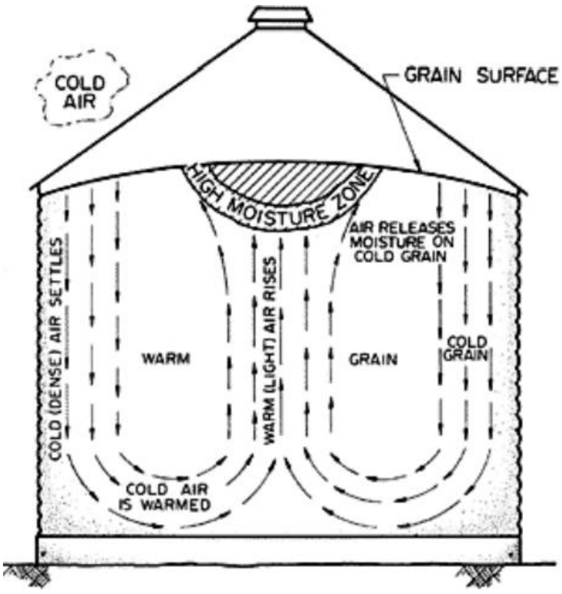

Figure 2. *Moisture migration in grain bins.*

The system will also be able to predict when drying is done so a maintenance phase can be carried out. In the maintenance phase, monitoring and aeration can be used to make the temperature in the bin uniform preventing grain rot, insect activity and heat buildup, which could cause combustion. Aeration also combats a naturally occurring phenomenon called moisture migration that occurs when warm spot appear in the grain. Air, affected by the heat, moves moisture to the grain surface where it condenses and encourages mold and insect activity. The concept of moisture migration can be seen in Figure 2. This high moisture zone at the top of the bin is difficult to rectify because it is the furthest from the fan input so precautionary action is needed so that farmers are not forced to discard any rotted grain.

2 Related work

Much research has been carried out by agricultural schools and institutes to understand the dynamics within a grain storage bin. This research helps farmers maintain and get the most from their crops by providing guidelines for drying and storage to avoid things like mold, rot or over drying ([3],[9]).

Academic research into the automation of drying and maintenance systems is limited but commercial control systems have been developed and patented for years ([2],[7],[10]). Currently, one company, Intelliair, is marketing a system to automate the drying based on sensors inside and outside the grain bin [4]. The system is easy to use and is wireless so the status of the bin can be seen by the farmer through an Internet connection. Another system that is currently under development by the Prairie Agriculture and Machinery Institute (PAMI) aims to automatically control the fan on/off to minimize power consumption and eliminate the guesswork for the farmers [1]. Unfortunately, systems developed and sold commercially are high priced which makes them largely unavailable to smaller farming operations.

3 Grain Drying System

Three mathematical models are generally used when describing in-bin, grain drying dynamics; the equilibrium, the partial differential equation (PDE) and the logarithmic models, the latter of which can be deduced from the PDE models. The equilibrium model is based off of mass and energy balances and assumes that an equilibrium will be found between the moisture in the air and that in the grain in a layer in a fixed amount of time. On the contrary, the PDE model assumes that, in a deep bed, there is no equilibrium; therefore it is based off of heat and mass transfer and the drying of a solid block. [6] Finally, to reduce the PDE model to one classified as logarithmic, the semi-empirical drying rate equations can be applied.

In the study Jingyun et al. [5], a comparison was made between the PDE and the logarithmic models. They showed that, as compared with experimental data obtained from a small scale experimental setup equipped with sensors to capture data throughout, the logarithmic model had slightly smaller error and was easier to use. More recently, Lopes et al. [6] conducted a comparison study to evaluate the performance of an equilibrium vs a logarithmic model. This study concluded that, though the equilibrium model is slightly more complicated, it performed slightly better and was able to hand diverse drying situations. For this reason, an equilibrium model is used in this work to simulate the r*eal* system. The equations, following the Thorpe model, are a system of partial differentials given by

$$\frac{\delta\theta}{\delta t}\left\{\rho_b[c_g + c_w U]\varepsilon\rho_a\left[c_a + R\left(c_w + \frac{\delta h_v}{\delta T}\right)\right]\right\} =$$
$$\rho_b h_s \frac{\delta U}{\delta T} - u_a p_a\left[c_a + R\left(c_w + \frac{\delta h_v}{\delta T}\right)\right]\frac{\delta\theta}{\delta y} + \rho_b\frac{dm_s}{dt}(Q_s - 0.6h_v) \quad (1)$$

$$\frac{\delta U}{\delta T} = -\frac{\rho_a u_a}{\rho_b}\frac{\delta R}{\delta y} + 0.6\frac{dm_s}{dt}(1 + 1.66U) \quad (2)$$

where q is the grain temperature (ºC), t is the time (s), r_b is the bulk density of the grain (kg m^{-3}), cg is the specific heat of grain (J kg^{-1} $ºC^{-1}$), T is the air temperature (ºC), c_W is the specific heat of water (J kg^{-1} $ºC^{-1}$), U is the grain moisture content (d.b.), ε is the grain porosity (decimal), r_a is the density of intergranular air (kg m^{-3}), c_a is the specific heat of air (J kg^{-1} $ºC^{-1}$), R is the humidity ratio of air (kg kg^{-1}), h_v is the latent heat of vaporization of water (J kg^{-1}), h_s is the differential heat of sorption (J kg^{-1}), u_a is the air velocity (m s^{-1}), y is the vertical coordinate (m), m_s is the grain's dry matter loss (decimal) and Q_r is the heat of oxidation of grain (J s^{-1} m-3).

If the grain is divided into layers along the direction of airflow, the equations can be approximated at each barrier, called node, with the first and second derivative approximations such as

$$\theta_m^{m+1} = \theta_i^m + \frac{\Delta t(A+B)}{\{\rho_b[c_g + c_w U_i^m] + \varepsilon\rho_a[c_a + R_i^m(c_w + D_v)]\}} \quad (3)$$

$$A = \rho_b h_{s\,i}\left(-\frac{\rho_a u_a}{\rho_b}\frac{R_i^m - R_{i-1}^m}{\Delta y} + 0.6M_{s\,i}^m(1 + 1.66U_i^m)\right) \quad (4)$$

$$B = -u_a\rho_a[c_a + R_i^n(c_w + D_v)]\frac{\theta_i^m - \theta_{i-1}^m}{\Delta y}$$

$$+\rho_b M_{s\,i}^m(Q_r - 0.6h_{v\,i}^m) \quad (5)$$

$$U_i^{m+1} = U_i^m + \Delta t\left(\frac{-\rho_a u_a}{\rho_b}\frac{R_i^m - R_{i-1}^m}{\Delta y} + 0.6M_{s\,i}^m(1 + 1.66U_i^m)\right) \quad (6)$$

where i denotes the nodes, m denotes the temporal step, D_v is the differential of latent heat of vaporization with relation to temperature (J kg^{-1} $ºC^{-1}$) and M_s is the rate at which dry matter is lost (s^{-1}). [6]

Using the simulation software developed by Lopes et al., shown in Figure 3, the model equations were solved for a particular set of initial conditions that would be common in the real world, detailed in Table 1. The software allows the user to vary the initial and drying conditions at the beginning of the software and the output, shown in Figure 4, details the temperature and grain moisture content at each node in the bin each hour. This data is considered the *real world* data that is used when approximating the model in the next section.

Table 1. The initial conditions used in simulation using the software developed by Lopes et al.

Category	Set point
Initial grain moisture content	18 %
Ambient air temperature	23 ºC
Ambient air relative humidity	50 %
Drying air temperature	26 ºC
Air flow speed	1 m^3/(min ton)
Bin size (diameter x height)	16 m x 19 m

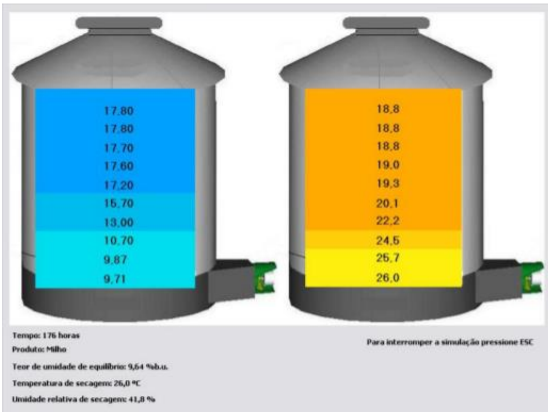

Figure 3. A screen-shot of the simulation software during simulation.

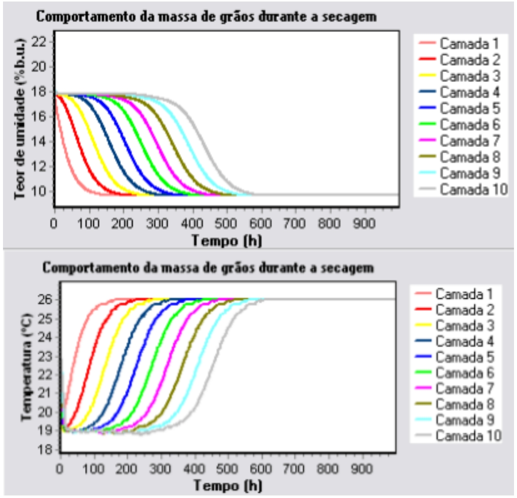

Figure 4. The output from the simulation software developed by Lopes et al.

5 Control Scheme

Model predictive control (MPC) is a control scheme that works by predicting the future system dynamics given a model according to an input. Using this prediction, an MPC controller can optimize the control to guide the system to the reference quickly while still respecting any constraints that are present. [8] As the MPC controller needs to compute the model output quickly, a simple model is better suited for this task. From the complex equations detailed in the previous section, where nonlinear terms are present, a model is needed that captures the most significant dynamics of the system but is still simple enough for solving the optimization problem. Upon examining the output given by the simulation software, it is apparent that each output closely relates to a first order system in the form

$$\frac{K}{Ts+1}e^{-\tau s} \qquad (7)$$

where K is the gain, T is the time constant and τ is the time delay. Using this approximation simplifies the system and removes the nonlinear terms. As the approximation will produce errors, the system will benefit from the constant update from the real system which will be used to reevaluate the optimal control.

6 Simulations

To test the MPC scheme, a model was built in Matlab's Simulink to control the first layer of the bin. Using the MPC toolbox, a controller was designed to regulate the input temperature in order to guide the moisture content to the reference of 13.8 %. As each node depends on the previous node, the next step of propagating the effect through numerous transfer functions that represent subsequent nodes is straight forward since it is assumed that these do not interact with the MPC controller directly or indirectly through back propagation of moisture. Figure 5 shows the resulting Simulink model.

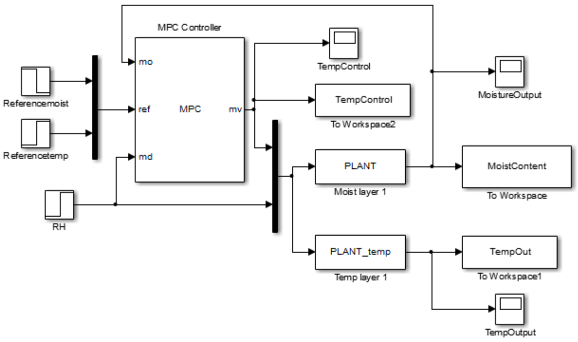

Figure 5. Simulink control scheme

All inputs and references were normalized to zero so the results shown in the next section represents the change in the parameter and not the absolute value.

7 Results

The MPC controller was designed using the controls and estimation tools manager which allows for the tuning of parameters and simulation of multiple scenarios and controllers. During controller design, constraints were placed on the inputs and outputs to ensure safe operation. The input temperature was restricted between 0 and 33 ºC to keep the air from over drying the bottom most grain. The output temperature was constrained to the same range in order to avoid heat buildup which can cause combustion. Finally, the moisture content was forced to stay between 8 and 20% moisture to keep it dry enough to prevent rot but moist enough to prevent over drying. As seen in Figures 6 and 7, only the input temperature limit was challenged.

After the design, the MPC controller was added to the system, which was ran for 500 hours. Figure 6 shows the evolution of the inputs to the plant during the length of the simulation. Temperature, shown on top, is the controlled input while relative humidity, shown on the bottom, is considered a measured disturbance. The stable behavior exhibited by the controlled input shows that the system is very capable of handling this problem quite well. Furthermore, the fast convergence to the reference while keeping the grain temperature low supports the idea of efficient drying. The small increase in grain temperature achieves the goal of not adding abundant heat that could cause over drying or combustion.

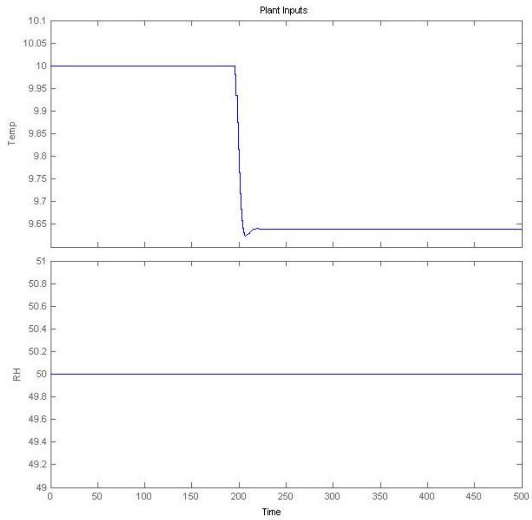

Figure 6. The evolution of the inputs to the plant during simulation. The controlled input, Temperature shown above, is used to optimize the drying while the relative humidity, shown below, is a measured disturbance.

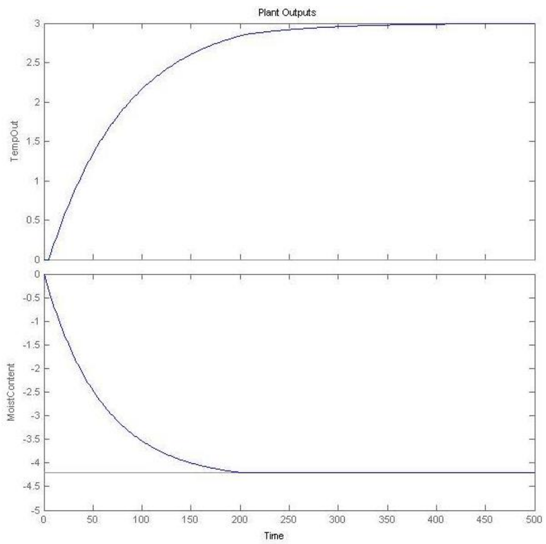

Figure 7. The evolution of the outputs of the system. Temperature, shown above, raises only 3 ºC during operation while the moisture content, shown below, is driven to the reference.

8 Conclusions

From the simulated results it can be seen that the system preforms well with the use of model predictive control. Using the approximated model to design the controller successfully captured the most prominent dynamics of the real system while allowing for fast computation. From these results, a multi-layer system can be designed to predict the time needed for drying which could be used to start a maintenance phase where the moisture content is maintained but periodic aeration occurs to discourage moisture migration which causes rot. Further investigation into the dynamics of moisture migration is needed before the model predictive control method can be applied to this phase.

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