Low Temperature Grain Drying for Reduced Energy Use and Greenhouse Gas Emissions

by

Adam Epstein

A Thesis
presented to
The University of Guelph

In partial fulfilment of requirements
for the degree of
Master of Applied Science
in
Engineering

Guelph, Ontario, Canada
© Adam Epstein, December, 2019
ABSTRACT

LOW TEMPERATURE GRAIN DRYING FOR REDUCED ENERGY USE AND GREENHOUSE GAS EMISSIONS

Adam Epstein
University of Guelph, 2019

Advisor(s):
William David Lubitz

Low temperature, fixed bed grain drying was investigated as an alternative to high temperature, fossil fuel-based drying. Drying data was collected in a full-scale on-farm storage bin drying system over three harvest seasons. A one-transient model of the grain drying process was developed, implemented, and evaluated against the three years of drying data. The drying model was shown to predict most aspects of the drying process with reasonable accuracy. A machine learning model was also trained against the same data. Preliminary calculations were completed to investigate the potential benefits of an air source heat pump as the low temperature heat source. Drying simulations were completed using typical meteorological year data. It was shown that low temperature grain drying could reduce greenhouse gas emissions by as much as 90% at a similar operating cost relative to high temperature drying fueled by natural gas or propane.
ACKNOWLEDGEMENTS

First of all, thank you to Dr. Lubitz for being an amazing advisor. You always provided excellent feedback and guidance at keeping me focused on the right work. I’ve learned a lot working with you and appreciate how you are always willing to answer question after question.

Thank you to Greg Dineen for teaching me more about farming than I ever could have imagined and for keeping such meticulous records. Any time I had a question I could usually find a note in your logs.

Thank you also to James Dyck from OMAFRA, Dr. Shohel Mahmud, and Dr. Hermann Eberl for the help you provided.

Thank you to my family and friends for all your support. Special shout out to Scott for the many technical issues you helped me work through and for dropping by my office for much needed breaks.

Finally, thank you to Anjuli for always being there for me and for helping me in countless ways along the way.
# TABLE OF CONTENTS

Abstract ............................................................................................................................................... ii

Acknowledgements ......................................................................................................................... iii

Table of Contents ............................................................................................................................. iv

List of Tables ....................................................................................................................................... viii

List of Figures ..................................................................................................................................... x

Abbreviations .................................................................................................................................. xvi

Nomenclature .................................................................................................................................... xvi

List of Appendices ............................................................................................................................ xix

1 Introduction ...................................................................................................................................... 1

1.1 Scope ........................................................................................................................................ 2

2 Literature Review ............................................................................................................................ 3

2.1 Grain Drying Overview ............................................................................................................. 3

2.2 Drying Air Properties ............................................................................................................... 7

2.3 Grain Drying Models ................................................................................................................. 7

2.3.1 Model Background ................................................................................................................. 7

2.3.2 Development of Grain Drying Models ................................................................................... 10

2.3.3 Evaluation of Grain Drying Models ....................................................................................... 13
2.3.4 Machine Learning Models ................................................................. 14
2.4 Summary .......................................................................................... 16
3 Experimental Data ........................................................................... 17
3.1 Measurement Campaign ................................................................. 17
3.2 Calibration of Sensors .................................................................. 22
  3.2.1 EL-USB-2-LCD+ Calibration ...................................................... 22
  3.2.2 Thermocouple Calibration .......................................................... 27
  3.2.3 HMP45 Relative Humidity Sensor ............................................. 29
  3.2.4 Calibration Summary ................................................................. 31
3.3 2016 Corn Drying Trial Results (Trial C16) ..................................... 32
3.4 2017 Corn Drying Trial Results (Trial C17) ..................................... 36
3.5 2018 Soybean Drying Trial Results (Trial S18) .............................. 42
3.6 Summary of Drying Trials ............................................................. 48
4 Grain Drying Model ......................................................................... 50
  4.1 Model Description .......................................................................... 50
  4.2 Solution Methods ........................................................................... 52
    4.2.1 Explicit Method ........................................................................ 53
    4.2.2 Fourth Order Runge-Kutta Method ......................................... 54
4.2.3 Method of Lines ................................................................. 55
4.2.4 Comparison of Solution Methods ........................................ 56
4.3 Model Output with Constant Inlet Conditions .......................... 60
4.4 Model Output with Varying Inlet Conditions ............................. 62
4.5 Summary .................................................................................. 65
5 Discussion .................................................................................. 66
5.1 Evaluation of Grain Drying Model with Experimental Data ........... 66
  5.1.1 Moisture Content (d.b.) ......................................................... 67
  5.1.2 Exit Air Conditions .............................................................. 71
  5.1.3 Temperatures Within the Grain Bed ....................................... 75
  5.1.4 Summary of Model Evaluation .............................................. 78
5.2 Sensitivity Analysis .................................................................. 78
  5.2.1 Sensitivity of Air Properties .................................................. 80
  5.2.2 Sensitivity of System Properties .......................................... 81
  5.2.3 Sensitivity of Grain Properties ............................................. 81
  5.2.4 Sensitivity of EMC formula constants ................................... 82
  5.2.5 Sensitivity of Drying rate constants ...................................... 84
  5.2.6 Sensitivity Analysis Summary .............................................. 85
5.3 Low Temperature Evaluation ................................................................. 85
  5.3.1 Performance based on typical meteorological year ......................... 85
  5.3.2 Low Temperature GHG Emissions and Cost Analysis .................. 88
5.4 Machine Learning Model ........................................................................ 90
  5.4.1 Model Results ................................................................................ 91
  5.4.2 Model Performance Across Trials .................................................. 94
  5.4.3 Model Runtime ............................................................................ 95
  5.4.4 Summary ..................................................................................... 95
6 Conclusions ............................................................................................... 97
  6.1 Future Work ...................................................................................... 97
References .................................................................................................... 99
Appendices ................................................................................................... 106
LIST OF TABLES

Table 2-1: Properties of corn and soybeans ........................................................................3

Table 2-2: Henderson and Chung constants for different crops (Brooker, Bakker-Arkema, & Hall, 1992) .................................................................................................................9

Table 3-1: Summary of drying trials ..................................................................................20

Table 3-2: Sensor operating range and uncertainty ...........................................................21

Table 3-3: Summary of relative humidity calibration trials. Equilibrium relative humidity from (Greenspan, 1976). .........................................................................................................................23

Table 3-4: Summary of calibration results .........................................................................32

Table 3-5: Evaluation metrics for low temperature drying trials ......................................49

Table 4-1: Model parameters for simulation of corn drying ..............................................52

Table 4-2: Trial dependent model parameters for modeling of corn ...............................52

Table 4-3: Parameters for evaluation of solution methods ...............................................57

Table 4-4: Model step sizes and simulation times ..............................................................57

Table 4-5: Model parameters for constant inlet test .........................................................60

Table 4-6: Model parameters for varying inlet ..................................................................63

Table 5-1: Model parameters for simulation of soybean drying (Brooker, Bakker-Arkema, & Hall, 1992) .........................................................................................................................66

Table 5-2: RMSE for model prediction of all drying trials ..................................................67
Table 5-3: RMSE for temperature measurements within the grain bed (C17 and S18 only) .................................................................................................................................................. 78

Table 5-4: Sensitivity analysis of time to half dry with 5% variation in parameters ........ 79

Table 5-5: Results of additional sensitivity trials .................................................................................................................................................. 80

Table 5-6: Typical ranges of properties of corn........................................................................................................................................................................... 82

Table 5-7: 2018 Ontario electricity carbon intensity (Intrinsik Corp., 2016) .............. 89

Table 5-8: GHG and cost analysis of various drying scenarios ........................................ 89

Table 5-9: Summary of trials for training the machine learning models ....................... 90

Table 5-10: RMSE for linear regression model and ANN ........................................... 91

Table 5-11: RMSE of linear regression model and ANN applied to different trial .......... 95

Table 5-12: Average model runtime for 1000 runs ................................................ 95
LIST OF FIGURES

Figure 2-1: Types of continuous flow grain dryers (Bucklin, Thompson, Montross, & Abdel-Hadi, 2013) ........................................................................................................................................................................... 4

Figure 2-2: Schematic of fixed bed grain drying ........................................................................................................................................................................................................... 8

Figure 2-3: Method of characteristic solution (dashed) and full simulation (solid) results (Ingram, 1979) .......................................................................................................................................................................................................................... 11

Figure 3-1: On-farm grain drying system bin (left) and GSI AgriDry 8-3000 gravity grain spreader (right) .............................................................................................................................................................................................................. 17

Figure 3-2: Drying air inlet to grain bin ......................................................................................................................................................................................................................... 18

Figure 3-3: Experimental bin dryer system schematic (not to scale) ........................................................................................................................................................................................................................................ 18

Figure 3-4: Partitioned brass probe used to collect grain samples at multiple depths for moisture content measurements ........................................................................................................................................................................................................ 19

Figure 3-5: Model of experiment setup showing location of temperature depth probes .......................................................................................................................................................................................................................... 21

Figure 3-6: EL-USB-2-LCD+ dataloggers in constant humidity enclosure generated by a saturated salt solution ........................................................................................................................................................................................................... 23

Figure 3-7: Comparison of EL-USB-2-LCD+ calibration readings .......................................................................................................................................................................................................................... 25

Figure 3-8: USB1 and USB2 readings during C16 trial ........................................................................................................................................................................................................................................... 26

Figure 3-9: USB2 and USB3 readings during C17 trial ........................................................................................................................................................................................................................................... 26

Figure 3-10: Thermocouple calibration set up. Boiling water (left) and ice bath (right) .................................................................................................................................................................................................................. 27

Figure 3-11: Ice bath (top) and boiling water (bottom) calibration trials .................................................................................................................................................................................................................. 28
Figure 3-12: Thermocouple calibration boiling measurement versus ice bath measurement ................................................................. 29

Figure 3-13: Individual readings of relative humidity during HMP45 calibration ........ 30

Figure 3-14: HMP45 Calibration Relative Humidity Measurements ............................................. 31

Figure 3-15: C16 Corn profile prior to shoveling level ................................................................. 32

Figure 3-16: C16 Corn profile after shoveling level (sensor locations shown in green). 33

Figure 3-17: C16 Relative Humidity measurements for ambient, lower plenum, and upper plenum (shoveled and undisturbed areas) ................................................................. 33

Figure 3-18: C16 Absolute humidity measurements for ambient, lower plenum, and upper plenum (shoveled and undisturbed areas) ................................................................. 34

Figure 3-19: C16 Temperature measurements for ambient, lower plenum, and upper plenum (shoveled and undisturbed areas) ................................................................. 34

Figure 3-20: C16 Moisture content (d.b.) in 0.125 m (5 in) intervals, measured from bin floor ........................................................................................................................................ 35

Figure 3-21: C16 Comparison of moisture content (d.b.) based on moisture samples (dashed) and calculation of difference in humidity (solid) .................................................. 36

Figure 3-22: C17 Moisture sampling areas .................................................................................. 37

Figure 3-23: C17 Moisture Content (d.b.) in 0.125 m (5 in) intervals, measured from bin floor ........................................................................................................................................ 38

Figure 3-24: C17 Temperature measurements for ambient, lower plenum, and upper plenum ........................................................................................................................................ 39
Figure 3-25: C17 Relative humidity measurements for ambient, lower plenum, and upper plenum ................................................................. 39

Figure 3-26: C17 Absolute humidity measurements for ambient, lower plenum, and upper plenum ........................................................................ 40

Figure 3-27: C17 Temperature profile at 0.125 m, 0.375 m, and 0.625 m above bin floor ........................................................................................................ 41

Figure 3-28: C17 Comparison between inner and outer ring moisture content (d.b.) for first 0.375 m ........................................................................ 41

Figure 3-29: C17 Comparison of moisture content (d.b.) based on moisture samples (dashed) and calculation of difference in humidity (solid) ........................................................................ 42

Figure 3-30: S18 Moisture sampling areas .............................................................. 43

Figure 3-31: S18 Moisture Content (d.b.) in 0.125 m intervals (primary sampling area) 43

Figure 3-32: S18 Moisture measurements (d.b.) from the main and secondary sampling area in 0.125 m increments ................................................................. 44

Figure 3-33: S18 Temperature measurements for ambient, lower plenum, and upper plenum ............................................................................................. 45

Figure 3-34: S18 Relative Humidity measurements for ambient, lower plenum, and upper plenum ............................................................................................. 46

Figure 3-35: S18 Absolute Humidity measurements for ambient, lower plenum, and upper plenum ............................................................................................. 46

Figure 3-36: S18 Temperature profile at 0.125 m, 0.375 m, 0.625 m above bin floor ... 47
Figure 3-37: S18 Comparison of moisture content (d.b.) based on moisture samples (dashed) and calculation of difference in humidity (solid) ................................................................. 48

Figure 4-1: Temperature output for explicit, Runge-Kutta, and MOL simulations with constant inlet conditions .................................................................................................................. 58

Figure 4-2: Moisture content (d.b.) output for explicit, Runge-Kutta, and MOL simulations with constant inlet conditions .................................................................................................................. 58

Figure 4-3: Temperature output for explicit, Runge-Kutta, and MOL simulations with varying inlet conditions .................................................................................................................. 59

Figure 4-4: Moisture content (d.b.) output for explicit, Runge-Kutta, and MOL simulations with varying inlet conditions .................................................................................................................. 59

Figure 4-5: Corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (right) profiles every 0.1 m for constant inlet conditions .................................. 61

Figure 4-6: Heat maps of corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (d.b.) (right) for constant inlet conditions .............................. 61

Figure 4-7: Comparison of moisture profiles for the Equation (4-5) (left) and Equation (4-6) (right) drying rate fits for constant inlet conditions ................................................................. 62

Figure 4-8: Corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (d.b.) (right) profiles every 0.1 m for constant inlet conditions ..................... 63

Figure 4-9: Heat maps of corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (d.b.) (right) for varying inlet conditions .................................. 64

Figure 4-10: Comparison of moisture profiles for the Equation 4-5 (left) and Equation 4-6 (right) drying rate fits for varying inlet conditions ................................................................. 64
Figure 5-1: Comparison of model output and sampled grain moisture (d.b.) content at 0.125 m intervals

Figure 5-2: C16 Comparison of average moisture content (d.b.) of grain bed based on model output, measured grain samples, and humidity difference between inlet and outlet

Figure 5-3: C17 Comparison of model output and sampled grain moisture content (d.b.) at 0.125 m intervals

Figure 5-4: C17 Comparison of average moisture content (d.b.) of grain bed based on model output, measured grain samples, and humidity difference between inlet and outlet

Figure 5-5: S18 Comparison of model output and sampled grain moisture content (d.b.) at 0.125 m intervals

Figure 5-6: S18 Comparison of average moisture content (d.b.) of grain bed based on model output, measured grain samples, and humidity difference between inlet and outlet

Figure 5-7: C16 Measured and simulated exit air temperature, relative humidity, and absolute humidity

Figure 5-8: C17 Measured and simulated exit air temperature, relative humidity, and absolute humidity

Figure 5-9: S18 Measured and simulated exit air temperature, relative humidity, and absolute humidity

Figure 5-10: C17 Comparison of model predicted temperatures at heights of 0.125 metres, 0.375 metres, and 0.625 metres above the bin floor
Figure 5-11: Comparison of model predicted temperatures at heights of 0.125 metres, 0.375 metres, and 0.625 metres above the bin floor .................................................. 77

Figure 5-12: Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of Henderson constant K ............. 82

Figure 5-13: Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of Henderson constant N ............. 83

Figure 5-14: Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of Henderson constant C ............. 83

Figure 5-15: Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of drying rate constant $k_1$ .......... 84

Figure 5-16: Grain moisture content (d.b.) of entire bed (left) and at height above the bin floor of 0.375 metres (right) for sensitivity test of drying rate constant $k_2$ .......... 85

Figure 5-17: Settling moisture for simulated TMY drying trials ............................................. 87

Figure 5-18: Specific energy consumption (MJ/kg) for TMY drying trials (excluding ambient) ............................................................................................................. 87

Figure 5-19: Specific energy consumption (MJ/kg) for TMY trials with heat pump as heat source .................................................................................................................. 88

Figure 5-20: Machine Learning model predictions for C16 outlet temperature .......... 92

Figure 5-21: Machine Learning model predictions for C16 outlet relative humidity ...... 92

Figure 5-22: Machine Learning model predictions for C16 outlet absolute humidity .... 93

Figure 5-23: Machine Learning model predictions for C16 moisture content (d.b.) .......... 93
ABBREVIATIONS

ANN artificial neural network
COP coefficient of performance
d.b. dry basis
EMC equilibrium moisture content
RMSE root mean square error
TMY typical meteorological year
w.b. wet basis

NOMENCLATURE

\( a_p \) grain specific area \((m^2 \ m^{-3})\)
\( c_a \) air specific heat \((kJ \ \text{kg}^{-1} \ \text{K}^{-1})\)
\( c_p \) grain specific heat \((kJ \ \text{kg}^{-1} \ \text{K}^{-1})\)
\( c_v \) water vapour specific heat \((kJ \ \text{kg}^{-1} \ \text{K}^{-1})\)
\( c_w \) water specific heat \((kJ \ \text{kg}^{-1} \ \text{K}^{-1})\)
\( G_a \) air mass flow rate per unit area \((\text{kg} \ \text{h}^{-1} \ m^{-2})\)
\( H \) Height of grain column \((m)\)
\( h \) Runge-Kutta step size
\( h_{\text{conv}} \) convection heat transfer coefficient \((kJ \ m^{-2} \ K^{-1} \ h^{-1})\)
\( h_{lg} \)  Heat of vaporization of water in grain (kJ kg\(^{-1}\))

\( k_1 \)  Runge-Kutta slope increment

\( k_2 \)  Runge-Kutta slope increment

\( k_3 \)  Runge-Kutta slope increment

\( k_4 \)  Runge-Kutta slope increment

\( M \)  moisture content (d.b.)

\( M_{eq} \)  equilibrium moisture content (d.b.)

\( T \)  air temperature (°C)

\( t \)  time (h)

\( t_{0.5} \)  time to half dry (h)

\( W \)  absolute humidity (kg H\(_2\)O/kg dry air)

\( x \)  height in grain bed above bin floor (m)

\( \varepsilon \)  porosity (%)

\( \rho_a \)  density of air (kg m\(^{-3}\))

\( \rho_p \)  dry bulk density of grain (kg m\(^{-3}\))

\( \theta \)  grain temperature (°C)

Empirical Constants

\( k_1 \)  Drying rate constant (theoretical equation)
$k_2$  Drying rate constant (empirical equation)

c  Drying rate constant (empirical equation)

$K$  Henderson EMC constant

$N$  Henderson EMC constant

$C$  Henderson EMC constant

$C_1$  Chung EMC constant

$C_2$  Chung EMC constant

$C_3$  Chung EMC constant
LIST OF APPENDICES

Appendix A. USB Calibration Figures ................................................................. 106
Appendix B. Additional Figures for Machine Learning Model............................... 111
1 Introduction

One of the largest costs associated with grain production is the energy used to dry the
grain to a moisture content that is safe for storage. Drying accounts for approximately
60% of the energy requirement for corn production in the midwestern United States
(Brooker, Bakker-Arkema, & Hall, 1992) and 14% of the production cost (Ontario
Ministry of Agriculture, Food and Rural Affairs, 2019). Drying grain to a moisture content
that is safe for storage is required to prevent spoilage due to mould. At harvest,
corn in the field contains moisture that is typically between 25% to 30% of its dry mass.
To be safely stored, moisture in corn must be reduced to 15% of the dry mass; the safe
storage moisture content varies with different grains.

Grain in Ontario is typically dried in high temperature dryers, although there are no
detailed statistics regarding grain drying methods. High temperature dryers are usually
fueled by propane or natural gas. Alternatives to high temperature drying include low
temperature and natural air drying. These alternatives have the potential to save
energy, reduce greenhouse gas emissions (GHG), and preserve grain quality (Brown,
Fulford, Daynard, Meiering, & Otten, 1979), although at a significantly increased drying
time compared to high temperature drying.

Further savings can be realized by using an air source heat pump as the heat source. In
the case of low temperature drying, heat is transferred from the surrounding ambient air
to the drying air before it enters the grain. The only energy requirement for a heat pump
is the work performed to move heat from one source to the other. The coefficient of
performance (COP) of a heat pump gives the ratio of heating output to work input. Air
source heat pumps can achieve a COP of three or higher when used to heat residential
buildings (Johnson, 2013). In low temperature drying the COP would be even higher as
the air is only heated a small amount above ambient in order to reduce the relative
humidity of the incoming air to increase its drying potential. The electrical heating load is
significantly reduced compared to resistance heating, although the fan load does not change significantly.

Low temperature drying can be completed on-farm in grain storage bins. Air heated slightly above ambient conditions is moved through the grain using a blower, until the grain reaches the safe storage moisture content. Depending on the season’s yield, multiple drying runs may be required to dry the entire amount of harvested grain.

1.1 Scope

This thesis investigates the potential energy savings and GHG reduction of on-farm, low temperature grain drying. Experimental data collected during the 2016, 2017, and 2018 drying seasons was analyzed. A one-dimensional transient grain drying model for a fixed bed of grain was developed based on the work of Brooker et al. (1992). Due to the uncertainty in many of the model parameters, a sensitivity analysis was completed. The drying model was tested against the three seasons of experimental data. A machine learning model was trained using the three years of drying data to predict the air outlet conditions based on the conditions of the air at the inlet to the grain, allowing for prediction of the overall moisture content.
2 Literature Review

The purpose of this review is to provide an overview of the research related to low temperature grain drying. The review will cover an overview of drying methods, drying experiments, drying models, and evaluation of models. Machine learning methods applied to modeling will be briefly discussed. The majority of research discussed here focuses on high temperature drying models and experiments. There is a gap in modeling and experimentation of low temperature grain drying.

2.1 Grain Drying Overview

Grain harvested at a moisture content above the safe storage level is dried either using high temperature, low temperature, or untreated air. Air with potential to dry has a lower vapor pressure than the vapor pressure of moisture within the grain. As the air is moved through the grain, moisture is absorbed until the vapor pressures are equal.

Moisture content of grain is measured in either dry basis (d.b.) or wet basis (w.b.). Dry basis safe storage moisture contents for corn and soybeans are shown in Table 2-1. Dry basis moisture content is the ratio of moisture in the corn to the dry mass of the corn and wet basis moisture content is the ratio of moisture in the corn to the total mass (corn and moisture).

<table>
<thead>
<tr>
<th>Property</th>
<th>Corn</th>
<th>Soybeans</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Safe storage moisture content (d.b.)</td>
<td>15%</td>
<td>13%</td>
<td>(Bucklin, Thompson, Montross, &amp; Abdel-Hadi, 2013)</td>
</tr>
<tr>
<td>Dry matter bulk density (kg m⁻³)</td>
<td>604</td>
<td>650</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>Specific heat (kJ kg⁻¹ K⁻¹)</td>
<td>2.13</td>
<td>1.64</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>Porosity</td>
<td>0.4</td>
<td>0.33</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>Heat of vaporization (kJ kg⁻¹)</td>
<td>2450 – 2800</td>
<td>2450 – 2700</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>Grain specific area (m² m⁻³)</td>
<td>784</td>
<td>1000</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
</tbody>
</table>

In high temperature drying, air is first heated to temperatures above 50°C before being moved through the corn, rapidly removing moisture. High temperature dryers are able to
dry large amounts of grain very quickly. Low temperature dryers use air that is heated slightly above ambient conditions, resulting in reduced energy consumption per mass of moisture removed but increased time to dry. Natural air drying does not supply any heat to the air and is often not practical in Ontario at harvest time.

Grain dryers can either be continuous flow, where the grain flows through the dryer, or fixed bed, where the grain is stationary. The four main types of continuous flow grain dryers are crossflow, counterflow, concurrent flow, and mixed flow (Figure 2-1). The majority of corn in Ontario is dried in high temperature dryers, typically the crossflow type, where the airflow is perpendicular to the flow of grain in the dryer. High temperature dryers often overheat and overdry the grain, which can cause deterioration such as cracking (Brooker, Bakker-Arkema, & Hall, 1992). Concurrent flow dryers reduce this effect because the drying air enters the wettest portion of the grain. In fixed bed dryers, the grain is stationary, and air is moved through the grain. Bin drying systems are fixed bed dryers that are often low capacity and low temperature, resulting in high quality grain.

Figure 2-1: Types of continuous flow grain dryers (Bucklin, Thompson, Montross, & Abdel-Hadi, 2013)
Grain drying can take place on-farm or at a grain elevator using high temperature air, low temperature air, or ambient air. The most common drying method is high temperature drying, with drying temperatures typically above 50°C. For low temperature drying, air is heated 2°C to 5°C above ambient conditions. After drying, grain must be cooled to below 25°C (McFarlane & Bruce, 1996). Hellevang and Reff (1987) found that to remove one kilogram of water requires 2.3 to 2.8 MJ for natural air drying, 2.8 to 3.5 MJ for low temperature drying, and 4.2 MJ to 7.0 MJ for high temperature drying, depending if air recirculation is used. A review of low temperature drying studies found that specific energy consumption is usually in the range of 1.5 MJ/kg to 4.0 MJ/kg, with lower values possible with favourable weather conditions (Sharp, 1982), although these conditions are unlikely to occur during the harvest season in Ontario. Combination drying involves drying grain in a high temperature dryer until approximately 20% moisture content followed by cooling and drying to the final moisture content at a lower temperature. Combination drying required 4.1 MJ per kilogram of water removed compared to 3.9 MJ/kg and 4.0 MJ/kg for low and high temperature drying, respectively (Otten & Brown, 1982). Dryer energy usage can be decreased by 20% to 40% through the use of heat exchangers or recirculation of air exiting the dryer (Dyck, 2017). The trade-off with recirculating the warm air is an increase in drying time due to the higher moisture content compared to the ambient air.

Brown et al. (1979) found that low temperature drying produced higher quality corn compared to high temperature drying and high temperature dryeration. High temperature drying resulted in more frequent occurrence of stress cracking regardless of the drying method. Dryeration requires drying the grain until it reaches 2% to 3% above the target moisture content, followed by steeping in an intermediate bin to equalize the moisture content. Finally, a fan cools the grain and dries to the desired level (Dyck, 2017).
The heat supplied for drying is typically from propane or natural gas. Alternatives to fossil fuels include solar assisted drying, microwave-based drying, or electrical heat input. In solar assisted drying, solar collectors are used to warm the drying air, with supplemental heat added, if required, using propane or electric heaters. Early studies found that solar assisted drying was not economical to implement in the midwestern United States (Morey, Cloud, Gustafson, & Petersen, 1979).

Air source heat pumps use electricity to power a refrigeration cycle that transfers heat extracted from ambient air to the air flowing into the drying system. The coefficient of performance (COP) of the heat pump is the ratio of heat transferred to the air divided by the electrical energy input. The COP of heat pumps used for drying typically range from three to five (Colak & Hepbasli, 2009). Early investigation into heat pumps for grain drying found it not to be economical due to low fossil fuel prices in the 1970s. However, an experiment comparing heat sources for low temperature drying of corn found a specific energy consumption of 2 MJ/kg using a heat pump compared to 3.3 MJ/kg using resistance heaters (Hogan, et al., 1983). Lifecycle cost analysis found that heat pumps are economical to dry grain in South Africa from 18% to 15% only if operating for a minimum of three months per year, which is less than the typical drying period in South Africa (Meyer & Greyvenstein, 1992). More recently, it has been shown that heat pump grain dryers require 3.5 to 7.2 MJ/kg of moisture removed (Adapa, Schoenau, & Sokhansanj, 2002) which is comparable to higher temperature drying methods. Heat pumps can reduce the greenhouse gas emissions compared to propane or natural gas fueled drying, especially in locations like Ontario that have electrical grids with low carbon intensity.

Due to the increased drying time and small temperature increase, low temperature drying systems are sensitive to the local climate of the dryer. Many studies have looked at the optimization of a specific drying process for maximum efficiency but have not completed a multi-variable optimization. A system wide optimization would allow for the
design of a low temperature drying system that is adaptable to the needs of a specific farm, based on the local weather conditions, grain type and production, energy costs, and dryer operating conditions.

2.2 Drying Air Properties

An important aspect of grain drying is the properties of the drying air. The air is a mixture of dry air and water vapor. The ratio of the water vapor mass to the dry air mass is the absolute humidity \( W \), which gives the total amount of moisture in the air. There is a limit to how much moisture that a given mass of dry air can hold. Once this point is reached, the air is saturated. The ratio of the absolute humidity to the absolute humidity of air that is saturated at the same temperature is the relative humidity \( RH \). The ability of air to absorb moisture from wet grain is related to the relative humidity of the air.

2.3 Grain Drying Models

2.3.1 Model Background

In fixed bed grain drying, warm air flows from the bottom of the bin through stationary, dry grain of a given height \( H \) resulting in heat and mass transfer between the two media. Assuming that there is only heat and mass transfer in the direction of airflow, balances are taken only in the vertical direction \( x \) in Figure 2-2), resulting in horizontal homogeneity. By examining the flows into and out of a control volume, and the dissipation and accumulation within, a system of differential equations are developed. The model consists of equations that can be used to determine the main variables of the model: air temperature \( T \) and absolute humidity \( W \), and corn temperature \( \theta \) and moisture content (d.b.) \( M \). Each of these variables vary with both height above bin floor and drying time (i.e. \( T = T(x, t) \)).
The transfer of moisture from a single kernel can be modelled as a diffusion reaction (Ingram, 1976; Misra & Young, 1980; Sokhansanj & Bruce, 1987) or based on an empirical relationship (Misra & Brooker, 1980; Mittal & Otten, 1982; White, Bridges, Loewer, & Ross, 1981). A common form of a thin layer drying equation is:

\[
MR = \frac{M - EMC}{M_0 - EMC} = f(t)
\]  

(2-1)

where \( MR \) is the moisture ratio, \( M_0 \) is the initial moisture content, \( EMC \) is the equilibrium moisture content, and \( f(t) \) is an empirically defined function, which is often an exponential function. All moisture contents are dry basis.

Equation (2-1) shows that the change in moisture content is related to the difference between the initial moisture content and the equilibrium moisture content (EMC). The EMC of grain is the moisture content that a grain will dry to if exposed to air at a constant temperature and humidity until steady state is reached, which occurs when the vapor pressure of the air is equal to the characteristic vapor pressure of moisture in the grain (Brooker, Bakker-Arkema, & Hall, 1992). There are many different empirical
formulas for calculating the EMC based on curve fitting of experimental data. The Henderson equation, developed based on Gibbs’s adsorption equation, was modified based on empirical data (Thompson, 1967), and is given by:

\[ EMC = \left( \frac{\ln(1 - RH)}{-K(\theta + C)} \right)^{1/N} \]  

(2-2)

where K, N, and C are constants that vary by grain. An alternative to the Henderson equation is the Chung equation, which is based entirely on empirical data, (Chung & Pfost, 1967), and is given by:

\[ EMC = C_1 - C_2 \ln \left( -(\theta + C_3) \ln(RH) \right) \]  

(2-3)

where C1, C2, and C3 are constants that vary by grain. Equations (2-2) and (2-3) give the moisture content in dry basis. Table 2-2 gives constant values for different crops for both relationships.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Henderson Equation Constants</th>
<th>Chung Equation Constants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K (x 10^-5)</td>
<td>N</td>
</tr>
<tr>
<td>Corn</td>
<td>8.6541</td>
<td>1.8634</td>
</tr>
<tr>
<td>Soybeans</td>
<td>30.5327</td>
<td>1.2164</td>
</tr>
<tr>
<td>Wheat (hard)</td>
<td>2.3007</td>
<td>2.2857</td>
</tr>
</tbody>
</table>

Single kernel drying equations are developed by drying a thin layer of grain and recording the change in mass over time. Misra and Brooker (1980) compiled data for thin layer drying of corn resulting in a thin layer drying equation in the form of:

\[ MR = \exp \left( -kt^c \right) \]  

(2-4)

where \( k \) and \( c \) are parameters that may depend on temperature, relative humidity and moisture content.
There has been less research completed on thin layer drying of soybeans, but drying rate equations in the form of \((2-4)\) have been determined through experiment (Hutchinson & Otten, 1983; White, Bridges, Loewer, & Ross, 1981). An alternative to thin layer drying rates is to use a linear diffusion model within the grain kernel with transfer of moisture to the air via a mass transfer coefficient (Misra & Young, 1980).

The energy required to evaporate moisture out of the grain is called the latent heat of vaporization of water within the grain \((h_{fg})\). This is different from the typical definition of latent heat of vaporization of water and is dependent on the grain and varies primarily with moisture content and temperature (Brooker, Bakker-Arkema, & Hall, 1992).

### 2.3.2 Development of Grain Drying Models

Grain drying models are either logarithmic, equilibrium, or non-equilibrium. A grain drying model based on the assumption that the energy loss of the air flowing through the grain is equal to the energy required to evaporate the moisture leads to a logarithmic relationship. A comparison between equilibrium and logarithmic models found that both models slightly overestimated drying times and diverged at large temperature differences (Lopes, Steidle Neto, & Santiago, 2014).

Both equilibrium and non-equilibrium models are developed using heat and mass balances to derive a system of differential equations. Equilibrium models assume thermal equilibrium conditions exist between the drying air and grain. By assuming the air and grain temperatures are equal, the system of differential equations is simplified. Non-equilibrium models do not make this assumption and must be solved using numerical techniques. Details of the non-equilibrium model of Brooker et al. (1992) are presented in Section 4.1.

Equilibrium models can be quickly solved using the characteristic method (Ingram, 1979). The solution obtained contains a discontinuity at the drying front (Figure 2-3).
where the solution immediately jumps from the inlet air properties (and resultant grain properties) to the initial grain properties (and resultant air properties). To account for this, an estimate of the drying width can be calculated based on the drying zone width of the logarithmic model (Barre, Baughman, & Hamdy, 1971). The calculated drying zone width was larger with this model than from the detailed simulation, but the velocity of the drying front was comparable for varying airflows and inlet temperatures. It was not clear how the detailed simulation was completed or how the width of the drying zone of the detailed simulation was calculated.

![Graph showing temperature vs distance from inlet](image)

**Figure 2-3**: Method of characteristic solution (dashed) and full simulation (solid) results (Ingram, 1979)

For non-equilibrium models, once a system of differential equations has been established, a solution can be obtained using numerical methods. The most common methods for solving include the explicit finite difference method (Aregba & Nadeau, 2007; Liu, Wu, Wang, Song, & Wu, 2015), the implicit finite difference method (Meiering, Daynard, Brown, & Otten, 1977; Sokhansanj & Bruce, 1987), and the Runge Kutta method (Spencer, 1969; Srivastava & John, 2002). Alternatives include orthogonal collocation (Sun, Pantelides, & Chalabi, 1995) and the method of lines (MOL) (Martinello, Muñoz, & Giner, 2013).

To simplify the solution of the set of differential equations, many models neglect the air accumulation terms (Brooker, Bakker-Arkema, & Hall, 1992; Sharp, 1982; Spencer,
Aregba and Nadeau (2007) found that this assumption may only be valid for near ambient grain drying without defining a threshold. Bowden, Lamond, and Smith (1983) compared four models (moisture deficit, logarithmic, equilibrium and non-equilibrium) to simulate near ambient drying. It was found that the equilibrium and non-equilibrium models performed better at predicting the moisture content but with an increased computation time. The moisture deficit model was found to be adequate only to provide rapid simulation when a low airflow and drying temperature are used.

Simulating low temperature drying of corn using the method of lines results in improved solution time with a small increase in approximate error of drying time when compared to both explicit and implicit methods using constant inlet conditions (Martinello, Muñoz, & Giner, 2013). The drying time was defined as the time for the top layer to dry to 17% (d.b.).

Sokhansanj and Bruce (1987) found that a conduction and diffusion model better predicted thin layer drying of barley at high temperature compared to a lumped heat model. The improved accuracy was due to better modelling of the initial stages of drying when there is a large temperature difference between the drying air and barley. In low temperature drying, the temperature differences are much smaller, but the diffusion model was not tested for low temperature drying. Additionally, the diffusion model increased the complexity of the model compared to empirical drying rate models.

Additional factors that may be considered by grain drying models include shrinkage (physical reduction in size of grain as it is dried), condensation resulting in rewetting of grain, conduction between grain kernels, and air leakage from the bin or dryer. Shrinkage has been modeled in thin layer drying of soybeans (Misra & Young, 1980) but most models neglect shrinkage during drying. Tiusanen et al. (2013) removed a single layer at a time based on a threshold of the total amount of moisture removed, redistributing the moisture in that layer to the remaining layers, but did not discuss how this changed the simulation results.
One method for handling condensation is to adjust how the model operates once the air humidity reaches equilibrium with the moisture content. In the model by Sun et al. (1995) a psychrometric balance between the air and condensed water is utilized above equilibrium until the moisture content begins decreasing, at which point moisture transfer is determined by the conventional drying equation. The temperature output of the model was plotted against experimental data, but was not compared to a model that did not account for condensation.

2.3.3 Evaluation of Grain Drying Models

Due to the many assumptions and uncertainties in parameters related to the grain, it is critical to validate drying models with experimental data. Evaluation of grain drying models can be done against thin layer drying experiments conducted in a laboratory, data collected from full scale dryers, or by comparison against an existing model. However, there is not a standard measure to check the validity of a grain drying model. Often, the model is compared graphically to experimental data (Spencer, 1969; Bowden, Lamond, & Smith, 1983; Sokhansanj & Bruce, 1987). An early review of low temperature drying models found that evaluation of many models had only been completed for high temperature scenarios (Sharp, 1982). A challenge of evaluating low temperature models is that deep bed experiments can take days or weeks to run, with inlet conditions that vary with the ambient weather.

One method to evaluate a model is to calculate the root mean square error (RMSE) of different properties predicted by the model compared to the measured values. The RMSE for the prediction ($\hat{y}$) of a known variable ($y$) is given by:

$$ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} $$
A study of low temperature drying of rough rice in Arkansas recorded temperature and relative humidity within the grain and used these measurements to calculate the RMSE, as well as Nash-Sutcliffe efficiencies (NSE) and percent biases (PBIAS) of the output of an equilibrium model (Atungulu, Zhong, Osborn, Mauromoustakos, & Singh, 2016). The RMSE was also calculated for various EMC equations after determining the constants for rough rice. The model had a RMSE of 0.57% for moisture content (d.b.) and 1.91°C for temperature. Mittal and Otten (1982) evaluated a low temperature drying model using four years of measurements of moisture content (w.b.) at six different depths. The model had a RMSE of 0.5% to 1% for the four years evaluated. An alternative to RMSE is to calculate the regression coefficient ($R^2$) for modeled values versus measured values. Morey et al. (1979) found $R^2$ values between 0.9 and 0.95 for moisture content (w.b.) measurements at depth of a solar assisted dryer taken over four years.

### 2.3.4 Machine Learning Models

To predict benefits of low temperature drying, accurate modeling of the drying process is required to determine the time to dry to a specific moisture content – typically the safe storage level. Traditional drying models involve heat and mass balances completed on drying air and grain resulting in multiple coupled differential equations. These models cannot be solved analytically, so numerical methods must be used. Another challenge is that the model is often very sensitive to empirical relationships, such as equilibrium moisture content or drying rate constants.

An alternative to heat and mass balance models is to use experimental data to train a machine learning model. Either a linear regression model or artificial neural network can be implemented to predict drying air conditions as it exits the grain based on inlet conditions. By determining the outlet conditions and sampling the starting moisture content, the difference in absolute humidity between the outlet and inlet can be used to calculate the moisture content at any time during the trial. The model can then be used to forecast drying time and energy requirements.
The application of machine learning to fixed bed grain drying is limited. There is more existing research completed for other crops, and for control of high temperature flow dryers. Early application for corn drying consisted of training an ANN using output from a traditional model of a high temperature dryer (Farkas, Reményi, & Biró, 2000). Moisture content in the top and bottom layers were predicted based on inlet and outlet air conditions, which could be implemented in the control of a dryer. Dai et al. (2018) used improved particle swarm techniques to model the moisture content of corn at the outlet of a radiation-convection dryer. The model was used to predict outlet grain moisture content and compared to data collected from a concurrent-counter flow grain dryer. Das and Akpinar (2018) used a support vector machine to predict the heat transfer coefficient based on experimental pear drying data. Balbay et al. (2012) used an artificial neural network with a sine transfer function to predict the moisture content of black cumin seeds as they were dried in a microwave dryer.

Alam et al. (2018) developed an ANN to model data collected from an experimental test setup for drying rice. Temperatures within the bed were recorded every ten seconds and moisture content was sampled every thirty minutes at five locations within the drying bed. Each experiment was run for approximately five hours. The ANN used time, air temperature, relative humidity, air flow rate, and initial moisture content as the inputs, with two hidden layers, and the moisture content as the output. The model was trained with the data collected during ten experiment trials and tested against ten other trials, resulting in a RMSE of 0.58% for the final moisture content. Momenzadeh et al. (2011) used an ANN to predict drying time in a microwave-assisted fluidized bed dryer. Genetic algorithms have been used to optimize constants in a solar grain drying model (Rahman, Mustayen, Mekhilef, & Saidur, 2015) and to tune the parameters of a neural network for an experimental grain dryer (Liu, Chen, Wu, & Peng, 2007).

A machine learning model that can accurately predict the outlet air conditions based on inlet air conditions of a low temperature, fixed bed dryer could be utilized to accurately
predict drying times and final moisture content, as an alternative to traditional models based on empirical relationships and grain properties with high uncertainty. To determine if this is practical, a machine learning model needs to be trained and tested on low temperature drying data.

2.4 Summary

Accurate modelling of grain drying is required to correctly forecast the time and energy requirements of drying. Additionally, overdrying of the lower layers of grain can be prevented while maintaining an optimal drying rate for the upper layers. To accurately model grain drying, models use parameters of grain and empirical constants that have large uncertainty. Many models add further complications (i.e. condensation or shrinkage) without demonstrating that they improve the model accuracy. Another challenge is that there is no standard for evaluating drying models. One option is to calculate the root mean square error for model outputs that have been measured experimentally.
3 Experimental Data

3.1 Measurement Campaign

Experimental drying data was collected on a farm in southwestern Ontario during the harvest seasons of 2016, 2017, and 2018. Trials were completed for the drying of corn and soybeans. Additional trials investigating the performance of a heat pump as the heat source were completed but are not discussed here. Drying was completed in a 9-metre diameter GSI bin (Figure 3-1) that had a blower installed to move air into the lower plenum of the bin and up through the grain with supplemental heat provided by electric resistance heaters. The grain is top-loaded with a GSI AgriDry 8-3000 gravity grain spreader is used to fill the bin evenly (Figure 3-1). The grain sits on a full aeration floor with a below-floor-unloading system underneath.

Figure 3-1: On-farm grain drying system bin (left) and GSI AgriDry 8-3000 gravity grain spreader (right)
Figure 3-2 shows the air inlet to the bin with the inlet duct, blower, and manifold housing the electric heaters. A blower was used to move air which has been heated through the bin containing the grain. Air enters through a single duct at the base of the bin into an open plenum space below the grain, enters the grain through a perforated floor, flows upward through the grain volume and exits the bin through roof vents (Figure 3-3).

![Figure 3-2: Drying air inlet to grain bin](image)

![Figure 3-3: Experimental bin dryer system schematic (not to scale)](image)
The blower for the 2016 drying trial (C16) was a GSI CF-7.5 (5.6 kW) centrifugal fan. The fan was replaced prior to the 2017 drying trial (C17) with a Canarm model DDA30T10300B (2.23 kW) axial fan. The fan was operated at a constant speed and the airflow was estimated by measuring pressure upstream and downstream of the fan. The fan curve was used to estimate the airflow. The voltage and current supplied to the fan was verified several times during the experiment. Prior to the 2018 drying trial (S18), aerodynamic improvements were made to the transition ducting from the fan to the bin and to the floor supports at the inlet to the bin.

Relative humidity and temperature were measured for ambient conditions, in the lower plenum for the drying air entering the grain, and in the upper plenum for the exit conditions of the drying air. Throughout the trials, samples were taken in 0.125 m (5-inch) depth intervals using a partitioned brass probe (Figure 3-4) and brought to a grain elevator to determine the moisture content (d.b.). The grain was tested using a Perten AM 5200-A Grain Moisture Tester.

Figure 3-4: Partitioned brass probe used to collect grain samples at multiple depths for moisture content measurements
Sensors in the upper plenum were located in the same location that the samples were taken from. In the C16 trial, samples were taken in two separate regions, based on how the corn had settled in the bin. In the C17 trial, samples were taken along a circular path at a constant radius containing each of the outer two depth probes. In the S18 trial, samples were taken along the radius where the depth probes and sensors were located. A summary of the three trials is shown in Table 3-1.

<table>
<thead>
<tr>
<th>Trial</th>
<th>Grain</th>
<th>Grain Height (m)</th>
<th>Initial Moisture Content (d.b.)</th>
<th>Start Time</th>
<th>Duration (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C16</td>
<td>Corn</td>
<td>0.78</td>
<td>27.9%</td>
<td>2016-11-04 17:48</td>
<td>410</td>
</tr>
<tr>
<td>C17</td>
<td>Corn</td>
<td>1.12</td>
<td>34.5%</td>
<td>2017-11-25 14:18</td>
<td>270</td>
</tr>
<tr>
<td>S18</td>
<td>Soybeans</td>
<td>1.07</td>
<td>27.4%</td>
<td>2018-10-31 18:35</td>
<td>317</td>
</tr>
</tbody>
</table>

EL-USB-2-LCD+ portable sensors with integrated dataloggers measured relative humidity and temperature of the ambient air, the incoming heated air in the lower plenum, and the air leaving the grain volume in the upper portion of the bin. For the 2017 and 2018 trials, Type E thermocouples and Campbell Scientific HMP45, HMP60, and HC-S3 combination temperature and relative humidity sensors were connected to a Campbell Scientific CR1000 datalogger and recorded additional temperature and humidity measurements (Table 3-2). Additionally, three plastic tubes outfitted with thermocouples that projected from the side at intervals were inserted into the grain to measure temperature at different heights. The tubes were placed along the same radius in the grain bed (Figure 3-5).
Table 3-2: Sensor operating range and uncertainty

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Measurements</th>
<th>Range</th>
<th>Accuracy</th>
<th>Manufacturer</th>
</tr>
</thead>
<tbody>
<tr>
<td>EL-USB-2-LCD+</td>
<td>Temperature, Relative Humidity</td>
<td>5 – 60°C, 20 – 80%</td>
<td>0.55°C, 2.25%</td>
<td>Lascar Electronics, Erie, PA, USA</td>
</tr>
<tr>
<td>HC-S3</td>
<td>Temperature, Relative Humidity</td>
<td>-40 – 60°C, 0 – 100%</td>
<td>0.2°C, 1.5%</td>
<td>Omega Engineering Inc., Stamford, CT, USA</td>
</tr>
<tr>
<td>HMP45</td>
<td>Temperature, Relative Humidity</td>
<td>-40 – 60°C, 0.8 – 100%</td>
<td>0.5°C, 2% 1</td>
<td>Vaisala, Vantaa, Finland</td>
</tr>
<tr>
<td>HMP60</td>
<td>Temperature, Relative Humidity</td>
<td>-40 – 60°C, 0 – 100%</td>
<td>0.6°C, 3% 2</td>
<td>Vaisala, Vantaa, Finland</td>
</tr>
<tr>
<td>Type E Thermocouple</td>
<td>Temperature</td>
<td>0 – 40°C</td>
<td>0.1°C</td>
<td>Omega Engineering Inc., Stamford, CT, USA</td>
</tr>
</tbody>
</table>

For the three trials presented, multiple electric resistance heaters were used to heat the incoming air. Electricity supplied to the fan and heaters was sampled using a CL210 digital clamp meter (Klein Tools), allowing accurate monitoring of the energy input to the air. The number of heaters in operation varied throughout the trial to adjust for the weather forecast. Electric heaters were used as the low temperature heat source to

---

1 2% for RH less than 90%, 3% for RH above 90%
2 3% for RH less than 90%, 5% for RH above 90%
achieve consistent heating which resulted in benchmark data for low temperature drying. Additional trials were completed on the site using an air source heat pump as the heat source but are outside the scope of this project.

3.2 Calibration of Sensors

Prior to the 2018 harvest season, the thermocouples and temperature/relative humidity sensors used in the experiment were calibrated. Calibration of five EL-USB-2-LCD+ relative humidity sensors was completed using a saturated salt environment to produce various constant relative humidity environments. Thirty-four Type E thermocouples were calibrated by immersion in both boiling water and an ice water bath. Twenty-one Type E thermocouples were calibrated again after the harvest season. During the S18 trial, it was apparent that there was an issue with the HMP45 humidity sensor relative humidity readings. A correction curve for the humidity sensor was developed by comparing against the other working humidity sensors. This calibration curve was used to correct the relative humidity readings from the HMP45.

3.2.1 EL-USB-2-LCD+ Calibration

A saturated salt solution in an enclosed environment will generate a constant relative humidity once it reaches equilibrium with the enclosed air (Greenspan, 1976). Five salts, shown in Table 3-3, were used to calibrate the EL-USB-2-LCD+ dataloggers. In each trial, the dataloggers were placed in an enclosure with a saturated solution (Figure 3-6) and left for a number of days, until a steady state was reached. See Table 3-3 for trial durations and target relative humidity. A final trial was completed over three days with the five dataloggers and an HMP60 humidity sensor placed in front of a bedroom fan for four days. In this trial the sensors were calibrated against each other, as the true humidity in the room was unknown.
Table 3-3: Summary of relative humidity calibration trials. Equilibrium relative humidity from (Greenspan, 1976).

<table>
<thead>
<tr>
<th>Trial</th>
<th>Duration (hours)</th>
<th>Relative Humidity at 20°C (%)</th>
<th>Relative Humidity at 25°C (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ambient Lab Humidity with Fan</td>
<td>91.5</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Ammonium Nitrate Trial 1</td>
<td>23.1</td>
<td>65.5¹</td>
<td>62.5²</td>
</tr>
<tr>
<td>Ammonium Nitrate Trial 2</td>
<td>25.9</td>
<td>65.5³</td>
<td>62.5³</td>
</tr>
<tr>
<td>Ammonium Sulfate Trial 1</td>
<td>23.8</td>
<td>81.34</td>
<td>80.99</td>
</tr>
<tr>
<td>Lithium Chloride Trial 1</td>
<td>65.1</td>
<td>11.31</td>
<td>11.30</td>
</tr>
<tr>
<td>Magnesium Chloride Hexahydrate Trial 1</td>
<td>154.8</td>
<td>33.07</td>
<td>32.78</td>
</tr>
<tr>
<td>Magnesium Chloride Hexahydrate Trial 2</td>
<td>54</td>
<td>33.07</td>
<td>32.78</td>
</tr>
<tr>
<td>Sodium Chloride Trial 1</td>
<td>20.7</td>
<td>75.47</td>
<td>75.29</td>
</tr>
<tr>
<td>Sodium Chloride Trial 2</td>
<td>39.3</td>
<td>75.47</td>
<td>74.29</td>
</tr>
<tr>
<td>Sodium Chloride Trial 3</td>
<td>73.4</td>
<td>75.47</td>
<td>74.29</td>
</tr>
</tbody>
</table>

Figure 3-6: EL-USB-2-LCD+ dataloggers in constant humidity enclosure generated by a saturated salt solution

During the calibration trials, there were issues reaching the targeted humidity. For the salts with low equilibrium relative humidity (Magnesium Chloride Hexahydrate, Lithium Chloride) the measured humidity continually decreased throughout the trial (Figure A-8, Figure A-9, and Figure A-10) but did not reach the target humidity. A small computer fan

¹ (Winston & Bates, 1960)
was added to the enclosure to improve mixing of the air and the saturated salt solution. A magnetic stir plate was used to ensure any undissolved salt was mixed with the solution to ensure saturation was reached.

At the beginning of each trial, the initial relative humidity readings were the ambient humidity of the lab. In all but one trial, the relative humidity readings continued to approach the target relative humidity from the initial readings until the end of the trial. A saturated salt solution could not be obtained for the second trial with Ammonium Nitrate (Figure A-3). The initial salt in the enclosure had dissolved by hour nineteen of the trial. The remainder of the salt available was added and had dissolved within four hours. At this point, the trial was abandoned.

During the final trial, when the dataloggers were reading the ambient lab conditions in front of a fan, the response time to changing humidity could be investigated. In the salt experiments, there was very low airflow and the distribution of humidity within the enclosure may have varied significantly. The fan ensured that each datalogger was exposed to the same conditions. Plotted results from these trials are included in Appendix A. At 21:00 each day there was a decrease in humidity of about 10 percentage points (Figure A-1). It is apparent that all of the dataloggers have a similar response time. Differences in the response times that can be observed in the salt trials (Figure A-2, and Figure A-5 for example) can be assumed to be related to an uneven distribution of humidity within the enclosure.

Conducting multiple trials that covered a wide range of humidity allowed for a comparison of the dataloggers against each other, by taking the average reading for the other sensors at each relative humidity reading from USB6 and plotting the results (Figure 3-7). Based on this comparison, it is apparent that USB2 reads lower than the other dataloggers when the relative humidity is above 60%.
During the grain drying trials, multiple sensors were placed in the same location for redundancy to confirm accuracy of recorded measurements. The issue with USB2 was not apparent in the C16 trial (Figure 3-8) but was apparent in the C17 trial from 2017-11-30 to 2017-12-06 (Figure 3-9). As a result, the C16 USB2 measurements were not adjusted, while the C17 USB3 measurements in the lower plenum were used for analysis. Based on the calibration results, USB2 was not used during the S18 trial.
Figure 3-8: USB1 and USB2 readings during C16 trial

Figure 3-9: USB2 and USB3 readings during C17 trial
3.2.2 Thermocouple Calibration

Calibration of the thermocouples was completed by immersion in both an ice bath and boiling water (Figure 3-10). Each thermocouple was submerged in one of the baths for two minutes, then removed for thirty seconds, and then submerged in the other bath for two minutes with temperature measured every second. The duration in each bath was reduced to one minute for the second trial. The temperature of boiling water was 99.1°C for the first calibration and 98.7°C for the second calibration based on the recorded atmospheric pressure from the Thornbrough rooftop weather station at the time of the experiment, (98.2 kPa and 96.1 kPa respectively).

Figure 3-10: Thermocouple calibration set up. Boiling water (left) and ice bath (right)

Figure 3-11 shows the results of each calibration from approximately five seconds before submersion until two minutes after submersion. Every thermocouple reach the target temperature within thirty seconds; the slower responding thermocouples had epoxy on the sensor so that they are less responsive to sudden changes. Low temperature grain drying experiments take days or weeks to complete so the response time of thirty seconds or less is acceptable.
The deviation of the thermocouples from the boiling and ice water targets are shown in Figure 3-12. The first trial, completed before the 2018 harvest season, showed that all thermocouples were within 0.5°C for the boiling water temperature and within 0.3°C for the ice bath temperature, except for TC1g. In the second trial, completed after the 2018 harvest season, TC1g was within the expected range. However, the boiling water temperature measurements in the second trial were approximately 1°C too low, even after correcting the target temperature for pressure (99.1°C for the first trial, 98.7°C for the second trial). The CR1000 used for the second calibration was removed from use due to the apparent issue with temperature readings. However, the same CR1000 had been used in the S18 trial and appeared to give readings that did not align with the other sensors (Figure 3-36).
3.2.3 HMP45 Relative Humidity Sensor

During the setup of the S18 trial, it was apparent that the HMP45 relative humidity sensor was not correctly measuring the relative humidity. Three calibration trials were conducted to obtain a correction curve for the sensor by comparison against two other sensors (HMP60, HS-C3). For each humidity value recorded by the HMP45 sensor, the average of the corresponding measurements from the other two sensors was taken to be the correct humidity. A linear fit given by Equation (3-1) was used to correct the HMP45 measurements (Figure 3-13).
\[ RH_{actual} = 1.1 \, RH_{HMP45} + 7.5 \] (3-1)

The measurements from all three trials and the corrected data are shown in Figure 3-14. In all three trials it is apparent that the HMP45 sensor is reading approximately 10% lower before correction than the other two sensors. The linear correction was applied to the HMP45 relative humidity readings collected during the S18 trial. For all measurements recorded during the three trials the RMSE was reduced from 11.9% to 2.6% after applying the correction.
3.2.4 Calibration Summary

The key findings of the calibration summary are shown in Table 3-4. The correction curve for the HMP45 was applied to the data collected in the S18 trial. No correction was required for the USB2 datalogger as it was operating correctly during the C16 trial, and it was redundant with USB3 in the C17 trial.
Table 3-4: Summary of calibration results

<table>
<thead>
<tr>
<th>Calibration</th>
<th>Manufacturer Accuracy</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>USB Dataloggers</td>
<td>2.05%</td>
<td>USB2 reads low when humidity is above 60%</td>
</tr>
<tr>
<td>Thermocouple calibration</td>
<td>0.005°C</td>
<td>Possible issue with CR1000 leading to low boiling readings</td>
</tr>
<tr>
<td>HMP45 Correction</td>
<td>1%</td>
<td>Linear correction curve given by Equation (3-1)</td>
</tr>
</tbody>
</table>

### 3.3 2016 Corn Drying Trial Results (Trial C16)

Trial C16 was completed from 2016-11-04 17:48 to 2016-11-21 19:58. Corn was dried from 27.9% to 15.5% (d.b.) over seventeen days. Prior to the start of the drying experiment, a portion of the corn in the bin was removed, resulting in the profile shown in Figure 3-15. The corn was shoveled until it was level (Figure 3-16) and sensors were placed in both the shoveled and undisturbed areas. To capture any effects of shoveled versus undisturbed corn, moisture samples were taken from each region and sensors were placed in on top of each region.

![Figure 3-15: C16 Corn profile prior to shoveling level](image)
Ambient air was used to dry until 2016-11-10, after which the applied heating load was adjusted based on ambient conditions. The added heat immediately resulted in a drop in relative humidity of the air in the lower plenum compared to the ambient conditions (Figure 3-17), while the absolute humidity was unaffected (Figure 3-18). There is no moisture transfer between the inlet to the system and the lower plenum so the drop in relative humidity is only due to an increase in temperature (Figure 3-19).

![Figure 3-16: C16 Corn profile after shoveling level (sensor locations shown in green)](image)

![Figure 3-17: C16 Relative Humidity measurements for ambient, lower plenum, and upper plenum (shoveled and undisturbed areas)](image)
Figure 3-18: C16 Absolute humidity measurements for ambient, lower plenum, and upper plenum (shoveled and undisturbed areas)

Figure 3-19: C16 Temperature measurements for ambient, lower plenum, and upper plenum (shoveled and undisturbed areas)
Drying samples were taken every two days beginning on 2016-11-07, three days after drying had started (Figure 3-20). It is immediately apparent in the first set of measurements that the corn that was shoveled into place dries at a quicker rate than the undisturbed corn, suggesting higher airflow in this area. As the experiment proceeds, the measurements in both areas converge. The corn that was shoveled into place may have been loosely packed (and therefore lower density and higher porosity) compared to the corn that was undisturbed, resulting in higher airflow. The relative humidity of the exit air in the shoveled region begins to drop on 2016-11-11 (Figure 3-17) which suggests that the drying front has reached the top of the grain, four days earlier than the undisturbed region.

![Graph showing moisture content over time](image)

**Figure 3-20: C16 Moisture content (d.b.) in 0.125 m (5 in) intervals, measured from bin floor**

The average moisture content (d.b.) of the corn could be calculated from the difference in absolute humidity in the upper and lower plenum and the initial moisture content (Figure 3-21). The calculated moisture content, assuming uniform airflow throughout the corn, results in moisture content that is too high in the shoveled area and too low in the undisturbed area compared to the samples. This confirms that the rate of drying in the
The shoveled area was higher than the undisturbed area, likely due to differences in airflow. The average calculated moisture content of two areas (green line in Figure 3-21) agrees well with the sampled moisture content. In the shoveled region, very little drying occurs after 2016-11-17. As a result, analysis for the shoveled region will assume the trial ended at this time, after 294 hours.

![Figure 3-21: C16 Comparison of moisture content (d.b.) based on moisture samples (dashed) and calculation of difference in humidity (solid)](image)

**3.4 2017 Corn Drying Trial Results (Trial C17)**

Trial C17 was completed from 2017-11-25 14:18 to 2017-12-06 21:13. Corn was dried from 34.5% to approximately 20% (d.b.) over eleven days. Samples for moisture determination were taken along two paths of constant radius, containing the temperature depth probes, as shown in Figure 3-22. Moisture sampling was only completed for the first six days of the trial, so the final moisture content is estimated based on the absolute humidity measurements.
The sampled moisture content (d.b.) is shown in Figure 3-23. By the sixth day, the drying front had progressed up to a height above the bin floor of 0.5 m, with the first 0.25 m approaching the desired 15% moisture content for safe storage. There are fluctuations in the moisture content of the wet layers that could be due to error in measurement, rewetting of the upper layers as the drying air reaches saturation, or uneven moisture distribution in the corn. It appears that the upper layers have converged by 2019-12-06, with drying just beginning at a height above the bin floor of 0.5 m.
Figure 3-23: C17 Moisture Content (d.b.) in 0.125 m (5 in) intervals, measured from bin floor

The recorded temperature, relative humidity, and absolute humidity for ambient conditions, heated air in the lower plenum, and air exiting the corn in the upper plenum are shown in Figure 3-24, Figure 3-25, and Figure 3-26 respectively. Due to the extreme initial moisture content, the air exiting the grain was close to saturation for the majority of the trial (Figure 3-25). When there is a sudden change in ambient conditions, the change is immediately noticeable in the lower plenum, but the thermal mass of grain causes a delay and reduction in the change being measurable at the outlet.
Figure 3-24: C17 Temperature measurements for ambient, lower plenum, and upper plenum

Figure 3-25: C17 Relative humidity measurements for ambient, lower plenum, and upper plenum
Figure 3-26: C17 Absolute humidity measurements for ambient, lower plenum, and upper plenum

The temperature profiles within the grain measured in the inner and outer rings at depths of 0.125 m, 0.375 m, and 0.625 m are shown in Figure 3-27, with Figure 3-28 showing the moisture content (d.b.) for the first 0.375 m in both rings. Initially temperatures at all three heights are similar. However, it is apparent that the outer ring was dried and warmed at a quicker rate than the inner ring. The outer ring temperature at 0.375 m diverges from the temperature at 0.625 m around 2017-11-29 12:00 but not until 2017-11-30 02:00 for the inner ring. It is suspected that the difference in heat and moisture between the inner and outer rings was caused by uneven airflow through the grain, which was due to the extreme moisture content.
Figure 3-27: C17 Temperature profile at 0.125 m, 0.375 m, and 0.625 m above bin floor

Figure 3-28: C17 Comparison between inner and outer ring moisture content (d.b.) for first 0.375 m

Comparison of the moisture content based on samples against calculated from difference in absolute humidity is shown in Figure 3-29. The moisture removal rate calculated by the sensor measurements is greater than the sampled measurements.
However, the relative humidity was above 90% in the upper plenum for the entire duration which is in the 5% error range of the HMP60 and beyond the normal operating range of the USB sensors and (Table 3-2).

![Figure 3-29: C17 Comparison of moisture content (d.b.) based on moisture samples (dashed) and calculation of difference in humidity (solid)](image)

**3.5 2018 Soybean Drying Trial Results (Trial S18)**

Trial S18 was completed from 2018-10-31 18:35 to 2018-11-13 23:06. Soybeans were dried from 27.4% to 12% (d.b.) over thirteen days. Samples for moisture determination were taken along the radius containing the temperature depth probes, as shown in Figure 3-30. Additional samples were taken along a second radius on three separate days for comparison.
The sampled moisture content (d.b.) is shown in Figure 3-31. For each individual layer, the rate of drying decreases as the layer gets dryer. By the end of the trial, the layers still had not converged, suggesting that almost the entire bed was still drying, with higher rates of drying occurring in the upper layers.
The secondary samples are plotted with the samples from the primary samples on the corresponding dates in Figure 3-32. The secondary samples were used to confirm that the drying throughout the bin was uniform, but there were no sensors placed on in the secondary area. The lower levels of the secondary sampling area were slightly dryer, but the higher levels were wetter. The secondary samples also had not converged by the end of the trial.

![Figure 3-32: S18 Moisture measurements (d.b.) from the main and secondary sampling area in 0.125 m increments](image)

The recorded temperature, relative humidity, and absolute humidity for ambient conditions, heated air in the lower plenum, and air exiting the corn in the upper plenum are shown in Figure 3-33, Figure 3-34, and Figure 3-35 respectively. For clarity, only the readings from the USB datalogger in the top centre position are shown. The other USB sensors are in good agreement with the measurements from the CR1000. Initially, the air exits the soybeans at approximately 89% relative humidity and 5°C, predicting a moisture content of 27.0% based on the Henderson equation (2-2) for equilibrium moisture content.
The relative humidity measurements recorded by the HMP45 and the USB dataloggers diverge at 2018-11-06 12:00, despite both sensors being located in the primary sampling area (Figure 3-30). The HMP45 records a drop in relative humidity suggesting that the uppermost layers are drying, and air is exiting the grain with remaining potential to dry. The USB dataloggers show a similar drop in relative humidity at 2018-11-10 07:30. The moisture samples confirm that drying in the uppermost layer beings around 2018-11-10 (Figure 3-31), suggesting that the USB dataloggers give a more accurate reading of the exit air relative humidity.
There was an issue with the temperature probe measurements during the S18 trial where they appeared to be reading higher than expected based on the temperatures recorded in the lower and upper plenum. Figure 3-36 shows that early in the trial, the
temperatures at 0.625 m above the bin floor were between the lower and upper plenum temperatures, but temperatures at 0.125 m and 0.375 m were greater than the lower plenum temperature. During the calibration of thermocouples that occurred after the S18 trial was completed, it appeared that the CR1000 datalogger was not accurately measuring the boiling temperature (Figure 3-12).

The comparison of the average moisture content based on samples and on the difference in humidity between the drying air at the inlet and outlet is shown in Figure 3-37. The humidity sensors show a similar rate of drying until 2019-11-08, which is when the drying front reaches the HMP45. The overall drying rate is consistent until around 2019-11-11, when it begins to decrease when the moisture content is between 16% and 18%.
Figure 3-37: S18 Comparison of moisture content (d.b.) based on moisture samples (dashed) and calculation of difference in humidity (solid)

3.6 Summary of Drying Trials

The three drying trials are summarized in Table 3-5. The total electricity input is the heating load and the fan power. Total moisture removed is calculated based on the airflow and difference in absolute humidity between the inlet and exit of the grain. Specific energy consumption is the amount of energy, including heaters and fan power, required to remove one kilogram of water. Both the specific energy consumption and moisture removal rate are cumulative values for the entire trial. Air heating efficiency is the ratio of energy gained by the ambient air to the heating input. It is less than the 100% that would be expected for electrical resistance heating due to losses to surroundings at the heaters and from the supply ducting before reaching the plenum. The drying system is a prototype and had not yet been optimized to capture these heat losses.

The specific energy consumption in all three trials is higher than the values found in the literature review of 1.5 to 4.0 MJ/kg. The C17 trial has the lowest specific energy...
consumption and highest moisture removal rate. At higher moisture contents, the energy required to vaporize water from grain is lower and drying is possible even at high relative humidity.

Table 3-5: Evaluation metrics for low temperature drying trials

<table>
<thead>
<tr>
<th>Trial</th>
<th>C16 (Shoveled)</th>
<th>C16</th>
<th>C17</th>
<th>S18</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total electricity input (GJ)</td>
<td>18.9</td>
<td>13.9</td>
<td>20.2</td>
<td>30.1</td>
</tr>
<tr>
<td>Total moisture removed (kg)</td>
<td>4202</td>
<td>2426</td>
<td>5218</td>
<td>5572</td>
</tr>
<tr>
<td>Duration (h)</td>
<td>410</td>
<td>294</td>
<td>271</td>
<td>317</td>
</tr>
<tr>
<td>Specific energy consumption (MJ/kg)</td>
<td>4.5</td>
<td>5.7</td>
<td>3.9</td>
<td>5.4</td>
</tr>
<tr>
<td>Moisture removal rate (kg/h)</td>
<td>10.2</td>
<td>8.3</td>
<td>19.3</td>
<td>17.5</td>
</tr>
<tr>
<td>Air heating efficiency (%)</td>
<td>93.3</td>
<td>94.6</td>
<td>89.1</td>
<td>77.9</td>
</tr>
</tbody>
</table>

The C16 trial demonstrates some of the difficulties in collecting high quality grain drying data. The portable USB sensors only allowed collection of data at the inlet and outlet of the grain. This only allows for evaluation of a grain drying model at an overall system level. To better understand the grain drying process, measurements within the bed are required. The C17 trial occurred during an extremely wet year where there was limited drying in the field before harvesting. These results presented a challenge for the modeling of each year, but are good test cases for the model as it should be able to handle abnormal years.
4 Grain Drying Model

4.1 Model Description

The one-dimensional transient grain drying model of Brooker et al. (1992) was used as the foundation of a model to simulate low temperature, fixed bed drying of grain. The model was developed by examining the moisture and energy flows into a control volume of grain and assuming that shrinkage of grain, temperature gradients within individual kernels, and conduction between kernels are negligible. Completing these balances leads to the following four differential equations:

\[
\frac{\partial T}{\partial x} + \varepsilon \frac{\rho_a \partial T}{G_a \partial t} = -\frac{h_{\text{conv}} \alpha_p}{G_a (c_a + c_v W)} (T - \theta) \tag{4-1}
\]

\[
\frac{\partial \theta}{\partial t} = \frac{h_{\text{conv}} \alpha}{\rho_p (c_p + c_w \dot{M})} (T - \theta) - \frac{h_{fg} + c_v (T - \theta)}{\rho_p (c_p + c_w \dot{M})} G_a \frac{\partial W}{\partial x} \tag{4-2}
\]

\[
\frac{\partial W}{\partial x} - \varepsilon \frac{\rho_a \partial W}{G_a \partial t} = - \frac{\rho_p}{G_a} \frac{\partial M}{\partial t} \tag{4-3}
\]

\[
\frac{\partial M}{\partial t} = \text{a single kernel drying equation} \tag{4-4}
\]

where \( x \) is the height above the bin floor in metres, \( t \) is the time in hours, and the remaining variables are defined in Table 4-1 and Table 4-2. There are many different single kernel drying equations. Two possible options suggested by Brooker et al. (1992) are of the form:

\[
\frac{\partial M}{\partial t} = -k_1 (M - M_{eq}) \tag{4-5}
\]

\[
\frac{M - M_{eq}}{M_{in} - M_{eq}} = e^{-k_2 t^c} \tag{4-6}
\]
where \( k_1, k_2 \) and \( c \) are experimental constants, with values for corn given by the following relationships (Brooker, Bakker-Arkema, & Hall, 1992):

\[
k_1 = 0.54 e^{\frac{5023}{1.8(\theta+273.15)}}
\]

(4-7)

\[
k_2 = 0.0347 + 0.00287 (1.8 \theta + 32)
\]

(4-8)

\[
c = 0.54 + 0.00324 RH
\]

(4-9)

For soybeans, only a drying rate equation in the format of Equation (4-6) was found in the literature (Hutchinson & Otten, 1983). The constants are given by:

\[
k_2 = 0.0333 + 0.0003T
\]

(4-10)

\[
c = 0.4002 + 0.00728 T \times RH
\]

(4-11)

Model parameters for drying of corn are shown in Table 4-1. Variables that are dependent on the trial being modeled are shown in Table 4-2. The convection heat transfer coefficient can be calculated in units of kJ h\(^{-1}\) m\(^{-2}\) K\(^{-1}\) using the following equation (Brooker, Bakker-Arkema, & Hall, 1992):

\[
h_{conv} = 0.2755c_dG_a \left( \frac{2r_0G_a}{0.06175 + 0.000165 T} \right)^{-0.34}
\]

(4-12)
Table 4-1: Model parameters for simulation of corn drying

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Value</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_p$</td>
<td>Grain specific area</td>
<td>784 m$^2$ m$^{-3}$</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$c_a$</td>
<td>Specific heat of dry air</td>
<td>1.005 kJ kg$^{-1}$ K$^{-1}$</td>
<td>(Cengel &amp; Boles, 2015)</td>
</tr>
<tr>
<td>$c_p$</td>
<td>Specific heat of grain</td>
<td>2.13 kJ kg$^{-1}$ K$^{-1}$</td>
<td>(Meiering, Daynard, Brown, &amp; Otten, 1977)</td>
</tr>
<tr>
<td>$c_v$</td>
<td>Specific heat of water vapour</td>
<td>1.87 kJ kg$^{-1}$ K$^{-1}$</td>
<td>(Cengel &amp; Boles, 2015)</td>
</tr>
<tr>
<td>$c_w$</td>
<td>Specific heat of water</td>
<td>4.18 kJ kg$^{-1}$ K$^{-1}$</td>
<td>(Cengel &amp; Boles, 2015)</td>
</tr>
<tr>
<td>$h_{fg}$</td>
<td>Heat of vaporization of water in grain</td>
<td>2695 kJ kg$^{-1}$</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$r_0$</td>
<td>Equivalent particle radius</td>
<td>0.0098 m</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$\rho_a$</td>
<td>Density of air</td>
<td>1.2 kg m$^{-3}$</td>
<td>(Cengel &amp; Boles, 2015)</td>
</tr>
<tr>
<td>$\rho_d$</td>
<td>Dry bulk density of grain</td>
<td>604 kg m$^{-3}$</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Grain porosity</td>
<td>0.4</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$K$</td>
<td>Henderson EMC constant</td>
<td>8.6541 x 10$^{-5}$</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$N$</td>
<td>Henderson EMC constant</td>
<td>1.8634</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$C$</td>
<td>Henderson EMC constant</td>
<td>49.81</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$k_{fa}$</td>
<td>Drying rate constant</td>
<td>0.54</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
<tr>
<td>$k_{fb}$</td>
<td>Drying rate constant</td>
<td>5023</td>
<td>(Brooker, Bakker-Arkema, &amp; Hall, 1992)</td>
</tr>
</tbody>
</table>

Table 4-2: Trial dependent model parameters for modeling of corn

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{in}$</td>
<td>Drying air inlet temperature</td>
<td>°C</td>
</tr>
<tr>
<td>$W_{in}$</td>
<td>Drying air inlet absolute humidity</td>
<td>kg/kg dry air</td>
</tr>
<tr>
<td>$\theta_0$</td>
<td>Initial grain temperature</td>
<td>°C</td>
</tr>
<tr>
<td>$M_0$</td>
<td>Initial grain moisture content (d.b.)</td>
<td>%</td>
</tr>
<tr>
<td>$G_{a}$</td>
<td>Flow rate per unit area</td>
<td>kg m$^{-2}$ h$^{-1}$</td>
</tr>
<tr>
<td>$h_{conv}$</td>
<td>Convection heat transfer coefficient</td>
<td>kJ m$^{-2}$ K$^{-1}$ h$^{-1}$</td>
</tr>
</tbody>
</table>

4.2 Solution Methods

An analytical solution is not known to exist for the system of equations (4-1 to 4-4), so numerical methods must be used to compute a solution. Three different solution methods were used in this study: the explicit method, the fourth order Runge-Kutta method, and the numerical method of lines (MOL). The space discretization utilized was forward differencing for the explicit and Runge-Kutta methods and backwards differencing for the MOL.
4.2.1 Explicit Method

Assuming the air accumulation terms $\left( \frac{\partial T}{\partial t}, \frac{dW}{dt} \right)$ are negligible compared to the spatial terms, the system of equations can be discretized and solved with an explicit method. Using $i$ to index the $x$ dimension and $j$ to index the $t$ dimension the discretized equations are given by:

\[
\frac{T_i - T_{i-1}}{\Delta x} = \frac{-h_{\text{conv}} a_p}{G_a} (c_a + c_p W) (T - \theta) \quad (4-13)
\]

\[
\frac{\theta_j - \theta_{j-1}}{\Delta t} = \frac{-h_{\text{conv}} a}{\rho_p (c_p + c_w M)} (T - \theta) - \frac{h_{fg} + c_v (T - \theta)}{\rho_p (c_p + c_w M)} G_a \frac{W_i - W_{i-1}}{\Delta x} \quad (4-14)
\]

\[
\frac{W_i - W_{i-1}}{\Delta x} = \frac{-\rho_p}{G_a} \frac{M_j - M_{j-1}}{\Delta t} \quad (4-15)
\]

\[
\frac{M_j - M_{eq}}{M_{j-1} - M_{eq}} = e^{-k_1 t} \quad (4-16)
\]

with boundary conditions of:

\[
T(0, t) = T_{in} \quad \text{and} \quad W(0, t) = W_{in} \quad (4-17)
\]

and initial conditions of:

\[
\theta(x, 0) = \theta_0 \quad \text{and} \quad M(x, 0) = M_0 \quad (4-18)
\]

These conditions are either constant values or time varying series for the boundary conditions and position dependent for the initial conditions. Due to uncertainty in the initial distribution in moisture content, the initial conditions are considered to be uniform.
For low temperature drying, the inlet conditions will vary significantly with the weather, so the inlet conditions should be defined as functions of time:

\[
\begin{align*}
T(0, t) &= T_{in}(t) \\
W(0, t) &= W_{in}(t)
\end{align*}
\]  

(4-19)

Starting with the boundary conditions, Equations (4-13) and (4-15) can be stepped forward in the spatial dimension to solve for the air conditions at the initial time step. Equations (4-14) and (4-16) can then be stepped forward in time. The explicit method has an error term proportional to the step size. As a result, a small step size is required resulting in long solution times.

**4.2.2 Fourth Order Runge-Kutta Method**

The Runge-Kutta (RK) method is an algorithm designed to improve upon the performance of the explicit method. The algorithm calculates multiple approximations of the slope at a given point, each based on the previous calculation, and then takes a weighted average to approximate the dependent variable \(y_n\) at the next step:

\[
y_{n+1} = y_n + \frac{h}{6} \cdot (k_1 + 2k_2 + 2k_3 + k_4)
\]  

(4-20)

where \(h\) is the step size, \(k_n\) is the approximation of the slope. For the grain drying model the dependent variables are the air temperature \((T)\), absolute humidity \((W)\), grain temperature \((\theta)\) and the dry basis grain moisture content \((M)\). The \(k\) values are given by:

\[
k_1 = h \cdot f(t_n, y_n)
\]  

(4-21)

\[
k_2 = h \cdot f\left(t_n + \frac{h}{2}, y_n + \frac{k_1}{2}\right)
\]  

(4-22)

\[
k_3 = h \cdot f\left(t_n + \frac{h}{2}, y_n + \frac{k_2}{2}\right)
\]  

(4-23)
\[ k_4 = h \cdot f(t_n + h, y_n + k_3) \]  

\( (4-24) \)

where \( t_n \) is the dependent variable (either \( t \) or \( x \)) and \( f(t, y) \) is any of Equations (4-1) to (4-4) with the air accumulation terms neglected. The fourth order Runge-Kutta method has an error that is proportional to the step size raised to the fourth power. As a result, a larger step size can be used compared to the explicit method resulting in faster simulation times.

### 4.2.3 Method of Lines

The numerical method of lines (MOL) finds a solution to a system of differential equations by discretizing the spatial derivatives to generate a system of ordinary differential equations in the time domain that can be solved efficiently using existing algorithms (Schiesser, 1991).

To solve the set of differential equations using the MOL a drying rate equation that takes the form of Equation (4-5) must be used and Equations (4-1) to (4-4) must be rewritten in matrix form.

\[
\frac{\partial \mathbf{u}}{\partial t} + \mathbf{A} \frac{\partial \mathbf{u}}{\partial x} = \mathbf{b} 
\]

\( (4-25) \)

where \( \mathbf{u} \) is the vector of dependent variables, \( \mathbf{A} \) is a four by four coefficient matrix, and \( \mathbf{b} \) is a vector:

\[
\mathbf{u} = \begin{bmatrix} T \\ \theta \\ W \\ M \end{bmatrix} 
\]

\( (4-26) \)
\[ A = \begin{bmatrix}
\frac{G_a}{\varepsilon \rho_a} & 0 & 0 & 0 \\
0 & 0 & \frac{h_{fg} + c_v(T - \theta)}{\rho_p(c_p + c_w M)} G_a & 0 \\
0 & 0 & \frac{G_a}{\varepsilon \rho_a} & 0 \\
0 & 0 & 0 & 0
\end{bmatrix} \tag{4.27} \]

\[ b = \begin{bmatrix}
-\frac{h_{conv} a_p}{\varepsilon \rho_a(c_a + c_v W)} (T - \theta) \\
\frac{h_{conv} a_p}{\rho_p(c_p + c_w M)} (T - \theta) \\
\frac{\rho_p}{\varepsilon \rho_a} k_1 (M - M_{eq}) \\
-k_1 (M - M_{eq})
\end{bmatrix} \tag{4.28} \]

The method of lines was implemented in Python using the ordinary differential equation solver, Odeint, from the Scientific Python library (Jones, Oliphant, & Peterson, 2001).

### 4.2.4 Comparison of Solution Methods

The three solution methods were evaluated by comparing model performance for both constant and varying inlet conditions. The comparison consisted of solving Equations (4-1) to (4-4) using each of the three solution methods with the parameters given Table 4-3. Each method was used to perform the simulation twenty times with the parameters shown in Table 4-3 and were run on a 2017 MacBook Pro running macOS Mojave. Twenty times was used to ensure a stable estimate of the overall completion time. The average run times are shown in Table 4-4. The method of lines was much faster for the constant inlet conditions but significantly slower for the varying inlet conditions compared to the other two methods. The constant inlet conditions result in a smooth solution that the MOL is able to efficiently solve.
Table 4-3: Parameters for evaluation of solution methods

<table>
<thead>
<tr>
<th>Variable</th>
<th>Constant Inlet Conditions</th>
<th>Varying Inlet Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height of grain column</td>
<td>1 m</td>
<td>1.1 m</td>
</tr>
<tr>
<td>Duration</td>
<td>100 h</td>
<td>100 h</td>
</tr>
<tr>
<td>Inlet air temperature</td>
<td>15°C</td>
<td>C17 inlet temperature data</td>
</tr>
<tr>
<td>Inlet air relative humidity</td>
<td>50%</td>
<td>C17 inlet relative humidity data</td>
</tr>
<tr>
<td>Initial corn temperature</td>
<td>5°C</td>
<td>7.5°C</td>
</tr>
<tr>
<td>Initial corn moisture (d.b.)</td>
<td>30%</td>
<td>34.5%</td>
</tr>
<tr>
<td>Airflow</td>
<td>300 kg m⁻² h⁻¹</td>
<td>257 kg m⁻² h⁻¹</td>
</tr>
</tbody>
</table>

Table 4-4: Model step sizes and simulation times

<table>
<thead>
<tr>
<th>Method</th>
<th>Grid Spacing (m)</th>
<th>Time Step (h)</th>
<th>Constant Inlet Conditions Average Solution Time (s)</th>
<th>Varying Inlet Conditions Average Solution Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explicit</td>
<td>0.005</td>
<td>0.05</td>
<td>14.7</td>
<td>16.6</td>
</tr>
<tr>
<td>RK</td>
<td>0.005</td>
<td>0.125</td>
<td>10.7</td>
<td>10.2</td>
</tr>
<tr>
<td>MOL</td>
<td>0.025</td>
<td>0.25</td>
<td>1.6</td>
<td>115.6</td>
</tr>
</tbody>
</table>

The temperature and moisture content (d.b.) for the constant inlet simulations are shown in Figure 4-1 and Figure 4-2. All three solution methods produce similar results. The explicit and Runge-Kutta methods have steeper curves than the MOL due to the smaller step size; each line in the graph represents a slice of grain 5 millimetres thick for the explicit and Runge-Kutta methods versus 25 millimetres for the MOL. The MOL curve for each layer plotted is comparable to an average of five layers from the other simulations.

All three solution methods produce similar results for temperature with varying inlet conditions (Figure 4-3). However, the moisture profile for the bottom layer predicted by the explicit method appears to be less responsive to variation in inlet conditions compared to the other methods (Figure 4-4).
Figure 4-1: Temperature output for explicit, Runge-Kutta, and MOL simulations with constant inlet conditions

Figure 4-2: Moisture content (d.b.) output for explicit, Runge-Kutta, and MOL simulations with constant inlet conditions
Figure 4-3: Temperature output for explicit, Runge-Kutta, and MOL simulations with varying inlet conditions

Figure 4-4: Moisture content (d.b.) output for explicit, Runge-Kutta, and MOL simulations with varying inlet conditions
The MOL is an efficient solution method for the constant inlet case and can be used to run simulations to test the sensitivity of different parameters. However, for accurate modeling of grain drying tests, Runge-Kutta is the preferred method due to the faster run time compared to the MOL and the explicit method.

4.3 Model Output with Constant Inlet Conditions

To test the grain drying model, the numerical solution was calculated for the parameters given in Table 4-5. This test used constant parameters at the inlet to understand how the model operates without the added complication of changing inlet conditions.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grain bed depth</td>
<td>1 m</td>
</tr>
<tr>
<td>Duration</td>
<td>100 h</td>
</tr>
<tr>
<td>Inlet air temperature</td>
<td>15°C</td>
</tr>
<tr>
<td>Inlet air relative humidity</td>
<td>50%</td>
</tr>
<tr>
<td>Initial corn temperature</td>
<td>5°C</td>
</tr>
<tr>
<td>Initial corn moisture content (d.b.)</td>
<td>24%</td>
</tr>
<tr>
<td>Airflow</td>
<td>300 kg m⁻² h⁻¹</td>
</tr>
</tbody>
</table>

From the constant inlet simulation (Figure 4-5), it is clear that there is a heat transfer front separate from the drying front. As air enters the grain, the lower layers immediately begin drying. Once the relative humidity of the air is balanced with the initial moisture content of the corn, the moisture content remains steady and the air continues to heat the grain. The air continues to cool, and the grain continues to warm until they reach the intermediate equilibrium temperature, at approximately 8.2°C. As the air cools, the relative humidity increases above the equilibrium value and some of moisture condenses and rewets the grain in the higher layers.

The two fronts are clear to see when the output is visualized in a heat map (Figure 4-6). The heat transfer front, where the heat map transitions from blue to white, progresses through the grain quickly and is very sharply defined. The drying front progresses much
slower and results in a second heat transfer, from the intermediate equilibrium temperature to the inlet air temperature, evident in the temperature heat map.

Figure 4-5: Corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (right) profiles every 0.1 m for constant inlet conditions

Figure 4-6: Heat maps of corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (d.b.) (right) for constant inlet conditions
The two drying rate equations presented (4-5 and 4-6) lead to similar moisture profiles for the constant inlet conditions (Figure 4-7). However, the drying front is much narrower when the model uses Equation (4-6). This equation was developed based on thin layer drying experiments (Misra & Brooker, 1980) and it appears that it may be overfit when applied to deep bed drying, although it is not easy to experimentally determine the width of the drying front for evaluation.

![Figure 4-7: Comparison of moisture profiles for the Equation (4-5) (left) and Equation (4-6) (right) drying rate fits for constant inlet conditions](image)

### 4.4 Model Output with Varying Inlet Conditions

Testing the model with constant inlet conditions allowed for a deeper understanding of how the model operates. High temperature dryers will have approximately constant inlet conditions, but low temperature drying air will vary with changes in the weather. The model was tested using the data collected in the lower plenum of the C17 trial and other parameters as listed in Table 4-6.
Table 4-6: Model parameters for varying inlet

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grain bed depth</td>
<td>0.5 m</td>
</tr>
<tr>
<td>Simulation duration</td>
<td>100 h</td>
</tr>
<tr>
<td>Inlet air conditions</td>
<td>C17 USB sensor data</td>
</tr>
<tr>
<td>Initial corn temperature</td>
<td>5°C</td>
</tr>
<tr>
<td>Initial corn moisture content (d.b.)</td>
<td>34.5%</td>
</tr>
<tr>
<td>Airflow</td>
<td>300 kg m⁻² h⁻¹</td>
</tr>
</tbody>
</table>

The model output for varying inlet conditions are shown in Figure 4-8 and Figure 4-9. The drying front is still clearly defined, but there are multiple temperature gradients visible due to fluctuations in the ambient air temperature. Changes in the drying air temperature rapidly progress through the grain.

**Figure 4-8**: Corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (d.b.) (right) profiles every 0.1 m for constant inlet conditions.

Figure 4-10 shows that a similar effect is observed when comparing the two different drying rate Equations (4-5) and (4-6) where the width of the drying front is much narrower, but the progression occurs at a similar rate when using Equation (4-6) for varying inlet conditions.
Figure 4-9: Heat maps of corn temperature (left), corn moisture content (d.b.) (centre) and equilibrium moisture content (d.b.) (right) for varying inlet conditions.

Figure 4-10: Comparison of moisture profiles for the Equation 4-5 (left) and Equation 4-6 (right) drying rate fits for varying inlet conditions.
4.5 Summary

The grain drying model presented is capable of generating solutions for both constant and varying inlets. In the next section the model is evaluated against three years of low temperature grain drying data. The Runge-Kutta solution method was selected as the preferred solution method and Equation (4-5) was selected as the drying rate equation for corn due to the smoother drying front. For soybeans, a drying rate equation of the form (4-5) could not be found so the drying rate equation used was Equation (4-6).
5 Discussion

5.1 Evaluation of Grain Drying Model with Experimental Data

The grain drying model was evaluated for three separate simulations, with results compared against experimental data for the C16, C17, and S18 trials. The models were evaluated based on the various measurements taken during each trial. This allowed for comparison of the model against experimental data in the following categories: moisture content at various depths, overall moisture content, outlet air conditions, and temperature at various depths (C17, S18 only). The constants for the C16 and C17 simulations are given in Table 4-1. For the S18 trial, the parameters are the same with the exceptions given in Table 5-1 and the drying rate equation utilized was Equation (4-6) with constants given by Equations (4-10) and (4-11).

Table 5-1: Model parameters for simulation of soybean drying (Brooker, Bakker-Arkema, & Hall, 1992)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_p)</td>
<td>Grain specific area</td>
<td>1000 m² m⁻³</td>
</tr>
<tr>
<td>(c_p)</td>
<td>Specific heat of grain</td>
<td>1.99 kJ kg⁻¹ K⁻¹</td>
</tr>
<tr>
<td>(h_{fg})</td>
<td>Heat of vaporization of water in Grain</td>
<td>2600 kJ kg⁻¹</td>
</tr>
<tr>
<td>(\rho_p)</td>
<td>Dry bulk density of grain</td>
<td>650 kg m⁻³</td>
</tr>
<tr>
<td>(\varepsilon)</td>
<td>Grain porosity</td>
<td>0.33</td>
</tr>
<tr>
<td>(K)</td>
<td>Henderson EMC constant</td>
<td>30.5327 x 10⁻⁵</td>
</tr>
<tr>
<td>(N)</td>
<td>Henderson EMC constant</td>
<td>12164</td>
</tr>
<tr>
<td>(C)</td>
<td>Henderson EMC constant</td>
<td>134.136</td>
</tr>
<tr>
<td>(k_{1a})</td>
<td>Drying rate constant</td>
<td>0.54</td>
</tr>
<tr>
<td>(k_{1b})</td>
<td>Drying rate constant</td>
<td>5023</td>
</tr>
</tbody>
</table>

The RMSE for simulation predictions of various measures are shown Table 5-2. The predicted moisture content is evaluated against the moisture calculated based on the change in absolute humidity to allow for comparison of the entire prediction, not just the limited number of grain moisture samples. For all three trials, the relative humidity of the exit air has the largest prediction error. The overall RMSE was taken for all three trials.
after averaging the shoveled and undisturbed regions from the C16 trial to avoid doubling the weight of this trial in the calculation.

<table>
<thead>
<tr>
<th>Outlet Variable</th>
<th>C16 RMSE</th>
<th>C16 Shoveled RMSE</th>
<th>C17 RMSE</th>
<th>S18 RMSE</th>
<th>Overall RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moisture Content (d.b.) (%)</td>
<td>2.83</td>
<td>1.15</td>
<td>0.63</td>
<td>1.04</td>
<td>0.98</td>
</tr>
<tr>
<td>Exit Air Temperature (°C)</td>
<td>1.30</td>
<td>1.52</td>
<td>0.65</td>
<td>1.23</td>
<td>1.13</td>
</tr>
<tr>
<td>Exit Air Relative Humidity (%)</td>
<td>10.31</td>
<td>7.81</td>
<td>3.63</td>
<td>3.33</td>
<td>5.00</td>
</tr>
<tr>
<td>Exit Air Absolute Humidity (g H₂O/kg dry air)</td>
<td>0.54</td>
<td>0.52</td>
<td>0.32</td>
<td>0.39</td>
<td>0.41</td>
</tr>
</tbody>
</table>

5.1.1 Moisture Content (d.b.)

Comparison of moisture predictions and measurements for C16 is shown in Figure 5-1 at 0.125 metre intervals. The model gives a good prediction for the rate of drying for each layer and the overall drying time. However, the model predicts the corn to settle at approximately 18% (d.b.), but the corn actually dried to 15.5% (d.b). The model produces a reasonable estimate of the average moisture content of the bed (Figure 5-2) during the first half of the trial, before lagging behind the sampled moisture readings.
The C17 trial was completed during a wet harvest year. For the majority of the trial, the relative humidity of the air at the exit of the grain was near 100%. Samples were only taken for the first half of the experiment (Figure 5-3). Based on the limited samples, the model appears to provide an accurate model for each layer within the corn. The average moisture content (d.b.) of the bed predicted by the model is lower than the sampled average over the first half of the trial (Figure 5-4) but initially agrees well with the moisture content calculated based on the difference in humidity between the inlet and outlet before diverging towards the end of the trial.
Figure 5-3: C17 Comparison of model output and sampled grain moisture content (d.b.) at 0.125 m intervals

Figure 5-4: C17 Comparison of average moisture content (d.b.) of grain bed based on model output, measured grain samples, and humidity difference between inlet and outlet
The S18 trial was the most thorough data set collected, allowing for complete evaluation of the model. The model provides a good prediction of the moisture content at each layer (Figure 5-5) and of the overall moisture content (Figure 5-6), with the final moisture content settling at 13%. The drying rate equation used for the soybean model was Equation (4-7), which will lead to a narrow drying front as discussed in Section 4.4. At each layer, the samples began drying sooner than the model predicted, but the model predicts faster drying of each layer, suggesting that the experimental data had a wider drying front than the front predicted by the model.

![Figure 5-5: S18 Comparison of model output and sampled grain moisture content (d.b.) at 0.125 m intervals](image)
The C16 trial had a larger moisture prediction RMSE for both shoveled and undisturbed regions (2.83% and 1.15%) compared to the C17 trial (0.63%) and the S18 trial (1.04%). Table 5-2. This is likely a result of the uneven airflow that appeared to occur during the C16 trial, as discussed in Section 3.3.

5.1.2 Exit Air Conditions

The exit air conditions measured in the upper plenum were compared to the predicted air conditions in the top layer of the model results for the three years of collected data. The time needed for the drying front to progress through the entire bed of grain can be compared by observing when the relative humidity of the exit air begins to decrease.

The exit air temperature, relative humidity, and absolute humidity for the C16 trial and model output are shown in Figure 5-7. The model yields an accurate solution for the exit temperature (RMSE of 1.30°C and 1.52°C) and absolute humidity (0.54 and 0.52 g H₂O/kg dry air), with a small overshoot when there is a peak in either variable. Prior to the drying front reaching the top, the model predicts a relative humidity slightly lower
than observed in the experiment in both the shoveled (RMSE of 10.31%) and the undisturbed (7.81%) regions. Assuming the air reaches equilibrium with the grain prior to exiting, the relative humidity should be the equilibrium value predicted by the EMC relationship, Equation (2-2). This suggests an issue with the EMC relationship for high values of relative humidity, but it should also be noted that the sensors have a higher error for relative humidity above 90% (Table 3-2). The predicted drop in relative humidity associated with the drying front reaching the top of the grain bed by the model occurs between the drops in the shoveled and undisturbed areas, suggesting that the overall progression of drying through the bed is reasonable.

Figure 5-7: C16 Measured and simulated exit air temperature, relative humidity, and absolute humidity.
The performance of the model for the C17 trial exit air conditions was similar to the C16 model (Figure 5-8) with decent predictions of temperature (RMSE of 0.65°C) and absolute humidity (0.32 g H₂O/kg dry air), but the relative humidity (3.63%) was lower than the measured values. The drying front had not reached the uppermost layer by the end of the drying trial.

The model of the S18 trial initially performs similarly to the C16 and C17 trials (Figure 5-9). The drying front reached the uppermost layer at the location of the HMP60 sensor.
much sooner than at the USB datalogger position (Figure 3-30). The model predicted that the drying front would not reach the uppermost layer by the end of the trial, after 317 hours of drying. The divergence in temperature and absolute humidity of the model from the sensor measurements occurs as the drying front reaches each sensor. There is a slight lag in the modeled temperature and humidity measurements.

Figure 5-9: S18 Measured and simulated exit air temperature, relative humidity, and absolute humidity
Overall, the model performance in the exit air conditions was consistent for the three experiment years. As with the moisture content, the C16 trial was the least accurate at predicting exit air conditions across the three trials.

5.1.3 Temperatures Within the Grain Bed

Within the bed of grain, the only measurements that were taken that can be used to evaluate the model were taken with the thermocouples attached to probes inserted into the grain. Temperatures were measured at three different locations at heights above the bin floor of 0.125 m, 0.375 m, and 0.625 m during the C17 and S18 trials.

The C17 trial for a two-day period is shown in Figure 5-10. The model temperature output is cooler than the measured output at 0.125 m, reasonably accurate at 0.375 m for the outer ring, and warmer at 0.625 m. There is a high temperature peak on 2019-12-01 at 18:00 visible at all three heights above the bin floor. The model predicts a larger rise in temperature at 0.625 m than recorded by the sensors.
As discussed in Section 3.5, the temperature probe measurements during the S18 experiment were not accurate, reading approximately 2°C high based on the incoming and exit air temperature. To better evaluate the model output, the inlet and outlet temperatures are also plotted to create bounds for the temperature within the bed.
The RMSE was calculated for each height above the bin floor at each location (Table 5-3). The error increased with height for both trials. In both trials, there is an offset in the predicted temperature that lags the measured temperature that gets larger as the height above the bin floor increases. Due to the issue with the temperature readings within the soybeans during the S18 trial, the RMSE was recalculated after subtracting 2°C from the measured values. The model performance appears to be consistent because the adjusted RMSE are comparable to the C17 RMSE.

Figure 5-11: S18 Comparison of model predicted temperatures at heights of 0.125 metres, 0.375 metres, and 0.625 metres above the bin floor
Table 5-3: RMSE for temperature measurements within the grain bed (C17 and S18 only)

<table>
<thead>
<tr>
<th>Height (m)</th>
<th>Probe Location</th>
<th>S18 RMSE (°C)</th>
<th>C17 RMSE (°C)</th>
<th>Overall RMSE (°C)</th>
<th>Adjusted S18 RMSE (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.125</td>
<td>Inner</td>
<td>1.68</td>
<td>0.54</td>
<td>1.28</td>
<td>0.63</td>
</tr>
<tr>
<td>0.125</td>
<td>Outer</td>
<td>2.05</td>
<td>1.01</td>
<td>1.64</td>
<td>0.54</td>
</tr>
<tr>
<td>0.375</td>
<td>Inner</td>
<td>1.95</td>
<td>1.35</td>
<td>1.69</td>
<td>0.77</td>
</tr>
<tr>
<td>0.375</td>
<td>Outer</td>
<td>2.22</td>
<td>0.80</td>
<td>1.70</td>
<td>0.76</td>
</tr>
<tr>
<td>0.375</td>
<td>Centre</td>
<td>1.74</td>
<td>1.87</td>
<td>1.80</td>
<td>0.98</td>
</tr>
<tr>
<td>0.625</td>
<td>Inner</td>
<td>2.12</td>
<td>1.20</td>
<td>1.74</td>
<td>0.91</td>
</tr>
<tr>
<td>0.625</td>
<td>Outer</td>
<td>2.22</td>
<td>1.00</td>
<td>1.75</td>
<td>0.90</td>
</tr>
</tbody>
</table>

5.1.4 Summary of Model Evaluation

The grain drying model was tested against three years of drying data both graphically and quantitatively. The drying trials presented some irregular cases due to the uneven airflow in the C16 trial and extreme moisture content in the C17 trial. The model performs reasonably well for all three trials compared to other models that provided quantitative evaluation. The RMSE found for the moisture content for the C17 trial (0.63%) was in the range of 0.5% to 1% that was observed in other models (Atungulu, Zhong, Osborn, Mauromoustakos, & Singh, 2016; Mittal & Otten, 1982) and the S18 (1.04%) and C16 shoveled region (1.15%) trials were just above this range.

5.2 Sensitivity Analysis

A sensitivity analysis was performed for each model input, shown in Table 4-1, as well as the airflow (G_a) and convection coefficient (h_{conv}). In each initial test, one parameter was varied by randomly generating values that assumed the variation in each parameter could be represented by a normal distribution with the values given in Table 5-4 as the mean, and 5% of the mean value as the standard deviation. The conditions used were the same as the constant inlet trial, shown in Table 4-5. The convection coefficient was recalculated using Equation (4-12) for each trial where one of the variables in the equation were altered.
Table 5-4: Sensitivity analysis of time to half dry with 5% variation in parameters

<table>
<thead>
<tr>
<th>Variable Type</th>
<th>Test Variable</th>
<th>Value</th>
<th>Time to half dry ($t_{0.5}$) (h)</th>
<th>Mean Value</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>System</td>
<td>$G_a$</td>
<td>300 kg m$^{-2}$ h$^{-1}$</td>
<td>89.71</td>
<td>4.49</td>
<td>76.20</td>
<td>105.12</td>
<td>28.92</td>
<td></td>
</tr>
<tr>
<td>System</td>
<td>$h_{conv}$</td>
<td>17.88 kJ m$^{-1}$ K$^{-1}$ h$^{-1}$</td>
<td>89.51</td>
<td>0.01</td>
<td>89.50</td>
<td>89.52</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>Grain</td>
<td>$\rho_p$</td>
<td>604 kg m$^{-3}$</td>
<td>89.53</td>
<td>4.59</td>
<td>74.62</td>
<td>104.28</td>
<td>29.66</td>
<td></td>
</tr>
<tr>
<td>Grain</td>
<td>$h_{lg}$</td>
<td>2695 kJ kg$^{-1}$</td>
<td>89.49</td>
<td>2.45</td>
<td>83.06</td>
<td>96.84</td>
<td>13.78</td>
<td></td>
</tr>
<tr>
<td>Grain</td>
<td>$c_p$</td>
<td>2.13 kJ kg$^{-1}$ K$^{-1}$</td>
<td>89.51</td>
<td>0.15</td>
<td>89.06</td>
<td>90.14</td>
<td>1.08</td>
<td></td>
</tr>
<tr>
<td>Grain</td>
<td>$a_p$</td>
<td>784 m$^2$ m$^{-3}$</td>
<td>89.51</td>
<td>0.01</td>
<td>89.50</td>
<td>89.52</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>Grain</td>
<td>$r_0$</td>
<td>0.0098 m</td>
<td>89.51</td>
<td>0.01</td>
<td>89.50</td>
<td>89.52</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>Grain</td>
<td>$e$</td>
<td>0.4</td>
<td>89.51</td>
<td>0.00</td>
<td>89.52</td>
<td>89.52</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>EMC</td>
<td>$N$</td>
<td>1.8634</td>
<td>90.45</td>
<td>2.74</td>
<td>53.22</td>
<td>106.34</td>
<td>53.12</td>
<td></td>
</tr>
<tr>
<td>EMC</td>
<td>$K$</td>
<td>8.6541 x 10$^{-5}$</td>
<td>89.50</td>
<td>0.61</td>
<td>87.70</td>
<td>91.48</td>
<td>3.78</td>
<td></td>
</tr>
<tr>
<td>EMC</td>
<td>$C$</td>
<td>49.81</td>
<td>89.54</td>
<td>0.41</td>
<td>88.40</td>
<td>91.06</td>
<td>2.66</td>
<td></td>
</tr>
<tr>
<td>Air</td>
<td>$c_a$</td>
<td>1.005 kJ kg$^{-1}$ K$^{-1}$</td>
<td>89.54</td>
<td>2.69</td>
<td>82.32</td>
<td>99.06</td>
<td>16.74</td>
<td></td>
</tr>
<tr>
<td>Air</td>
<td>$\rho_a$</td>
<td>1.2 kg m$^{-3}$</td>
<td>89.52</td>
<td>0.00</td>
<td>89.52</td>
<td>89.52</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Drying Rate</td>
<td>$k_{1b}$</td>
<td>5023</td>
<td>89.53</td>
<td>0.11</td>
<td>89.46</td>
<td>91.24</td>
<td>1.78</td>
<td></td>
</tr>
<tr>
<td>Drying Rate</td>
<td>$k_{1a}$</td>
<td>0.54</td>
<td>89.51</td>
<td>0.01</td>
<td>89.50</td>
<td>89.52</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>$c_w$</td>
<td>4.18 kJ kg$^{-1}$ K$^{-1}$</td>
<td>89.51</td>
<td>0.08</td>
<td>89.26</td>
<td>89.78</td>
<td>0.52</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>$c_v$</td>
<td>1.87 kJ kg$^{-1}$ K$^{-1}$</td>
<td>89.51</td>
<td>0.03</td>
<td>89.44</td>
<td>89.62</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td></td>
<td>89.58</td>
<td>1.93</td>
<td>53.22</td>
<td>106.34</td>
<td>53.12</td>
<td></td>
</tr>
</tbody>
</table>

The sensitivity of each parameter was evaluated based on the time to reach the point at which half the drying was complete ($t_{0.5}$) based on the average moisture content of the entire bed of grain. For this analysis, this was a moisture content of 22.55% (d.b.), which is the halfway point between the initial moisture content of 30% (d.b.) and the equilibrium moisture content of 15.1% (d.b.) based on the inlet air at 15°C and 50% relative humidity. When any of the three constants from Equation (2-2) ($K$, $N$, $C$) are varied the final equilibrium moisture content will vary, resulting in a different target. The purpose of the sensitivity analysis is to determine parameters that are critical to model prediction accuracy. The analysis suggests which variables are worthwhile to investigate adjusting at each iteration for any that vary due to temperature or moisture content (specific heats, bulk density) and have high sensitivity. Updating the parameter at each iteration should increase the accuracy of the model but also increase computation times.
The overall results of the sensitivity analysis are presented in Table 5-4. For each variable analyzed, 1000 trials were run in which all variables were held constant except the variable being tested, and $t_{0.5}$ was logged. The mean, standard deviation, and maximum and minimum values of $t_{0.5}$ were determined for each parameter and overall.

After the initial testing of 5% variation, certain parameters were further investigated (Table 5-5). Additional trials with larger variation ranges were conducted for parameters that would be expected to have a normal variation greater than 5% ($h_{\text{conv}}$, $a_p$). The specific heat of air ($c_a$) varies much less than the values taken from the initial sampling, so additional trials were completed with a standard deviation of 0.5%.

<table>
<thead>
<tr>
<th>Test Variable</th>
<th>Value</th>
<th>Mean Value</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_{\text{conv}}$</td>
<td>17.88 kJ m$^{-2}$ K$^{-1}$ h$^{-1}$</td>
<td>89.51</td>
<td>0.02</td>
<td>89.42</td>
<td>89.54</td>
<td>0.12</td>
</tr>
<tr>
<td>$a_p$</td>
<td>784 m$^2$ m$^{-3}$</td>
<td>89.50</td>
<td>0.04</td>
<td>89.12</td>
<td>89.56</td>
<td>0.44</td>
</tr>
<tr>
<td>$c_a$</td>
<td>1.005 kJ kg$^{-1}$ K$^{-1}$</td>
<td>89.52</td>
<td>0.27</td>
<td>88.76</td>
<td>90.36</td>
<td>1.60</td>
</tr>
</tbody>
</table>

### 5.2.1 Sensitivity of Air Properties

In the initial analysis with a 5% variation, the time to half dry was sensitive to the specific heat of air, but not to the air density. Based on extreme low temperature drying conditions (-10°C to 35°C) the specific heat of air will vary 0.5% (1.004 to 1.007 kJ kg$^{-1}$ K$^{-1}$) and the air density will vary 7.6% (1.15 to 1.34 kg m$^{-3}$). An additional 1000 trials were completed for specific heat of air with a standard deviation of 0.5%, in which the specific heat was between 0.99 and 1.02 kJ kg$^{-1}$ K$^{-1}$, and $t_{0.5}$ only varied by 1.60 hours. The air density varied from 0.997 kg m$^{-3}$ to 1.40 kg m$^{-3}$ over the 1000 trials without changing $t_{0.5}$ so no additional trials were necessary.
5.2.2 Sensitivity of System Properties

The airflow rate is the most sensitive parameter of the model. The drying time ranged from 76.20 hours to 105.12 hours, with lower drying times at higher air flow rates. For modelling of drying experiments, airflow rate needs to be carefully monitored. Simulations to project energy requirements of drying should investigate various airflows to find the optimal drying conditions.

The convection heat transfer coefficient had an insignificant effect on the drying time. Additional trials were completed with a random sampling with a standard deviation of 20% of the mean value, with the standard deviation of $t_{0.5}$ only increasing 0.02 hours.

5.2.3 Sensitivity of Grain Properties

Of the six grain properties in the model, only the specific heat and the dry matter bulk density had a significant impact on the drying time. Unlike the properties of air, properties of grain are subject to much more uncertainty. Typical ranges of the properties are given in Table 5-6 based on typical values from Brooker et al. (1992) and a review of modeling papers, although many grain drying papers do not report the values used in the simulation. The typical ranges are based on conditions likely to occur during low temperature drying.

The values tested for bulk density ($\rho_p$), specific heat ($c_p$), heat of vaporization ($h_{fg}$), and porosity ($\varepsilon$) covered a wider range than would be expected based on typical values. Variation in $\rho_p$ and $h_{fg}$ each resulted in a significant variation in $t_{0.5}$. Increasing the standard deviation of the specific area ($a_{sp}$) to 217 m$^2$ m$^{-3}$ (Brooker, Bakker-Arkema, & Hall, 1992) resulted in an increase in the range of $t_{0.5}$ to two hours, which is only a 2.2% variation and is not considered significant.
Table 5-6: Typical ranges of properties of corn

<table>
<thead>
<tr>
<th>Variable</th>
<th>Typical range</th>
<th>Range of values tested</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_p$</td>
<td>$784 \text{ m}^3\text{ m}^{-3}$ (217 SD)</td>
<td>669 – 911</td>
</tr>
<tr>
<td>$c_p$</td>
<td>$1.93 – 2.29 \text{ kJ kg}^{-1} \text{K}^{-1}$</td>
<td>1.75 – 2.46</td>
</tr>
<tr>
<td>$h_{tg}$</td>
<td>$2450 – 2750 \text{ kJ kg}^{-1}$</td>
<td>2270 – 3080</td>
</tr>
<tr>
<td>$\rho_t$</td>
<td>$550 – 680 \text{ kg m}^{-3}$</td>
<td>500 – 701</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>0.40 – 0.44</td>
<td>0.33 – 0.46</td>
</tr>
<tr>
<td>$r_0$</td>
<td>0.0077 – 0.0098</td>
<td>0.0084 – 0.0107</td>
</tr>
</tbody>
</table>

5.2.4 Sensitivity of EMC formula constants

The grain drying model uses the Henderson equation (2-2) to determine the EMC. The EMC is calculated based on the air temperature and relative humidity and determines the drying potential of the air. The equation contains three constants that have been determined for many different grains. Small changes to any of the values results in variation in the drying time, especially for the exponent constant ($N$). The grain moisture content (d.b.) of the overall bed of grain and at a height above the bin floor of 0.375 metres for the trials involving the EMC constants are shown in Figure 5-12, Figure 5-13, and Figure 5-14.

Figure 5-12: Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of Henderson constant $K$
Figure 5-13: Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of Henderson constant N

Figure 5-14: Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of Henderson constant C
5.2.5 Sensitivity of Drying rate constants

The drying rate constants are the empirical constants used to determine the drying rate constant in Equation (4-7). The second constant \(k_2\) has a moderate effect on the drying time for the overall bed of grain, but has a large effect on each individual layer (Figure 5-16). For simulations where each individual layer dries faster, the drying air quickly reaches a state where no additional moisture can be removed in downstream layers; when the individual layers dry slower, the drying air will not reach saturation as quickly and will continue to dry higher layers resulting in a wider drying front.

![Figure 5-15](image_url)

**Figure 5-15:** Grain moisture content (d.b.) of entire bed (left) and at height of 0.375 metres above the bin floor (right) for sensitivity test of drying rate constant \(k_1\)
5.2.6 Sensitivity Analysis Summary

The model was most sensitive to the airflow (\( G_a \)), bulk density (\( \rho_p \)), the Henderson EMC exponent (\( N \)), and the heat of vaporization (\( h_{fg} \)). Recalculating the bulk density and heat of vaporization at each iteration should be investigated to evaluate the trade-off in improved accuracy of the model versus the increase in simulation time. In the optimization of a low temperature fixed bed dryer, the airflow is a critical parameter to investigate.

5.3 Low Temperature Evaluation

5.3.1 Performance based on typical meteorological year

The grain drying model was used to evaluate the potential of low temperature drying in Ontario by assuming typical meteorological year (TMY) weather data from the Mount Forest, Ontario weather station. Simulations were run for the drying of 0.5 metres of
corn at 30% moisture content (d.b.) for 360 hours. Drying trials were investigated starting every 15 days from September 15 to December 15 of the TMY data, for ambient drying and with heating loads varying from 5 kilowatts to 25 kilowatts.

Additional simulations were run by assuming that the heating load is sufficient to provide a relative humidity of 65% and a temperature of 0°C for the drying air. While this method is useful for evaluating low temperature drying, it is not practical to implement as it would require perfect weather forecasts.

The simulations were evaluated based on the time for drying to be considered complete. Drying was considered to be complete when the standard deviation of the moisture content of the top 0.3 metres of corn dropped below 0.3%, which was used as the indication of the moisture content of the grain of bed converging. The moisture content and drying time at this point were tabulated and used to calculate the overall specific energy consumption and moisture removal rate.

The settling moisture for the various tests are shown in Figure 5-17. Natural air drying does not result in moisture below 20% for drying starting after October suggesting it is not feasible to fully dry corn harvested late in the year without supplemental heat. As the heating load is increased, the settling moisture continues to decrease with only a slight increase in specific energy consumption (Figure 5-18). The specific energy is between 3 MJ/kg and 5 MJ/kg in September and October, rising to 8 MJ/kg to 9 MJ/kg for November and above 10 MJ/kg for December.
If the heat source was a heat pump with a COP of 5, the specific energy consumption is significantly reduced (Figure 5-19). This assumes that the heat pump is able to provide the heating input required resulting in the same drying air conditions entering the grain. Based on the specific energy consumption, drying with a heat pump is practical starting
as late as December 15 in a typical year. However, the COP of the heat pump will be lower in as the ambient temperature decreases. To confirm the practicality of drying later in the year, heat pump performance must be integrated into the model.

![Graph showing specific energy consumption (MJ/kg) for TMY trials with heat pump as heat source.](image)

**Figure 5-19: Specific energy consumption (MJ/kg) for TMY trials with heat pump as heat source**

### 5.3.2 Low Temperature GHG Emissions and Cost Analysis

The greenhouse gas emissions (GHG) and operating cost of the low temperature grain drying system can be estimated based on the energy inputs shown in Table 3-5. The carbon intensity of the Ontario electricity grid is 34.5 g CO$_2$e/kWh (Table 5-7). During combustion, propane releases 181 g CO$_2$e/kWh and natural gas releases 216 g CO$_2$e/kWh (U.S. Energy Information Administration, 2019).
Table 5-7: 2018 Ontario electricity carbon intensity (Intrinsik Corp., 2016)

<table>
<thead>
<tr>
<th>Source</th>
<th>2018 Ontario Electricity Production (TWh)</th>
<th>2018 % of Total Electricity</th>
<th>Carbon Intensity (g CO2e/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear</td>
<td>90.1</td>
<td>61.0%</td>
<td>0.15</td>
</tr>
<tr>
<td>Hydro</td>
<td>36.2</td>
<td>24.5%</td>
<td>0</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>9.6</td>
<td>6.5%</td>
<td>525</td>
</tr>
<tr>
<td>Wind</td>
<td>10.7</td>
<td>7.2%</td>
<td>0.15</td>
</tr>
<tr>
<td>Biofuel</td>
<td>0.4</td>
<td>0.3%</td>
<td>70(^1)</td>
</tr>
<tr>
<td>Solar</td>
<td>0.6</td>
<td>0.4%</td>
<td>6.15</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>147.6</strong></td>
<td><strong>100%</strong></td>
<td><strong>34.5</strong></td>
</tr>
</tbody>
</table>

Table 5-8 summarizes the GHG emissions and specific fuel cost. The costs of fuels are $6.40/GJ for natural gas and $14.70/GJ for propane (Ministry of Energy, 2016) and $0.12/kWh for electricity. Low temperature drying is more expensive than high temperature drying fueled with propane or natural gas, but reduces GHG emissions by 60% to 90%. Using a heat pump with a COP of 5 as the low temperature heat source is cost competitive with propane and natural gas and reduces GHG emissions by over 90%.

Table 5-8: GHG and cost analysis of various drying scenarios

<table>
<thead>
<tr>
<th>Heating Type</th>
<th>Specific Energy Consumption (MJ/kg)</th>
<th>Carbon Intensity (g CO2e/kg)</th>
<th>Specific Fuel Cost ($/tonne)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C16</td>
<td>Resistance 5.7</td>
<td>55</td>
<td>$190</td>
</tr>
<tr>
<td>C16 (shoveled)</td>
<td>Resistance 4.5</td>
<td>43</td>
<td>$150</td>
</tr>
<tr>
<td>C17</td>
<td>Resistance 3.9</td>
<td>37</td>
<td>$130</td>
</tr>
<tr>
<td>S18</td>
<td>Resistance 5.4</td>
<td>52</td>
<td>$180</td>
</tr>
<tr>
<td>TMY (Sep/Oct)</td>
<td>Resistance 3 – 5</td>
<td>29 – 48</td>
<td>$100 – $167</td>
</tr>
<tr>
<td>TMY (Nov)</td>
<td>Heat Pump 1 – 1.5</td>
<td>10 – 14</td>
<td>$33 – $50</td>
</tr>
<tr>
<td>Typical High</td>
<td>Propane 4 – 7</td>
<td>201 – 352</td>
<td>$59 – $103</td>
</tr>
<tr>
<td>Temperature</td>
<td>Natural Gas 4 – 7</td>
<td>240 – 420</td>
<td>$26 – 45</td>
</tr>
</tbody>
</table>

\(^1\) (Weisser, 2007)
5.4 Machine Learning Model

A low temperature drying experiment that sampled inlet and outlet conditions every five minutes for two weeks would yield 4,032 datapoints that could be used to train a machine learning model, as an alternative to traditional models that are based on empirical relationships and grain properties with high uncertainty. Using the data collected in the C16, C17, and S18 trial, two different models machine learning models were tested; a linear regression model and an artificial neural network model. A unique model for each method was trained for each drying year. Trials are summarized in Table 5-9. Each dataset was split into a training set containing 80% of the samples and a testing set containing 20% of the samples.

Table 5-9: Summary of trials for training the machine learning models

<table>
<thead>
<tr>
<th>Trial</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grain</td>
<td>Corn</td>
<td>Corn</td>
<td>Soybeans</td>
</tr>
<tr>
<td>Start</td>
<td>2016-11-04</td>
<td>2017-11-25</td>
<td>2018-10-31</td>
</tr>
<tr>
<td>End</td>
<td>2016-11-21</td>
<td>2017-12-06</td>
<td>2018-11-14</td>
</tr>
<tr>
<td>Airflow</td>
<td>305 kg/min</td>
<td>228 kg/min</td>
<td>275 kg/min</td>
</tr>
<tr>
<td>Initial Moisture</td>
<td>27.9%</td>
<td>34.5%</td>
<td>27.4%</td>
</tr>
<tr>
<td>Sampling Rate</td>
<td>5 min</td>
<td>1 min</td>
<td>5 min</td>
</tr>
</tbody>
</table>

The linear regression model takes the form of Equation (5-1), where \( c_1 \) to \( c_6 \) are constants. The artificial neural network (ANN) contains two input nodes \( (T_{in}, W_{in}) \) and two output nodes \( (T_{out}, W_{out}) \). The ANN contained two hidden layers with ten nodes each. Each model was implemented in Python using Scikit-learn library (Pedregosa, et al., 2011). For each year, models were evaluated by calculating the RMSE of the model output against the measured values.

\[
T_{out} = c_1 T_{in} + c_2 R_{in} + c_3 \\
R_{out} = c_4 T_{in} + c_5 R_{in} + c_6
\]  (5-1)
5.4.1 Model Results

The output of the models for the C16 trial are shown in Figure 5-20 to Figure 5-23. The output for the C17 and S18 trial are shown in Appendix B. The regression model and ANN both appear capable of predicting the outlet conditions. The RMSE for all three trials are shown in Table 5-10. Both models accurately predicted temperature and absolute humidity in all trials with an overall RMSE of 1.42°C and 0.55 g H$_2$O/kg dry air for the linear regression model and 1.56°C and 0.58 g H$_2$O/kg dry air for the ANN. The relative humidity had the largest error of the exit air conditions. The air exiting the grain was close to saturation for the majority of the trials with little variation (Figure 5-20, Figure B-2, and Figure B-6) which does not allow for either model to determine a relationship to the input variables.

Table 5-10: RMSE for linear regression model and ANN

<table>
<thead>
<tr>
<th>Model</th>
<th>Year</th>
<th>Temperature (°C)</th>
<th>Relative Humidity (%)</th>
<th>Absolute Humidity (g H$_2$O/kg air)</th>
<th>Moisture Content (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reg.</td>
<td>C16</td>
<td>1.61</td>
<td>10.18</td>
<td>0.59</td>
<td>1.28</td>
</tr>
<tr>
<td></td>
<td>C17</td>
<td>1.80</td>
<td>2.09</td>
<td>0.74</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
<td>S18</td>
<td>0.84</td>
<td>3.02</td>
<td>0.33</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>1.42</td>
<td>5.10</td>
<td>0.55</td>
<td>0.74</td>
</tr>
<tr>
<td>ANN</td>
<td>C16</td>
<td>1.89</td>
<td>8.81</td>
<td>0.62</td>
<td>1.43</td>
</tr>
<tr>
<td></td>
<td>C17</td>
<td>1.84</td>
<td>2.03</td>
<td>0.74</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>S18</td>
<td>0.95</td>
<td>3.01</td>
<td>0.37</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>1.56</td>
<td>4.62</td>
<td>0.58</td>
<td>0.80</td>
</tr>
</tbody>
</table>
Figure 5-20: Machine Learning model predictions for C16 outlet temperature

Figure 5-21: Machine Learning model predictions for C16 outlet relative humidity
Figure 5-22: Machine Learning model predictions for C16 outlet absolute humidity

Figure 5-23: Machine Learning model predictions for C16 moisture content (d.b.)

The application of this drying model is to accurately forecast drying time and cost. As a result, the moisture content is the most important variable to accurately predict. The predicted moisture content calculated from the difference in absolute humidity between
the inlet and outlet had an RMSE of 0.74 for the linear regression model and 0.80 for the ANN compared to 0.98 for the grain drying model presented in Section 4. However, as seen in Figure 5-23 (and Figure B-4), the moisture content based on samples taken from the grain bed is higher than this calculated moisture content, suggesting an issue between moisture determination methods. Additional drying trials are required to see if this discrepancy persists because there are not enough data points to train the model with the sampled measurements.

The insets in Figure 5-20 and Figure 5-22 demonstrate a limitation of both models. When there is an increase in the inlet temperature, the measured outlet temperature increases after a delay corresponding to the time for the bed of grain to warm. However, the models predict an immediate increase in outlet temperature. To improve the accuracy of the models, the outlet conditions at the previous step should be incorporated as an input.

5.4.2 Model Performance Across Trials

The regression models are given by Equation (5-2) for C16 and Equation (5-3) for C17. Although the C16 and C17 trials both were completed with corn, the regression models varied significantly. This is due to variables that changed from year to year that are not incorporated in the models, including grain type, height of grain in the bin, and airflow.

\[
\begin{align*}
T_{out} &= 0.83T_{in} + 0.096RH_{in} - 7.22 \\
RH_{out} &= 0.47T_{in} - 0.088RH_{in} + 91.67
\end{align*}
\]

\[
\begin{align*}
T_{out} &= 0.61T_{in} + 0.013RH_{in} - 0.88 \\
RH_{out} &= 0.036T_{in} + 0.034RH_{in} + 96.85
\end{align*}
\]

The RMSE for the application of each model to the other year’s data is shown in Table 5-11. When each model is used to predict a different trial, the error increases for all parameters. To accurately predict multiple trials with one model, more trials need to
be completed before the model will be able to determine the effect of variables like grain type, grain height in the bin, and airflow.

<table>
<thead>
<tr>
<th>Model</th>
<th>Model Used</th>
<th>Predicted</th>
<th>Temperature (°C)</th>
<th>Relative Humidity (%)</th>
<th>Absolute Humidity (g H₂O/ kg air)</th>
<th>Moisture Content (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reg.</td>
<td>C17</td>
<td>C16</td>
<td>2.36</td>
<td>15.34</td>
<td>0.63</td>
<td>1.51</td>
</tr>
<tr>
<td></td>
<td>C16</td>
<td>C17</td>
<td>2.03</td>
<td>10.45</td>
<td>0.92</td>
<td>2.12</td>
</tr>
<tr>
<td>ANN</td>
<td>C17</td>
<td>C16</td>
<td>2.38</td>
<td>15.43</td>
<td>0.67</td>
<td>2.12</td>
</tr>
<tr>
<td></td>
<td>C16</td>
<td>C17</td>
<td>2.14</td>
<td>9.95</td>
<td>0.85</td>
<td>1.80</td>
</tr>
</tbody>
</table>

### 5.4.3 Model Runtime

The model performance was evaluated by the average time to complete training and testing of the model over 1000 runs, completed on a 2017 MacBook Pro running macOS Mojave. Average run times are shown in Table 5-12. The linear regression model is significantly faster, taking an average of 0.08 seconds to run compared to 2.12 seconds for the ANN. The 2017 trial was the largest dataset due to the sampling rate of 1 minute, which led to longer runtimes for both models compared to other years.

<table>
<thead>
<tr>
<th>Model</th>
<th>Year</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>2016</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>2018</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>0.010</td>
</tr>
<tr>
<td>ANN</td>
<td>2016</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td>2017</td>
<td>2.46</td>
</tr>
<tr>
<td></td>
<td>2018</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td>1.44</td>
</tr>
</tbody>
</table>

### 5.4.4 Summary

The linear regression model and artificial neural network were both able to predict outlet conditions of a fixed bed grain dryer. Both models had similar accuracy when evaluated with RMSE and were slightly better at predicting moisture content than the model based
on heat and mass transfer. The linear regression model algorithm was faster based on an average of 1000 trials. Neither model captured the time response of the bed of grain; each model immediately reflected a change in inlet conditions in the predicted outlet conditions. Additional trials are required in order to develop a single model capable of predicting all trials instead of individual models for each trial.
6 Conclusions

Low temperature grain drying with a heat pump has been shown to have the potential to save both energy and greenhouse gas emissions compared to conventional drying methods. Experiments completed during three harvest seasons with electrical resistance heaters found specific energy consumption of 3.9 MJ/kg to 5.7 MJ/kg on a prototype grain drying system. Further analysis with a numerical model suggested that a heat pump could operate at 1.0 MJ/kg to 1.5 MJ/kg based on typical meteorological year data and reduce greenhouse gas emissions by over 90% compared to high temperature drying fueled by fossil fuels.

The grain drying model was tested against three years of drying data. The RMSE of the moisture content was 0.98% which is comparable to other models that have reported RMSE. A sensitivity analysis identified the airflow and grain dry bulk density as critical parameters that should be characterized as accurately as possible in the model. The heat of vaporization of moisture within the grain and exponent term in the Henderson equation also had a significant effect.

Initial investigation into a machine learning model showed the potential to improve performance compared to a traditional mathematical model, with an RMSE of moisture content of 0.74% for the regression model and 0.80% for the ANN. One of the main benefits is that the machine learning model does not depend on many empirical values that are difficult to define. The machine learning model can handle these intrinsically.

6.1 Future Work

There are still many ideas to explore in the field of low temperature grain drying. Integrating a model of a heat pump with the grain drying model could add further accuracy to forecasting drying time and energy savings. The model could be integrated with weather forecasts to predict accurate drying times and energy consumption. With
these additions, the model could be used to optimize the design and performance of a fixed bed low temperature grain dryer.

Based on the sensitivity analysis, the performance of the model should be compared to an improved model that updates the bulk density and heat of vaporization at each iteration step. The output should be evaluated to determine if this additional complexity results in an accuracy that is worth the implementation cost.

The machine learning model could be further developed by training against outputs of the mathematical model. Performance could be investigated by training a model in real time as data is collected to forecast the remainder of the drying trial. This would allow evaluation of the ability of the machine learning model to overcome the difficulties in determining the empirical constants that the mathematical model depends on.
REFERENCES


APPENDICES

Appendix A. USB Calibration Figures

Figure A-1: USB Datalogger Calibration – Ambient with Fan

Figure A-2: USB Datalogger Calibration – Ammonium Nitrate Trial 1
Figure A-3: USB Datalogger Calibration – Ammonium Nitrate Trial 2

Figure A-4: USB Datalogger Calibration – Ammonium Sulfate Trial 1
Figure A-5: USB Datalogger Calibration – Sodium Chloride Trial 1

![Graph showing relative humidity over time for USB Datalogger Calibration - Sodium Chloride Trial 1.]

Figure A-6: USB Datalogger Calibration – Sodium Chloride Trial 2

![Graph showing relative humidity over time for USB Datalogger Calibration - Sodium Chloride Trial 2.]

108
Figure A-7: USB Datalogger Calibration – Sodium Chloride Trial 3

Figure A-8: USB Datalogger Calibration – Magnesium Chloride Trial 1
Figure A-9: USB Datalogger Calibration – Magnesium Chloride Trial 2

Figure A-10: USB Datalogger Calibration – Lithium Chloride Trial 1
Appendix B. Additional Figures for Machine Learning Model

Figure B-1: Machine Learning model predictions for C17 outlet temperature

Figure B-2: Machine Learning model predictions for C17 outlet relative humidity
Figure B-3: Machine Learning model predictions for C17 outlet absolute humidity

Figure B-4: Machine Learning model predictions for C17 moisture content (d.b.)
Figure B-5: Machine Learning model predictions for S18 outlet temperature

Figure B-6: Machine Learning model predictions for S18 outlet relative humidity
Figure B-7: Machine Learning model predictions for S18 outlet absolute humidity

Figure B-8: Machine Learning model predictions for S18 moisture content (d.b.)