Chapter 1

Introduction

1.1 Diffusion Controlled Drying

Drying is one of the basic unit operations in processing of agricultural and food products, and many other chemical processing industries. However, one of the major problems in industrial drying operations is the accurate prediction of the drying time. In a simplified approach, drying rate is represented using empirical models of explicit time-dependent functions essentially by curve fitting. It serves the purpose of prediction of the drying time within a range of operating conditions similar to those used in deriving the empirical relation. However, in case of food materials it is important to know the internal distribution of moisture as various phenomena such as local stress formation, local biological activities, or surface behavior relating to crust formation and crack formation are related to the moisture distribution within the material. The simplified models such as the drying rate characteristic curve model or simple explicit time-dependent models are not sufficient to predict the internal distribution of moisture, and, are not equipped to deal with the time-varying drying conditions such as intermittent drying. This emphasizes the relevance of drying models developed on the basis of adequate description of the transport phenomena taking place in the drying mass during drying.

There have been a number of continuum type mechanisms proposed and the associated mathematical models established for drying. These include liquid diffusion (Lewis 1921), capillary flow forwarded by Buckingham and as summarized in Fortes and Okos (1980), evaporation-condensation (Henry, 1939), dual (temperature, and water content gradient) and triple (temperature, water content and pressure gradient) driving force mechanisms by Luikov (1968), another dual driving force mechanism by Philip and De Vries as summarized in Fortes and Okos (1980), and dual phase (liquid and vapor) transfer mechanism of Krischer as summarized by Fortes and Okos (1980). Whitaker (1977) has proposed detailed transport equations to account for the macro- and micro-scale structures in biological materials. Among these, the liquid diffusion model is the simplest mathematical model that can predict the spatial distribution of (liquid) moisture content. Apparently, recent trends of drying studies would indicate that the diffusion model is being used more frequently than other mathematical models.

Successful application of the diffusion model for analysis of the drying behaviour revolves around the knowledge about the diffusion coefficient (Crank, 1990). As all the effects of different transport mechanisms are lumped into this single parameter, i.e. the diffusivity coefficient D, in general, one will observe that this apparent diffusion coefficient is strongly dependent on concentration (moisture content) and to a lesser degree on temperature. During a typical drying run, the evolution of moisture is dependent on time, and other drying conditions. Hence, instantaneous moisture diffusivity may be expressed as a function of time, product specification and drying conditions. Artificial Neural Network (ANN) has recently come in vogue and promises to be a powerful tool in modeling time dependent phenomenon. Therefore an effort has been made to use this technique for studying the time dependent drying phenomenon.

1.2 ANN Modeling

ANN is a relatively newer approach to modeling and identification of process parameters. These networks, shaped after biological neural systems, are composed of multiple interconnected non-linear processing elements. Computational capabilities of ANN result from their ability to learn, i.e., to form internal representation of the function or the process dynamics, when exposed to experimental data. Additionally, these networks are capable of approximating with high accuracy an arbitrary continuous non-linear mapping function of many variables. There is a firm theoretical basis for using ANN as a universal approximator of non-linear systems and are being applied successfully for function approximation and process dynamics modeling in the fields of chemical and bioprocess engineering (Baughman and Liu, 1995).

The advantage of developing an ANN model for diffusivity is that it establishes inherently a functional relationship of diffusivity, expressing it as a function of drying conditions and the instantaneous moisture content or the drying time. An ANN model of prediction of instantaneous diffusivity values developed on the basis of data available in data bases or generated through experimentation at different drying conditions could effectively be used for reconstructing of drying plot for diffusion controlled drying. Present work aims at comparison of the reconstructed drying curves obtained from instantaneous moisture content.

A mathematically valid approach of reconstruction of drying plots is the numerical solution of the diffusion equation with adequate initial and boundary condition. Also, the same numerical solution scheme is also used in an iterative manner to predict diffusivity values from the observed drying data, popularly known as numerical method of diffusivity estimation. The procedure involved is to have an initial assumption of the diffusivity values distributed in the space domain, and to compare the predicted mass averaged moisture values with the observed drying data. The assumed values of diffusivity are updated till the predicted drying plot approaches the observed drying plot. This method of updating of the assumed diffusivity values can be formalized to a learning algorithm for recurrent neural network (RNN), where the RNN would consist predominantly of predetermined weights as decided by the numerical discretization scheme. With suitable construction of the network, the diffusivity can be given a functional form as a parameter dependent on moisture. This work aims at the construction of a RNN model for estimation of moisture dependent diffusivity, with a systematic approach for validating the outputs.

1.3 RNN Structures for Process Modeling

The concept of RNN representation of the system of equations is extended to deep bed drying process. The deep bed drying process, when applied to food grains have primary concern on the spatial distribution of moisture, and grain temperature during drying, across the bed, instead of the internal distribution of moisture. It is evident from the nature of reported results, where results consists primarily of moisture and temperature distribution of grains, and humidity and temperature distribution of drying air across the bed. Apparently, for the prediction of mass loss from grains an equation based on lumped parameter approach is used. The lumped parameter is either in the form of the air temperature dependent drying rate constant, or bulk grain moisture and grain temperature dependent diffusivity. Through the RNN modeling of the solution of the deep bed drying equations, the rule governing the moisture loss rate may be extracted. This study will help in process-scheduling and controlling of static bed drying process as follows: the drying parameters for desired final moisture can be estimated from the measured discrepancy of moisture content at the end of the previous batch of the load. The updated drying parameters can be used to predict the drying schedule for the subsequent loads and hence can enhance the drying quality effectively. Therefore, one aim of the present work is developing the RNN architecture for estimation of drying rate parameters from static bed drying data and application of the same for static bed drying of barley.

The estimation of quantities characterizing a given process is in fact, the inverse modeling of the process. Its application to the estimation of diffusion coefficient from experimental drying data, and estimation of drying constant from deep bed drying data can be modeled as an inverse ANN problem. In the present work, an investigation is carried out on estimation of drying rate constant from static bed drying data, obtained by neural network inversion. The specific objectives of the present work are listed in the next section.

1.4 Objectives

1. To develop ANN models for prediction of moisture diffusivity of potato slices dried in the form of slabs.
2. To develop an RNN model for numerical determination of diffusivity for slab drying.
3. To apply RNN for estimation of diffusivity in potato slices dried as slab and barley dried as a static bed.
4. To reconstruct drying plots by applying ANN models of diffusivity.
5. To apply method of neural inversion for estimation of drying rate constant from deep-bed drying data.

For the fulfillment of the objectives, firstly drying experiments were carried out in the laboratory under specific drying conditions, temperature 45-74^{o}C, air velocity 0.5-1.5 (m/s), air relative humidity 0-40% and varying sample thicknesses between 3-10 mm. The drying data were analyzed and an empirical model is developed. Further, diffusivity values were estimated by the slope method. Two neural networks were developed for prediction of diffusivity with different combinations of inputs. (1) The first ANN (ANN_1) is for the prediction of diffusivity with the six inputs viz. moisture content, initial moisture content, velocity, temperature, humidity, and sample-thickness, and (2) The second ANN (ANN_2) is for the prediction of diffusivity with the six inputs as time, initial moisture content, velocity, temperature, humidity, and sample-thickness. Genetic algorithm based optimization technique is used to optimize the neural network architectures. The predicted values of ANN_2 are used to reconstruct the drying curve based on the first term of the series solution of the diffusion equation with constant diffusivity. The iterative solution scheme of determination of diffusivity is modified to develop into an RNN, to work out an updating rule for the diffusivity values. The RNN is trained with moisture versus time data, to obtain moisture dependence of diffusivity in the form of a multi-layered perceptron (MLP). Similar RNN structure was constructed for deep bed drying and the RNN is trained for determining the drying rate constants. Finally, principle of neural inversion was done to obtain the drying rate constant, and is compared with available expressions.

1.5 Organization of the Thesis

The second chapter of this Thesis summarizes recent works related to the present work. The areas highlighted include, diffusion model of drying and recent trends in diffusion studies, application of artificial neural networks in modeling of food processes, development of RNN architecture from numerical solution schemes, deep bed drying and concept and use of neural inversion in food processes.

The third chapter highlights the theoretical backgrounds of the present work. They are further developed into deriving some of the rules and solution methods in the present work. The contributory deductions of the present work include simplified method of reconstruction of drying plots from instantaneous diffusivity data, improvisation of numerical method of diffusivity determination to develop into an RNN, development of RNN architecture for estimation of drying rate constant, and the rule for implementing neural inversion in static bed drying problems.

The fourth chapter is about the methodologies used in the experimental determination of drying data, method used for analysis, model development and model validation. The results of the works carried out are discussed in the fifth chapter on Results and Discussion, and specific conclusions are enlisted in sixth chapter.