

Physics-Informed Neural Networks (PINNs) for Grain Drying Problem

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What is drying process ?

Defintion

Drying is a mass transfer process consisting of the removal of water or another solvent by evaporation from a solid, semi-solid or liquid.

Drying applications

The drying process can help lower costs of transportation and storage by removing unnecessary liquid volume in a material. It is used in :

- 1 Food science and vegetables
- 2 Industry (e.g., drying wood)
- 3 Pharmacy (e.g., drying vaccines)
- 4 Agriculture (e.g., grain drying)

Grain Drying Process !

Grain drying is the process of drying grain to prevent spoilage during storage. It can be modeled by a couple (or not) between :

- 1 The heat transfer equation
- 2 The mass transfer equation.

Numerical methods

The grain drying process is numerically solved using the following approach :

- 1 Finite difference method ;
- 2 Finite element method ;
- 3 Volume element method ;

Disadvantages

However these methods present some disadvantages :

- 1 Meshing almost impossible for complex study areas ;
- 2 Discretization too difficult for high dimensional PDEs ;
- 3 Stability study ;
- 4 Consistency study ;
- 5 ...

Towards Scientific Machine Learning (SciML)!

- 1 SciML is multidisciplinary and draws on expertise from applied and computational mathematics, computer science, and physical laws.
- 2 It is a data-driven scientific discovery method that relies on machine learning and scientific computing tools.
- 3 PINNs is one example.

Benefits

- 1 Use of a deep neural network ;
- 2 Collection of a large amount of data (Big Data) ;
- 3 Regularity of the approaching solution ;
- 4 Automatic differentiation (e.g., Backpropagation)
- 5 Free mesh

Thinking about the project !

This project relies on/involves :

- 1 agricultural research engineering (e.g., Grain drying process),
- 2 and applied mathematics problem (e.g., PDEs).

Research question

The main research question of this thesis is the following :

How can we approach the grain drying problem, together with associated storage, with scientific machine learning (SciML), in particular PINNs?



Underlying abstract grain drying process

To develop such a novel PINNs-based model for grain drying, it is necessary to have a fundamental understanding of :

- 1 Type of grain (e.g, peanut, maize, rice, soya beans, coffee) ;
- 2 Grain's geometry (e.g, cylindrical) ;
- 3 Drying method (e.g, solar drying, hot-air drying) ;
- 4 Type of storage (e.g., Deep-bed Dryer) ;
- 5 Heat and Mass transfert equations between grain and air ;
- 6 Parameters affecting drying process.

Research Objectives

The main research objectives of this thesis are listed below :

- 1 Choose of a grain which should be relevant in Africa (Modeling).
- 2 Implement PINNs for this problem.
- 3 Convergence analysis for PINNs.
- 4 Real world application

Contribution

- 1 **Motivation** : No PINNS-based grain drying
- 2 Contribution to future research in drying applications
- 3 Comprehensive theoretical and computational investigations of PINNs

Initial Research Project (Mathematical model)

Below is the system of semilinear parabolic equations to describe the grain drying process :

$$\left\{ \begin{array}{l} \rho_a C_{pa} \left(\epsilon \frac{\partial T_a}{\partial t} + V_x \frac{\partial T_a}{\partial x} \right) - \frac{\partial}{\partial x} \left(\lambda_a \frac{\partial T_a}{\partial x} \right) - h_1(T_g - T_a) - h_2(T_L - T_a) = 0 \\ \rho_g C_{pg} (1 - \epsilon) \frac{\partial T_g}{\partial t} - \frac{\partial}{\partial x} \left(\lambda_g \frac{\partial T_g}{\partial x} \right) - h_1(T_a - T_g) - h_3(T_L - T_g) \\ \quad - h_4 \alpha \left(W - \frac{M}{\Gamma(T_g)} \right) - w(T_g) = 0 \\ \epsilon \frac{\partial W}{\partial t} + V_x \frac{\partial W}{\partial x} - \frac{\partial}{\partial x} \left(D_W(T_a) \frac{\partial W}{\partial x} \right) + \alpha \left(W - \frac{M}{\Gamma(T_g)} \right) = 0, \quad 0 < x < L, \\ \frac{\partial M(x, r, t)}{\partial t} - \frac{D_M(T_g)}{r^2} \frac{\partial}{\partial r} \left(r^2 \frac{\partial M}{\partial r} \right) = 0, \quad 0 < r < R, 0 < t < t_f \end{array} \right. \quad (1)$$

Initial Research Project (Variables)

where :

- 1 T_a is the air temperature,
- 2 T_g is the grain temperature,
- 3 W is the air humidity,
- 4 M is the grain moisture content,
- 5 α is the grain surface,
- 6 h_j are heat transfer coefficients,
- 7 C_{pg} and C_{pa} are the specific heat of grain and air,
- 8 ρ_g and ρ_a are the specific mass of grain and air,
- 9 ε is the porosity,
- 10 V_x is the air velocity,
- 11 $w(T_g)$ is the biological heat,
- 12 D_W and D_M are diffusivities.

Initial Research Project (Initial conditions)

The system (1) is equipped with the following initial conditions :

$$\begin{cases} T_a(x, 0) - T_a(x) = 0, \\ T_g(x, 0) - T_g(x) = 0, \\ W(x, 0) - W(x) = 0, \\ M(x, r, 0) - M(x, r) = 0, \end{cases} \quad (2)$$

and boundary conditions :

Initial Research Project (Boundary conditions)

$$\left\{ \begin{array}{l} T_a(0, t) - T_0 = 0, \\ \lambda_a \frac{\partial T_a}{\partial x} - k(T_L - T_a(L, t)) = 0, \\ -\lambda_g \frac{\partial T_g}{\partial x} - k(T_0 - T_g(0, t)) = 0, \\ \lambda_g \frac{\partial T_g}{\partial x} - k(T_L - T_g(L, t)) = 0, \\ W(0, t) - W(T_0) = 0, \\ D_W(T_a) \frac{\partial W}{\partial x} - \nu(W(T_L) - W(L, t)) = 0, \\ r^2 \frac{\partial M}{\partial r} = 0, \\ D_M(T_g) R^2 \frac{\partial M}{\partial r} - \mu \left(W - \frac{M(x, R, t)}{\Gamma(T_g)} \right) = 0, \end{array} \right. \quad (3)$$

Problem Description

Problem :

We consider the Boundary Initial Value Problem (BIVP) : Find the unknown function $u = [T_a, T_g, W, M]$ such that the systems (1) – (3) are satisfied.

The main aim is to approximate the classical solution u of this problem with PINNs.

PINNs approach (step1)

Residuals functions

Before we proceed, let us introduce the residuals R_{pde} , R_{ini} and R_{bou} by :

$$\begin{cases} R_{pde}[u](x, r, t) = D_1(x, t) + D_2(x, r, t) + D_3(x, t) + D_4(x, t) \\ R_{ini}[u](x, r, 0) = I_1(x, 0) + I_2(x, r, 0) + I_3(x, 0) + I_4(x, 0) \\ R_{bou}[u](x, r, t) = [B_1 + B_2](x, t) + [B_3 + B_4](x, t) \\ \quad \quad \quad + [B_5 + B_6](x, t) + [B_7 + B_8](x, r, t) \end{cases} \quad (4)$$

PINNs approach (step2)

where

- 1 $\{D_i\}$ represents the four equations in order in the system (1),
- 2 $\{I_i\}$ represents the four equations in order in the system (2),
- 3 and $\{B_i\}$ represents the eight equations in order in the system (3).

Using these residuals, one measures how well a function u satisfies our BIVP. Note that the exact solution u_e will satisfy :

$$R_{pde}[u_e] = R_{ini}[u_e] = R_{bou}[u_e] = 0. \quad (5)$$

PINNs approach (step3)

Our goal is to approximate the solution u of our BIVP with deep neural networks u_θ , where θ represents the neural network's parameters. To this end, we have the following minimization problem :

$$\min_{\theta} L(\theta) = \|R_{pde}[u_\theta](x, r, t)\|_2^2 + \|R_{ini}[u_\theta](x, r, 0)\|_2^2 + \|R_{bou}[u_\theta](x, r, t)\|_2^2 \quad (6)$$

This formula (6) is called the generalization error. It involves integrals (due to the L_2 -norm) and can therefore not be directly minimized in practice.

PINNs approach (step4)

Since the training is done on these sampling points $\{\{(x_s, r_s, t_s)\}_{i=1}^{N_s}\}$ for $s = i, j, k$, equation (6) is replaced by the empirical loss function (e.g., training error) :

$$\begin{aligned} \min_{\theta} L(\theta) = & \sum_{i=1}^{N_i} |R_{pde}[u_{\theta}](x_i, r_i, t_i)|^2 + \sum_{j=1}^{N_j} |R_{ini}[u_{\theta}](x_j, r_j, 0)|^2 \\ & + \sum_{k=1}^{N_k} |R_{bou}[u_{\theta}](x_k, r_k, t_k)|^2 \quad (7) \end{aligned}$$

Schematic diagram of PINNs

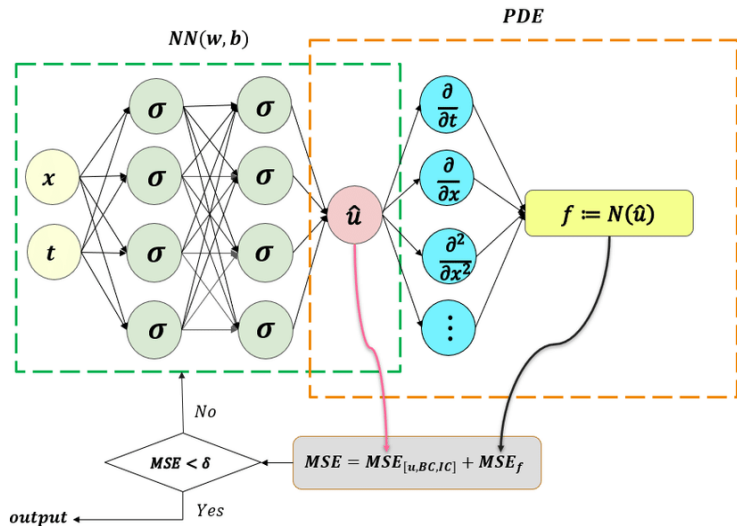


Figure:

Expected results

- 1 A model that can be interpreted with a level of confidence.
- 2 Obtain certifiable methods i.e., we want to be able to stick a label on the solution saying that it is going to be accurate for all reasonable inputs.
- 3 Good agreement with the experiment.

Further works

- 1 Sampling methods (e.g., numerical integration)
- 2 Approximation theory
- 3 Data-driven Loss function
- 4 Optimisation (by using ML tools)

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End

Thanks for listening!

