Artificial Intelligence for Visualization, Processing and Predict of Temperature and Fluid Flow Modeling

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Abstract: In this paper we propose python code written anaconda terminal run Windows OS usage for visualization and processing of big data having 4 million data points of size 36.2 MB file vector $\vec{x}$ of $4m\ by\ 4m\ by\ 4m$ uniform meshed 100 points and solver opensource software OpenFOAM to calculate temperature profile of steel whose thermal diffusivity is $14.76 \times 10^{-6}\ m^2/s$ by Laplacian partial differential equations. The software in use in AISoft visualization and processing commercial software (Sidharth and Vishal, 2022). Here we also use data driven model for predict match experiments of turbulent flow and low temperature measurements on copper core arrangements and silicon, respectively. The software in use is AISoft Windows 800 commercial software (Luke, Vishal and Jay, 2021). To compile the model train_number.csv vector measurements are uploaded in the software. The model uses RNN-LSTM method and Adam optimization minimization to calculate the learning parameters. We predict the new locations and states vector measurements. The model shows 3-order speed up in computational time compared to unclear traditional turbulence models and conduction additions to the model. Also the predicted solution shows 98% accuracy. Artificial Intelligence for big data, visualization, processing, predict models is in use for AI Agents, AI ethics, cinemas, art, electronics, calendar planner and engineering applications.

1 INTRODUCTION

Data Driven turbulent flow simulations has progressed the science ecology to solve for fluids in states of incompressible and compressible regimes (Sarthak, Shriram, Guru, Shania, Huzaifa, Naresh, Nilotpal and Vishal, 2021). Also the solutions are used in fluid machine systems turbines, blowers, fans, propellers, conditioners, fans electronics, paper mills grinders, rollers (Ananyananda, Deepak and Vishal, 2020). The data has large number of mesh points to solve probe and pixel flow measurements using CFD, FVM, FEM due to the tedious algorithms (Robert and Parviz, 1984). Further these traditional algorithms in evolution needed computer clusters, cloud computing and optimization models. The machine learning models enhancements uses physics and physics less methods to solve fluid flows to fine grid visualize (Maziar, Paris and George, 2019). Furthermore data driven methods are also in use in history, geography land maps, art, cinemas, ethics to thermal management systems and energy that pushed towards artificial intelligence, math+machine learning for better visualize, analyse and predict match the experiment measurements at user locations and time (Asad, Gayane, Bernard, Jos and Stéphanie, 2023).

In this paper, we show simulation of heat conduction of steel to obtain the temperature profile. The temperature profile is processed in fine grid resolution to enhance the visualization. Next we show Artificial Intelligence models to process train temperature measurements of silicon (James and Ben, 1961). Also Artificial Intelligence models are used to predict match temperaure measurements of silicon. The objective of using Artificial Intelligence models is to match experiments compared to unclear traditional conduction additions to model silicon at low temperatures. Next we show Artificial Intelligence models to process train turbulent flow pixel measurements of copper core arrangements (Erwin and Kermal, 2022). Also Artificial Intelligence models are used to predict match turbulent flow pixel measurements of copper core arrangements. We use Artificial Intelligence models

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to match experiments compared to unclear traditional turbulence models.

Further our Artificial Intelligence models can find applications as AI Agents programs in temperature sensor devices for room temperature measurements and also learn from the temperature data our AI visualization models also incorporated in the same devices can process the data to perceive the temperature visualization HD sensor quality. Furthermore our AI models can also find applications for these agents to model thermal convection distribution inside video games, and also simulatenously monitor temperature readings in video game play stations, amusement parks etc.

2 MATHEMATICAL MODELING

1. Heat Conduction of Steel

Steel cube of 3D geometry of 4 m× 4 m × 4 m of fine resolution grid points of (100, 100, 100) in (x, y, z) directions is meshed using blockMesh to create the polyMesh file in OpenFoam software (Henry and Hrvoje, 2005). The numerical heat conduction simulation is performed using laplacianFoam compiler in OpenFoam. Further the time step used in the simulation is 0.5 seconds. The results reported here are ensured to be independent of the grid size. The temperature output file for 1 million grid points is stored for every 180 seconds. The simulation is performed for 1800 seconds. Central differencing scheme of finite volume method is used to solve the three dimensional heat conduction partial differential equations (as given by Eq. (1)) and Euler model is used to solve the time derivative.

$$\frac{\partial \mathbf{T}}{\partial \mathbf{t}} = \boldsymbol{\alpha}\left[\frac{\partial^2 \mathbf{T}}{\partial \mathbf{x}^2} + \frac{\partial^2 \mathbf{T}}{\partial \mathbf{y}^2} + \frac{\partial^2 \mathbf{T}}{\partial \mathbf{z}^2}\right] \quad (1)$$

Here α is the thermal diffusivity of steel given by Eq. (2) and is assumed $14.76176 \times 10^{-6}\ m^2/s$.

$$\alpha = \frac{k}{\rho c_p} \quad (2)$$

where k = thermal conductivity of steel 54 W/mK, 2001) , ρ = mass density of steel 7850 kg/m^3, c_p = specific heat capacity of steel 466 J/kgK. We performed two simulations with different boundary conditions. The boundary conditions for two jobs are given below.

Job 1:

$$\begin{aligned} &T_{leftface} = 293\ K; T_{rightface} = 393\ K; \\ &T_{topface} = 323\ K; T_{bottomface} = 353\ K; \\ &\boldsymbol{T_{frontface} = zero\ gradient;\ T_{backface}} \\ &\qquad \boldsymbol{= zero\ gradient} \end{aligned} \quad (3)$$

Job 2:

$$\begin{aligned} &T_{leftface} = 293\ K; T_{rightface} = 313\ K; \\ &T_{topface} = 303\ K; T_{bottomface} = 298\ K; \\ &T_{frontface} = zero\ gradient;\ T_{backface} \\ &\qquad = zero\ gradient \end{aligned} \quad (4)$$

The CFD simulation is performed using high performance computing facility, Aqua cluster at IIT Madras, Chennai, India. The Aqua cluster details are given below.

Total Compute Power:
11680 Cores, 30 GPU Accelerators
734 TFlops Rmax (1,106 TFlops Rpeak)

System Performance:
CPU – 587 TFlops Rmax (896 Tlops Rpeak)
GPU – 147 TFlops Rmax (210 TFlops Rpeak)

In this paper, the simulation is carried out using Linux OS in the Aqua cluster. 1 CPU node is used for simulation and data generation. The CPU node details of the Aqua cluster is given below.

CPU Nodes:
The CPU nodes are implemented in a HPE Apollo 2000 Gen10 based solution (2U Chassis) with HPE Apollo XL170rGen10 Servers. Each node is configured with:

Dual Intel Xeon Gold 6248 20-core, 2.5 GHz processors 192GB/node

2 TB SATA disk

Single port Mellanox HDR100 HCA

The temperature profile OpenFoam result is converted to csv file using python code written anaconda terminal run Windows OS compiler. The temperature profile has 4 million data points of size 36.2 MB. The visualization of the processed data is carried out using python language import of Mayavi compatible with anaconda terminal run (Vishal and Lindsay, 2020). The visualization and processing of data is carried out using HP Laptop Windows OS. The CPU node details of the HP Laptop is Processor 11th Gen Intel(R) Core (TM) i3-1115G4 @ 3.00 GHz, 290 Mhz, 2 Core(s), 4 Logical Processor(s); 8 GB RAM.

2. Predict Temperature Measurements of Silicon

In this paper we show Artificial Intelligence models to compile and predict low temperature measurements of silicon. Here Distributed Artificial

Neural Network (DANN) algorithm is used. The details of the DANN model is given below.

Distributed Artificial Neural Network (DANN)
DANN is data driven algorithm whose input is vector measurements. Eq. (5) shows the input is given for the entire location and states and the DANN compiler model Eq (6) shows the learning parameters and Eq (7) shows the mean square loss minimization of the learning parameters. Adam optimization (Yinhao, Nicholas, Phaedon-Stelios and Paris, 2019) is used to minimize the mean-squared loss. The compiler learning parameters are used to predict for new locations and states vector measurements. The schematic of DANN algorithm is shown in Fig. 1. The dense layer is input vector measurements and the dropout layer is the DANN algorithm for train the learning parameters and predict the new locations and states vector measurements. The algorithm ensures that the data input information doesn't transmit within each input as the weights are calculated for each scalar independent of neighbouring data points.

$$DANN = \forall \left\{ \begin{matrix} 0 \quad if\ x \leq 0 \\ \oint_{\Omega} \int_{j=1}^{m} \left(h_{j_i} + b_{2_i}\right) dj d\Omega_i \ \ if\ x > 0 \end{matrix} \right\} \tag{5}$$

$$h_j = \forall \left(W_{1_i} \cdot h_{j-1_i} + W_{2_i} \cdot x_{j-1_i} + b_{1_i}\right) \tag{6}$$

$$MSE_i = \frac{1}{m} \sum_{n=1}^{m} \left| T_{output_i} - T_{Act_i} \right|^2 \tag{7}$$

where i is a spatial coordinate, x is the input data at each coordinate, h is the hidden cell state, W_{1_i}, b_{1_i} and W_{2_i} are the weight and bias matrices for hidden-hidden and input-hidden connections. $\oint_{\Omega}$ is the integral over the engineering geometry of interest, j is the training sample and m is the total number of training samples. Further, x_i is called features. The boundary condition for each grid point i, for sample j, is denoted as b_{2_i}.

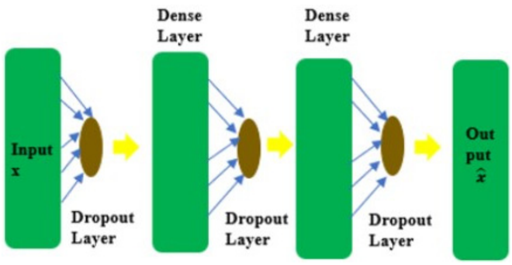


Figure 1: Schematics of DANN Algorithm.

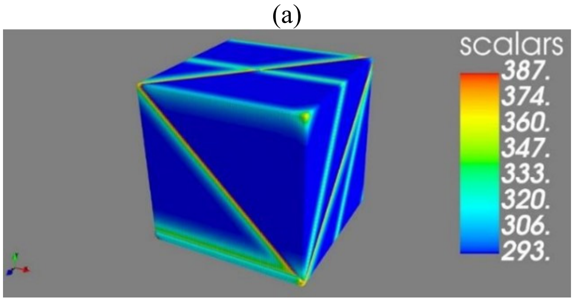
The AI model is python code written anaconda terminal run in Windows OS. The simulations are carried out using HP laptop Windows OS.

3. *Predict Flow Measurements of Copper Core Arrangements*
In this paper we show Artificial Intelligence models to compile and predict flow measurements of copper core arrangements. Here DANN algorithm is used and the details are given earlier.

3 RESULTS

The heat conduction simulation of steel for job 1 at 1440 seconds and 1800 seconds showed convergence of the temperature with difference of 1 K for each mesh points. Similar results of convergence were also ensured for job 2. Fig. 2 (a) shows visualization of steel 4 m× 4 m × 4 m using AISoft visualization and processing commercial software. Fig. 2(b) shows the temperature profile at 1800 seconds for job 1 boundary condition Eq. (3). The scalars in the figure is Temperature (K). Fig. 3 shows the temperature profile at 1800 seconds for job 2 boundary condition Eq. (4). The scalars in the figure is Temperature (K).

(a)



(b)

Figure 2: (a) Visualization of steel 4 m × 4 m × 4 m using AISoft visualization and processing commercial software (b) Temperature profile at 1800 seconds for job 1 boundary condition Eq. (3). The scalars in the figure is Temperature (K).

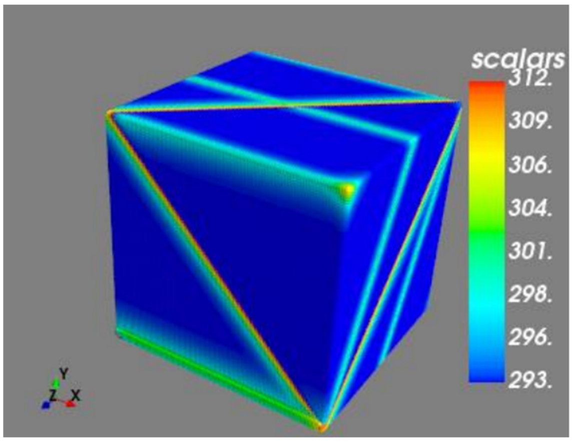


Figure 3: Temperature profile at 1800 seconds for job 2 boundary condition Eq. (4). The scalars in the figure is Temperature (K).

Data driven AI simulation using DANN algorithm to predict low temperature of silicon (see Fig. 4). We use epochs of 200. Also the mean square loss obtained is 10^{-6}. Also, the maximum error is 1% compared to experiments. To compile the model train_nunmber.csv vector measurements are uploaded in the AISoft software (Vishal and Lindsay, 2020).

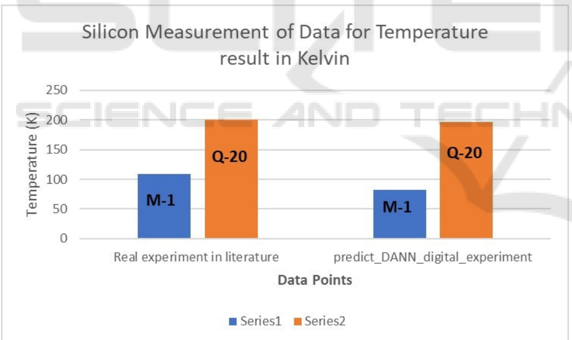
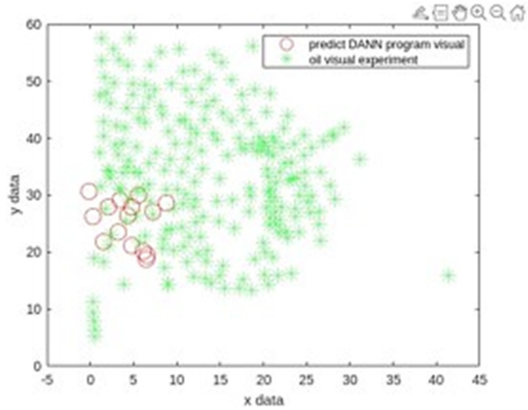
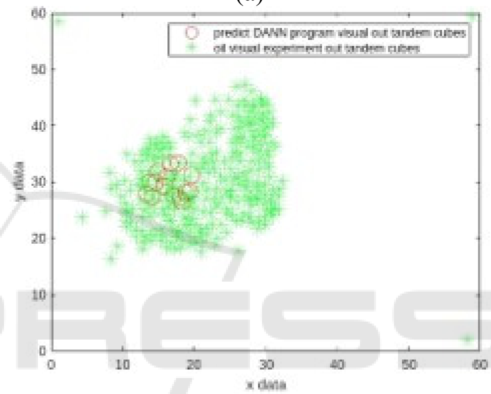


Figure 4: Comparison of temperature between DANN algorithm and silicon experiments (James and Ben, 1961).

Data driven AI simulation using DANN algorithm to predict flow measurements of copper core arrangements. Fig. 5.(a) shows the comparison of flow measurements of in-line arrangements of copper core between data driven model and experiments (Erwin and Kermal, 2022). Fig. 5(b) shows the comparison of flow measurements of staggered arrangements of copper core between data driven model and experiments (Erwin and Kermal, 2022). We use epochs of 200. Also the mean square loss obtained is 10^{-4} . Also, the maximum error is 2% compared to experiments. To compile the model flow_data.csv vector measurements are uploaded in the AISoft software.



(a)



(b)

Figure 5: Comparison of flow measurements of (a) in-line arrangements of copper core (b) staggered arrangements between DANN algorithm and experiments (Erwin and Kermal, 2022).

4 CONCLUSIONS

In this paper we propose python code written anaconda terminal run Windows OS for visualization, processing of 4 million vector measurements of temperature of steel of geometry 4m×4m×4m. The software in use is AISoft visualization and processing commercial software. Here we also use data driven models to predict match experiments of turbulent flow of copper core arrangements and temperatures of silicon. The software in use is AISoft Windows 800 commercial software. We use RNN-LSTM model and Adam optimization minimization to obtain the learning parameters. To compile the model Train_data.csv vector measurements are uploaded in the software. The predict results shows 3-order speed up in computational time and 98% accuracy compared to unclear traditional turbulence models and conduction additions to model silicon at low temperatures. Further our Artificial Intelligence models and AI visualization models can find applications as AI Agents programs in temperature sensor devices to perceive the temperature visualization HD sensor quality and also find applications for these agents to model thermal convection distribution inside video games, and also simulatenously monitor temperature readings in video game play stations, amusement parks etc

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REFERENCES

Sarthak, S., Shriram, E., Guru, V., Shania, M., Huzaifa, M. U., Naresh, K., Nilotpal, C., Vishal, N. (2021). Product Design of Cartoon Characters for Software Feature Film, American Journal of Software Engineering and Applications, 10, 2, 36-38.

Luke, D., Vishal, N., Jay, P. G. (2021). Artificial Intelligence Application in Combustion Modeling, AIAA Scitech 2021 Forum, 0928.

Sidharth, T., Vishal, N. (2022). Convolutional Neural Networks for Heat Conduction, Case Studies in Thermal Engineering, 38, 1-10.

Vishal, N., Lindsay, A. (2020). https://aicartoon.today - Copyright © - All Rights Reserved, by GoDaddy.

Robert, S. R., Parviz, M. (1984). Numerical simulation of turbulent flows, Annual Review of Fluid Mechanics, 16, 99-137.

Maziar, R., Paris, P., George, E. K. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, Journal of Computational Physics, 378, 686-707.

Asad, A., Gayane, S., Bernard, P. V., Jos, V. H., Stéphanie, M. v. d. B. (2023). Students feedback analysis model using deep-learning based method and linguistic knowledge for intelligent educational systems, Soft computing 27, 14073-14094.

Ananyananda, D., Deepak, S., Vishal, N. (2020). Deep learning for engineering problems, Bull. Am. Phys. Soc., 65.

Yinhao, Z., Nicholas, Z., Phaedon-Stelios, K., Paris, P. (2019). Physics-constrained deep learning for high-dimensional surrogate modeling and uncertainty quantification without labeled data, Journal of Computational Physics, 394, 56-81.

James, C. T., Ben, A. Y. (1961). Thermal conductivity of silicon at low temperatures, Journal of Physics and Chemistry of Solids, 20, 1–2, 146-149.

Erwin, R. M., Kermal, H. (2022). Experimental study of the convective heat transfer from in-line and staggered configurations of two wall-mounted cubes, International Journal of Heat and Mass Transfer, 45, 3, 465-482.

Henry, W., Hrvoje, J. (2005). https://www.openfoam.com/ Copyright ©.