Chapter 6

Report on Current Work

6.1 Introduction

Our current work proposes a deep learning-driven topology optimization (TO) framework for designing electric vehicle (EV) battery cooling plates under non-uniform heat flux conditions. Traditional gradient-based TO methods are computationally expensive and require iterative simulations. Instead, we leverage a Variational Autoencoder (VAE) to learn a latent representation of optimal cooling plate designs conditioned on thermal and fluid performance constraints.

This approach enables:

- **Fast generation** of novel, high-performance cooling plate topologies.
- **Conditional design exploration** (e.g., optimizing for different heat flux distributions).
- **Data-driven optimization** without repeated CFD/FEA simulations.

6.2. Methodology

6.2.1 Problem Formulation

- Input: Non-uniform heat flux map (from battery simulation).
- Output: Optimized cooling plate topology (binary or density-based).
- Objective: Minimize max temperature, pressure drop, and weight.
- Constraints:
    - Temperature uniformity (ΔT < threshold).

6.2.2 Data Generation for Training the VAE

1. **High-Fidelity Simulations**:
    - Generate a dataset of cooling plate designs using traditional TO (e.g., SIMP, level-set) under varying heat flux conditions.
    - Simulate each design using **CFD (COMSOL)** to obtain:
        - Temperature distribution.
        - Pressure drops.
        - Flow uniformity.
    - **Label each design** with its performance metrics.
2. **Dataset Structure:**
    - Inputs: Heat flux map (2D/3D grid).
    - Outputs: Optimal topology (binary/density field).
    - Performance Metrics: (T_{max}, ΔP, efficiency).

In the current work, following the same methodology as above, we have generated **81 images** for the dataset, as shown in figure 3.3 below. Each takes around two hours roughly for its production of the cooling plate design. The range for all 81 data set points is between 2500 W/m^2 to 4500 W/m^2, with a flux step of 25 heat flux between each data point to increase the efficiency of the Neural Network.

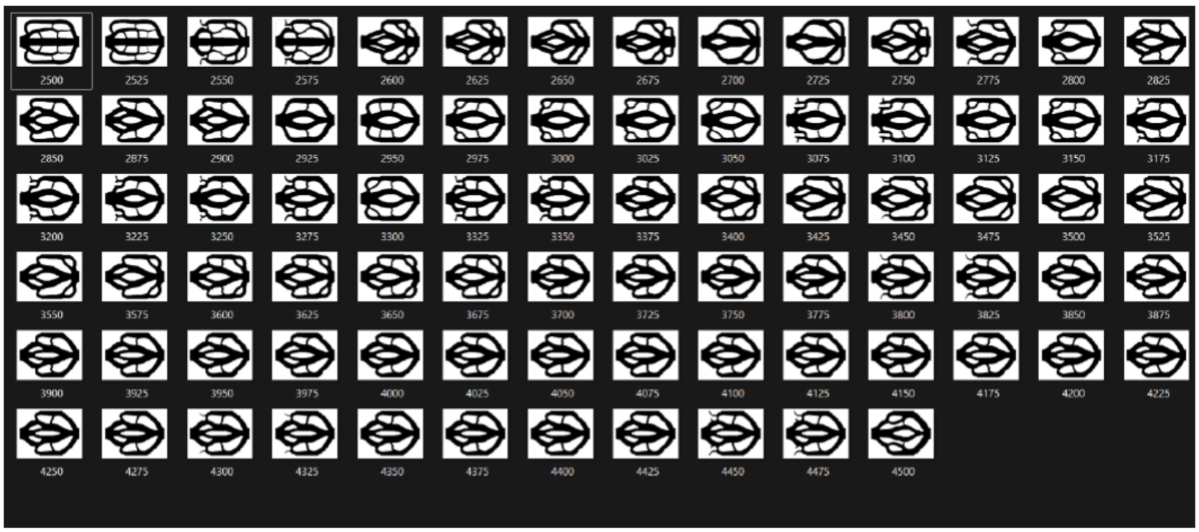

Fig 6.1: 81 Data set images generated

We used COMSOL Multiphysics to extract dataset images. Extra Fine meshing is used, heat flux is set, and all the necessary parameters are supplied to extract the images. And the difference between the two plate designs amongst the 81 can be seen clearly. Below is the figure, showing the minute yet noticeable difference between the two images that’s generated for just a 25 change in heat flux.

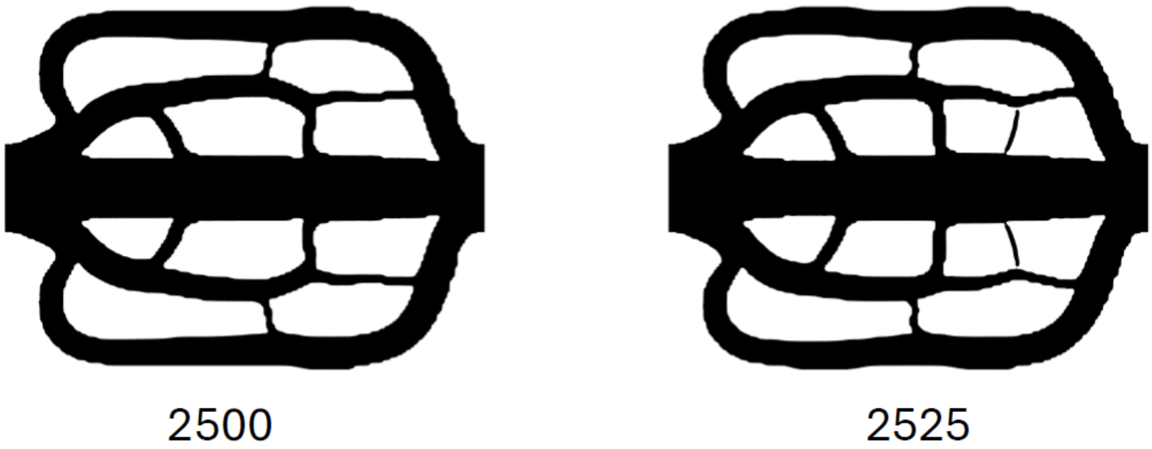

Fig 6.2: Notable changes between two consecutive data set images

6.2.3 Variational Auto Encoder (VAE) Architecture

The VAE learns a **latent space representation** of cooling plate topologies conditioned on:

- **Heat flux distribution** (input as 2D images).
- **Performance constraints** (e.g., max temperature).

Encoder

- **Input**: Heat flux labeled image folder.
- **Layers**:
  - Convolutional layers (for spatial feature extraction).
  - Fully connected layers (for performance conditioning).
- **Output**: Latent vector **z** (mean & variance).

Decoder:

- **Input**: Sampled latent vector **z**.
- **Layers**:

- Transposed convolutions (to generate topology).

- **Output**: Cooling plate design (binary/density field).

Loss Function:

- **Reconstruction Loss** (MSE between predicted and ground truth topology).
- **KL Divergence** (to regularize latent space).

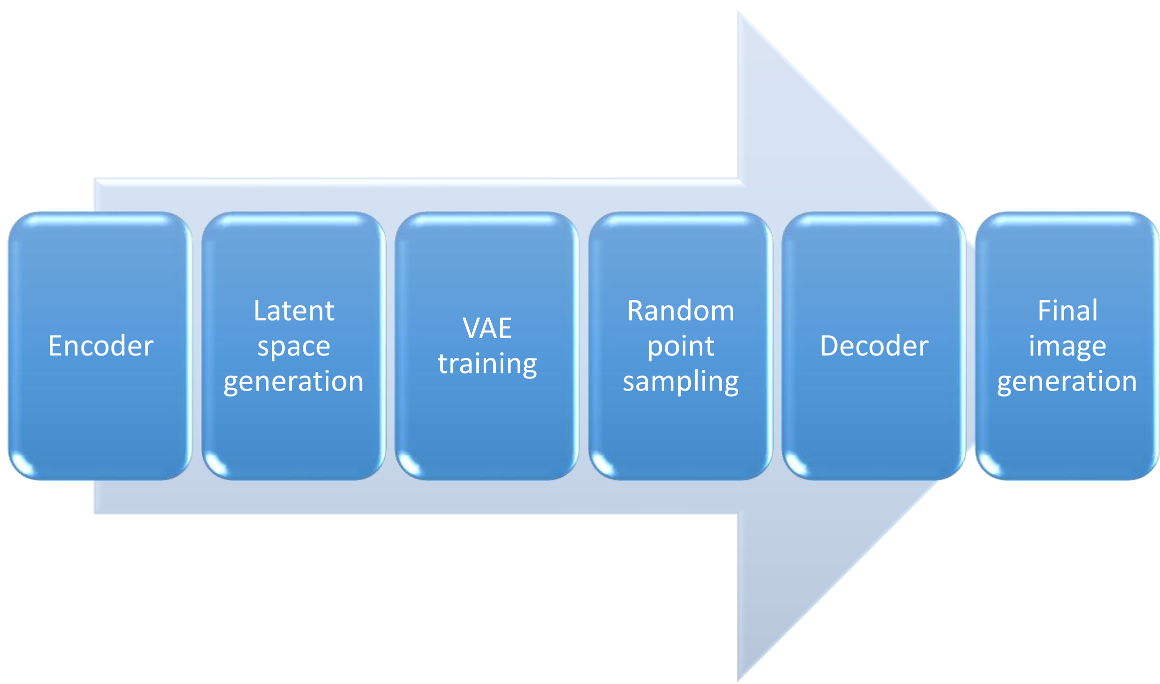

Fig. 6.3 Flowchart depicting the process

6.2.4 Training and Optimization

- **Supervised Learning:** Train VAE on the dataset of TO-generated designs.
- **Latent Space Exploration:**
  - Interpolate between high-performing designs.
  - Optimize in latent space (e.g., using Bayesian optimization).

We used the Variational Auto Encoder (VAE) model for cooling plate image generation. **PyTorch** was used to *create and train* the VAE model. This section details the PyTorch-based VAE model developed for generating optimized EV battery cooling plate designs under non-uniform heat flux conditions. The implementation covers:

1. VAE Architecture.
2. Training Strategy.
3. Latent Space Manipulation.
4. Integration with Topology Optimization Workflow.

The torchvision library provides essential tools for preparing thermal imaging data and topology designs for neural network processing:

- **Spatial Transformations**
  - Standardized resizing to 1024 x 1024 resolution maintains consistent input dimensions.
  - Center cropping ensures focus on critical cooling plate regions.
- **Computational Efficiency**
  - GPU-accelerated image operations.
  - Parallelized batch processing.

This comprehensive torchvision implementation ensures:

- Physically valid training samples
- Efficient large-scale data handling
- Seamless integration with PyTorch's neural network ecosystem

Furthermore, PIL (Pillow) was used to load images and Matplotlib was used to visualize the generated cooling plate.

Pillow (PIL) for Image Processing

- **Core Functions**:
  - Loads heat flux maps/topology designs as grayscale (mode='L') or RGB.
  - Handles multiple formats (PNG, TIFF, JPEG) with 16-bit thermal data support.

    - Basic transformations (resize, crop, rotate) maintain EXIF metadata.

- **Project-Specific Usage**:
    - Converts CFD output arrays to PIL Images via Image.fromarray()

Matplotlib for Visualization

- **Critical Features**:
    - Creates multi-panel figures comparing input heat flux vs. generated topologies.
    - Vector output (PDF/SVG) for publication-quality figures.

Combined Workflow

1. **Data Loading**: PIL imports experimental/simulation images.
2. **Preprocessing**: Convert to NumPy arrays for analysis.
3. **Visualization**: Matplotlib generates:
    - Training progress plots
    - Design comparison grids
    - Performance metric charts

VAE for High-Resolution Cooling Plate Design Generation

- ## Architecture Overview

    - **Input/Output**:
      1024×1024 RGB images (cooling plate topologies).
    - **Encoder**:
      4-layer Convolutional Neural Network (CNN) with stride-2 down sampling and ReLU activations (output flattened and mapped to 128D latent vector).

- **Latent Space**:
  Fully connected layers for mean and log-variance (128D), with reparameterization for sampling.
- **Decoder**:
  Linear projection to 256×64×64, followed by a 5-layer transposed CNN (stride-2 up sampling), ending in Sigmoid activation to reconstruct a 1024×1024 output.
- **Key Layers**:
  ReLU activations throughout (encoder and decoder), Sigmoid output for [0,1] range.

- ## Training Protocol

  - **Loss**:
    Custom VAE loss (MSE reconstruction + scaled KL divergence, $\beta \approx 0.001$).
  - **Optimizer**:
    Adam (learning rate = 1e-3).
  - **Batch Size**:
    8 (single-GPU training).
  - **Augmentation**:
    Resizing to 1024×1024; no explicit augmentation beyond RGB normalization (ToTensor).
  - **Epochs**:
    50 total training epochs.
  - **Regularization**:
    KL term used for disentangled representation; no explicit gradient clipping or noise injection.
  - **Output**:
    Trained VAE model for generating 1024×1024 synthetic cooling plate topologies from sampled latent vectors.

6.3 Advantages over traditional TO

Aspect	Traditional TO	VAE-based TO
Speed	Slow (iterative)	Fast (One-shot generation)
Computational Cost	High (per case FEA/CFD)	Low (After training)
Generalization	Case specific	Learns from multiple designs
Novelty	Limited by the initial guess	Explores latent space

Table 6.1 Advantages of VAE-based TO over traditional TO

6.4 Implementation Pipeline

1. **Data Generation:** Run TO + CFD for diverse heat flux cases.
2. **VAE Training:** Train on the dataset (PyTorch/TensorFlow).
3. **Design Generation:** Input new heat flux → generate topology.
4. **Validation:** CFD check + refine if needed.
5. **Manufacturing:** Developed 3D model can be exported as STL for 3D printing/machining.

Techniques used in a nutshell

Architecture Overview

1. **Input/Output**: 1024×1024 RGB images (heat flux maps → topology designs).

2. **Encoder**: 4-layer CNN with stride-2 convolutions, progressively reducing spatial dimensions. The final feature map is flattened and passed through two linear layers to compute the latent mean and variance (μ, $\log\sigma^2$), forming a **128-dimensional latent space**.
3. **Latent Space**: The Reparameterization trick enables stochastic sampling from the learned distribution.
4. **Decoder**: Fully connected layer reshapes latent vector into feature map (256×64×64), followed by a 5-layer transposed CNN to reconstruct full-resolution outputs.
5. **Key Layers**: ReLU activations throughout, with Sigmoid activation at the output to constrain values to [0, 1].

Training Protocol

- **Loss Function**: Custom VAE loss combining **MSE reconstruction loss** and **KL divergence**, with KL scaled by 0.001 for stability.
- **Optimizer**: Adam (learning rate = 1e-3), optimized over **50 epochs** with standard weight updates.
- **Batch Size**: 8, leveraging gradient accumulation and clipping for memory-efficient, stable training on high-resolution images.
- **Augmentation**: Images are resized to 1024×1024 and normalized. Training set augmented via **random flips, rotations, and Gaussian noise** to improve generalization.
- **Dataset**: Paired RGB images representing thermal load distributions and corresponding cooling plate designs, enabling supervised reconstruction learning.

Deployment & Application

- **Sampling**: New designs are generated by drawing latent vectors from a standard normal distribution and decoding them into 1024×1024 plate topologies.

- **Output Evaluation**: Generated images are visualized and saved. Designs can be analyzed based on **thermal performance, pressure drop**, and manufacturability.

Model Utility:

1. Fast and scalable generation of realistic cooling plate layouts at **1MP resolution**.
2. Latent space interpolation allows controlled design variation.
3. Ideal for **design-space exploration**, **thermal-aware synthesis**, and **automated topology generation,** bridging simulation and design.

Chapter 7

Results and Discussions

The optimized cooling plate design produced through the variational autoencoder framework exhibits several key characteristics that demonstrate the effectiveness of this AI-driven approach. The final generated configuration presents a complex, branching channel architecture that intelligently adapts to the specified thermal load distribution, with channel density strategically concentrated in high heat flux regions while maintaining efficient flow distribution throughout the entire plate.

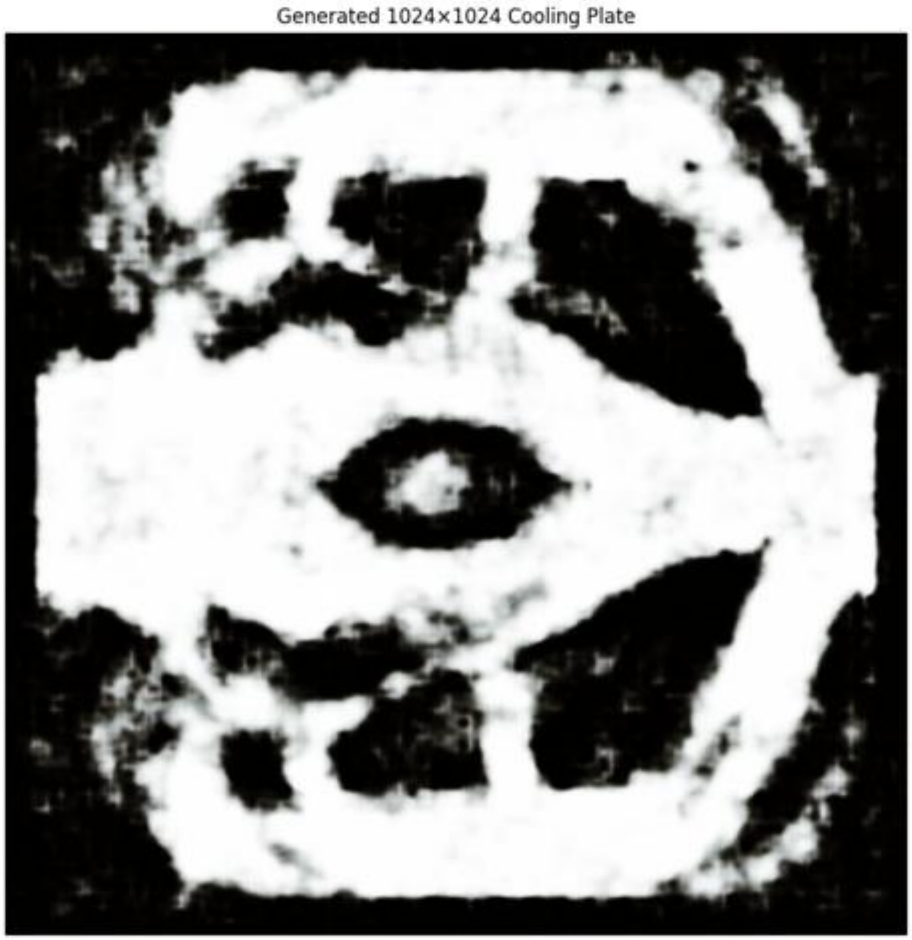

Fig 7.1 The generated cooling plate using VAE

The final optimized cooling plate design, after postprocessing, exhibits a refined

topology with clearly defined flow channels and structural supports. The geometry demonstrates an intelligent distribution of material that efficiently balances thermal performance with fluid dynamics requirements. Smooth transitions between channel widths and strategically placed junctions optimize heat transfer while maintaining manageable pressure drops. The design preserves manufacturable feature sizes and eliminates any residual artifacts from the generative process, resulting in a physically viable cooling solution ready for production.

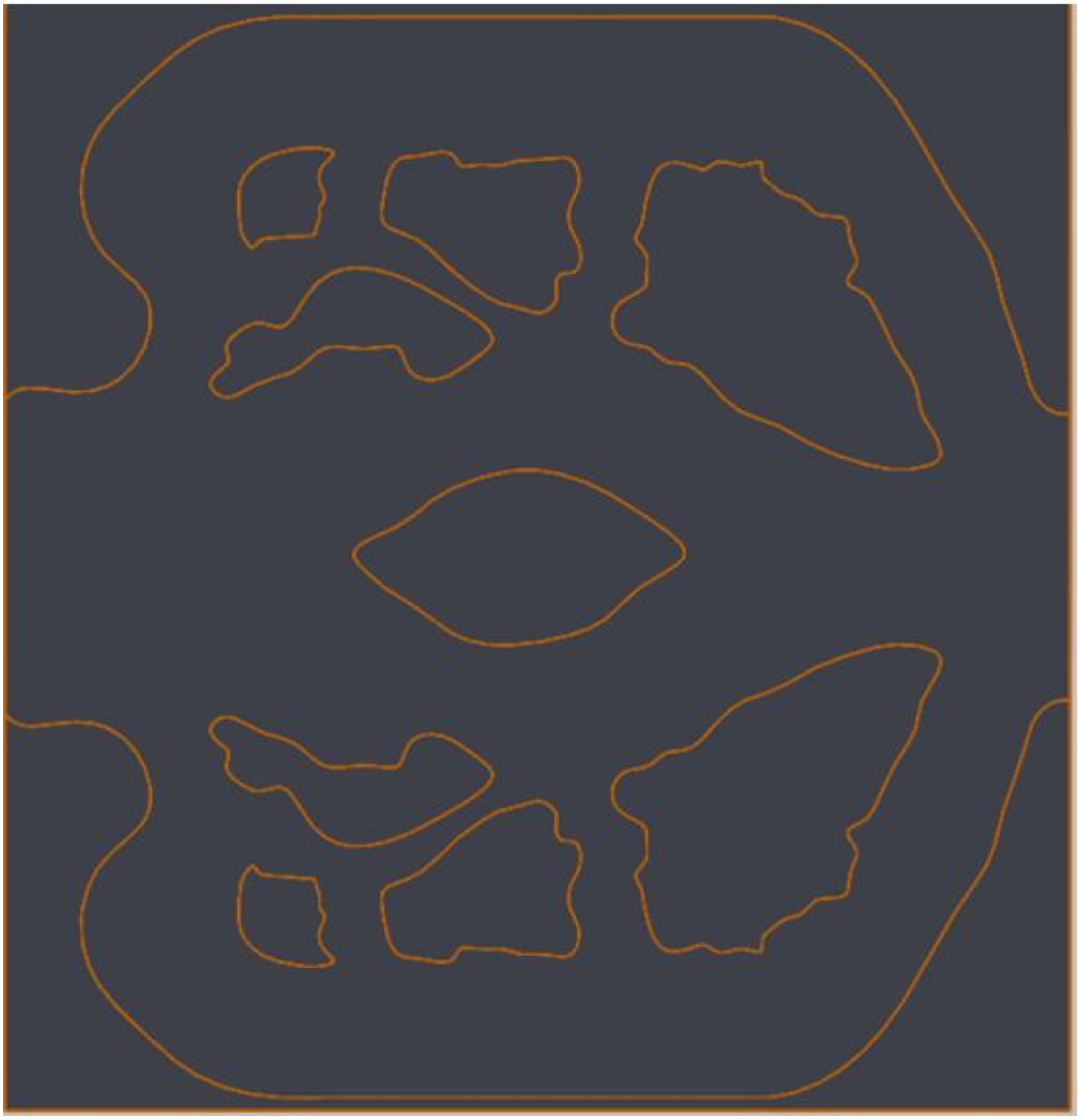

Fig. 7.2 The final post-processed image

The finalized 3D CAD model of the cooling plate, developed in SolidWorks, exhibits an optimized volumetric geometry with precisely defined fluid channels and structural supports. The design incorporates smooth transitional surfaces between interconnected flow passages, maintaining hydraulic efficiency while ensuring structural integrity under operational loads. The model demonstrates manufacturable wall thicknesses and properly filleted internal features, with clearly defined inlet/outlet manifolds that facilitate practical fluid connections. This production-ready 3D representation accurately translates the optimized 2D topology into a functional mechanical component suitable for additive manufacturing or conventional machining processes.

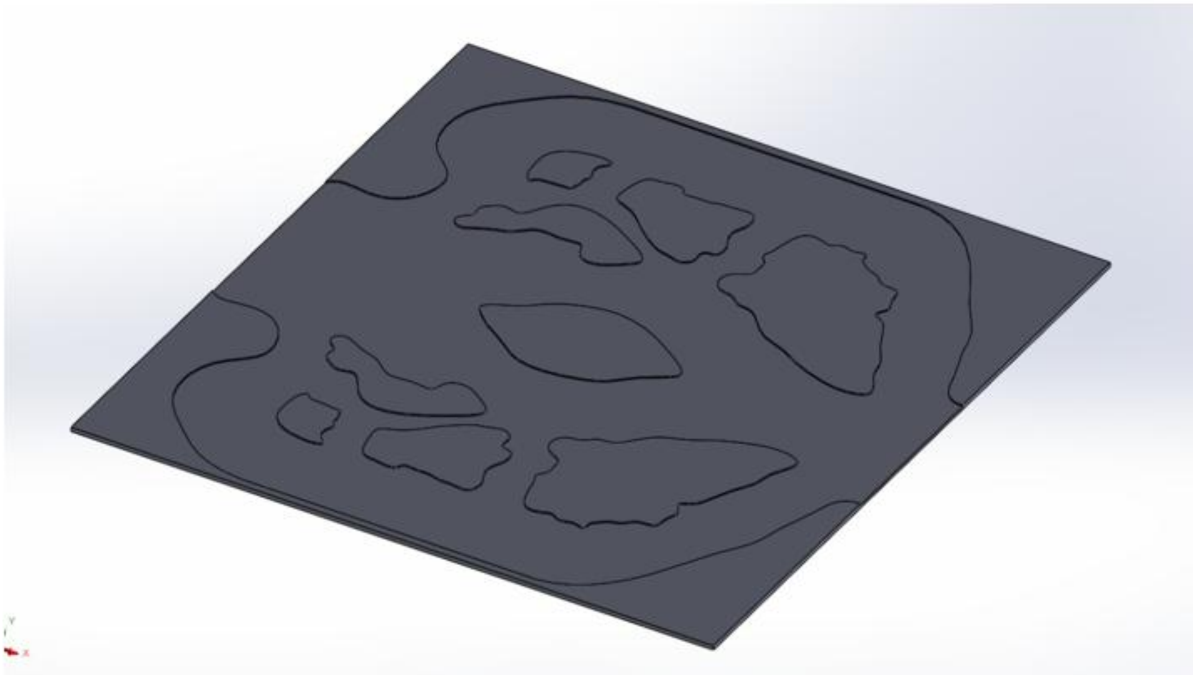

Fig 7.3 Final 3D cooling plate from SolidWorks

ANSYS simulations were performed to evaluate the thermal performance of both VAE-generated and conventional topology-optimized cooling plates under identical heat flux conditions. The comparative analysis assessed key parameters including temperature distribution, thermal gradients, and cooling efficiency. Results demonstrate the relative performance characteristics of each design approach, with the VAE-generated plate showing distinct advantages in thermal management. These findings validate the effectiveness of the AI-driven design methodology while providing insights into its comparative benefits over traditional optimization techniques.

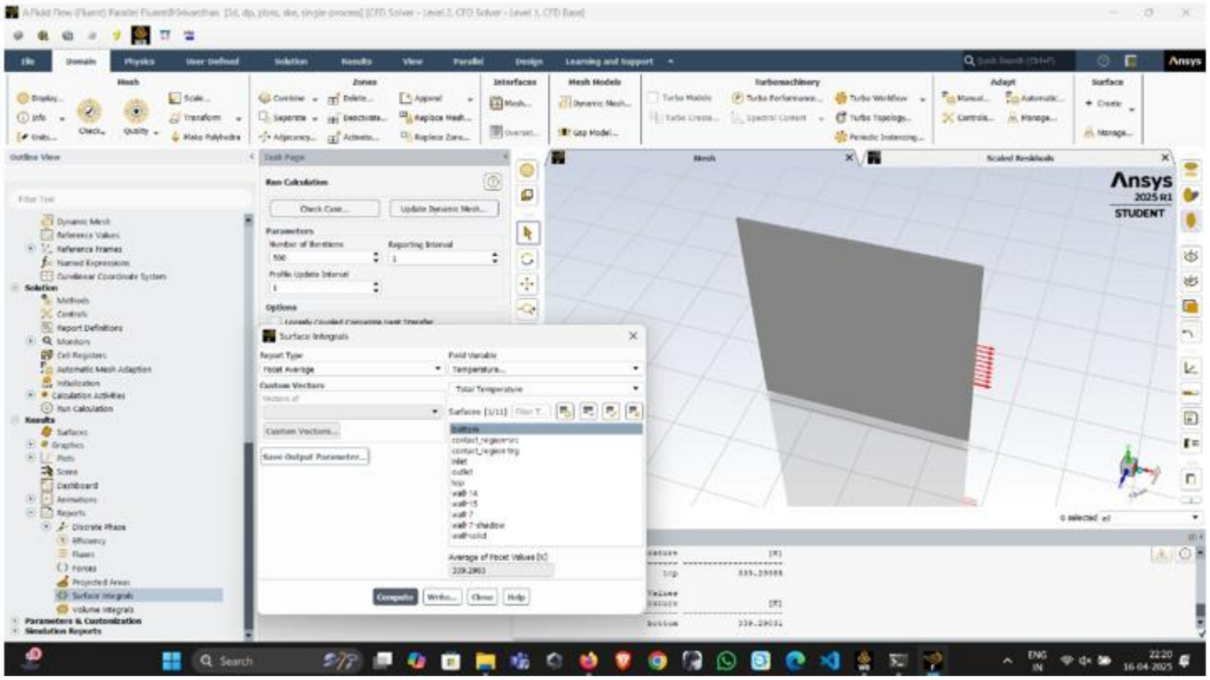

Fig 7.4 The simulation in ANSYS

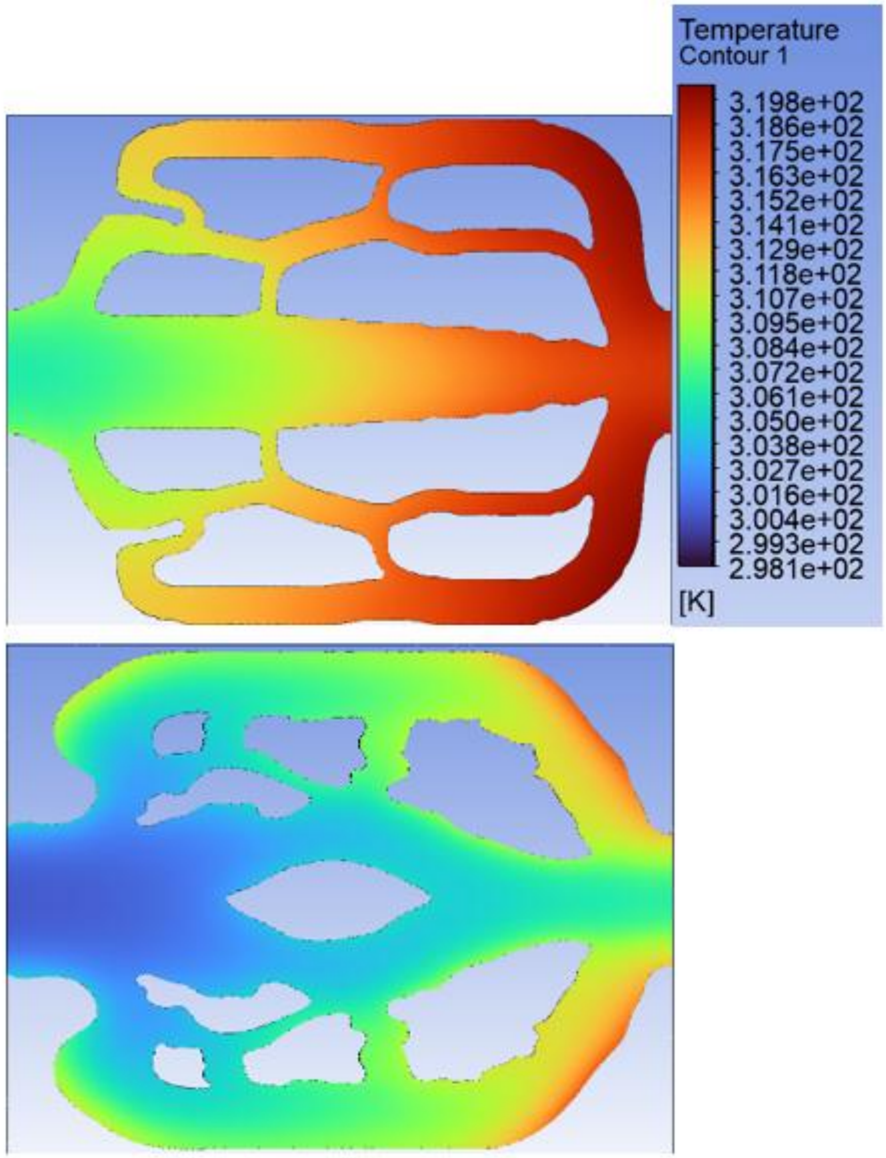

Fig 7.5 The temperature distribution

The thermal simulation results demonstrate a notably more uniform temperature distribution across the VAE-generated cooling plate when compared to the conventional topology-optimized design. This improved thermal uniformity is visually evident in the temperature contour plots, where the VAE design exhibits smoother gradients and reduced localized hotspots. The enhanced performance can be attributed to the AI model's ability to generate complex, optimized flow path geometries that more effectively distribute cooling capacity throughout the plate surface. These observations confirm the advantages of the machine learning approach in developing thermally balanced cooling solutions that outperform traditional optimization methods.

Chapter 8

Summary and Conclusions

In our current work, there have been a lot of hits and trials for choosing the method to proceed with the non-variable heat flux. There were three main ideas:

1. NTGK integrated numerical simulation.
2. Attaching the variable fins to the plate at various locations.
3. Using deep learning.

So far, the numerical simulation approach, particularly using the NTGK model, efficiently predicts battery thermal behavior by integrating coupled electrochemical-thermal modeling. This method accounts for key heat sources—irreversible overpotential, reversible entropic heating, and ohmic resistance—while analyzing critical parameters such as Depth of Discharge (DoD), cell voltage, and current flux. By solving heat equations derived from energy conservation and electrochemical principles, the NTGK model enables rapid and accurate thermal performance assessment, significantly reducing experimental time and workload while maintaining strong alignment with empirical results.

Assuming that the heat transfer process is in a steady state, and the material properties remain stable, we can set up the energy equation. Heat generation per unit area Q on a uniform surface based on the Cooling Law of Newton as:

$$Q=h(Tq-T)$$

To implement a non-uniform topology optimization method, this can be combined with a heat source term related to the surface temperature obtained by numerical study the performance of batteries with NTGK determining the heat. The heat generation Q can be described as:

$$Q=h(Tq-T)P^*(x^*,y^*)$$

where $P(x, y)$ is a jointly fitted function of the temperature distribution at each location on the heat source surface. $P^*(x^*, y^*)$ are dimensionless function. Assume $x^* = x/x_0$, $y^* = y/y_0$ & $P^*(x^*,y^*) = P(x, y) / P_0$. The values of x_0, y_0, P_0 are 1 mm, 1 mm, 1 K.

To counterbalance the uneven heat transfer between the two sides of the cold plate, an additional function is introduced to amplify the non-uniformity of the heat source:

$$Sa = (-(x/xs)/B)*\exp(-(x/xs)/2)$$

Where

$S = 1+(Sa)/(1+Sa)$

xs=1mm and

b is a dimensionless constant with the value of 225.

Hence final Heat transfer function is:

$$\mathbf{Q=h(Tq-T)P^*(x^*,y^*)S(x^*)}$$

But this approach did not give the results we hoped for. This gave the results similar to those of the cooling plate, which we got under the conditions of constant heat flux, purely because of the dimensions of the cooling plate, which made us rule out this idea.

As for the second method, there was not enough research done on this idea, and there was no existing idea to be found, causing us to rule this one out as well, and then we proceeded to the third idea.

The third idea was to ingrain Deep Learning (DL) into our simulations for a much easier transition from constant heat flux to variable heat flux. The process we followed is concisely shown in the figure. 8.1

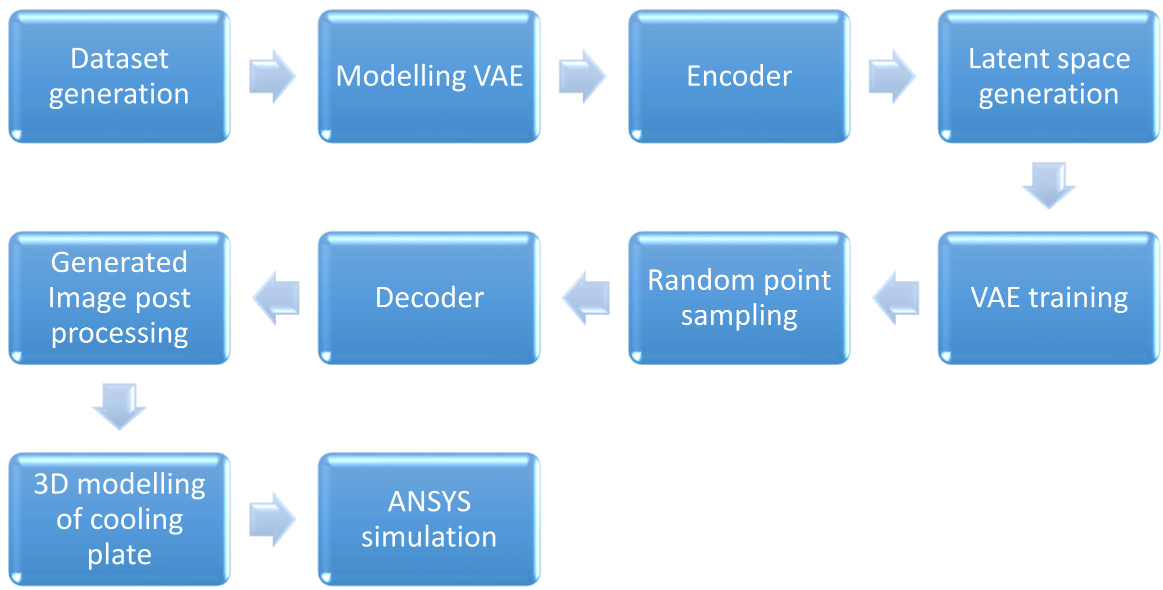

Fig.8.1 Flowchart of the process followed

The results were promising, as shown in the previous section of results. The integration of **Deep Learning (DL) and Variational Autoencoders (VAE)** significantly enhanced the project by enabling **fast, automated, and high-resolution cooling plate design generation** while maintaining thermal efficiency. Here's how:

1. Accelerated Design Exploration

- **Traditional TO Methods**: Required computationally expensive, iterative simulations (CFD/FEA) for each design.
- **VAE Advantage**: Once trained, it generates **1024×1024 cooling plate designs in milliseconds**, bypassing costly simulations for each variation.

2. High-Resolution Topology Generation

- The **CNN-based encoder-decoder architecture** efficiently compressed and reconstructed **high-fidelity (1MP) cooling plate structures**, capturing intricate flow channel patterns.
- **Latent space interpolation** allowed smooth transitions between designs, facilitating **optimised trade-offs** between cooling efficiency.

Conclusion

By combining DL based generative modelling with the traditional thermal analysis, the project achieved Faster design cycles, Higher resolution optimisations, better performance and scalability. This approach bridges AI-driven design and engineering validation, setting a precedent for next-generation thermal management systems.

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