LIMITS OF MODELING APPROACH FOR REFRIGERANT CHARGE ASSESSMENT

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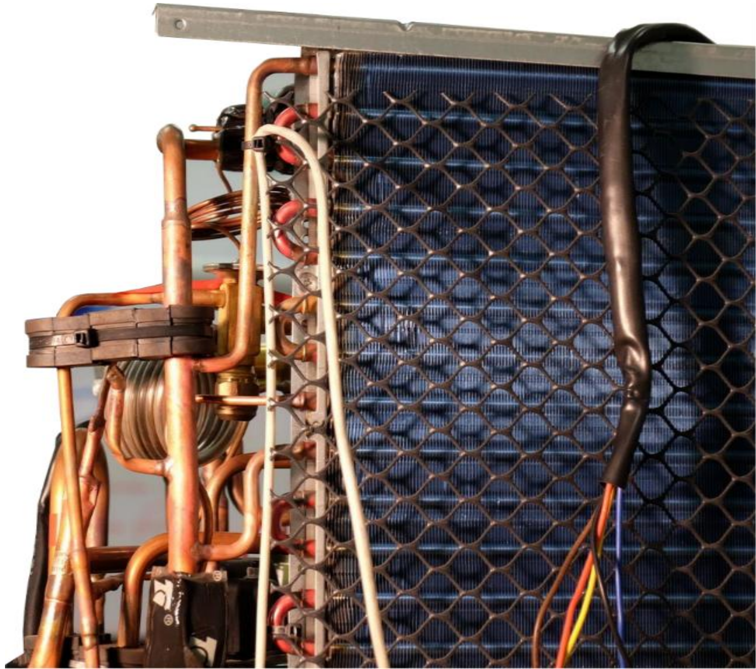


The necessity for smart HPs

- **To support the deployment of HPs on the market, we need Smart HPs**:
  - Real-time **performance** assessment
  - **Predictive maintenance** (soft faults)

- Why focus on **refrigerant leakage** ?

  - Soft fault with the **most important impact on HP performances**, but only after a certain loss of refrigerant (30-50 % of the nominal charge depending on the quality of the controls)

  - Also a **safety aspect** regarding flammable refrigerants → stringent safety regulations

Early detection of leakages and real-time quantification of the refrigerant charge is thus a major challenge.

1. Context and objectives - Refrigerant charge prediction methods

- To **detect leakages**: **monitor internal operating parameters** of the HP (pressures, temperatures)

- To quantify: **Refrigerant charge = f (Charge-sensitive feature, operating conditions)**

Subcooling, evaporator inlet vapor quality

Low and high pressures, compressor frequency…

Charge prediction model

Empirical approaches require **extensive experimental data**, across **multiple charge levels** AND **operating conditions**…

Why not use a **physical model of the HP** to generate **synthetic training data** for the charge prediction model ?

1. Context and objectives - Pros and cons of the different approaches

	+	−
Empirical approach	• High **accuracy**	• Large amount of experimental data across **various conditions and charge levels** • Difficulty to obtain high-quality experimental data → **Time- and resource-consuming**
Numerical approach, using a **physical model of the HP**	• Deeper **understanding** of HP behavior • Ability to cover any operating condition → a large amount of data can easily be generated • Can be validated using **limited experimental data**	• **Complex** to develop • **Deep knowledge** of the system is required + information : **Dimensions & geometries: storage volumes are key in a closed-loop system**

1. Context and objectives – Objectives of the study

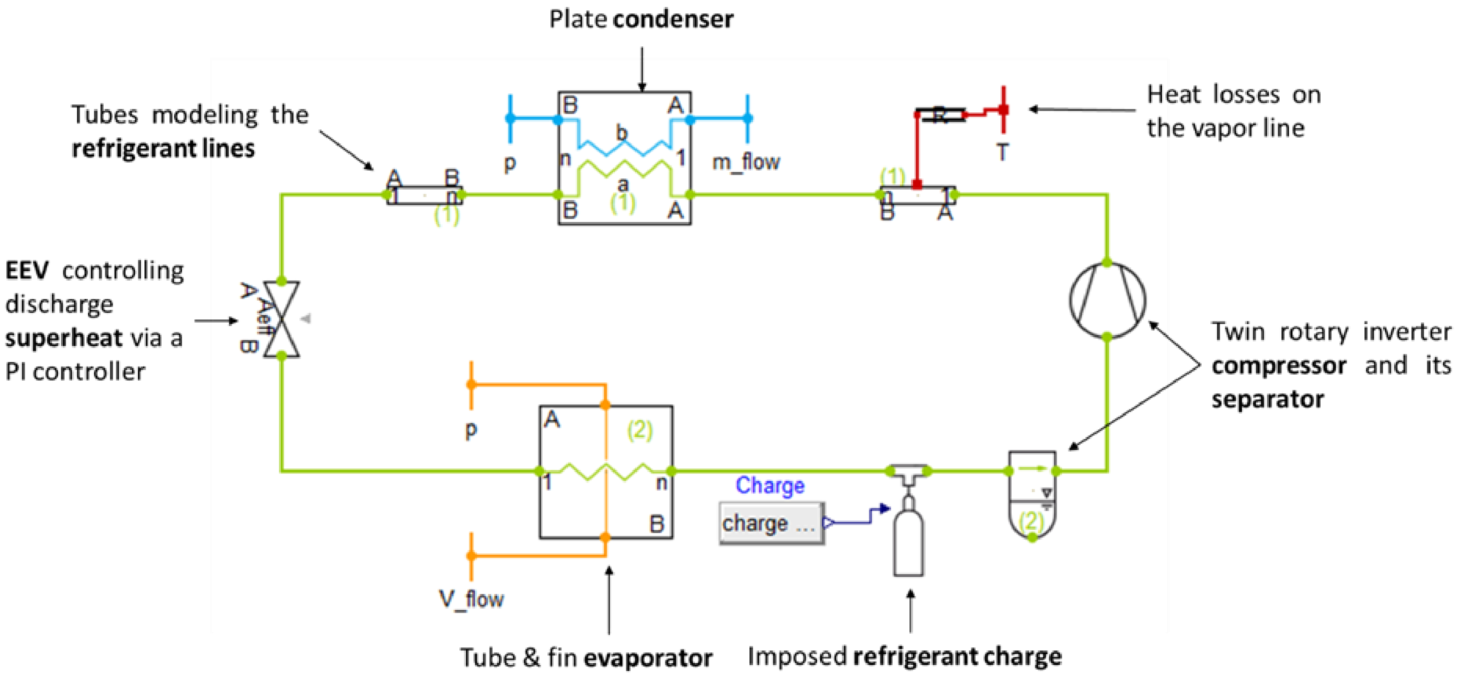
Necessity to accurately account for **all refrigerant storage volumes** and associated **physical phenomena**

How can **uncertainties** or **simplifications** in the HP physical model affect the **reliability** of the resulting **charge estimation** ?

Assess the influence of the **physical model accuracy** on the overall **performance** of refrigerant **charge prediction** methods based on **model-generated data**

2. Methods – HP model and experimental validation

- **6 kW**
- **Split system**
- **R32**, nominal charge: **1,3 kg**
- Modeled using **Dymola + TIL library** → physical approach based on
  - **energy**,
  - **mass**,
  - **momentum balances**
  - exception: compressor → mapping of the efficiencies



Model validated against **experimental data**:

- Various **conditions**, **charge levels** 80-110 % of nominal charge
- **Steady-state** AND **dynamic** (HiL test bench)
- Errors < 5 %

Experimental observations:

- **No superheat** at compressor inlet (R32)
- **Very low subcooling**, 0 K for slightly undercharged system

2. Methods – Modeling key ancillary components for refrigerant storage

Condenser filter (~10-20 %)

Filled with filtering particles

? Filling ratio

→ Hypothesis: 60 %

Compressor crankcase and oil (~10 %)

? Internal volume

→ ~40% of compressor internal volume (manufacturer data)

? Refrigerant-oil solubility

→ Tables available in literature

$$Solubility = f(discharge\ temperature\ \&\ pressure)$$

→ Compromise for model efficiency: fixed oil retention rate of 15 %

Suction accumulator (~40 %)

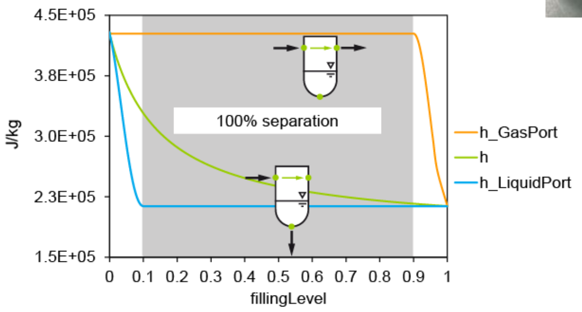
R32 → No superheat at compressor inlet
→ **key storage component**

? Internal volume

→ Manufacturer data

? Liquid-vapor equilibrium

→ Simplified approach: ideal separation



→ Selected threshold: 80 % (arbitrary)

2. Methods – Charge prediction model, training and testing data

HP physical model → Generated training data → Charge prediction model

	Min	Max	Step
Refrigerant charge level (% of nominal charge)	80	110	2
Outdoor temperature (°C)	-10	10	5
Return water temperature (°C)	30	50	10
Compressor Frequency (Hz)	40	100	20

- Regression method: **Histogram Gradient Boosting** (HGB) regressor
  → Compromise between **accuracy** and **computational efficiency**
- **Charge-sensitive features: subcooling** and **evaporator inlet vapor quality**
- Operating features: **low** and **high pressures**, compressor **frequency**

2. Methods – In a nutshell

1

Reference model

→ perfect representation of the real system (no error)

→ a unique **reference testing dataset** – operating conditions **randomly sampled** following a uniform distribution

(Training and) testing

2

Degraded models 1 component

Misestimation of the **filter**'s internal volume	$\boxed{+ 10\ \%}$ $\boxed{- 10\ \%}$
Misestimation of the **crankcase**'s internal volume	+ 25 % - 25 %
Ideal separation thresholds in the **suction accumulator**	$\boxed{90\ \%}$ 70 %

3

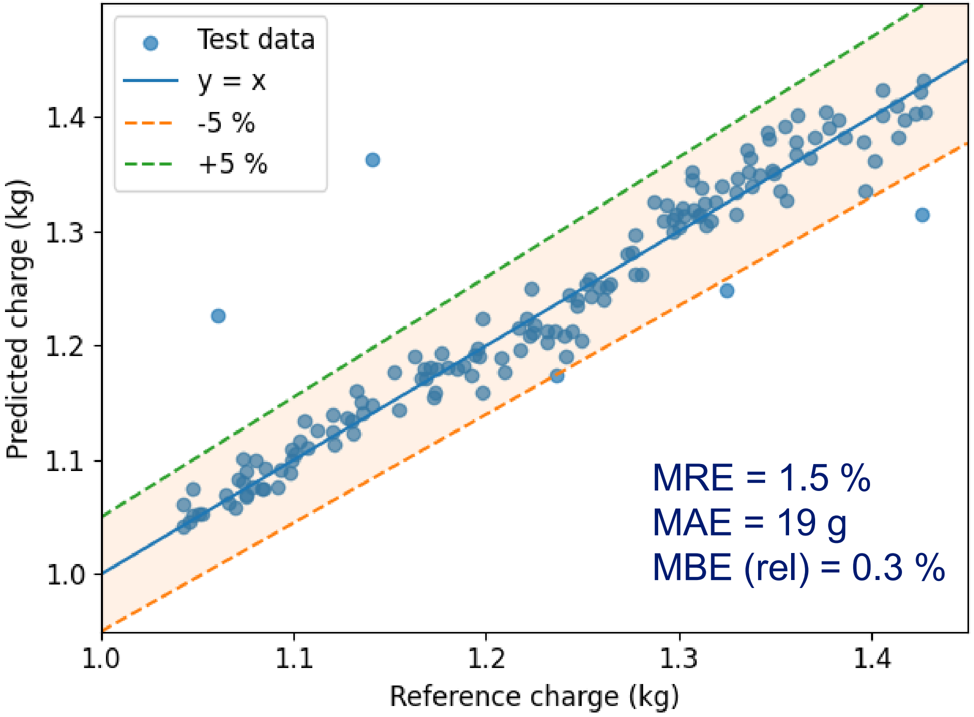
Degraded models 2 components

- Filter **under**estimation / accumulator **over**estimation
- Filter **over**estimation / accumulator **over**estimation

Training only

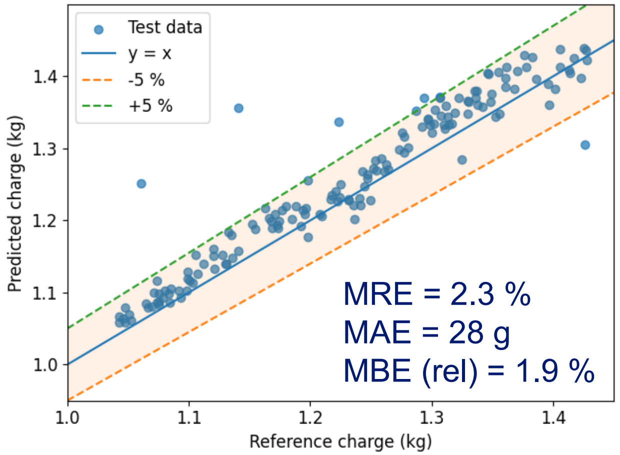
3. Results and discussion - Reference scenario: training conducted on a perfect HP model

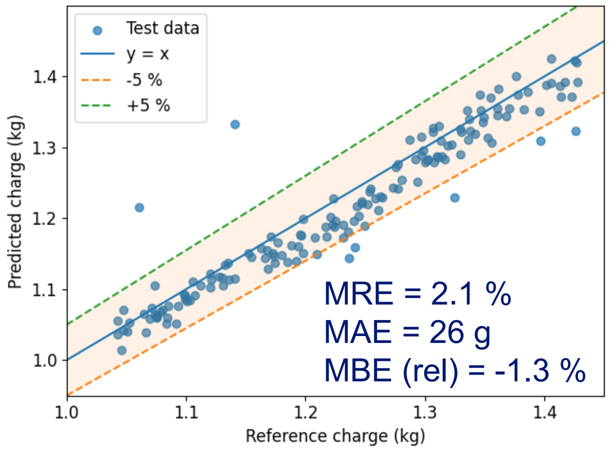
Charge prediction model **trained** using data generated by the **reference model** and tested on the **testing** dataset generated by the same model.



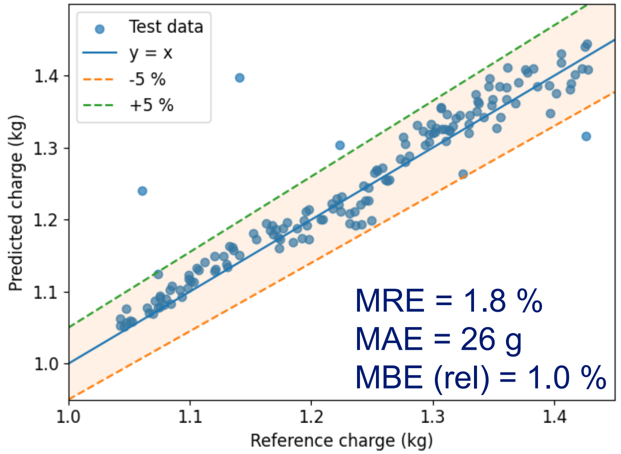
3. Results and discussion – Mischaracterization of one component

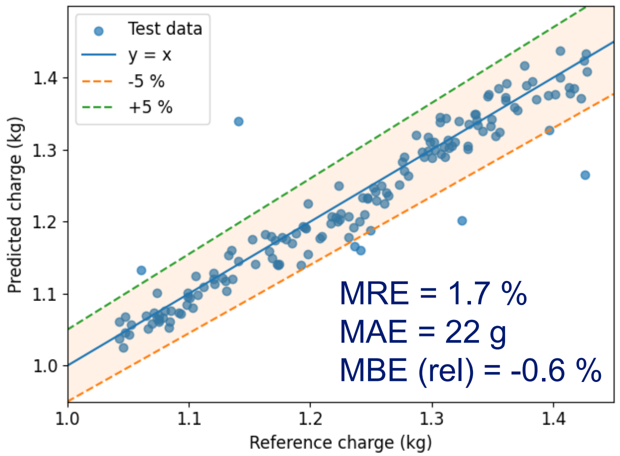
+ Condenser filter



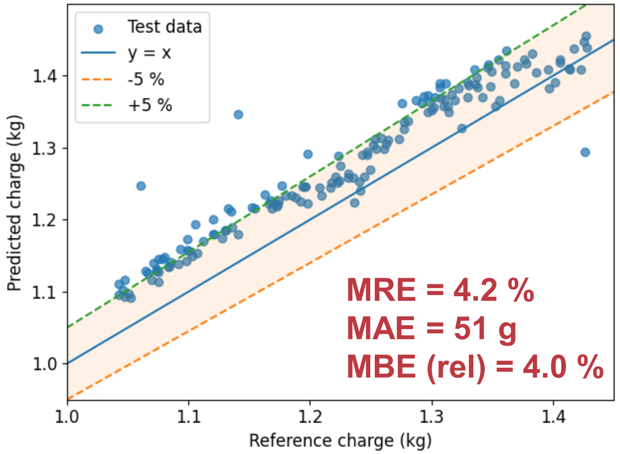


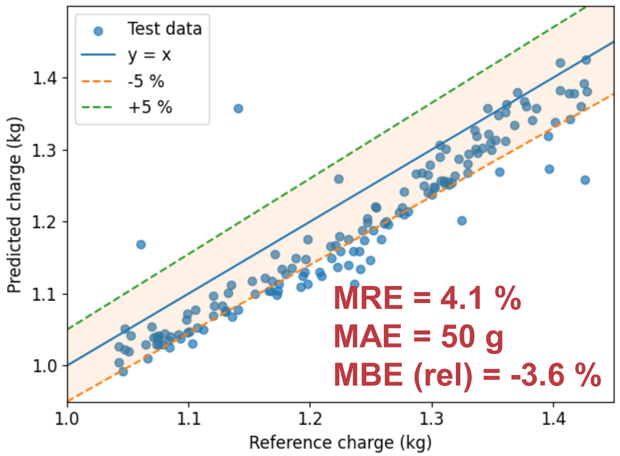
+ Compressor crankcase and oil





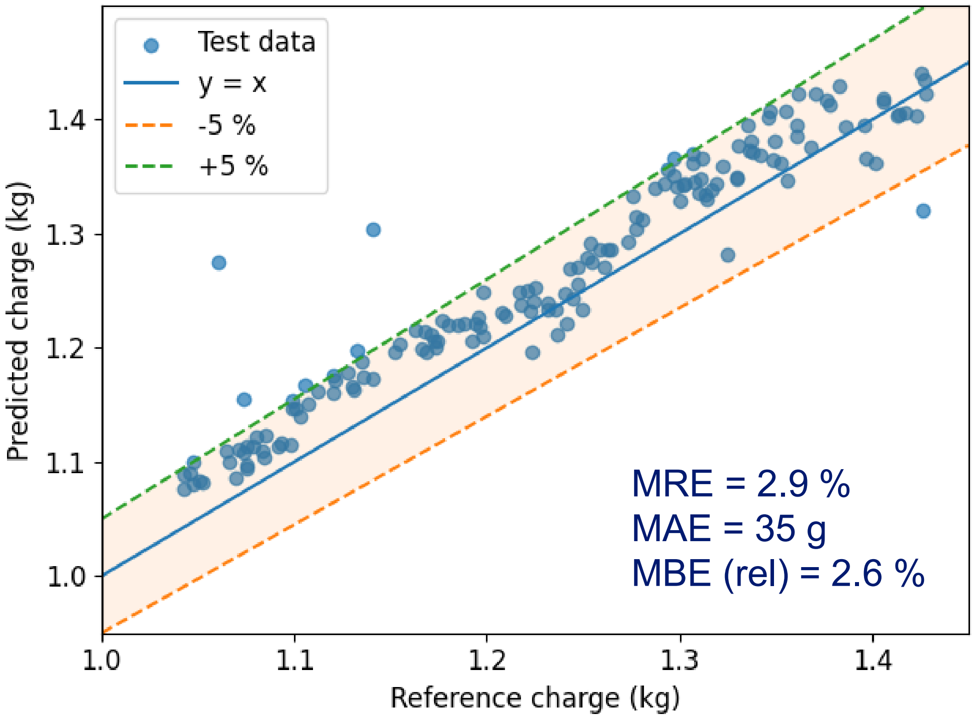
+ Suction accumulator





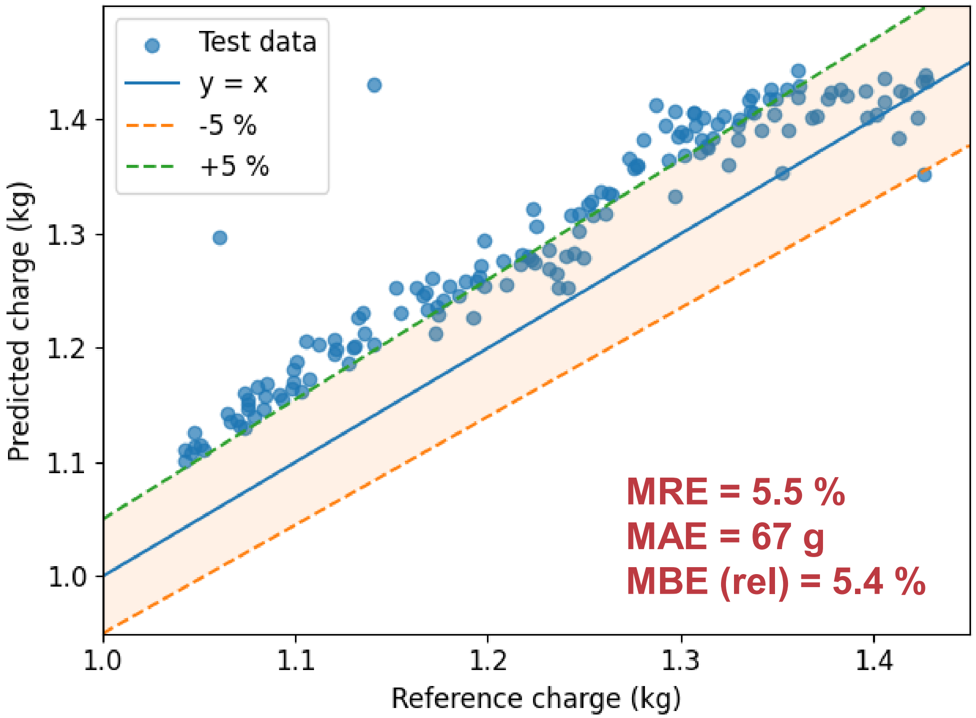
3. Results and discussion – Mischaracterization of two components

− Condenser filter + Suction accumulator



→ The errors can somehow **compensate** each other

+ Condenser filter + Suction accumulator



→ But they can also **add up**…

3. Results and discussion – Summary

- Impact on charge prediction:

Suction accumulator — Especially with R32

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Condenser filter

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Compressor crankcase and oil

Consistent with refrigerant storage:

~ 40 %

~ 10-20 %

~ 10 %

- **Prediction performance** impacted by:
  - ~ 4 % for individual component error
  - **Up to 5.5 % with multiple errors**

- Even though the error may remain **acceptable**: the model will **systematically under- or overpredict** the refrigerant charge

4. Conclusion & Perspectives

Can **model-generated data** support **refrigerant charge prediction** ?

Physical model of an R32 HP treated as an **ideal representation** of the real system

↳ (Training data +) **testing data**

+

Degraded models with **mischaracterized** components

↳ **Training data**

- Modeling of **suction accumulator**: particularly **critical** (compared to filter or compressor crankcase)
- If multiple components mischaracterized: error **up to 5.5 %**
- Most cases: **acceptable error** → Difficult to draw definitive conclusions.

Accurately **modeling refrigerant distribution** for charge prediction in **closed-loop systems** is a **complex** task

➔ Using **physical models** to generate **synthetic data** for **charge prediction** may be more **challenging** than anticipated.

4. Conclusion & Perspectives

Limits of the current approach and **perspectives**:

- Only a **subset of modeling uncertainties** are addressed
- **Dimensions** and **geometries** considered, but what about **correlations** ? Heat transfer, void fraction
  → Extend this work to other components, such as **heat exchangers**
- **Danger: if the errors add up !**

- Real systems may exhibit **more complex behaviors**, more so with **refrigerant storage phenomena** in **dynamic operation**

Model-generated data may support charge prediction **BUT:**

- This approach requires **deeper investigation** and **careful validation**.
- The **limitations of physical modeling** must be clearly understood before relying on it as a **substitute for experimental data**.