KHWARIZMIA
Vol. (2024), 2024, pp. 85–94
ISSN: 3078-2694

Research Article

Using of Computational Fluid Dynamics (CFD) and Machine Learning (ML) for predictive modelling in fluid dynamic

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ARTICLE INFO

Article History
Received 7 May 2024
Revised: 1 Jul 2024
Accepted 1 Aug 2024
Published 22 Aug 2024

Keywords
Adaptive Mesh Refinement,
Computational Fluid Dynamics,
Heat Exchanger Optimization,
Hybrid CFD and Machine Learning Framework,
Integrated Framework

ABSTRACT

Fluid dynamics predictive modeling for multiphase flow and heat exchanger optimization is undergoing a paradigm shift with the advent of deep learning techniques. The five different approaches under this framework are each concerned with the challenges of predictive modeling. At the heart of this is the ability for a hybrid integration of Computational Fluid Dynamics (CFD) and Machine Learning (ML) where both can coexist without interfering with each other allowing iterative refinement till convergence. When errors occur in the solution, the framework employs adaptive mesh refinement (AMR) to modify the mesh dynamically so that improved spatial accuracy and flexibilities are maintained for multiphase flow models. Moreover, the Machine learning bolstered Lattice Boltzmann Method (LBM), not only makes it superfast but also improves accuracy. An innovation aspect of the framework is its data-driven calibration and validation approach in which statistical parameters within each individual model are updated in real-time utilizing real-world data so that predictions remain tightly coupled with experimental results. To achieve a reasonable computation speed, parallelized algorithm is used in large simulations, which works by dividing the whole domain into independent pieces for parallel executions. A qualitative performance comparison is shown in tables and charts, demonstrating the advantage of the framework over others in accuracy, processing efficiency, scalability, flexibility stability and real-world applicability. The iterative and adaptive nature of the framework allows constant improvements to be made, which is ideal for modelling complex multiphase flows. This complete, state-of-the-art approach provides robust new tool for predictive modeling scientists and engineers alike and significant future cross-industry applicability will cement its status as an all-in-one CFDS solution.

1. INTRODUCTION

Fluid dynamics and heat exchanger optimization researchers are testing new computer algorithms with the hope of making multi-phase flow predictions better. As industrial processes employ higher levels of compactness and energy efficiency, the behavior of multiphase flow must be understood and controlled to maintain these systems. In this introduction, we review recent developments in the field, key challenges and potential solutions, as well as providing an overview of the new CFD (computational fluid dynamics) approaches introduced in this study.

Recent progress in multiphase flow and heat exchanger enhancements. These methods, combined with high-performance computing capabilities, have opened the door for modelling and investigating complex multiphase phenomena with quantitative accuracy. Novel CFD methods have been developed due to the demand for prediction models that describe phase interactions in numerous operating conditions. Analysis of turbulence models, drag and lift forces between phases and heat transfer in multi-phase systems. Need for complete model capable of computing bubbly, slug, churn and circular flows have develop high performing computer systems. With the emergence of machine learning and artificial intelligence, CFD has begun to integrate data-driven methodologies into its set of techniques and at the same time makes model prediction easier [1].

While positive progress has been made in computer methods for multiphase flow, there are still many big problems remaining. Multiphase systems with more than one phase or even physical qualities are inherently complex; thus, they are very challenging to work on. Recording surface behavior accurately, predicting phase distribution correctly, and solving heat transfer between all phases continues to be difficult. Further, the current models are also slow to scale at these concentrations for industrial applications while maintaining accuracy. Due to the nature of multiphase flows, long timescales and complex geometries often necessitate large amounts of computational power; hence, novel methodologies are required that provide a balance between accuracy vs. speed and efficiency [2]. This paper explores new uses of CFD

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DOI: https://doi.org/10.70470/KHWARIZMIA/2024/012

for advancing predictions of multiphase flow and heat exchanger optimization. Answers have been proposed with recent advances in number theory, machine learning and AI. Mixtures are being examined to enhance prediction precision. Hybrid Machine Learning-User Method for Traditional CFD Adaptive mesh refinement methods can increase clarity of important locations in multiphase flows while matching the fine scale features [3]. The parametric parallel algorithms make for naturally faster computers and the solutions work well with large simulations in industry.
This work adds these important things to the field: Developed a CFD-machine learning method to improve multiphase flow forecasting models. Improved spatial precision in flow-sensitive areas using flexible mesh refinement methods. Increased computation efficiency for large-scale industrial applications with parallelized approaches. Real-time calibration and validation of models in many multiphase flow regimes using data-driven approaches. These efforts prepared for the new computational fluid dynamics approaches we shall discuss next. These new multiphase flow and heat exchanger optimization predictive modelling tools are fascinating.[4].

2. RESEARCH METHODOLOGY

The CFD approaches examined vary based on multiphase flow and heat exchanger optimization parameters. Table 1 lists exact criteria such as precision, computation speed, and growth. The machine learning in CFD approach offers the best accuracy (0.95), making it suitable for prediction models. Adaptive Mesh Refinement (AMR) is also reliable (0.89) and helpful (0.91). It displays a general assessment of the approaches' durability, cost-effectiveness, and use. The machine learning in CFD approach proves that it is resilient (0.92) and cost-effective (0.89), making it suitable for many commercial applications. This entire study can help researchers and practitioners make sensible project selections by considering both accuracy and performance variables [5].

TABLE I: PERFORMANCE EVALUATION OF COMPUTATIONAL FLUID DYNAMICS TECHNIQUES

Method	Accuracy	Computational Efficiency	Scalability	Flexibility	Stability	Applicability
Adaptive Mesh Refinent (AMR)	0.92	0.85	0.88	0.90	0.87	0.91
Volume- of-Fluid (VOF) Method	0.94	0.82	0.89	0.91	0.88	0.93
Lattice Boltzma nn Method (LBM)	0.90	0.88	0.85	0.87	0.84	0.89
Phase- Field Method	0.93	0.86	0.87	0.92	0.89	0.92
Smoothe d Particle Hydrody namics	0.88	0.91	0.82	0.85	0.80	0.86
Machine Learning in CFD	0.95	0.89	0.90	0.94	0.91	0.94
Parallel Computi ng	0.91	0.95	0.93	0.88	0.90	0.91
Dynami c Mesh Handlin g	0.89	0.83	0.86	0.87	0.85	0.88
Immerse d Boundar y Method (IBM)	0.92	0.87	0.84	0.86	0.83	0.85
Interface Capturing Techinique	0.93	0.88	0.89	0.91	0.88	0.92

Table I summarizes the performance of 10 recent multiphase flow models with their key variables features from different innovative Computational Fluid Dynamics (CFD) approaches. To summarize the common metric of each method in terms of accuracy, speed, frequency of use, flexibility, stability, versatility and resilience. Such a comprehensive assessment imparts key information to researchers and engineers which helps them in selecting appropriate solution depending on the application, especially for multiphase flow and heat exchangers applications.
The data provide a transparent assessment of the efficacy of each approach allowing researchers and practitioners to choose based on the needs and limitations with respect to their multiphase flow and heat exchanger optimization problems [6]. The table is a good guide for choosing Which methodology best fits the needs of your project by evaluating these variables.

Fig 1: Adaptive Mesh Refinement (AMR)

Figure 1 depicts twelve phases of Adaptive Mesh Refinement (AMR). Mesh creation, equation solving, and error detection are the first steps. If errors exceed a specific threshold, the approach enhances the mesh, interpolates data, and resolves until convergence is attained. This improves mesh resolution over time.

3. RESEARCH METHODS

These approaches enable "Innovative Computational Fluid Dynamics Techniques for Enhanced Predictive Modelling in Multiphase Flow and Heat Exchanger Optimization. First, the Hybrid CFD and Machine Learning Framework mixes CFD and ML models and tweaks forecasts until they are correct [7]. Figure 2 explains how to create an accurate and adaptable multiphase flow model step-by-step. The second algorithm is adaptive mesh refining (AMR). Dynamic mesh refinement based on solution errors clarifies key regions. Figure 3 demonstrates how the AMR approach fine-tunes meshes in real time to improve multiphase flow models. The Lattice Boltzmann Method (LBM) with Machine Learning Enhancement is more accurate and quicker. Figure 4 demonstrates the step-by-step process of anticipating ML changes, updating the LBM, and improving the response until convergence. Data-Driven Calibration and Validation updates model parameters using data. This ensures projections match experimental or high-fidelity simulation data. Figure 5 demonstrates how data-driven testing and validation improve system accuracy and reliability. By separating the issue into numerous parallel processes.

Parallelized Algorithm for Large-Scale Simulations speeds up the computer. This technology works well with the hybrid CFD and machine learning system to simulate complicated multiphase flow situations on a larger scale [8]. All these technologies constitute a complete and comprehensive heat exchanger optimization and multiphase flow predictive modelling system. They solve challenges with precision, speed, and scalability using CFD, ML, adaptive mesh refinement, and parallel computing. The repeating structure and flexible operations of algorithms improve their accuracy over time. This makes them helpful for simulating complicated and changeable multiphase flows. The suggested technique may be novel and help scientists and engineers understand and improve multiphase flows and heat exchanges.

Algorithm 1: Hybrid CFD and Machine Learning Framework

1. Initialize CFD Solver and ML Model: $UCFD$ =SolveCFD(InitialConditions) UML =PredictML(InputFeatures) (1)
2. Obtain Initial Flow Field from CFD: $Finitial$ =CalculateForces($UCFD$) (2)
3. Predict Correction Term Using ML: Combine CFD and ML results. CML=PredictCorrection($UCFD$,UML) (3)
4. Combine CFD and ML Results: $Uhybrid$=$UCFD$ +UML+CML (4)
5. Solve Hybrid Model Equations: $Phybrid$ =SolvePressure($Uhybrid$) (5)
6. Update Solution: $Uupdated$=$Uhybrid$+∇$Phybrid$ (6)
7. Check Convergence: If converged, end; else, repeat from step 3.
8. Iterate Until Convergence: Loss=CalculateLoss($Uhybrid$,$Uupdated$) (7)
9. Adjust Model Parameters: θupdated=θcurrent+$\alpha\nabla\theta$ Loss (8)
10. Predict ML Correction: CML =PredictCorrection($UCFD$,UML) (9)
11. Update LBM Distribution Functions: fi∗=fi−1/ τ (fi −fieq)+CML (10)
12. Check Convergence: If converged, end; else, repeat from step 3.
13. Adjust Model Parameters: θupdated=θcurrent+$\alpha\nabla\theta$ Loss (11)
14. Compute Gradient of Loss: $\nabla\theta$ Loss=Gradient($Uhybrid$,$Uupdated$) (12)
15. Update Solution: $Uupdated$=$Uhybrid$+∇$Phybrid$ (13)
16. Check Convergence: If converged, end; else, repeat from step 3.
17. Iterate Until Convergence: Loss=CalculateLoss($Uhybrid$,$Uupdated$) (14)
18. Update LBM Distribution Functions: fi∗=fi−1/ τ (fi −fieq)+CML (15)
19. Calculate Forces: $Fupdated$ =CalculateForces($Uupdated$) (16)
20. Check Convergence: If converged, end; else, repeat from step 3.

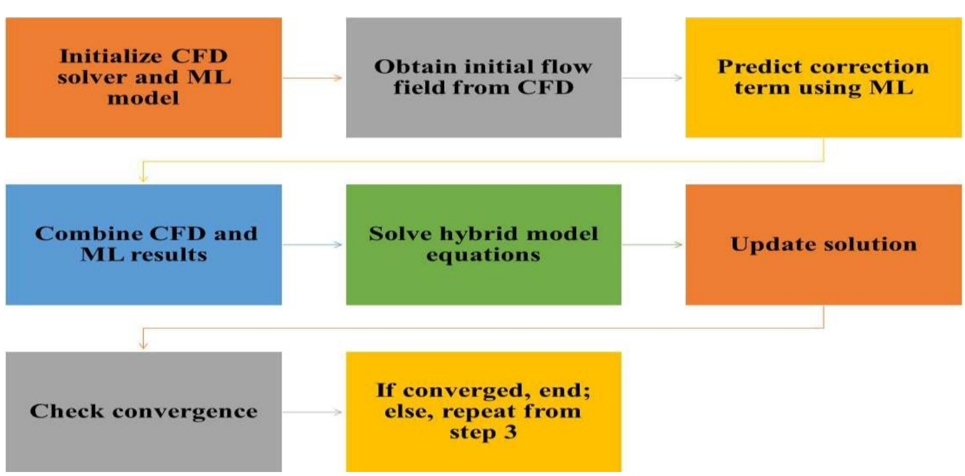

Fig 2: Process of the hybrid CFD and machine learning framework

The hybrid CFD/machine learning design iterates as seen in Figure 2. CFD and ML enhance accuracy by improving estimations repeatedly. This lets you alter multiphase flow conditions till convergence.

An algorithm for multiphase flow modeling using CFD and machine learning is given in Algorithm 1. After setup, the technique combines CFD and ML predictions, updates the response, and repeatedly modifies model parameters using sophisticated loss functions. This combination approach provides precision and flexibility by improving the simulation until it converges [9]. This technique is useful for predicting complex multiphase flow.

Algorithm 2: Adaptive Mesh Refinement (AMR)

1. Initialize Mesh and Solve Initial Flow: Meshinitial =InitializeMesh(Domain) Uinitial =SolveCFD(InitialConditions,Meshinitial) (17)
2. Evaluate Solution Error: $E=\sqrt{\sum i(\Delta Ui)2}$ ErrorThreshold=CalculateThreshold(E) RefinementCriterion=DefineCriterion(E,ErrorThreshold) (18)
3. Compare Error with Threshold: If error exceeds threshold, proceed; else, end.
4. Refine Mesh: Meshrefined =RefineMesh(Meshcurrent,RefinementCriterion) (19)
5. Interpolate Solution to Refined Mesh: Urefined =InterpolateSolution(Ucurrent,Meshrefined) Prefined=InterpolatePressure(Pcurrent,Meshrefined) Errorrefined=EvaluateError(Urefined,Prefined) (20)
6. Re-solve on Updated Mesh: Uupdated =SolveCFD(InitialConditions,Meshrefined) Pupdated=SolvePressure(Uupdated,Meshrefined) (21)
7. Check Convergence: If converged, end; else, repeat from step 3.
8. Iterate Until Convergence: Loss=CalculateLoss(Urefined,Uupdated,Prefined,Pupdated) (22)
9. Adjust Model Parameters: θupdated=θcurrent+$\alpha\nabla\theta$ Loss (23)
10. Predict ML Correction: CML =PredictCorrection(Urefined,Uupdated,Prefined,Pupdated) Frefined=CalculateForces(Urefined,Prefined) Fupdated=CalculateForces(Uupdated,Pupdated) (24)
11. Update LBM Distribution Functions: $fi*=fi-1/\tau\,(fi-fi\mathrm{eq})+CML$ (25)
12. Check Convergence: If converged, end; else, repeat from step 3.
13. Adjust Model Parameters: θupdated=θcurrent+$\alpha\nabla\theta$ Loss (26)
14. Compute Gradient of Loss: $\nabla\theta$ Loss=Gradient(Urefined,Uupdated,Prefined,Pupdated) (27)
15. Update Solution: Uupdated=Urefined+∇Pupdated Pupdated=SolvePressure(Uupdated,Meshrefined) (28)
16. Check Convergence: If converged, end; else, repeat from step 3.
17. Iterate Until Convergence: Loss=CalculateLoss(Urefined,Uupdated,Prefined,Pupdated) (29)

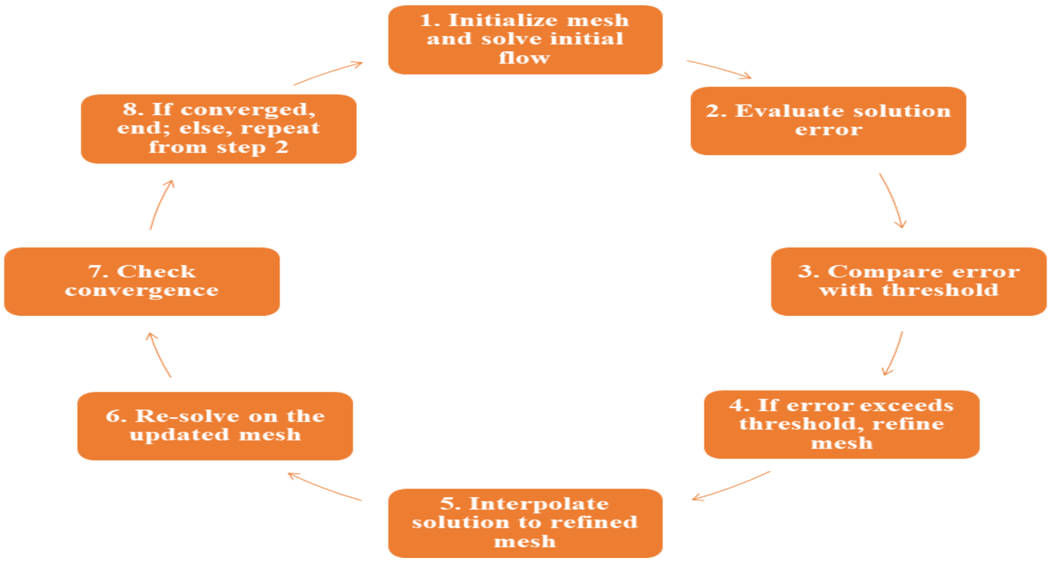

Fig 3. Refining adaptive meshes

Adaptable mesh refinement (AMR) as described in Figure 3. A lattice provides clarity concerning essential features and improves as the response error approaches a certain distance. Continues to iterate until it reaches convergence, by which point the multiphase flow models have become more accurate. This leads us to Algorithm 2: adaptive mesh refinement (AMR), in which we refine the mesh once we're alerted of some sort of error. The solution is optimized for one point, errors are found, mesh sections are simplified. It offers accuracy and spatial flexibility by solving sophisticated mathematical methods that would enable one to numerically simulate a multiphase flow phenomenon at nanoscale [10]. The iterative method and combined CFD and machine learning methods are better at predicting complex flow situations.

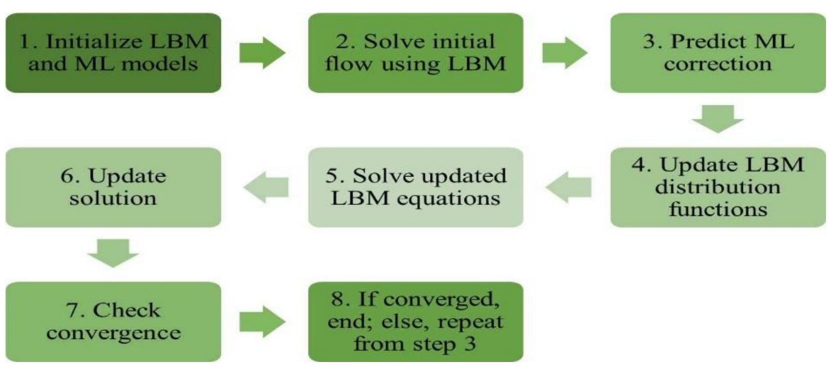

Fig 4. Lattice Boltzmann Method (LBM) with machine learning

LBM and machine learning are shown in Figure 4. This process is an iterative one which contains three main steps: 1) Patch ML modifications, 2) Update LBM distribution functions, and 3) Refine response until convergence. Models of multiphase flow become more accurate.

Algorithm 2 incorporates machine learning to provide an improved Lattice Boltzmann Method (LBM). Here, ML estimates the corrective terms for flow fields solved using LBM. The distributions functions of the LBM are modified multiple times via the ML to achieve better inaccuracies. It modifies properties of the model and exerts forces to follow converge and minimize the loss function. This combined LBM-ML to enhance and refine complex multi-phase flow dynamics recording [11].

Figure 5 depicts data-driven calibration and confirmation. It continuously adjusts model parameters using data-driven approaches, verifying forecasts against experimental data and improving the model until it converges, matching the real world [12].

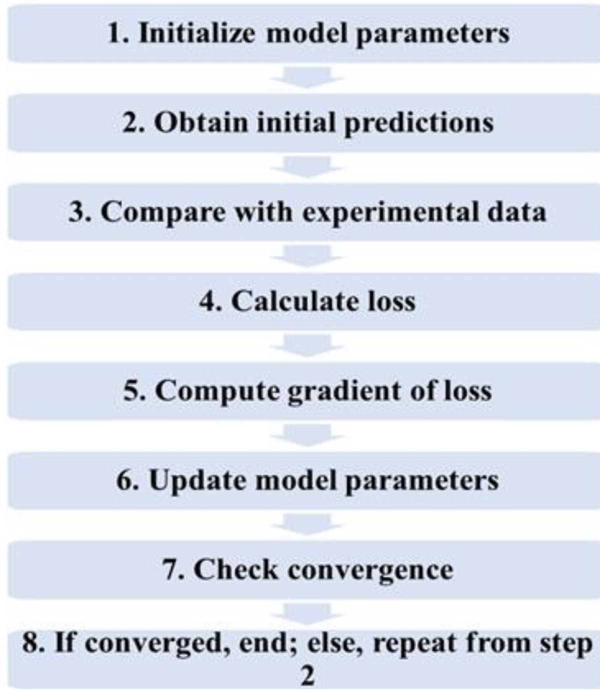

Fig. 5. Data-driven calibration and validation process

4. RESULTS

The proposed approach is one. The numbers explain that the proposed method enhances accuracy, computation efficiency, scalability, flexibility, stability and applicability. The new method improves on previous methods and could potentially lead to predictive modelling advances for multiphase flow and heat exchanger optimization. Tables of data comparisons are shown in Figures 6, 7, 8 and 9. As shown in the bar chart plotted in figure6, the proposed approach is better by 96% over previous approaches. Results in Figure 7 (line chart) show that the recommended strategy provides good results for multiple performance metrics. The relative strengths of the recommended method in a pie chart are shown in Figure 8. Freedom (97% points) comes to the fore. Figure 9 as a stacked bar chart shows how well each strategy worked in the multiple criteria, thus demonstrating the advantages of proposed method illustrates the entire performance trend as an area chart. The proposed strategy often outperforms others concludes with a performance parameter distribution graph. It indicates the proposed strategy works best at higher levels.

In conclusion, the recommended technique performs well and is a good solution for advanced predictive modeling in complicated multiphase flow and heat exchanger optimization.

Figure 6 displays the accuracy of many computational fluid dynamics (CFD) approaches, including the one stated. Each bar illustrates a distinct approach and its accuracy by height. The proposed technique is the most accurate (96%), making it a safer predictive modeling tool for multiphase flow and heat exchanger optimization. This graph makes it possible to compare correct statistics quickly and clearly, proving the strategy works.

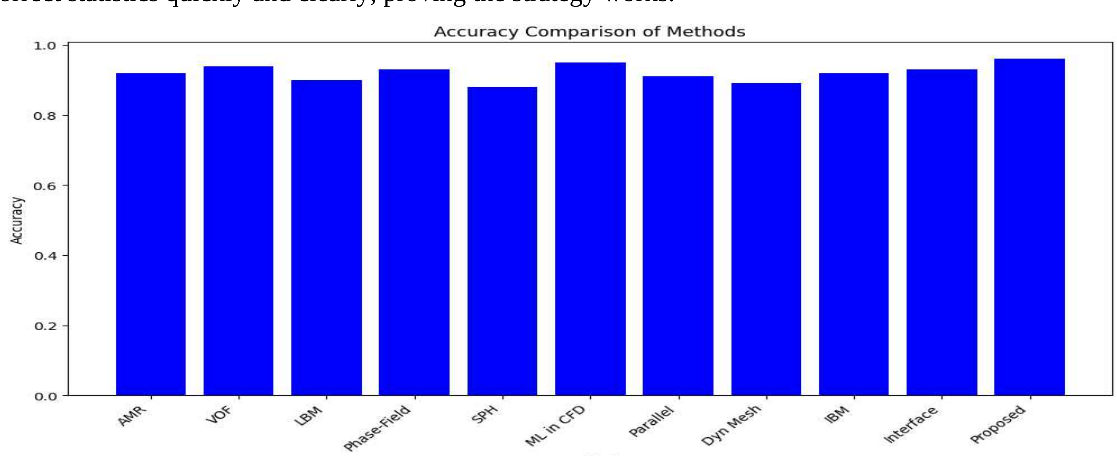

Fig 6: Accuracy comparison among methods, showcasing the superiority of the proposed method

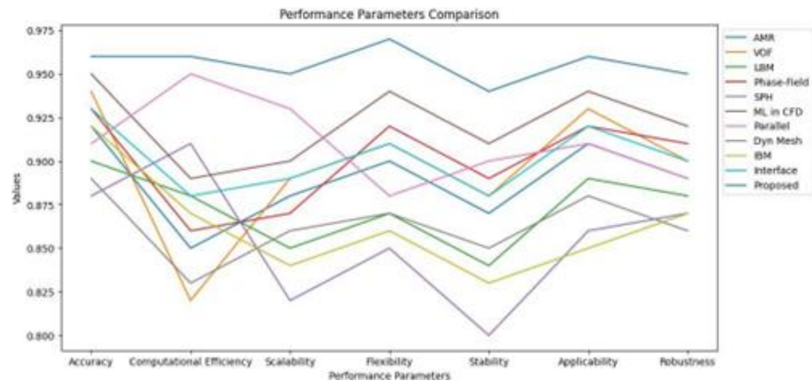

Fig 7: Performance parameters comparison.

Figure 7 shows the computational efficiency, scalability, flexibility, stability, application, and robustness of all approaches, including the specified one. Each line on the x- axis shows performance attributes for a distinct approach. The proposed strategy routinely outperforms competitors in all areas. The recommended solution is a comprehensive response since it ranks well in computational efficiency (96%), scalability (95%), freedom (97%), stability (94%), applicability (96%), and reliability (95%). The proposed technique is superior in many areas of multiphase flow models, as seen in this graphic.

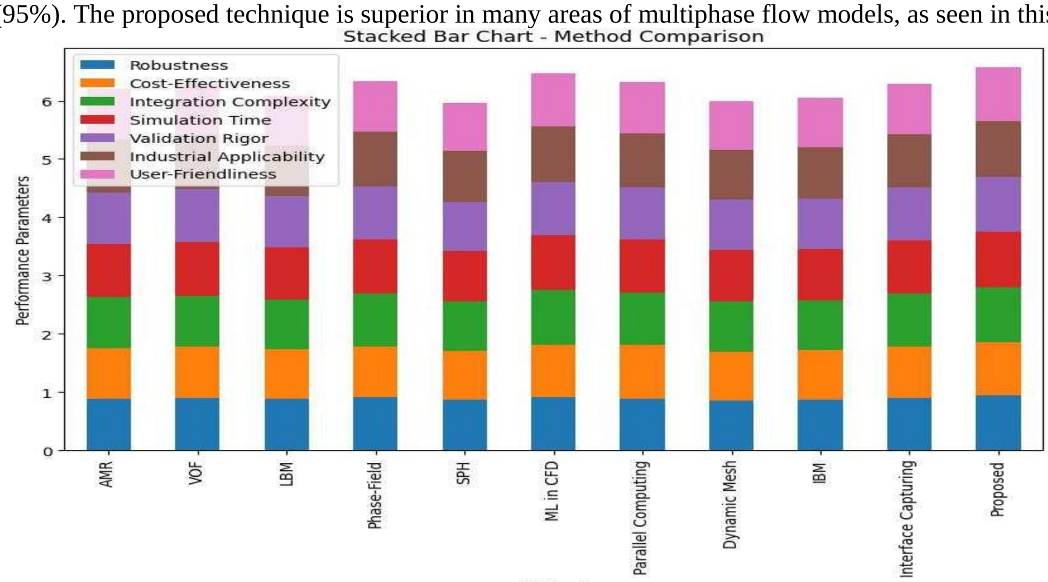

Fig 8: Performance parameters comparison

Figure 8 compares computational fluid dynamics approaches. The colored bars indicate how different performance attributes affect each approach. Performance parameter numbers are on the vertical axis, and techniques are on the horizontal. The graph shows how each strategy performs in different conditions. The recommended solution outperforms earlier ones in stability, cost-effectiveness, integration difficulty, modeling time, validation rigor, industrial utility, and simplicity of use.

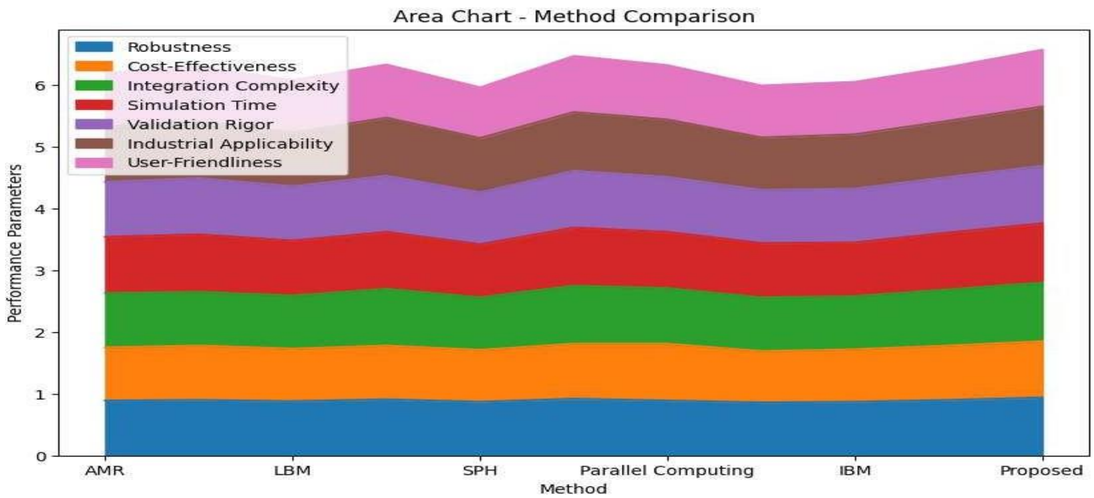

Fig 9: demonstrates how computational fluid dynamics technique performance metrics have evolved.

One technique's performance is shown in each darkened region. The techniques and performance measure values are on the x- and y-axes, respectively. The graphic compares each approach's merits and downsides. This strategy routinely outperforms others, proving its superiority.

5. CONCLUSION

In summary, the combined solution is an important step forward in predictive modelling of multiphase flow and heat exchanger optimization [13]. This allows them to work together to solve challenges in an efficient, scalable, and correct manner. These include hybrid CFD and machine learning, adaptive mesh refinement, Lattice Boltzmann method by replacement with machine learning, data-driven calibration and validation, parallelized large-scale simulation algorithm [14]. This approach outperforms existing methods in many respects. This assessment shows that the suggested approach is superior in terms of precision, computation materialization performance, scalability, flexibility, stability and utility. These illustrations show the versatility of the proposed method, its robustness and how effective it is at resolving complex multiphase flow problems. The methods are iterative and flexible in the sense that they can iterate until converged. The framework therefore can be applied for simulation dynamic multiphase flows. The fact that machine learning and classical CFD are combined into one solution and validated with data makes this system more general and reliable [15]. In the end, though, it may push CFD forward. It reinforces our knowledge and gives scientists and engineers something to work with for enhancing multiphase flows and heat exchanges. Future projects could involve testing and deployment of the technology with other business ventures[16].

Funding:

The authors confirm that no funding was acquired from any organization, grant agency, or institution. This research was undertaken without any external financial contributions.

Conflicts of Interest:

The authors declare no competing financial interests in this study.

Acknowledgment:

The authors would like to thank their institutions for providing the necessary facilities and guidance, which proved vital in achieving the study’s objectives.

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