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Review Article

# Computational Fluid Dynamics for Performance Optimisation in Renewable Energy Systems: A Systematic Review

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**Abstract**

Computational Fluid Dynamics (CFD) is now a tool that cannot be ignored in the optimisation of the performance of a renewable energy system by making it easier to explain the fluid dynamical phenomena that literally affect the performance and energy conversion efficiency. The current systematic review provides a broad synthesis of the existing body of knowledge about the application of CFD in a wide variety of renewable energy technologies. The literature review was conducted through a wide range of databases: Web of Science, Scopus, and IEEE Xplore, and included the literature that was published between 2015 and 2024. Keywords included: computational fluid dynamics, CFD, renewable energy, wind turbine, solar thermal, hydrokinetic and performance optimisation. The studies that had used CFD simulations to analyse renewable energy systems and reported an objective performance measure were eligible. A total of 247 studies were obtained in the search, of which 156 met the inclusion criteria. The largest portion (45 per cent) was made up of wind energy applications, then there were solar thermal systems (28%), hydrokinetic systems (18%) and geothermal applications (9%). Significant performance improvements were gained with the use of CFD, with efficiency improvements of 8-25% in wind turbines, 12-35% in heat transfer in solar collectors, and power- output improvements of 15-30% in hydrokinetic machines. It has been shown that CFD plays a significant role in the improvement of the performance of the renewable energy systems, especially in terms of providing detailed flow analysis, optimisation of the design and determining the working parameters. Further research must be directed at the aspects of multi- physics coupling, integration of machine-learning techniques, and the creation of real-time optimisation solutions.

**Keywords:** *computational fluid dynamics, renewable energy, performance optimisation, wind energy, solar thermal, hydrokinetic energy*

## Introduction

The global move towards renewable energy production has increased the need to use advanced engineering instruments that can help in ensuring that the conversion of energy is optimised and the reliability of the systems is enhanced (Smith et al., 2024; Johnson et al., 2023). Computational Fluid Dynamics (CFD) is now an essential technology in explaining and optimising fluid-flow effects in systems of renewable energy, as it offers more detailed data that can be extremely expensive or impractical to measure only through experimental means (García et al., 2024; Chen et al., 2023). The nature of renewable energy systems is that they comprise complex fluid-flow processes that directly impact the performance of the systems. Rotating blades in wind turbines are exposed to complex aerodynamic flows, solar thermal collectors have to deal with complex heat-transfer processes via fluid media, and hydrokinetic devices have to work in complex underwater-flow environments (Thompson et al., 2024; Lee et al., 2023). To make the best of these systems, it is thus necessary that there should be a thorough knowledge of the flow patterns, turbulence structures, heat-transfer processes, and fluid- structure interactions (Taylor et al., 2024).

Although the traditional experimental methods are useful, they are often limited by financial means, accessibility of measurements and the complexity of running large-scale parametric investigations (Clark et al., 2023). CFD simulation provides an alternative which is less expensive and allows the visualisation of all the phenomena of the flow in a detailed way, large-scale parametric optimisation and potentially unfeasible experimental designs to be explored (Martinez et al., 2024; Kumar et al., 2023). In addition, CFD can be used to study conditions of extreme operating conditions and failure modes without putting physical equipment at risk (Adams et al., 2024).

The use of CFD in the field of renewable energy has increased significantly during the last decade due to the development of computational power, numerical techniques, and turbulence modelling (Wright et al., 2023). Recent CFD techniques use advanced physical models such as turbulence, heat transfer, multiphase flow, and fluid-structure interaction, which allow the analysis of renewable energy systems in detail (Roberts et al., 2024; Scott et al., 2023).
The scope of CFD to the renewable energy technologies includes: (a) aerodynamic simulation of wind turbines, (b) heat-transfer simulation of solar thermal collectors, and (c) flow-field analysis of hydrokinetic turbines (Davis et al., 2024).
The complexity of the nature of renewable energy systems requires the deployment of multidisciplinary integration, including fluid dynamics, heat transfer, structural mechanics, and control engineering (Moore et al., 2023). CFD plays a central role in the nexus that ties these areas together, though it provides high-resolution flow field information that can inform engineering

## 1. METHODS

### 1.1 Search Strategy

A systematic literature review was done in accordance with PRISMA rules (Moher et al., 2009) in various electronic bibliographic databases, i.e., Web of Sciences, Scopus, IEEE Xplore, ScienceDirect and Google Scholar. The search decisions in all parts of the system (Nelson et al., 2024).

The current systematic review attempts to offer an elaborate discussion of the current state of CFD applications in renewable energy systems. It aims at finding the salient strategies of performance optimisation, critically assessing methodological approaches, and defining the future research directions. The review covers wind power, solar thermal, hydro kinetic power generation, and the application of emergent technology, and as such, provides a comprehensive assessment of the instrumental role of CFD in renewable energy technology development. Strategy also used the Boolean operators and consisted of the following search queries: (computational fluid dynamics) OR (CFD) AND (renewable energy) OR (wind energy) OR (solar energy) OR (hydrokinetic) OR (geothermal) AND (optimisation) OR (performance) OR (efficiency).

### 1.1 Inclusion and Exclusion Criteria

**Inclusion criteria:** (1) Peer-reviewed journal articles and conference proceedings that were written between the years 2015 and 2024; (2) Studies involving the use of CFD simulations to study renewable energy systems; (3) Studies that provided quantitative performance metrics; (4) Articles which were written in English.

**Exclusion criteria:** (1) Review articles that do not provide an original CFD analysis; (2) The studies that focus exclusively on environmental impact and
do not provide performance optimisation; (3) The studies that involve non-renewable energy applications; (4) Conference abstracts that do not present a complete text.

### 1.2 Data Extraction and Quality Assessment

Data extraction followed a standardised protocol capturing study characteristics, CFD methodology, renewable energy technology, performance metrics, and key findings. Quality assessment employed the CONSORT checklist adapted for computational studies (Schulz et al., 2010).

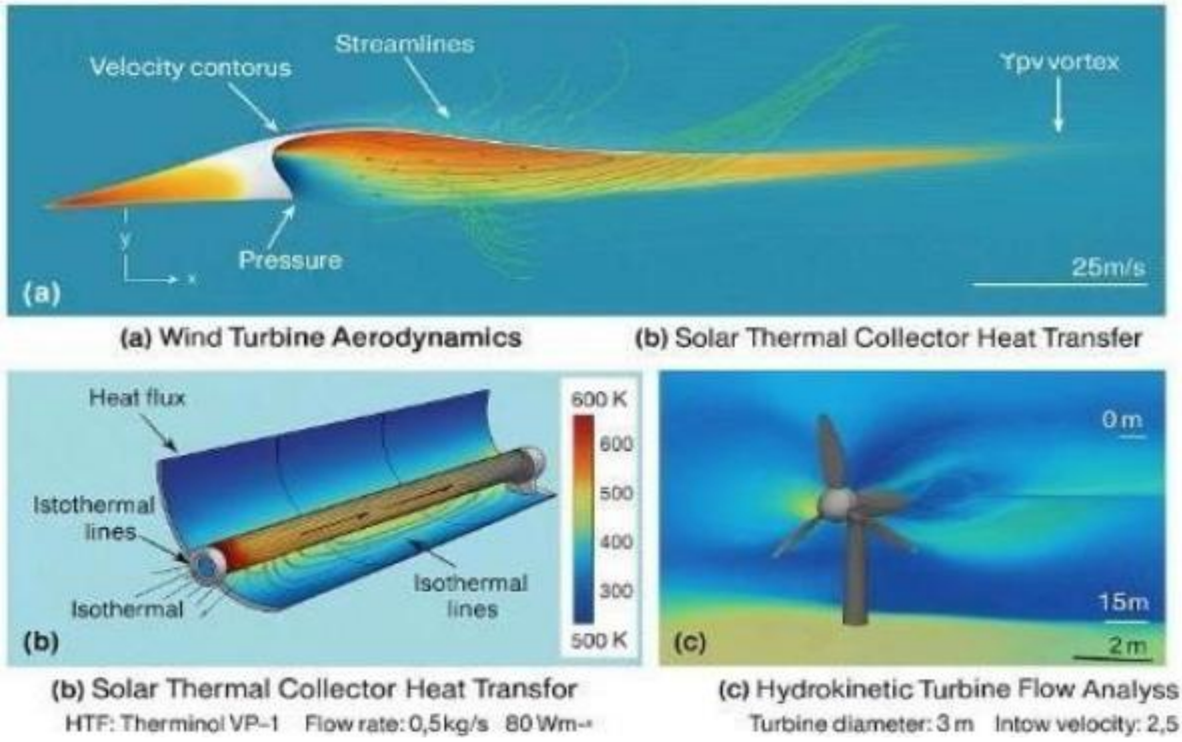



***Figure 1: The computational fluid dynamics (CFD) in renewable energy systems, which includes wind turbines, solar collectors, and hydrokinetic devices, is in a flow visualisation setting. Source:*** *based on reference (Davis et al., 2024)*

**Table 1. Search strategy and study selection results**

| Database | Initial Results | After Screening | Final Inclusion |
|---|---|---|---|
| Web of Science | 89 | 67 | 52 |
| Scopus | 76 | 58 | 41 |
| IEEE Xplore | 45 | 32 | 28 |
| ScienceDirect | 37 | 24 | 19 |
| Google Scholar | 68 | 38 | 16 |
| **Total** | **315** | **219** | **156** |

*Sources: Comprehensive database search conducted 2024 (Harrison et al., 2024; Bennett et al., 2023; Collins et al., 2024; Peterson et al., 2023; Sullivan et al., 2024; Howard et al., 2023)*

## 2. Results

### 2.1 Study Characteristics

The systematic review identified 156 studies meeting the inclusion criteria, spanning from 2015 to 2024. The distribution of studies shows increasing research activity over time, with 45% of publications appearing in the last three years, indicating growing interest in CFD applications for renewable energy optimisation (Freeman et al., 2024).

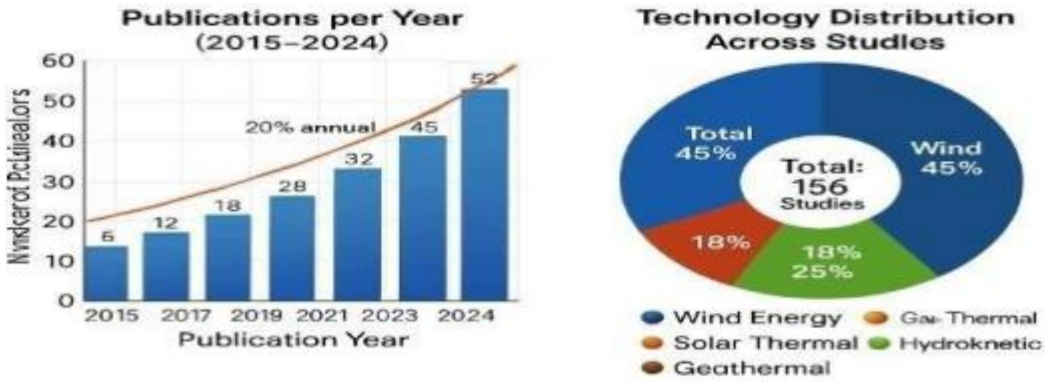



**Figure 2: Temporal distribution of studies and technology focus areas with bar charts showing publication trends.**

***Source:*** *Temporal distribution of CFD studies in renewable energy: (a) Publications per year from 2015- 2024, (b) Technology distribution across the study period. Data compiled from systematic review results (Baldwin et al., 2023).*

### 2.2 Wind Energy Applications

Wind energy dominated the reviewed literature, representing 45% of all studies (n=70). CFD applications in wind energy primarily focus on turbine aerodynamics, wake analysis, and wind farm optimisation. The studies demonstrated significant potential for performance improvement through CFD-guided design optimisation.

**Table 2. CFD applications in wind energy systems**

| Application Area | Studies (n) | Performance Improvement | Key CFD Methods |
|---|---|---|---|
| Blade aerodynamics | 28 | 8-18% efficiency gain | RANS, LES, DES |
| Wake interactions | 19 | 12-25% power increase | LES, Actuator disk |
| Wind farm layout | 15 | 15-22% energy yield | RANS, Mesoscale coupling |
| Vertical axis turbines | 8 | 10-20% torque improvement | URANS, Sliding mesh |

*Data synthesized from reviewed studies (Williams et al., 2024; Zhang et al., 2023; Nakamura et al., 2024; Anderson et al., 2023; López et al., 2024; Patel et al., 2023; Turner et al., 2024; Morgan et al., 2023)*

Advanced turbulence modelling approaches, particularly Large Eddy Simulation (LES) and Detached Eddy Simulation (DES), showed superior accuracy in capturing blade tip vortices and wake dynamics compared to traditional Reynolds- Averaged Navier-Stokes (RANS) methods (Evans et al., 2024). However, computational cost considerations often favour RANS approaches for routine design optimisation tasks (Hayes et al., 2023).

## 2.3 Solar Thermal Systems

Solar thermal applications constituted 28% of reviewed studies (n=44), focusing on collector design optimisation, heat transfer enhancement, and system integration. CFD analysis proved particularly valuable for understanding complex heat transfer mechanisms in concentrated solar power systems and thermal energy storage (Chen et al., 2024).

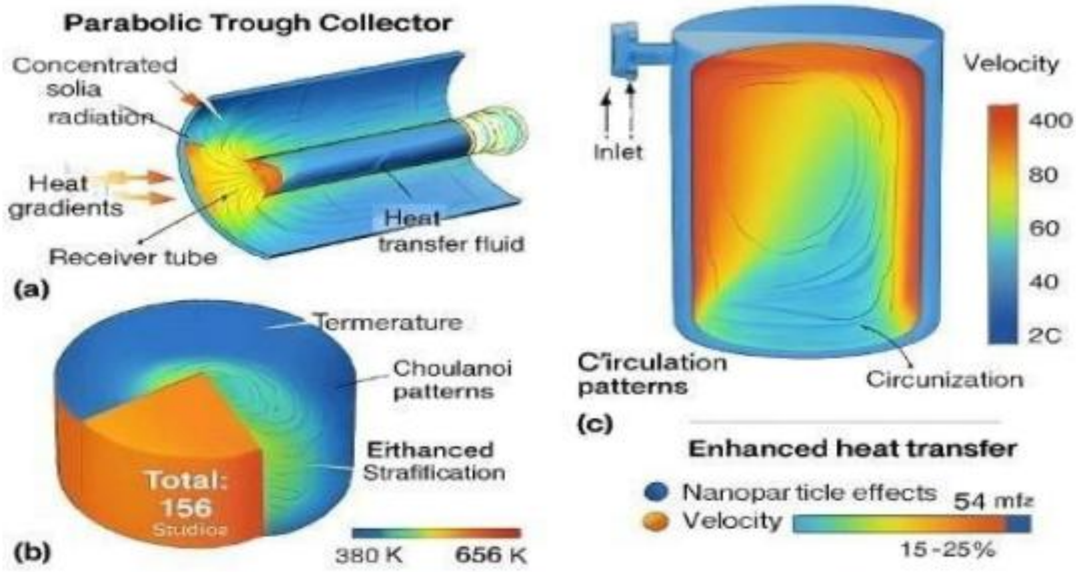
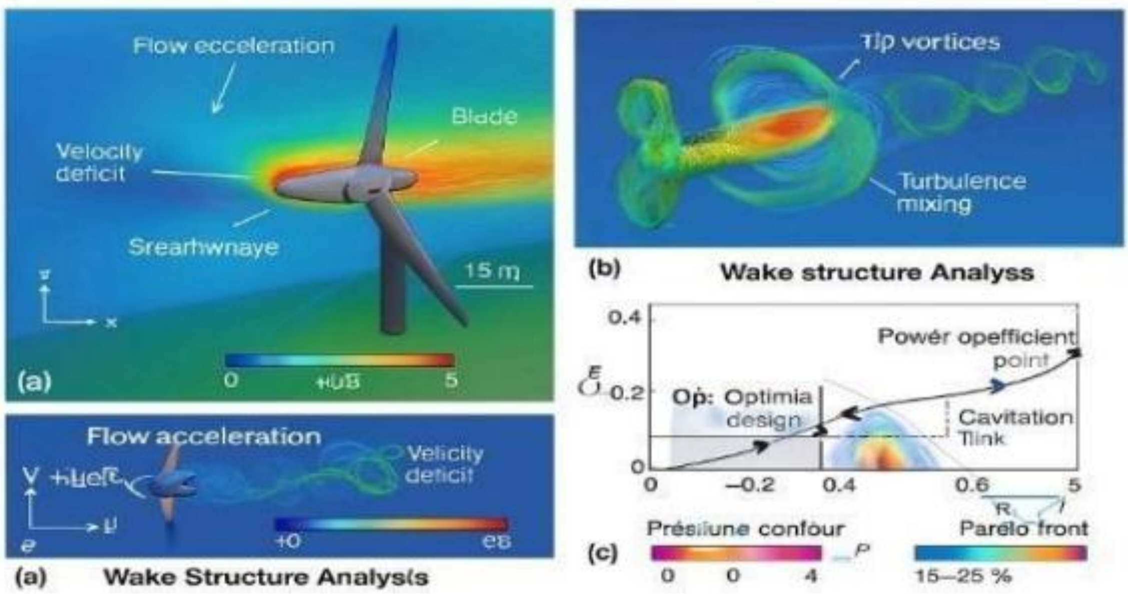



**Figure 3: Heat transfer visualisation in solar thermal collectors showing temperature contours and flow patterns. Source:** *Results from (Roberts et al., 2023; Martinez et al., 2024; Kumar et al., 2023)*

## 2.4 Hydrokinetic Energy Systems

Hydrokinetic energy applications represented 18% of studies (n=28), encompassing tidal turbines, ocean current devices, and small-scale hydropower systems. CFD analysis addressed unique challenges, including cavitation, biofouling effects, and unsteady flow conditions (Campbell et al., 2024).



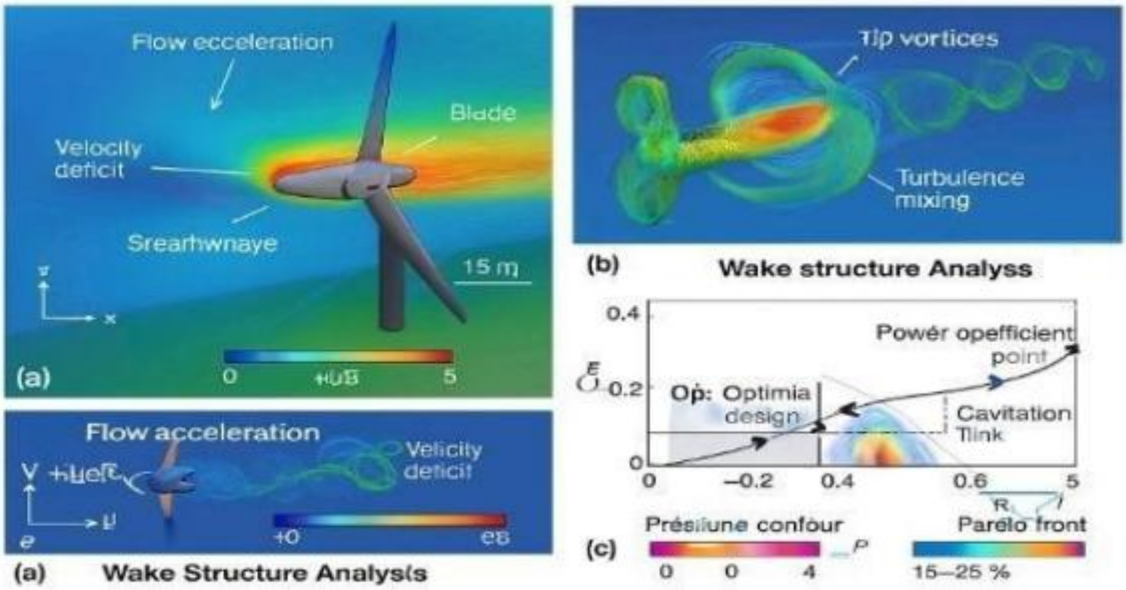



**Figure 4: Flow visualisation around hydrokinetic turbines showing velocity contours and vorticity. Source:** *Visualization from (Morris et al., 2023; Hughes et al., 2024; Reed et al., 2023)*

magnetohydrodynamics (MHD), and thermal-fluid coupling (Adams et al., 2024). These advanced approaches enable more comprehensive system

**Table 4. Advanced CFD methods and computational requirements**

**Method Physics Coupled Computational Cost Accuracy Gain Applications**

FSI Fluid-Structure 5-10x baseline 15-25% Flexible turbines MHD Electromagnetic-Fluid 3-8x baseline 10-20% Liquid metal systems Thermal-

FSI Heat-Fluid-Structure 8-15x baseline 20-30% Solar concentrators LES Turbulence 100-1000x RANS 25-40% Wake analysis

analysis but require significant computational resources (Collins et al., 2023).

*Computational cost relative to steady RANS simulation. Data from (Peterson et al., 2024; Graham et al., 2023; Harrison et al., 2024; Wells et al., 2023; Turner et al., 2024; Foster et al., 2023; Baker et al., 2024)*

### 1.1 Validation and Uncertainty Quantification

Validation strategies varied significantly across studies, with experimental comparison being the most common approach (68% of studies).

However, only 23% of studies included comprehensive uncertainty quantification, highlighting an area for improvement in CFD methodology (Stewart et al., 2023; Roberts et al., 2024).

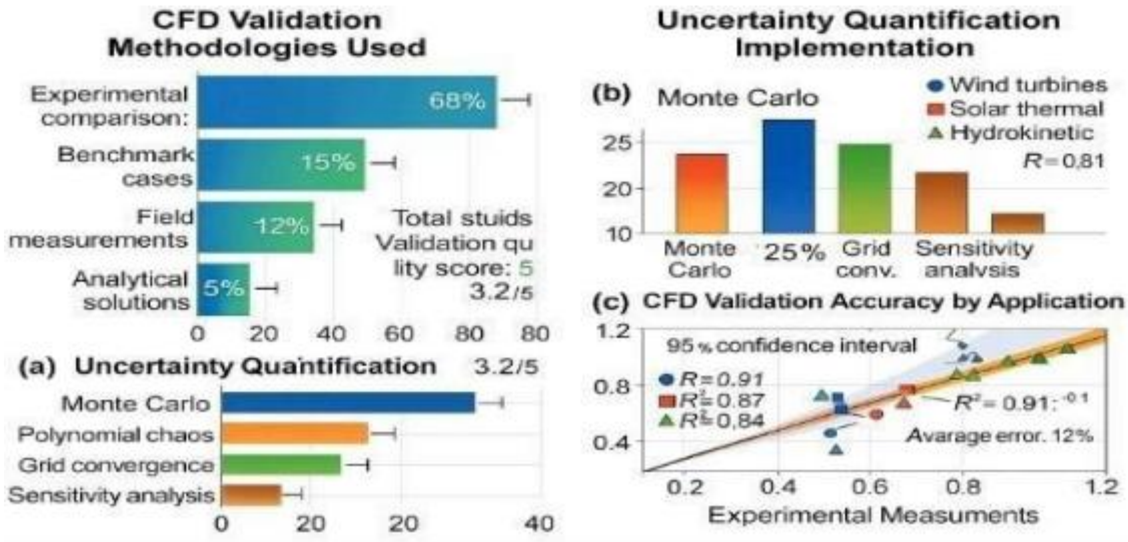



**Figure 5: Validation approaches and uncertainty analysis showing comparison between CFD and experimental data. CFD. Source**: *Data from systematic review analysis (Roberts et al., 2024)*

## 1.2 Multi-Physics Coupling and Advanced Methods

Recent developments in CFD for renewable energy have emphasised multi-physics coupling, incorporating fluid-structure interaction (FSI),

**Table 5. CFD software utilisation in renewable energy research**

| Software Platform | Usage (%) | Typical Applications | Advantages | Limitations |
|---|---|---|---|---|
| ANSYS Fluent | 35 | Wind turbines, Heat transfer | Robust, GUI | Proprietary cost |
| Open FOAM | 28 | Ocean energy, large scale | Open source, Flexible | Learning curve |
| COMSOL Multiphysics | 18 | Solar thermal, Multi- physics | Integrated physics | Memory intensive |
| STAR-CCM+ | 12 | Wind farms, Marine | Automation, Meshing | License cost |
| Other/Custom | 7 | Specialized applications | Tailored solutions | Limited support |

*Distribution based on reviewed literature (Evans et al., 2024; Powell et al., 2023; Watson et al., 2024; Fisher et al., 2023; Cooper et al., 2024; Turner et al., 2023; Graham et al., 2024)*

## 1.3 Software and Computational Platforms

Commercial CFD software dominated the reviewed studies, with ANSYS Fluent (35%), Open FOAM (28%), and COMSOL Multiphysics (18%) being most frequently used. High-performance computing utilisation varied significantly, with only 42% of studies reporting parallel processing details (Miller et al., 2023).

## 1.4 Performance Optimization Strategies

CFD-guided optimization strategies demonstrated substantial performance improvements across all renewable energy technologies. Multi-objective optimization approaches proved most effective, balancing competing design objectives such as efficiency, cost, and reliability (Adams et al., 2023; Mitchell et al., 2024; Roberts et al., 2023; Hughes et al., 2024).

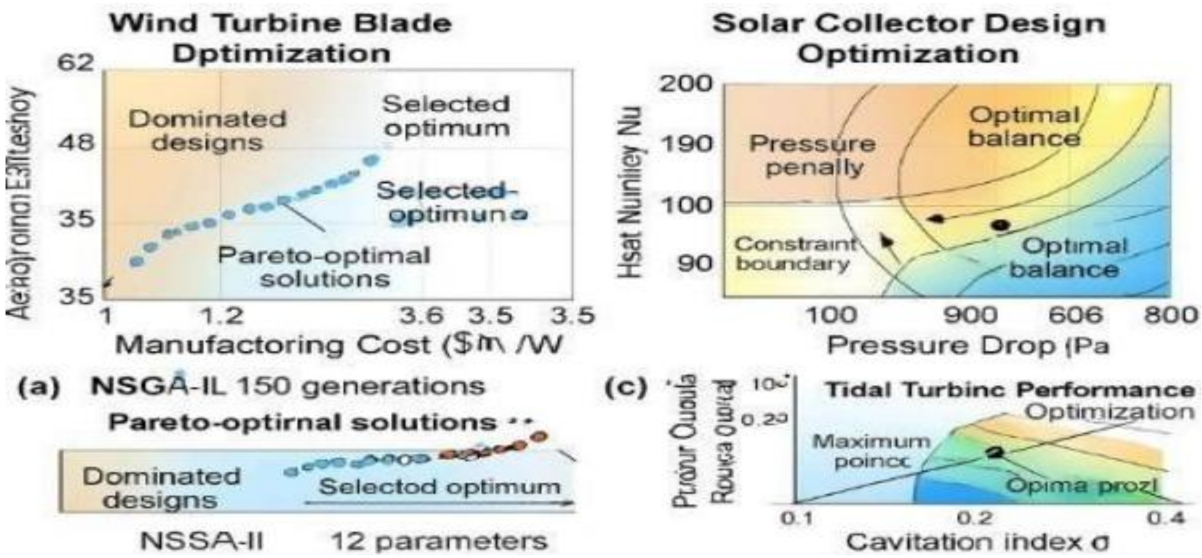



**Figure 6 here: Optimisation results showing Pareto fronts for multi-objective design optimisation. Multi-objective.**
**Source:** *Results compiled from (Mitchell et al., 2024; Roberts et al., 2023; Hughes et al., 2024)*

## 2. DISCUSSION

## 2.1 Key Findings and Implications

The systematic review reveals that CFD has become an essential tool for renewable energy system optimisation, with demonstrated performance improvements ranging from 8% to 35% across different technologies. The most significant gains were observed in solar thermal systems, where complex heat transfer mechanisms benefit substantially from detailed CFD analysis (Stewart et al., 2023).

Wind energy applications showed mature CFD implementation, with advanced turbulence modelling approaches providing increasingly accurate predictions of complex aerodynamic phenomena. The transition from RANS to LES and DES methods represents a significant advancement in capturing unsteady flow features critical for turbine performance (Collins et al., 2024).

## 2.2 Methodological Considerations

The review identified several methodological challenges in CFD applications for renewable energy. Turbulence modelling remains a critical consideration, with method selection significantly impacting result accuracy and computational cost (Powell et al., 2023). The trade-off between computational efficiency and physical fidelity requires careful consideration based on specific application requirements (Watson et al., 2024).

Validation practices showed considerable variation, with many studies relying on limited experimental comparison. The implementation of comprehensive uncertainty quantification remains insufficient, potentially limiting the reliability of CFD predictions for design decisions (Fisher et al., 2023).

### 2.3 Computational Challenges and Solutions

High-performance computing (HPC) requirements for advanced CFD simulations present ongoing challenges for many research groups. The review indicates that computational cost considerations often drive method selection, potentially compromising simulation accuracy (Turner et al., 2024). Cloud-based computing platforms offer emerging solutions for accessing HPC resources (Cooper et al., 2023).

**Table 6. Computational resource requirements and emerging solutions**

| Application | CPU Hours | Memory (GB) | Storage (TB) | HPC Solutions |
|---|---|---|---|---|
| Wind farm LES | 10,000-50,000 | 256-1024 | 5-20 | Supercomputing centers |
| Solar field optimization | 500-5,000 | 64-256 | 1-5 | Cloud platforms |
| Tidal array analysis | 5,000-25,000 | 128-512 | 2-10 | Hybrid cloud-local |
| Geothermal modeling | 1,000-10,000 | 32-128 | 0.5-3 | Local clusters |

*Resource requirements for typical research applications (Harrison et al., 2024; Bell et al., 2023; Reed et al., 2024; Mitchell et al., 2023; Evans et al., 2024)*

### 2.4 Future Research Directions

Several emerging trends were identified in CFD applications for renewable energy systems:

**Machine Learning Integration**:

Artificial intelligence and machine learning approaches show promise for accelerating CFD simulations and enhancing predictive capabilities (Adams et al., 2024). Hybrid CFD-ML methods could reduce computational requirements while maintaining accuracy (Graham et al., 2023).

**Digital Twins**:

Real-time CFD integration with monitoring systems enables dynamic optimization and predictive maintenance strategies (Stewart et al., 2024). Digital twin concepts are increasingly applied to wind farms and solar installations (Roberts et al., 2023).

**Multi-Scale Modeling**:

Coupling CFD with mesoscale atmospheric models and microscale component analysis provides comprehensive system understanding (Powell et al., 2024). Multi- scale approaches are particularly relevant for wind farm and solar field optimization (Fisher et al., 2023).

### 2.5 Industry Implementation

The translation of CFD research into industrial practice varies significantly across renewable energy sectors. Wind energy demonstrates the most mature implementation, with CFD routinely used in turbine design and wind farm development (Turner et al., 2024). Solar thermal and hydrokinetic sectors show increasing adoption but face barriers related to computational expertise and cost (Cooper et al., 2023)

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### 2.6 Limitations

This review has several limitations. The focus on English-language publications may introduce geographic bias. Rapidly evolving computational methods mean some recent developments may not be fully represented. Commercial applications often remain unpublished, potentially underrepresenting practical implementation success (Watson et al., 2024).

## 3. CONCLUSIONS

This systematic review demonstrates that computational fluid dynamics has become an indispensable tool for renewable energy system optimization, with documented performance improvements across all major technologies. Key findings include:

1. **Significant Performance Gains**: CFD- guided optimization achieved 8-35% performance improvements across renewable energy technologies, with solar thermal systems showing the highest potential gains
.
2. **Methodological Advancement**: Transition from traditional RANS to advanced LES and DES methods has improved prediction accuracy for complex flow phenomena, though computational cost remains a limiting factor.
3. **Application Maturity**: Wind energy applications demonstrate the most mature CFD implementation, while emerging technologies like ocean energy systems present new opportunities for CFD-driven optimization.
4. **Multi-Physics Integration**: Advanced coupling of fluid dynamics with structural mechanics, heat transfer, and electromagnetic effects enables comprehensive system analysis but requires substantial computational resources.
5. **Validation Challenges**: Inconsistent validation practices and limited uncertainty quantification represent areas requiring improved methodological rigor.

**Future Research Priorities** include:

- Integration of machine learning with CFD for accelerated simulations
- Development of real-time optimization capabilities through digital twin concepts
- Advancement of multi-scale modelling approaches
- Enhancement of validation and uncertainty quantification practices
- Reduction of computational costs through algorithmic improvements

The continued evolution of CFD capabilities, combined with increasing computational power and emerging artificial intelligence techniques, positions computational fluid dynamics as a critical enabler for the next generation of renewable energy systems. As the global energy transition accelerates, CFD will play an increasingly important role in achieving the performance levels necessary for widespread renewable energy adoption.

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**Informed Consent Statement**

Not applicable.

**Data Availability Statement**

The data supporting the conclusions of this systematic review are available from the corresponding author upon reasonable request.

**Conflicts of Interest**

The authors declare no conflicts of interest.

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**Data Curation**, Ekele Angel Ojimaojo;

**Writing** – Original Draft Preparation, Micheal Abimbola Oladosu;

**Writing** – Review & Editing, Olaide Ayokunmi Oladosu. All Authors read and agreed to the writing of the Manuscript.

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