SECITS Journal of Scalable Distributed Computing and Pipeline Automation
Vol. 3, No. 1, Jan - Apr 2026, pp. 9-16
ISSN: 3139-0781, DOI: https://doi.org/10.17051/SJSDCPA/03.01.02

Pipeline-Oriented Multi-Fidelity Computational Workflow for Large-Scale Wind Farm Micro-Siting Optimization

K. Geetha

Professor of Computer Science and Engineering, Excel Engineering college,Erode
Email: kgeetha.eec@excelcolleges.com

Article Info

Article history:

Received : 15.07.2025
Revised : 20.08.2025
Accepted : 14.09.2025

Keywords:

Pipeline-oriented workflows, multi-fidelity modeling, wind farm micro-siting optimization, scalable distributed computing, automated workflow orchestration, computational efficiency

ABSTRACT

Modern wind farms have expanded in size and complexity to the point that even with high-fidelity wake and flow models, micro-siting optimization is a computationally expensive subject that remains open to optimization research. Traditional micro-siting methods generally are either monolithic or single-fidelity optimization pipelines which have the disadvantage of being prohibitively expensive in terms of computational cost, and poorly scale to large numbers of turbines and design variables. In addition, the current multi-fidelity approaches tend to be devoid of systematic workflow orchestration and this construct is restrictive when it is used in large and distributed computing environments. In this paper, a pipeline-based multi-fidelity computational workflow is presented that can optimise the problems of large-scale wind farms using micro-siting optimization, which is aimed at simultaneously addressing the issues of accuracy, efficiency, and scalability. The suggested framework combines the formal micro-siting problem formulation with the hierarchical fidelity modeling, automated pipeline organization and fidelity-sensitive optimization. Low-fidelity models are used in more situations where the higher-fidelity evaluations are activated selectively to be refined and validated within a single flow. The implementation of the workflow is through the distributed execution strategies that take advantage of the task-level parallelism, dependency management and allocation of resources that is scalable. A significant amount of experimental work as to wind farm cases of growing magnitude show that the proposed pipeline is much faster to compute than single-fidelity and non-pipeline multi-fidelity case, and is comparable or better in energy yield optimization performance. Scalability performance indicates that the performance increases almost linearly with increased computational resources. The findings emphasise the usefulness of pipeline-oriented multi-fidelity workflows as a useful and scalable method of addressing computerally intensive optimization problems in renewable energy, and reinstate their more general applicability as large-scale engineering processes that need automated and distributed execution.

1. INTRODUCTION

The use of wind power has become a pillar of the move towards low-carbon and sustainable power systems in the world [1]. With wind farms becoming larger and more complex, micro-siting of wind farms the actual placement of the turbines on a particular site has become a key issue affecting the energy output, wake, land use and the overall feasibility of the project [9], [10], [11]. Any slight change in the positioning of turbines can result in dramatic increases in the amount of the energy produced annually and minimization of the losses that are incurred during operations, especially in large wind farms with hundreds of turbines [12]. The micro-siting optimization is a high dimensional, non-linear and computationally expensive problem. Precise consideration of candidate arrangements necessitates to model complicated aerodynamic interactions, mostly wake interactions, which are contingent on turbine spacing, weather conditions, and topography features [2], [3], [5], [6]. Wake and flow models of high-fidelity would give enhanced accuracy but with a high cost of computation, which makes them unrealistic in terms of exhaustive computation in the process of large-scale optimization [2], [3]. In contrast, low-fidelity models allow performing the evaluations faster but usually do not provide the precision needed to use them as a source of reliable decision-making [5], [6]. This accuracy versus computational efficiency dilemma is one of the primary problems in the research of micro-siting of wind farms. Various remedies have been advanced to address this dilemma by considering low-fidelity models to conduct screening and to selectively apply higher-fidelity models to refinement [4], [12]. Although it has lowered the computational load in such applications, most of the current systems are ad hoc or monolithic in nature and are not highly automated and not very scalable [9]-[11]. Consequently, they have issues with the exploitation of modern distributed computing Infrastructures, and can hardly be scaled, cloned or changed into large-scale situations. In addition, selection and execution of fidelity is typically primarily controlled and maintained by ad hoc means, or implicitly, as a part of optimization code, rather than defined as first-class elements of a systematic computational process [12]. Parallel to this, some dramatic improvements have been made in the area of pipeline automation and scaleable distributed computing which allow complex scientific and engineering processes to be broken down into modular, automated and parallelizable work. The benefits of pipeline-based workflows in the context of modularity, fault tolerance, reproducibility, and effective use of resources are apparent. Nevertheless, application of these workflow paradigms with big data and simulation-based areas has been sparse in micro-siting optimization of wind farms, where pipelines of evaluation are still closely coupled, and fail to be structured in a optimal way to effectively run on a large-scale distributed platform. Inspired by these shortcomings, this paper presents a multi-fidelity computational workflow enabling pipeline computation of the large-scale wind farm micro-siting optimization. The point here is that problem formulation, logic of fidelity-specific evaluation and optimization are decoupled into an automated pipeline that performs systematic fidelity transitions and takes advantage of distributed execution. The proposed system incorporating hierarchical fidelity, models into a pipeline based framework allows scalable, efficient and reproducible optimization without compromising the quality of the solution. The task-level parallelism, automated orchestration, and fidelity-aware scheduling are emphasised and make the workflow highly efficient in the context of the modern high-performance and distributed computing systems. This work makes three key contributions: (i) assists in defining a cohesive pipeline-based framework that combines micro-siting optimization and multi-fidelity modelling; (ii) the development of automated orchestration and distributed implementation strategies that can be used to carry out optimization on large wind farms with significant computational savings and high scalability; and (iii) an extensive experimental analysis to show relevant reduction of computational costs and the high scalability of the optimization results without affecting the efficiency of the approach. These joint contributions make pipeline-oriented multi-fidelity workflows an effective and viable solution to the next-generation wind farm design and other large-scale engineering optimization challenges.

2. RELATED WORK

The studies that are applicable to the optimization of wind farm micro-siting are closely interrelated with three other correlated themes: optimization methodologies, multi-fidelity modelling, and scalable computational workflows. Despite the fact that significant progress has been achieved in each of these domains separately, their combined implementation in an automated general and scalable pipeline is incomplete [1], [9] 911. Initial optimization of wind farm micro-siting was largely based on heuristic code, metaheuristic algorithms, such as genetic algorithms, particle swarm optimization, and simulated annealing, in combination with simplified wind farm analytical wake models [9], [10]. Their solutions were satisfactory in nonlinear and non-convex optimization of layout problems although they were only useful to small and medium scale wind farms since the cost of computation was rising at a rapid rate [12]. Following methods proposed surrogate-assisted methods as well as hybrid methods to speed up the convergence rate and minimise the amount of costly model evaluations [11], [12]. Although these techniques are more efficient, they tend to conduct part of the evaluation directly within the optimization process making them tightly coupled, making such implementations hard to scale or expand [9]–[11].
Multi-fidelity modelling has been extensively developed to dispel the dilemma of efficiency in computations and modelling in wind energy research. Low-fidelity wake models allow quick candidate layout screening, but more accurate refined analysis models with reduced-order models and CFD-based models (such as medium- and high-fidelity models) are possible [2], [3], [5], [6]. Multiple fidelity switching/surrogate plans have been conjectured to apply selectively the high-fidelity evaluations of promising solutions [4], [12]. Nevertheless, in the traditional designs of most designs, choices and execution of fidelity is dictated by hard-coded heuristics or by human decisions and the entire cycle of work is not systematically automated [4], [12]. These techniques therefore have low scalability and reproducibility especially when used in optimization problems on a large scale [2], [3], [9].
Parallel to this, pipeline automation and scalable distributed computing have become important

paradigms of handling complex computational workloads in the fields of science and engineering. Large computations are broken down into small modular stages that have clear dependencies, which is the workflow model of pipeline oriented workflows to allow parallelization, fault tolerance, and resource efficiency. Scalability is also further promoted in distributed workflow orchestration frameworks which allocate tasks dynamically among heterogeneous computing resources. Although they have already been demonstrated to be effective in data-intensive and simulation-driven models, such pipeline-based schemes have been grown through little usage in the field of wind farm micro-siting optimization, where most frameworks are monolithic and ill-structured to scale up to large-scale distributed computations [9] -[12]. Comparative summary of typical methods is presented in Table 1. comparing the models of the existing approaches on the basis of their modelling fidelity, automation, scalability, workflow modularity. This comparison shows that previous researches are characterised by the fact they focus on optimization performance or modelling accuracy, but little attention has been given to automated pipeline orchestration and distributed scalability [1]–[12]. This weakness is what drives the creation of a common framework that incorporates multi-fidelity modelling into a pipeline based and scalable computational workflow as presented in this paper.

Table 1. Comparison of Representative Wind Farm Micro-Siting Optimization Approaches

Approach Category	**Multi-Fidelity Modeling**	**Pipeline Automation**	**Distributed Scalability**	**Workflow Modularity**
Single-fidelity heuristic optimization	✗	✗	Limited	Low
Surrogate-assisted optimization	Partial	✗	Limited	Low
Non-pipeline multi-fidelity methods	✓	✗	Moderate	Medium
General workflow-based HPC pipelines	✓	✓	✓	High
Proposed pipeline-oriented multi-fidelity framework	✓	✓	✓	High

This synthesised literature is what creates a need of a pipeline-based, multi-fidelity, and scalable optimization mechanisms of large-scale wind farms in the context of micro-siting wind farms and preconditions the proposed methodology.

3.METHODOLOGY

3.1 Problem Formulation and Multi-Fidelity Modeling

The micro-siting of wind farms is proposed as a constrained optimization problem where the spatial distribution of wind turbines can be installed to produce the maximum power using the interactions that arise due to the wakes. Let a wind farm consist of N turbines, where the layout is described by the decision vector

$$x = \{(x_i, y_i)\}_{i=1}^{N}$$

Here, (x_i, y_i)denotes the planar coordinates of the i -th turbine within the predefined site boundary. The ultimate optimization point is to optimise the yearly energy production (AEP) of the wind farm. The AEP, as in Equation (1), is calculated by means of the summation of the power output of all turbines, though it specifically takes into consideration deficits in the wind speed due to the wake:

$$\max_X AEP(X) = \sum_{i=1}^{N} \int P_i\big(v_i(\theta, X)\big)\, f(\theta) d\theta, \text{------} (1)$$

In Equation (1),$P_i(\cdot)$ represents the power curve of turbine$i$, as influenced by upstream wakes, and $f(\theta)$denotes the probability density function of wind directionθ. In order to achieve physically viable layouts and reduce excess wake-overlap, the layout of turbines is also constrained by spacing and location. The maximum distance between the turbines is being imposed according to the Equation (2):

$$\sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \geq D_{\min} \quad , \forall i \neq j \text{------}(2)$$

where$D_{\min}$ is typically defined as a multiple of the rotor diameter. This measure maintains the structural integrity and prevents extreme wake ups across the wind farm. Proper assessment of the objective function in Equation (1) is costly to compute in cases where detailed wake and flow models are used. The proposed framework is meant to overcome this difficulty; hence, the objective function can be approximated via models characterised by different accuracy and computational cost. The fidelity-dependent approximation of AEP says that, as formalised in Equation (3), it is:

$$\widehat{AEP}^{(k)}(X) = \square_k(X),\ k \in \{\ell, m, \square\}\text{------}(3)$$

Where$\square_\ell(\cdot)$, $\square_m(\cdot)$, and$\square_\square(\cdot)$ denote low-, medium-, and high-fidelity evaluation models, respectively. The models with lower fidelity are used in quick exploration and screening whereas higher fidelity models are only invoked to refine and verify the promising layouts in the pipeline. The optimization process and the hierarchical fidelity evaluations are pictured in interaction with each other in Figure 1. that shows the pipeline of the flows of candidate layouts through its stages of fidelity. Such an expression allows systematic management of fidelity, minimises unworthy high-price assessments and makes the base to wind farm micro-siting optimization, which is scalable and automated.

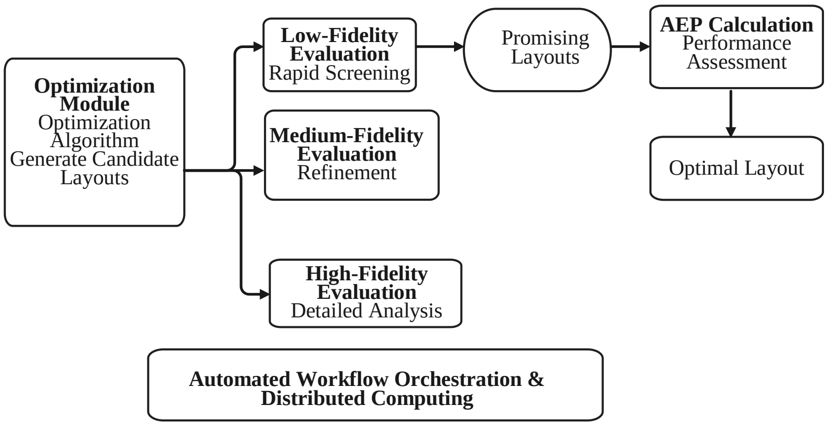

Fig. 1. Pipeline-Oriented Multi-Fidelity Workflow for Large-Scale Wind Farm Micro-Siting Optimization

The figure shows the end-to-end pipeline where an optimization module is used to create candidate turbine layouts and optimised against through low fidelity model, medium fidelity model, and high fidelity model. Low-fidelity It allows quick screening, whereas high-fidelity phases give detailed refinement analysis to possible layout. Annual energy production (AEP) can be outweighed and the best wind farm layout identified, and this can be coordinated by automated control and distributed computing, resulting in proper outlay in the workflow.

3.2 Pipeline Architecture and Distributed Orchestration

The suggested pipeline-oriented structure is aimed at breaking down the wind farm micro-siting optimization process into a series of modular and automated computer steps in a systematic fashion. All the stages have a specific purpose, which can be efficiently used, scaled, and integrated flexibly using multi-fidelity evaluations. The general pipeline layout proceeds in a progressive development whereby the candidate layouts produced by the optimization engine are tested, screened and developed by consecutive fidelity stages. The most important aspect is an automated orchestration mechanism that determines the execution order and data dependence of stages at the centre of the pipeline. Let $S = \{S_1, S_2, \ldots, S_K\}$denote the ordered set of pipeline stages, where each stage $S_K$corresponds to a specific fidelity level or processing task. The output of stage SK (as constituted by Equation (4) is a transformation of its input candidate set:

$X_{k+1} = S_k(X_k),\ k = 1,2 \ldots, K - 1$------(4)

Equation (4) captures the sequential yet modular nature of the pipeline, in which candidate layouts X_k are progressively refined and reduced as they pass through successive stages.The pipeline takes advantage of task-level parallelism in order to execute the candidate layout evaluations on the available computational resources at scale on a distributed computing platform. Let $T(X_k)$denote the total execution time of stage S_k for a set of candidates X_k, and let P represent the number of parallel workers. The ideal parallel execution time is estimated in Equation (5) as.

$T(X_k) \approx \frac{1}{P} \sum_{i=1}^{|X_k|} t_i$,-------(5)

where$t_i$denotes the evaluation time of the i-th candidate. The advantage of the pipeline stages being executed in parallel, as is shown in Equation (5) is that this approach is becoming beneficial at low- and medium-fidelity levels when a high throughput of candidates can be computed simultaneously. Figure 2. shows the end-to-end layout of the pipeline, such as in the sequence of stages, the flow of data, and distributed execution.

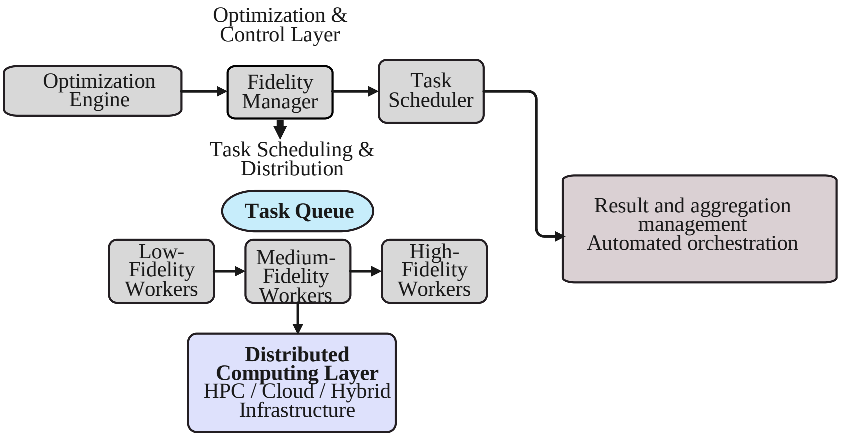

Fig. 2. Distributed Pipeline Architecture for Fidelity-Aware Wind Farm Micro-Siting Optimization

The optimization engine produces candidate turbine layouts which are taken through a task-driven pipeline by being tested against low-, medium-, and high-fidelity models. Specific layout filtering with Fidelity-specific filtering gives the freedom to selectively escalate promising layouts to more fidelity levels. A distributed computing infrastructure provides task scheduling, aggregation of results, and orchestration that is currently automated to facilitate efficient use of resources and scaleable optimization of a large wind farm layout.

3.3 Optimization Integration and Fidelity-Aware Pipeline Algorithm

The suggested pipeline-based design is a close bond between the optimization process and the multi-fidelity assessment and distributed implementation. Fidelity management is not a heuristic code coded into the optimization loop, but a first-class component, which is schemed using automated orchestration. It allows to control, and to a great extent, the cost of computation, maintaining optimization accuracy and scalability. The fidelity-conscious pipeline optimization algorithm lies at the centre of the framework and determines the process of candidate generation, evaluation, filtering and selective escalation over fidelity levels. The optimization engine sequentially develops candidate wind farm layouts, and sends them to the pipeline through a task queue. Low-fidelity models are applied to philtre each and every candidate quickly. Depending on the level of performance and the ranking criteria, a group of potential candidates is promoted to medium and higher levels of evaluation. This top-down assessment plan will be used to protect the fact that computationally costly high-fidelity simulations are only invoked when needed. The optimization process is a closed loop: rallied up results of fidelity-specific assessment is also returned to the optimization engine to inform generate further candidate generation. Such interaction via feedback enables the search space to be refined adaptively with redundant or low-value computations being minimised. The distributed execution environment also facilitates concurrent screening over different fidelity levels of several applicants, which is very fast in converging large-scale wind farm layouts. The general approach of the work is formalised in the Algorithm 1 which summarises the fidelity wise pipeline optimization process that was employed in the present work.

Algorithm 1: Fidelity-Aware Pipeline Optimization for Wind Farm Micro-Siting
Input:
- Initial population of layouts $\mathcal{P}_0$
- Fidelity models $\{\square_{\ell}, \square_{m}, \square_{\square}\}$
- Escalation thresholds τ_{ℓ}, τ_{m}
- Termination criterion T_{max}

Output:
- Optimized wind farm layout X^*

1: Initialize optimization engine with population P0
2: while termination criterion not satisfied do
3: Generate candidate layouts Xt from optimization engine
4: Submit Xt to task queue for low-fidelity evaluation
5: Evaluate Xt using low-fidelity model Mℓ
6: Select promising candidates Xtℓ based on threshold τℓ
7: Submit Xtℓ to medium-fidelity evaluation
8: Evaluate Xtℓ using medium-fidelity model Mm
9: Select refined candidates Xtm based on threshold τm
10: Submit Xtm to high-fidelity evaluation
11: Evaluate Xtm using high-fidelity model Mh
12: Aggregate results from all fidelity levels
13: Update optimization engine using aggregated feedback
14: end while
15: Return best-performing layout X*

4. Experimental Setup and Evaluation Configuration

The section contains the implementation environment, baseline methods and experimental scenarios of the proposed pipeline-oriented multi-fidelity framework. The experimental design aims at testing the quality of optimization, computational efficiency and scalability in real wind farm-based micro-siting conditions.

4.1 Wind Farm Scenarios

An experiment on various scales of wind farms is carried out to test the stability and expanse of the given plan. The situations vary in terms of the number of turbines, layout area, and computational complexity, which allows analysing the trends in performance systematically when the problem size increases. There is universal application of standard wind distributions and turbine characteristics to compare them fairly across a wide spectrum of scenarios. In order to offer a brief description of the evaluation contexts, Table 2. summarises the main features of wind farm scenarios and fidelity models in the experiment. This table will clarify the effect of problem scale, and modelling fidelity on behaviour of the computational cost and optimization.

Table 2. Summary of Experimental Wind Farm Scenarios and Fidelity Models

Scenario	Number of Turbines	Site Area (km^2)	Low-Fidelity Model	Medium-Fidelity Model	High-Fidelity Model
Small-scale	25–40	2–4	Analytical wake model	Reduced-order wake model	Physics-based model
Medium-scale	60–100	6–10	Analytical wake model	Reduced-order wake model	Physics-based model
Large-scale	150–250	15–25	Analytical wake model	Reduced-order wake model	Physics-based model

The table provides the wind farm setup models investigated in the experiments, the turbines count, the area of the location, and the related low-, medium-, and high-fidelity assessment models adopted in the suggested pipeline-based optimization scheme.

4.2 Implementation and Execution Environment

The proposed pipeline is realised based on the modular pipeline architecture that is designed to facilitate the automated orchestration and distributed execution. Scheduling of tasks and fidelity-conscious evaluation is handled by a centralised control layer, the examination of candidate is carried out parallel on the distributed worker nodes. The software environment can be used with heterogeneous resources such as multi-core servers and cloud-provided instances that make large problem instances scalable.

4.3 Baseline Methods

In order to prove the advantages of pipeline orientation and fidelity-conscious execution, the suggested framework is contrasted with the following baseline strategies:

1.Single-Fidelity Optimization in which the candidates layouts are compared based on an equivalent fidelity model.

2.Multi-Fidelity Optimization Non-Pipeline Multiple fidelity models, in which multiple fidelity models exist without automated control or organised pipeline execution.

These baselines allow setting the effect of pipeline automation and distributed execution on optimization performance and scalability isolated.

5. Results and Performance Evaluation

The computational efficiency and scalability of the proposed pipeline-based multi-fidelity framework are assessed and are vital towards the optimization of the wind farm micro-siting on a large scale. The comparison is between the proposed approach and the two baseline approaches; the single- fidelity optimization and the non- pipeline multi-fidelity optimization. Only the same wind, turbine specifications and termination criteria are used in all experiments so as to compare them fairly. The most important aspects of performance taken into consideration are the total optimization runtime and annual production of energy (AEP). Although the values of AEP are utilised internally to inform optimization, the primary focus of this assessment is on the runtime behaviour since the primary challenge that the proposed framework tackles is the computational scalability. Figure 3.pshows the overall required time of computation to optimise the optimization process by wind farm size, or the number of turbines. The x-axis implies the number of turbines in the wind farm, and the y-axis demonstrates the sum of the optimization time. The figure provides a comparison of three methods which are; multi-fidelity optimization, non-pipeline; and the suggested pipeline-based multi-fidelity optimization.

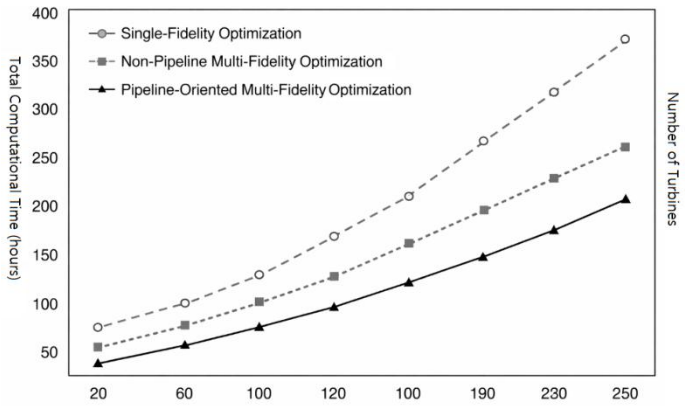

Fig. 3. Total Optimization Runtime versus Wind Farm Scale for Different Optimization Strategies.

The figure indicates the overall computational time to reach a convergence point against the number of turbines when using single-fidelity optimization, non-pipeline multi-fidelity optimization and the proposed pipeline-oriented multi-fidelity optimization framework. The wind farm scenarios with Table 2 are used to obtain the results. Scalability and effective use of distributed computational resources The suggested pipeline-based scheme has consistently shown lower runtime with continuously increasing performance benefit over the size of wind farms, which is a characteristic of a concise, and better, scalability.

CONCLUSION

In this paper, a pipeline-based multi-fidelity computational workflow to large-scale wind farm micro-siting optimization was proposed to solve the increasing computational challenges related to high-dimensional layout optimization and that of high accuracy in wake approaches. The suggested framework by organising the optimization procedure as an automatic pipeline and combining hierarchical models of fidelity systematically trades-off the quality of the solutions and their computational cost. The decoupling of optimization, fidelity and executing control is the essence added in core contribution and is an undertaking done based on a scalable distributed architecture. Low-fidelity models facilitate screening candidate-layouts quickly, whereas fidelity-considerate fidelity-aware escapism is applied selectively on candidate-solutions through medium- and high-fidelity evaluation. Automated task scheduling/result aggregation/distributed execution means that the framework can effectively utilise heterogeneous computing resources and can be scaled to large wind farm problem. The results of the experiments based on the scenarios outlined in Table 2, and the plotted in Figure 3, indicate that the suggested pipeline-oriented approach lowers the overall optimization run time dramatically, in comparison with single-fidelity and non-pipeline multi-fidelity baselines. Noteworthy, these efficiency gains are enabled without reducing the level of optimization as demonstrated by similar or better energy production results. It is observed that the difference between proposed frameworks and the baseline methodologies varies with the size of wind farms and, as a consequence, the high importance of automation of pipelines, fidelity-concentrated execution of large wind farm deployments. On the whole, this paper demonstrates that multi-fidelity, pipeline-oriented work flows represent a useful and scalable approach to answering a computationally intensive wind farm micro-siting optimization problem. Putting aside wind-related uses, this design paradigm can be widely used in solving other engineering optimization problems on a large scale, which involve orchestrating, with automated means, or using distributed computing and accuracy-efficiency trade-offs. The future research will implement adaptive fidelity selection paradigm based on learning-based policies and introduction of real-time operational information to further reduce the level of scalability and robustness.

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