Aleksi Hasu

SEQUENTIAL OPTIMIZATION OF OFFSHORE WIND FARM LAYOUT AND CABLE ROUTING FOR BALTIC SEA APPLICATIONS

Master's Thesis
Faculty of Information Technology and Communication Sciences
Examiners: Jussi Rasku
Hamed Badihi
September 2025

ABSTRACT

Aleksi Hasu: Sequential Optimization of Offshore Wind Farm Layout and Cable Routing for Baltic Sea Applications
Master's Thesis
Tampere University
Master's Programme in Information Technology
September 2025

Offshore wind farm design presents a complex multi-objective optimization challenge involving turbine layout and electrical cable routing. This thesis develops and evaluates a sequential optimization framework specifically tailored for Baltic Sea conditions, where gravity-based foundations offer advantages over conventional foundation types. The research addresses four main objectives: validating sequential optimization effectiveness, developing a gravity-based foundation cost model, comparing cable routing algorithms, and demonstrating the framework through a comprehensive case study.

The methodology employs a two-stage sequential approach using the TopFarm optimization framework. First, turbine layout optimization maximizes energy production or economic metrics using the COBYLA algorithm, incorporating a custom gravity-based foundation cost model that accounts for depth-dependent excavation and installation costs. Second, cable routing optimization compares genetic algorithm and Large Neighborhood Search approaches for both radial and branched network topologies. The framework is demonstrated through a 300 MW offshore wind farm case study located off the coast of Pori, Finland.

Results validate the sequential approach through preliminary analysis showing cable costs vary by only 1.5-3% across different layouts. Layout optimization achieves 1.85% average energy production improvement and 13.6% net present value enhancement through foundation cost optimization. Cable routing optimization reveals genetic algorithm outperforms Large Neighborhood Search, achieving total costs of 153-155 M€ compared to 165-168 M€, with branched topologies providing marginal advantages over radial configurations. The final integrated design achieves 48.7% net capacity factor and 39.93 €/MWh levelized cost of energy.

The thesis demonstrates that sequential optimization provides an effective balance between solution quality and computational efficiency for offshore wind farm design in the Baltic Sea region. The developed framework successfully combines specialized algorithms for layout and cable routing optimization while maintaining practical computational requirements for industry applications.

Keywords: Offshore Wind, Sequential Optimization, Cable Routing, Layout Optimization, Genetic Algorithm, Large Neighborhood Search

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

TIIVISTELMÄ

Aleksi Hasu: Merituulivoimalan sijoittelun ja kaapelireitityksen peräkkäinen optimointi Itämeren olosuhteisiin
Diplomityö
Tampereen yliopisto
Tietotekniikan DI-ohjelma
Syyskuu 2025

Merituulivoimalan suunnittelu on monimutkainen ja monikriteerinen optimiointihaaste, joka kattaa sekä turbiinien sijoittelun sekä sähkökaapelien reitityksen. Tässä työsseä kehitetään ja arvioidaan kaksivaiheinen peräkkäinen optimointimenetelmä, joka on erityisesti sovitettu Itämeren olosuhteisiin, joissa gravitaatioperustukset tarjoavat etuja perinteisiin perustustyyppeihin nähden. Tutkimuksella on neljä päätavoitetta: peräkkäisen optimointimenetelmän tehokkuuden validointi, gravitaatioperustusten kustannusmallin kehittäminen, kaapelireititysalgoritmien vertailu sekä menetelmän havainnollistaminen kattavan tapaustutkimuksen avulla.

Menetelmä hyödyntää kaksivaiheista optimointia TopFarm-optimointikehyksellä. Ensimmäisessä vaiheessa optimoidaan turbiinien sijoittelu energiantuotannon tai taloudellisten mittareiden maksimoimiseksi COBYLA-algoritmin avulla. Optimoinnissa hyödynnetään kehitettyä gravitaatioperustusten kustannusmallia, joka ottaa huomioon syvyydestä riippuvat kaivuu- ja asennuskustannukset. Toisessa vaiheessa optimoidaan kaapelireitit käyttämällä ja vertailemalla geneettistä algoritmia ja suurten naapurustojen etsintäalgoritmia (Large Neighborhood Search). Optimionti tehdään sekä lineaarisille että haarautuneille topologioille. Menetelmä havainnollistetaan Porin edustalla sijaitsevalla 300 MW:n merituulipuiston tapaustutkimuksella.

Tulokset vahvistavat peräkkäisen optimointimenetelmän toimivuuden alustavalla analyysillä, jossa kaapelointikustannusten vaihtelu eri sijoitteluratkaisujen välillä on vain 1,5–3 %. Sijoitteluoptimointi saavuttaa keskimäärin 1,85 % paremman energiantuotannon sekä 13,6 % parannuksen nykyarvossa perustuskustannusten optimoinnin kautta. Kaapelireittien optimointi osoittaa, että geneettinen algoritmi tuottaa parempia tuloksia kuin suurten naapurustojen etsintäalgoritmi, saavuttaen kokonaiskustannukset 153–155 M€ verrattuna 165–168 M€, ja haarautuneiden topologioiden tarjoavan marginaalisia etuja säteittäisiin nähden. Lopullinen integroitu suunnittelu saavuttaa 48,7 % kapasiteettikertoimen ja 39,96 €/MWh energian tasoitetun tuotantokustannuksen

Työssä osoitetaan, että peräkkäinen optimointi tarjoaa tehokkaan tasapainon ratkaisun laadun ja laskennallisen tehokkuuden välillä Itämeren alueen merituulipuistojen suunnittelussa. Kehitetty optimointimenetelmä yhdistää onnistuneesti erityiset algoritmit sijoittelu- ja kaapelireititysoptimointiin, pitäen samalla laskennalliset vaatimukset käytännöllisinä teollisuuden sovelluksia varten.

Avainsanat: Merituulivoima, Optimointi, Geneettinen Algoritmi, Large Neighborhood Search

Tämän julkaisun alkuperäisyys on tarkastettu Turnitin OriginalityCheck -ohjelmalla.

USE OF ARTIFICIAL INTELLIGENCE IN THIS WORK

Artificial intelligence (AI) has been used in generating this work:

☐ No
☒ Yes

I hereby declare, that the AI-based applications used in generating this work are as follows:

Application	Version
ChatGPT	GPT-4o
Grammarly	8.931.0
GitHub Copilot	1.338.0

Purpose of the use of AI

The mentioned tools were used both in writing this thesis and in developing the optimization tool. ChatGPT was used to improve the readability and flow of the text. Parts of the thesis were first written in Finnish, and then ChatGPT was used to translate the text into English. ChatGPT was also used to receive feedback on the thesis structure and to get ideas on areas for improvement. Grammarly was used for grammar checking and for improving sentence structures around the text. GitHub Copilot was used to assist in the development of the tool.

Parts of this work, where AI was used

ChatGPT and Grammarly were used while writing Chapters 1-6. Copilot was used while developing the tool described in Chapter 3.

Acknowledgement of risks

I hereby acknowledge, that as the author of this work, I am fully responsible for the contents presented in this thesis. This includes the parts that were generated by an AI, in part or in their entirety. I therefore also acknowledge my responsibility in the case, where use of AI has resulted in ethical guidelines being breached.

PREFACE

I would like to thank Arenso Oy for providing the thesis topic and allowing me to do this research.

Tampere, 1st September 2025

Aleksi Hasu

CONTENTS

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

c_{ij}^t	Installation cost per unit length for cable type t between nodes i and j
CF_t	Cash flow at year t
C_T	Thrust coefficient of wind turbine
$\mathbf{CWF}(x, y)$	Cash flow array as a function of turbine coordinates
D	Rotor diameter
$\Delta U/U_\infty$	Normalized velocity deficit in wake models
E_t	Total energy produced at time t
E	Set of potential cable connections
f_i	Frequency of different wind conditions
FC_t	Cash flow at time t
h	Vertical height (depth) of excavation cone
I_t	Investment cost at time t
k	Wake expansion coefficient
l_{ij}	Cable length between nodes i and j
λ	Economic parameter for electrical losses valuation
M_t	Operation and maintenance cost at time t
N	Set of network nodes
n	Number of turbines
P_i	Power output of turbine i considering wake losses
P_{ij}	Power flow through cable between nodes i and j
R_1	Radius of bottom (smaller) base of truncated cone
r	Discount rate
R_2	Radius of top (larger) base of truncated cone
r	Radial distance from wake centerline
r_t	Resistance of cable type t
σ	Wake width parameter in Gaussian wake model
T	Project duration
τ	Economic parameter for electrical losses over project lifetime
T	Set of cable types
V	Excavation volume for foundation
(x_i, y_i)	Coordinates of turbine i
x_{ij}	Binary decision variable for cable connection from node i to node j
x_{ij}^t	Binary variable for installation of cable type t between nodes i and j
ABC	Artificial Bee Colony
ABEX	Abandonment Expenditures
ACO	Ant Colony Optimization
AEP	Annual Energy Production
CAPEX	Capital Expenditures
COBYLA	Constrained Optimization BY Linear Approximation
CoV	Coefficient of Variation
CSA	Cuckoo Search Algorithm
DE	Differential Evolution

DEVEX	Development Expenditures
DTU	Danish Technical University
FA	Firefly Algorithm
GA	Genetic Algorithm
GBF	Gravity-Based Foundations
GOA	Grasshopper Optimization Algorithm
GTK	Geological Survey of Finland
GW	Gigawatt
GWh	Gigawatt-hour
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
kV	Kilovolt
LCOE	Levelized Cost of Energy
LNS	Large Neighborhood Search
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
MST	Minimum Spanning Tree
MW	Megawatt
MWh	Megawatt-hour
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
OPEX	Operational Expenditures
PSO	Particle Swarm Optimization
QIP	Quadratic Integer Programming
SSA	Sparrow Search Algorithm
WFCR	Wind Farm Cable Routing
WFLO	Wind Farm Layout Optimization

1. INTRODUCTION

Offshore wind energy has grown dramatically over the past decades. According to the Global Wind Report 2024, the cumulative installed wind power capacity surpassed 1TW in 2023, and forecasts indicate that this figure is expected to reach 2TW before 2030 with yearly installations increasing from 117 GW to 320 GW [7].

The design of offshore wind farms presents a complex multi-objective optimization challenge that significantly impacts both capital expenditure (CAPEX) and operational expenditure (OPEX). The electrical collection system, which connects individual turbines to offshore substations and ultimately to the onshore grid, represents approximately 15% of total project costs [32]. Similarly, foundation systems account for about 30% of project CAPEX [39, 28], making their optimization essential for project economics. These substantial cost components, combined with complex interactions between subsystems, create an optimization environment where combined design decisions can produce improvements in the order of 10-15 million euros per wind farm [5, 16].

The Baltic Sea region presents unique opportunities and challenges for offshore wind development. Relatively shallow waters and favorable seabed conditions make gravity-based foundations (GBFs) a viable alternative to conventional monopile or jacket foundations. However, the region's seasonal ice formation, specific soil conditions, and environmental constraints require specialized design approaches that are not adequately addressed by existing optimization frameworks. Furthermore, the growing scale of Baltic Sea offshore wind projects demands efficient optimization methodologies that can handle hundreds of turbines while maintaining computational tractability.

Offshore wind farm optimization traditionally involves two interconnected problems: Wind Farm Layout Optimization (WFLO) and Wind Farm Cable Routing (WFCR). WFLO seeks to determine optimal turbine positions that maximize energy production while minimizing wake effects, while WFCR aims to minimize electrical infrastructure costs by optimizing cable connections between turbines and offshore substations. The inherent conflict between these objectives, a larger turbine spacing reduces wake losses but increases cable costs, represents a central challenge in wind farm design.

Two primary optimization paradigms have emerged to address this challenge. Combined approaches that optimize turbine placement and cable routing simultaneously, and sequential approaches that decompose the problem into manageable stages. While combined optimization theoretically captures critical dependencies between layout and electrical design, practical computational limitations often make it intractable for large-scale projects. Recent studies by Cazzaro et al. [5] demonstrate that combined approaches can achieve up to 12 million euros in net present value (NPV) improvements, but at substantial computational cost that may exceed practical project development timelines.

This thesis addresses these challenges by developing and evaluating a sequential optimization framework specifically tailored for offshore wind farm design in the Baltic Sea region. The primary research objectives are:

1. To validate the effectiveness of sequential optimization for offshore wind farm design by analyzing the sensitivity of cable costs to layout variations under Baltic Sea conditions
2. To develop and integrate a gravity-based foundation cost model within the TopFarm optimization environment to enable realistic economic assessments for Baltic Sea applications
3. To implement and compare two distinct cable routing optimization algorithms, genetic algorithm and Large Neighborhood Search, for radial and branched network topologies
4. To demonstrate the sequential framework through a case study of a 300 MW offshore wind farm located off the coast of Pori, Finland

Figure 1.1 illustrates the thesis structure and sequential optimization framework adopted in this thesis. The research begins with introductory and background content (Chapters 1 and 2), followed by a sequential optimization methodology presented in Chapter 3, including both layout optimization (turbine positioning and foundation design) and cable routing optimization (electrical network design). Chapter 2 presents a literature review examining offshore wind farm design, layout optimization methodologies, cable routing algorithms, and the trade-offs between sequential and combined optimization approaches. Chapter 3 describes the research methodology, including the development of the gravity-based foundation cost model, implementation of layout optimization within TopFarm, and the adaptation of cable routing algorithms. The framework demonstrates how layout and cable routing optimization are handled separately and sequentially, with the Levelized Cost of Energy (LCOE)-optimized layout selected as input for cable routing optimization. Chapter 4 reports the optimization results, beginning with validation of the sequential approach and proceeding through layout optimization and cable routing results. Chapter 5 provides discussion of the results and combines the results from both optimization stages to produce the final wind farm design. Chapter 6 concludes with a summary of key findings.

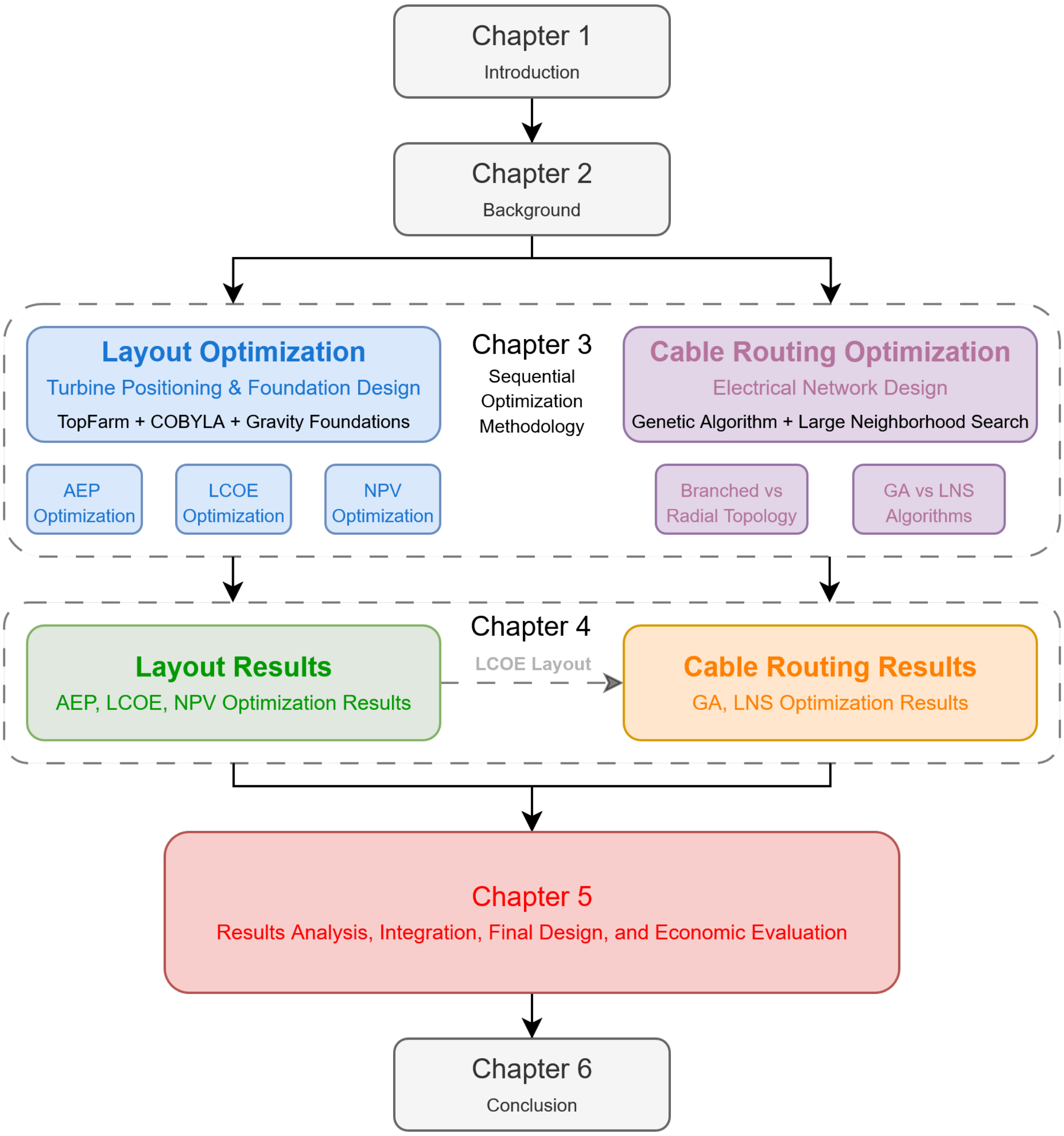

Figure 1.1. *Overview of the thesis structure and methodology for offshore wind farm optimization.*

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

This chapter provides a review of the theoretical background and existing literature relevant to offshore wind farm optimization. The review is structured to cover the fundamental aspects of offshore wind farm design, examine specific optimization challenges for layout and cable routing, and analyze different optimization paradigms. This foundation establishes the context for the methodological choices and research contributions presented in subsequent chapters.

2.1 Offshore Wind Farm Design and Optimization Overview

Offshore wind farm design represents one of the most complex engineering optimization challenges in renewable energy infrastructure development. The rapid growth of offshore wind capacity, which surpassed 1TW globally in 2023 with forecasts indicating 2TW before 2030 [7], has intensified the need for sophisticated optimization approaches that effectively balance technical performance with economic viability.

The complexity of offshore wind farm systems arises from the dependencies between multiple subsystems, each characterized by distinct optimization requirements and conflicting objectives. The cable procurement and installation alone represents around 15% of total project capital expenditure (CAPEX), while foundation costs account for about 30% [39, 28]. These substantial cost components, combined with the complex interactions between subsystems, create a challenging optimization environment where changes in one domain significantly impact performance and costs in others.

Offshore wind farm design involves two main optimization problems that are fundamental to project economics: *Wind Farm Layout Optimization* (WFLO) and *Wind Farm Cable Routing* (WFCR). WFLO seeks to determine optimal turbine positions that maximize energy production while minimizing wake effects, when WFCR aims to minimize electrical infrastructure costs by optimizing cable connections between turbines and offshore substations. [13] The inherent conflict between these objectives, where a larger turbine spacing reduces wake losses but increases cable costs, represents a central challenge in wind farm design.

The combinatorial nature of both subproblems contributes significantly to the overall complexity. WFLO is classified as an NP-hard problem [20], with computational complexity increasing exponentially with the number of potential turbine positions. Similarly, WFCR is independently NP-hard [15], requiring simultaneous consideration of network topology, cable sizing, and routing constraints while respecting electrical and spatial limitations.

Economic drivers for optimization are substantial and continue to grow with project scale. Beyond the direct capital expenditure considerations, operational expenditure (OPEX) factors such as energy losses, maintenance accessibility, and long-term reliability significantly influence the optimization landscape. Recent studies demonstrate that optimization can contribute cost reductions in the order of 10-15 million per wind farm [5, 16].

The technical constraints that govern offshore wind farm design add additional layers of complexity to the optimization process. Wake effects reduce downstream turbine performance by 10-20% on average in large offshore wind farms [2], creating nonlinear interactions that must be accurately modeled throughout the optimization process. Environmental and navigational exclusion zones, minimum spacing requirements, and grid connection constraints further constrain the feasible design space, necessitating optimization approaches capable of handling complex constraint sets while maintaining solution quality.

This complexity has led to the development of two distinct optimization paradigms: integrated approaches that optimize turbine placement and cable routing simultaneously, and sequential approaches that decompose the problem into manageable stages. While integrated optimization theoretically captures the critical dependencies between layout and electrical design, practical computational limitations have driven the widespread adoption of sequential strategies.

2.2 Wind Farm Layout Optimization

The wind farm layout optimization problem forms the foundation of offshore wind farm design. This section examines the mathematical formulation, objectives, and solution approaches for determining optimal turbine positions within a given site.

2.2.1 Problem Formulation and Objectives

Wind farm layout optimization is characterized as an NP-hard problem, with computational complexity increasing exponentially as the number of potential turbine positions grows [20]. For example, with n possible positions and k turbines to place, the possible configurations reach $\binom{n}{k}$. Modern wind farms often have over 100 turbines, making solution spaces enormous. [38]

The optimization problem involves finding optimal turbine coordinates (x_i, y_i) that satisfy constraints and improve specific objectives. The primary objectives commonly appearing in literature include maximizing Annual Energy Production (AEP), minimizing LCOE, and maximizing NPV. Recent studies show increasing preference for LCOE and NPV as these metrics balance technical performance with economic viability [33].

The AEP objective focuses on maximizing total energy production while accounting for wake interactions:

$$\max_{x,y} \mathsf{AEP}(x,y) = \sum_{i=1}^{n} P_i(x,y) \cdot f_i \tag{2.1}$$

where P_i is turbine i's power output considering wake losses, and f_i represents the frequency of different wind conditions.

The LCOE objective aims to minimize the average cost of electricity generation over the project lifespan:

$$\min_{x,y} \mathsf{LCOE}(x,y) = \frac{\sum_{t=0}^{n} \frac{I_t(x,y)+M_t(x,y)}{(1+r)^t}}{\sum_{t=0}^{n} \frac{E_t(x,y)}{(1+r)^t}} \tag{2.2}$$

where I_t is the investment, M_t is operation and maintenance cost, E_t is total energy produced at time t, r is the discount rate, and n is the project's duration [33]. Investment and maintenance costs depend on turbine placement, impacting foundation and electrical infrastructure expenses.

The NPV objective maximizes the sum of discounted cash flows across the project lifespan:

$$\max_{x,y} \mathsf{NPV}(x,y) = -\mathsf{CAPEX}(x,y) + \sum_{t=1}^{n} \frac{FC_t(x,y)}{(1+r)^t} \tag{2.3}$$

where CAPEX represents capital expenditures, and FC_t indicates the project's cash flows, considering revenues and operational costs [33].

2.2.2 Technical Constraints

The optimization process must respect several practical constraints that ensure feasible and safe wind farm operation. These constraints include minimum spacing requirements between turbines, site boundaries defined by lease areas or geographical features, environmental exclusion zones, and maximum cable length limitations from turbines to substations.

The complexity of layout optimization arises from multiple interrelated factors. Wake effects create nonlinear interactions between turbines, with downstream performance reductions ranging from 10% to 40% [2]. The combination of discrete placement decisions with continuous positioning creates a mixed-integer optimization challenge. Additionally, the optimization landscape typically contains numerous local optima, making the search for globally optimal solutions particularly challenging.

When economic objectives such as LCOE or NPV are considered, the complexity increases further. The optimization must simultaneously balance energy production, infrastructure costs, and time-based financial considerations. Despite this increased complexity, economic focused optimization provides better alignment with real-world project requirements [33].

2.2.3 Wake Modeling for Layout Optimization

Accurate wake modeling forms the foundation of layout optimization, as wake-induced power losses represent the primary source of energy reduction within wind farms. The selection of an appropriate wake model requires careful consideration of the trade-off between computational efficiency and prediction accuracy

The Jensen model [23] remains widely used due to its computational simplicity. This model assumes a top-hat velocity profile with linear wake expansion:

$$\frac{\Delta U}{U_\infty} = \left(1 - \sqrt{1 - C_T}\right)\left(\frac{D}{D + 2kx}\right)^2 \tag{2.4}$$

where $\Delta U/U_\infty$ is the normalized velocity deficit, C_T is the thrust coefficient, D is the rotor diameter, k is the wake expansion coefficient (typically 0.04-0.05 for offshore conditions), and x is the downstream distance. Despite its widespread use in commercial software, the Jensen model's assumption of uniform velocity deficit limits its accuracy [40].

The Gaussian wake model developed by Bastankhah and Porté-Agel [3] addresses these limitations by assuming a more realistic Gaussian distribution for velocity deficit:

$$\frac{\Delta U}{U_\infty} = \left(1 - \sqrt{\frac{1 - C_T}{8(\sigma/D)^2}}\right)\exp\left(-\frac{r^2}{2\sigma^2}\right) \tag{2.5}$$

where σ represents the wake width and r is the radial distance from the wake centerline. This model's continuous differentiability facilitates gradient-based optimization approaches while providing improved accuracy for downstream turbine power predictions [38].

When multiple turbines affect a single downstream turbine, wake superposition methods combine individual effects. The square-root-of-sum-of-squares method [24] is commonly used:

$$\left(\frac{\Delta V}{V_\infty}\right)_{total} = \sqrt{\sum_{k=1}^{N_T}\left(\frac{\Delta V_k}{V_\infty}\right)^2} \tag{2.6}$$

The selection of an appropriate wake model must consider the optimization algorithm used, available computational resources, and required solution accuracy.

2.2.4 Layout Optimization Methods and Algorithms

Wind farm layout optimization uses many different solution approaches, each with distinct advantages and limitations. The methods can be broadly categorized into mathematical programming, metaheuristic algorithms, and hybrid approaches [20, 34].

Mathematical programming methods apply deterministic optimization techniques to solve reformulated versions of the WFLOP. Linear Programming (LP), Mixed-Integer Linear Programming (MILP), and Quadratic Integer Programming (QIP) approaches typically require linearization or simplification of the wake model to create tractable problems [20]. The primary advantage of these methods lies in their ability to guarantee optimality within their simplified problem formulations and their rapid convergence when applicable. However, the linearization process may compromise solution accuracy, and computational requirements grow exponentially with problem size, often becoming intractable for large wind farms [20].

Metaheuristic algorithms have become as the dominant approach for WFLOP due to their flexibility and robustness in handling non-convex multimodal optimization landscapes [20, 34]. These population-based methods do not require gradient information and can escape local optima through various search mechanisms.

Genetic Algorithms (GA), first used for wind farm optimization by Mosetti et al. in 1994 [29], use evolutionary principles of selection, crossover, and mutation to evolve populations of solutions [34, 25]. Their main advantages include robustness to problem characteristics, effectiveness across various scales, and the ability to handle discrete and continuous variables simultaneously. However, GA typically requires careful parameter tuning and may converge slowly for large problems.

Particle Swarm Optimization (PSO) simulates collective behavior, with particles exploring the solution space guided by individual and collective best positions [34, 19]. PSO offers advantages of conceptual simplicity, fewer parameters than GA, and good convergence characteristics. The method has proven particularly effective for large-scale problems, though it may struggle with highly constrained design spaces. Variants such as Binary PSO with time-varying acceleration coefficients have been developed to address specific limitations [19, 26].

Multiple nature-inspired algorithms have been implemented in recent years, each offering unique search mechanisms [34]. Ant Colony Optimization (ACO) uses pheromone-based communication to guide the search process, showing particular effectiveness in discrete optimization scenarios [36, 10]. The Sparrow Search Algorithm (SSA) mimics foraging behavior and has demonstrated better performance compared to traditional methods in comparative studies [27]. Other metaheuristic approaches include, for example, Artificial Bee Colony (ABC), Grasshopper Optimization Algorithm (GOA), Firefly Algorithm (FA), Differential Evolution (DE), and Cuckoo Search Algorithm (CSA), each offering specific advantages for particular problem characteristics [34].

The choice between grid-based and coordinate-based problem formulations fundamentally impacts the optimization approach. Grid models divides the wind farm area into predefined cells, significantly reducing the solution space and simplifying the optimization problem [20]. This discretization enables faster computation and easier constraint handling but may miss optimal configurations that fall between grid points. Coordinate models allow continuous positioning of turbines anywhere within the feasible region, providing access to the complete solution space at the cost of increased computational complexity and more challenging constraint management [20].

Hybrid approaches attempt to combine the strengths of different methodologies. Common strategies include using metaheuristics for global exploration followed by mathematical programming for local refinement, or combining multiple metaheuristics to leverage their complementary search characteristics [20]. These methods can achieve solutions satisfying mathematical optimality conditions while maintaining the global search capabilities of metaheuristics.

The selection of an appropriate optimization method depends on multiple factors including problem size, available computational resources, required solution quality, and time constraints. While mathematical programming methods excel for small problems requiring guaranteed optimality, metaheuristics become essential for large-scale wind farms where computational tractability is paramount. The ongoing trend toward larger offshore wind farms with hundreds of turbines increasingly favors scalable metaheuristic and hybrid approaches [20].

2.3 Wind Farm Cable Routing Optimization

The electrical collection system design represents a critical component of offshore wind farm optimization, typically accounting for approximately 15% of total project capital expenditure [39, 28]. The WFCR problem seeks to determine the optimal network topology and cable sizing that connects individual turbines to offshore substations while minimizing total system costs and satisfying technical constraints [32].

The WFCR problem uses two fundamental design decisions that significantly impact both capital and operational expenditures. First, the selection of network topology determines the physical structure of electrical connections between turbines and substations. Second, the optimization of cable routing and sizing within the chosen topology minimizes installation costs while ensuring adequate electrical capacity and system reliability. These interconnected decisions create a complex optimization landscape where topology constraints directly influence the mathematical formulation and solution approaches.

2.3.1 Network Topologies and Mathematical Formulations

The choice of network topology fundamentally shapes both the optimization complexity and the mathematical formulation of the WFCR problem. Two primary topologies for offshore wind farm design are radial and branched topologies [32]. The two topologies are visualized in Figure 2.1

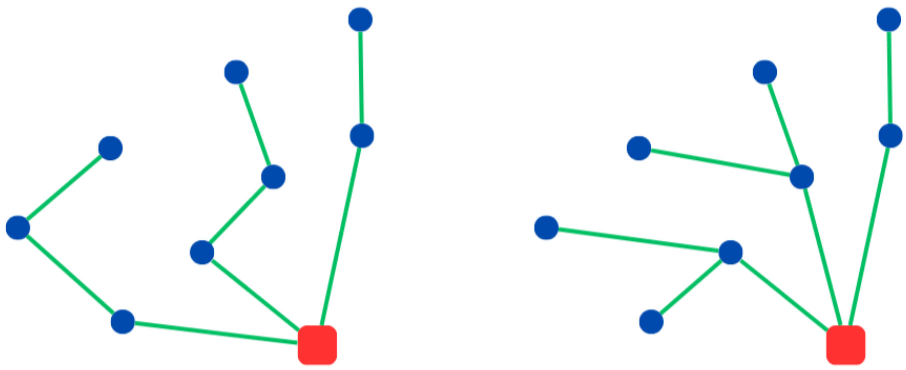

Figure 2.1. *Visualization of radial (left) and branched (right) topologies. The red square represents a substation and blue circles mark turbines.*

Radial topology connects turbines in sequential strings, where each turbine receives at most one incoming cable and outputs exactly one outgoing cable. This configuration simplifies protection system design and fault isolation procedures, making it the preferred choice for many operational wind farms. The mathematical formulation for radial topology incorporates string capacity constraints and maintains tree structure throughout the network. For each turbine i in the network, the radial constraint can be expressed as $\sum_{j \in N} x_{ji} \leq 1$, ensuring at most one incoming connection per turbine, where N represents the set of all network nodes, x_{ji} represents the binary decision variable for cable connection from turbine j to turbine i. [6]

Branched topology allows multiple cables to connect at individual turbines, creating a more flexible network structure that can achieve shorter total cable lengths. [41] demonstrated that branched designs can achieve approximately 5% reduction in total cable length compared to radial configurations. However, this topology requires more sophisticated protection systems and increases the complexity of fault management procedures. The mathematical formulation for branched topology relaxes the incoming connection constraint, allowing $\sum_{j \in N} x_{ji} \leq k$ where k represents the maximum number of allowable connections at turbine i. [6]

The fundamental MILP formulation for both topologies can be expressed as minimizing total cable costs subject to flow conservation, capacity constraints, and topology-specific restrictions:

$$\min \sum_{(i,j) \in E} \sum_{t \in T} c_{ij}^t \cdot l_{ij} \cdot x_{ij}^t + \sum_{(i,j) \in E} \lambda \cdot P_{ij}^2 \cdot r_t \cdot \tau \tag{2.7}$$

where x_{ij}^t indicates the installation of cable type t between nodes i and j, c_{ij}^t represents the installation cost per unit length, l_{ij} denotes the cable length, P_{ij} represents power flow, r_t is cable resistance, and λ and τ capture the economic value of electrical losses over the project lifetime.

2.3.2 Algorithmic Approaches for Cable Routing Optimization

The WFCR problem has motivated the development of diverse solution methodologies, ranging from exact mathematical programming approaches to sophisticated heuristic and metaheuristic algorithms. The selection of solution approach depends on problem size, desired solution quality, computational resources, and the specific constraints present in the wind farm design.

Exact mathematical programming methods provide theoretical optimality guarantees but face significant scalability challenges for realistic problem sizes. MILP formulations have been successfully applied to smaller instances with up to 50-80 turbines [5, 15]. These approaches typically employ branch-and-cut algorithms or Benders decomposition to handle the complex constraint structure. However, the exponential growth in computational requirements with problem size limits their practical applicability to modern large offshore wind farms, which can have more than 100 turbines.

The computational complexity of exact methods has driven widespread adoption of heuristic and metaheuristic approaches for large-scale cable routing optimization. These methods sacrifice optimality guarantees in favor of computational tractability, enabling the solution of realistic problem instances within practical time constraints. The most prominent approaches include evolutionary algorithms, local search methods, and hybrid techniques that combine multiple optimization paradigms.

Genetic algorithms have emerged as particularly effective metaheuristic approaches for WFCR optimization. [41] developed a genetic algorithm framework that evolves cable configurations through crossover and mutation operations, achieving near-optimal solutions for wind farms with over 100 turbines. The genetic algorithm approach naturally handles the discrete decision variables inherent in cable routing while maintaining population diversity to avoid premature convergence. The algorithm represents cable configurations as chromosomes encoding connection decisions and cable types, with fitness functions incorporating both installation costs and operational considerations such as electrical losses.

The effectiveness of genetic algorithms comes from their ability to explore large solution spaces through population-based search mechanisms. Crossover operations combine promising cable routing segments from parent solutions, while mutation operators introduce controlled randomness to maintain solution diversity. [41] demonstrated that genetic algorithms can consistently identify high-quality solutions within computationally reasonable time frames, typically requiring less than one hour for wind farms with 100 turbines.

Large Neighborhood Search (LNS) represents a powerful hybrid approach that combines the global exploration capabilities of metaheuristics with the intensification strength of exact optimization methods. [6] developed a LNS framework for balanced cable routing that employs multiple neighborhood structures of increasing complexity. The approach utilizes a modified sweep algorithm to generate high-quality initial solutions, followed by iterative improvement through specialized neighborhood operators including swap moves, cycle swaps, and repartitioning operations.

Swap-based neighborhood operators form the foundation of many local search approaches for cable routing optimization. These operators exchange turbines between different root-branches or strings, enabling exploration of alternative cable configurations while maintaining problem feasibility. Simple swap operations exchange individual turbines between adjacent branches, while more sophisticated variants such as cycle swaps can move multiple turbines simultaneously across several branches. The computational efficiency of swap operations enables their integration into larger optimization frameworks as intensification mechanisms.

Repartitioning methods represent exact optimization approaches applied to subproblems of the overall cable routing challenge. These methods typically focus on optimizing connections within localized regions of the wind farm, such as pairs of adjacent root-branches or clusters of nearby turbines. [6] demonstrated that repartitioning approaches can achieve optimal solutions for subproblems involving 20-30 turbines, providing high-quality improvements when integrated into larger heuristic frameworks.

2.3.3 Computational Complexity and Scalability Considerations

The computational complexity of cable routing optimization scales significantly with problem size, creating substantial challenges for large offshore wind farms. [6] analyzed the performance characteristics of various optimization approaches across different problem scales, demonstrating that algorithm selection critically depends on the specific size and structure of the wind farm instance.

For small to medium-scale problems involving fewer than 50 turbines, exact MILP formulations can often achieve optimal solutions within reasonable computational time limits. However, the exponential growth in decision variables and constraints quickly renders exact approaches intractable for larger instances. The number of potential cable routing configurations grows combinatorially with the number of turbines, creating solution spaces that exceed the capabilities of exact optimization methods.

Metaheuristic approaches demonstrate better scalability characteristics, maintaining solution quality while accommodating larger problem instances. [41] reported successful optimization of wind farms with over 100 turbines using genetic algorithms, with computational requirements growing polynomially rather than exponentially with problem size. Similarly, LNS approaches have been successfully applied to instances with multiple substations and complex constraint patterns, indicating robust scalability properties [6].

The practical implications of computational complexity extend beyond pure algorithmic considerations to include the integration of cable routing optimization within broader wind farm design workflows. Interactive optimization approaches that provide incremental improvements and intermediate solutions enable engineering teams to evaluate trade-offs and make informed design decisions throughout the development process. This consideration has driven the development of anytime algorithms that can provide improving solutions given additional computational time, rather than requiring complete optimization runs before yielding useful results.

2.4 Sequential versus Integrated Optimization Approaches

This section examines the two primary paradigms that have emerged to address the coupled WFLO and WFCR problems, analyzing their relative merits, limitations, and practical applicability based on recent advances in the field.

The complexity of offshore wind farm optimization comes from the inherent conflict between the layout and cable routing objectives. As noted by Cazzaro et al. [5], the sequential approach misses the interrelation between the two problems because WFLO tends to scatter turbines to minimize wake effects, while WFCR seeks to minimize cable lengths, creating conflicting optimization objectives that must be carefully balanced.

2.4.1 Sequential Optimization Approach

Sequential optimization addresses the combined WFLO and WFCR challenge by decomposing it into a sequence of subproblems [5]. The usual workflow optimizes turbine layout first to minimize wake losses and maximize energy production, followed by cable routing optimization that uses turbine positions as fixed inputs to minimize electrical infrastructure costs.

The primary advantage of sequential optimization lies in its computational efficiency [5]. By decomposing the problem, each subproblem can be addressed using algorithms optimized for the specific mathematical structure and constraints of that domain. Layout optimization can employ gradient-based methods or metaheuristics specifically designed for continuous positioning problems, while cable routing can utilize graph-based algorithms or integer programming approaches tailored to network design. This approach demonstrates better scalability characteristics for large offshore wind farms compared to integrated methods [5]. While integrated formulations face exponential growth in decision variables, sequential methods can handle each subproblem with algorithms designed for their specific mathematical structure, enabling optimization of large-scale projects with hundreds of turbines that would be computationally heavy for integrated approaches.

Sequential optimization also provides important practical advantages in terms of validation, debugging, and incremental improvement. Each optimization stage can be independently verified and validated, facilitating the identification and correction of modeling errors or constraint violations. This modularity enables progressive refinement of individual components without requiring complete system redesign, supporting iterative development processes common in engineering practice. The decomposed approach allows different domain experts to focus on their areas of specialization, leveraging established methodologies and tools for each subproblem independently.

Despite these computational advantages, sequential optimization suffers from several fundamental limitations. The most significant limitation is that sequential approaches miss dependencies between layout and cable routing decisions [5]. When WFLO is solved first, the optimization tends to scatter turbines across the available area to minimize wake effects, but this strategy will cause the cable routing to be longer and have a high cost. Fischetti and Fischetti [14] provide examples where sequential approaches can produce infeasible solutions. In cases with complex terrain features, obstacles, or limited substation connection capacity, solving the design process in two steps would lead to having very isolated turbines that are very expensive to connect through cables. They demonstrate scenarios where the optimal layout cannot be feasibly connected due to infrastructure constraints not considered during the layout phase. Sequential methods also cannot identify optimal trade-offs between wake losses and cable costs, potentially missing economically better solutions that sacrifice some energy production for substantially reduced infrastructure costs.

2.4.2 Integrated Optimization Approach

Integrated optimization approaches attempt to solve WFLO and WFCR problems simultaneously, capturing the full interdependency between turbine placement and electrical infrastructure design [5]. This paradigm recognizes that optimal solutions to individual subproblems may not constitute an optimal solution to the combined system.

The most compelling advantage of integrated optimization is its demonstrated economic benefits. Cazzaro et al. [5] report improvements of up to 12 million euros in NPV compared to sequential approaches, with average improvements of 8.48 million euros for low energy density cases and 2.94 million euros for high energy density cases across their benchmark of 10 synthetic offshore wind farm instances. Fischetti and Fischetti [14] further validated these findings, showing up to 10% reduction in up-front investment costs when layout and cable routing decisions are optimized simultaneously.

Integrated approaches can identify economically better trade-offs that sequential methods cannot discover. Cazzaro et al. [5] demonstrate that by reducing the power production by 0.33% over the lifetime of the wind farm, the cost of cables is reduced by 35%, resulting in improved overall net present value despite energy production revenues being more than 30 times larger than cable costs. Fischetti and Fischetti [14] show that integrated optimization can find feasible solutions in scenarios where sequential approaches fail, particularly in complex terrain with obstacles and infrastructure constraints.

Integrated approaches provide advantages beyond pure economic metrics. These include reduced risk through shorter submarine cables, environmental benefits from minimized seabed impact, and better spatial efficiency through coordinated placement decisions [5]. Tao et al. [37] demonstrate that integrated optimization provides benefits beyond wind farm-level economics when considering power system integration, showing improvements in power quality metrics, capacity factors, and reduced generation costs for conventional generators.

Despite these theoretical advantages and documented benefits, integrated optimization faces significant practical challenges. The primary limitation is its computational demands [5]. Cazzaro et al. acknowledge that the combined approach is more computationally demanding than the sequential approach. The mathematical formulation requires simultaneous consideration of continuous positioning variables, discrete network topology decisions, and mixed-integer cable sizing choices, creating a mixed-integer nonlinear programming problem of substantial dimension.

The combined MILP formulation becomes intractable even for small wind farm instances due to exponential growth in decision variables. The number of cable variables increases from $O(|K||T|^2)$ in standalone cable routing to $O(|K||N|^2)$ in the combined problem, where K represents the set of available cable types, T is the number of turbines to be placed, and N is the set of available turbine positions. In realistic scenarios, N can be two orders of magnitude larger than T. [5] This scalability limitation necessitates the development of specialized heuristic methods to achieve tractability for industry-scale problems, requiring significant algorithm development effort and expertise. Fischetti and Fischetti [14] report that their exact mixed-integer programming approach, while successful for small instances, faces severe scalability limitations, often requiring heuristic approaches that sacrifice optimality guarantees.

2.4.3 Comparative Analysis

The economic performance comparison clearly favors integrated optimization when computational resources permit its application. The documented improvements of up to 12 million euros in NPV represent substantial value creation that must be weighed against the additional computational investment required [5]. The magnitude of economic benefits appears to correlate strongly with project characteristics. Cazzaro et al. [5] observe that improvements are particularly significant when the energy density is low, suggesting that the value of integrated optimization is project-dependent. For low energy density projects, where the trade-off between wake losses and cable costs is most pronounced, integrated optimization provides the greatest economic value.

To validate that these improvements result from true optimization rather than implementation differences, Cazzaro et al. [5] conducted additional testing by running sequential optimization starting from combined solutions. They found that while sequential methods could improve energy production from the combined starting point, the resulting cable costs increased, leading to lower overall NPV. This confirms that the difference in NPV is not due to inferior performances in the sequential optimization, but to the advantage of combining the two problems in a joint optimization.

The computational requirements present the biggest contrast between the two approaches. Sequential optimization maintains computational tractability through problem decomposition, allowing specialized algorithms for each subproblem. In contrast, integrated optimization faces fundamental scaling challenges that limit practical applicability [5]. Fischetti and Fischetti [14] demonstrate this limitation through their exact approach, which achieves optimal solutions for small instances but becomes computationally intractable for realistic problem sizes. Their mixed-integer programming formulation finds optimal solutions in few seconds for small instances but exceeds practical time limits for larger instances without achieving optimality.

While integrated optimization generally produces better economic solutions, the comparison in terms of solution robustness and reliability presents a more complex picture.

Sequential optimization benefits from the use of well-established, specialized algorithms for each subproblem, often providing more predictable and reliable solution quality. Integrated optimization, while achieving better overall performance, relies on sophisticated heuristic approaches that may be more sensitive to parameter settings and problem characteristics. However, the documented improvements across diverse test cases suggest that well-designed integrated approaches can consistently outperform sequential methods [5].

2.4.4 Methodology Selection Guidelines

The choice between sequential and integrated optimization approaches should be based on careful consideration of project characteristics, available computational resources, and economic objectives. The following guidelines emerge from the comparative analysis based on the research findings.

Integrated optimization is recommended for low energy density projects where the cable-wake trade-off is most significant and provides the greatest economic benefit [5]. Projects with complex terrain features, obstacles, or infrastructure constraints that may cause sequential approaches to produce infeasible solutions benefit significantly from integrated optimization [14]. The approach is suitable for projects where the potential economic benefits, justify the additional computational complexity and development effort. Cases where substantial computational resources are available and the project timeline can accommodate extended optimization runs are good candidates for integrated optimization [5].

Sequential optimization remains the practical choice for projects with hundreds of turbines where computational tractability is paramount and integrated approaches become computationally intractable [5]. Projects with short development schedules requiring rapid optimization and decision-making benefit from sequential approaches. Cases where computational resources are constrained or specialized algorithm development expertise is not available should use sequential optimization. Projects where energy density is high and cable costs represent a smaller fraction of total project economics, reducing the potential benefit from integrated optimization, are better suited for sequential approaches [5].

The literature suggests emerging trends toward hybrid approaches that attempt to capture the benefits of both paradigms [5, 14]. These methodologies use integrated optimization for critical high-level decisions while employing sequential methods for detailed refinement with specialized algorithms. Such approaches may provide a practical compromise between solution quality and computational tractability, though their development remains an active area of research.

2.4.5 Implications for Tool Development

The analysis of sequential versus integrated optimization approaches has direct implications for the development of practical optimization tools for offshore wind farm design. The substantial economic benefits demonstrated by integrated optimization, up to 12 million euros NPV improvements, suggest that the additional computational investment may be justified for many offshore wind farm projects, particularly given the scale of these investments and the long operational lifetimes involved [5].

However, the computational challenges associated with integrated optimization require careful consideration of algorithm design and implementation strategies. The successful heuristic approaches developed by Cazzaro et al. [5] and the exact methods with enhanced formulations by Fischetti and Fischetti [14] provide valuable guidance for developing practical tools that can achieve much of the benefit of integrated optimization while maintaining computational tractability.

The choice of approach should ultimately depend on the specific requirements of the application domain, balancing solution quality requirements against computational constraints and development complexity. For many practical applications, hybrid approaches that combine the global search capabilities of integrated methods with the computational efficiency of sequential decomposition may provide the optimal balance [5, 14].

This analysis provides the foundation for the optimization framework developed in this thesis, which considers both computational efficiency and solution quality requirements for realistic offshore wind farm design scenarios. The subsequent chapters detail the specific methodologies employed and demonstrate their effectiveness on a case study.

3. OPTIMIZATION APPROACH

This chapter presents the research methodology and optimization framework developed for offshore wind farm design in the Baltic Sea region, with specific consideration for gravity-based foundations. The study uses a sequential optimization approach, first addressing turbine layout optimization followed by cable routing optimization. The methodology is demonstrated through a comprehensive case study, with detailed descriptions of data requirements, optimization algorithms, and implementation considerations that enable practical application to real-world projects.

3.1 Research Overview

This study employs optimization methodologies to address the challenge of offshore wind farm design, focusing on developing practical, cost-effective solutions within real-world constraints. After consideration of computational requirements and the scope of this thesis, a sequential optimization approach was selected over a combined approach. This decision was supported by a preliminary analysis that evaluated the impact of turbine layout variations on cabling costs for the specific Baltic Sea site under investigation. The analysis revealed minimal economic variation in total project LCOE across different random layouts, suggesting that the potential benefits of computationally intensive combined approach would be limited for this specific site.

This research uses the Baltic Sea as a case study region. The characteristics of the site make gravity-based foundations a viable option for turbine installations, requiring the development of cost models to accurately represent foundation economics in the optimization framework.

The sequential approach starts with turbine layout optimization using the open-source framework TopFarm [35], customized to include cost models for gravity-based foundations. This is followed by cable routing optimization using two distinct algorithms, a genetic algorithm approach and large neighborhood search approach, to enable comparison of optimization techniques and validation of results. Both optimization methods uses bathymetric and soil condition data to achieve realistic and implementable designs.

3.2 Case Study Definition

This thesis applies the developed optimization framework to a planned offshore wind farm located off the coast of Pori, Finland, in the Baltic Sea. The selection of this site provides a realistic testbed for the optimization methodologies while leveraging existing operational experience in the region. The designated wind farm area accommodates 30 turbines and is characterized by gradually varying seabed conditions that present a representative optimization challenge for Baltic Sea developments.

The site exhibits relatively level bathymetry with water depths that change gradually across the development area. This gentle bathymetric profile allows for systematic consideration of depth-dependent foundation costs while maintaining computational tractability in the optimization process. The soil conditions are predominantly homogeneous throughout the site, though some variations exist that must be accounted for in detailed foundation design. The generally consistent geotechnical properties support the use of gravity-based foundations (GBFs), a technology previously deployed successfully by the developer in adjacent wind farm projects in the region. This prior experience with GBFs in similar conditions provides valuable cost data and operational insights that inform the optimization models developed in this thesis.

The wind farm utilizes the DTU 10MW reference turbine [1], a well-documented design that provides consistent baseline performance data for optimization studies. These turbines are integrated within the TopFarm optimization framework, ensuring compatibility with the layout optimization algorithms described in subsequent sections. To maintain operational efficiency and minimize wake interactions, a minimum spacing constraint of 800 meters is enforced between adjacent turbines. This spacing requirement represents a balance between wake loss minimization and cable cost considerations, serving as a hard constraint in the layout optimization process.

The electrical collection system operates at 33 kV, representing a standard voltage level for offshore wind farms of this scale. The offshore substation is positioned at the south-western corner of the development area. This placement reduces the number of viable cable chains and branches extending from the substation to the turbine array, creating an asymmetric optimization problem that tests the robustness of the cable routing algorithms. The fixed substation location reflects practical considerations including seabed lease boundaries, grid connection points, and marine spatial planning constraints that commonly affect offshore wind developments.

3.3 Data Requirements

The optimization framework integrates multiple data sources to realistically represent the physical and economic characteristics of offshore wind development in the Baltic Sea.

Wind resource data forms the foundation of the energy production calculations and were obtained from the Finnish Meteorological Institute's (Ilmatieteen laitos) Finnish Wind Atlas (Suomen tuuliatlas) [11], which provides annual wind speed information at 100m height in the Sea of Bothnia region. The wind distribution shown in Figure 3.1 was used to initialize a PyWake site class to represent the wind farm wind conditions. This dataset provides high-resolution wind speed and direction distributions validated against regional measurement campaigns, enabling accurate wake modeling and energy production estimates throughout the optimization process.

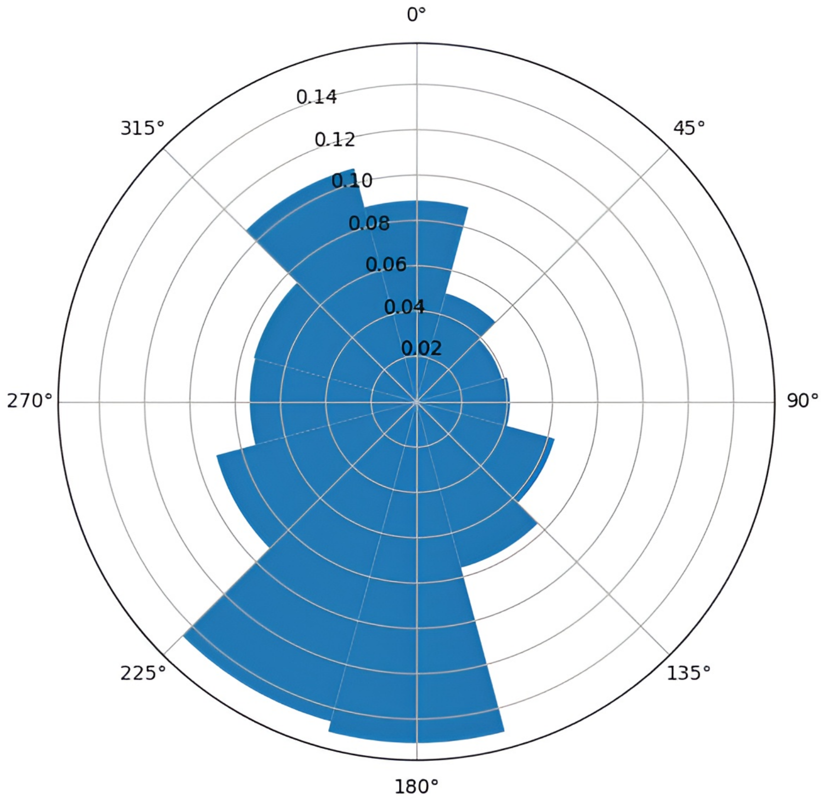

Figure 3.1. *Wind rose showing wind direction distribution for the case study area off the coast of Pori, Finland. The data represents annual wind conditions at 100m height, with predominant winds from the south and southwest directions. Data gathered from [11].*

Bathymetric data representing seabed depth variations were acquired from the Finnish Transport and Communications Agency (Traficom) through their open data service Oskari [12]. These depth measurements enable accurate modeling of depth dependent foundation costs across the site. The integration of these bathymetric datasets into the optimization framework allows for realistic representation of foundation installation costs that vary with water depth.

Seabed soil classification data were obtained from the Geological Survey of Finland (GTK) [18]. The dataset classifies seabed substrate into five Folk classes: (1) clay + silt (mud), (2) sandy clays, (3) clayey sands, (4) coarse sediments, and (5) mixed sediments, plus bedrock. The data describes seabed composition from the surface to 30 cm depth, with a resolution of 1:100,000 (generalized from the original 1:20,000 scale data). This classification directly influences excavation requirements, foundation design, and cable installation costs within the optimization framework. While the dataset's 30 cm depth limitation presents some constraints for foundation design that typically requires deeper soil information, it provides sufficient detail for preliminary optimization and comparative analysis of alternative designs. The mostly consistent soil conditions across the site, support the application of gravity based foundation designs while allowing for site specific cost adjustments where substrate conditions vary.

Technical specifications for the DTU 10MW reference turbine provide detailed power and thrust coefficient curves as functions of wind speed, enabling accurate wake modeling within the TopFarm framework. Economic parameters for the optimization framework include a fixed electricity price of 80€/MWh. Cable specifications and associated costs were adopted from Yi et al. [41], providing validated parameters for cable prices per unit length and other parameters needed for economic evaluation of the cabling within 33 kV collection system.

Additional exclusion zones representing shallow waters and protected areas were incorporated as polygon constraints within the optimization algorithms. These exclusion zones ensure that the optimized designs comply with regulatory requirements and practical implementation constraints. The site contains exclusion zones mostly on the eastern side, and with substation placement in southeastern corner, the exclusion zones greatly limit the feasible configurations of cable branches connecting to the substation. Operational constraints include the minimum turbine spacing requirement of 800 meters and maximum cable capacity limits based on the cables given by Yi et al.

3.4 Layout Optimization Framework

TopFarm was selected as the primary framework for turbine layout optimization based on several factors. It is open-source, allowing for the necessary customization needed. Its integration with PyWake module allows to calculate wake losses and turbine interactions. TopFarm supports constraints such as minimum spacing between turbines and exclusion zones, needed for realistic offshore wind farm planning. The framework has ready-made implementations of optimization algorithms like COBYLA. [35, 30]

3.4.1 Gravity Based Foundation Cost Model Development

TopFarm includes ready-made models for jacket and monopile foundations, but given the site-specific conditions of the Baltic Sea favoring gravity-based foundations, a custom economic cost model was developed and integrated into the framework.

The foundation cost modeling begins with excavation calculations for seabed preparation. Foundation footprint radius typically averages around 15 m, with an additional 4 m extension beyond the foundation to ensure sufficient bearing area [8]. Excavation depths were defined according to water depth, 4 m for depths up to 15 m, 5 m for depths between 15 and 30 m, and 7 m for depths beyond 30 m [31].

The model accounts for variations in excavation pit stability across different seabed soil types through differentiated side slope ratios. Total excavation volume is calculated using the truncated cone formula, defined as:

$$V = \frac{1}{3}\pi h \left(R_1^2 + R_1 R_2 + R_2^2\right) \tag{3.1}$$

where h is the vertical height (depth) of the cone, R_1 is the radius of the bottom (smaller) base, and R_2 is the radius of the top (larger) base, defined as:

$$R_2 = R_1 + h * Slope\ ratio \tag{3.2}$$

Following excavation, the model incorporates the placement of a 0.5-meter thick gravel layer with a density of 2.3 tonnes per cubic meter at the excavation base. A leveling cost factor of 50 €/m² is applied to ensure proper foundation placement. Foundation material costs are calculated based on dimensions and current market rates, with concrete volume determined according to water depth and turbine specifications.

The cost model further incorporates mobilization costs for specialized vessels and equipment, transportation expenses, and installation activities. These costs are computed individually and then scaled appropriately for the entire wind farm.

The foundation cost model was implemented as a Python class that inherits from TopFarm's economic evaluation class, allowing integration with the existing optimization framework. This implementation enables the optimization algorithm to make turbine placement decisions that reflect the economic realities of foundation construction in the Baltic Sea environment.

3.4.2 Wake Modeling and Energy Production Calculation

For wake effect modeling, TopFarm's integrated PyWake module was utilized as the computational framework. PyWake provides a comprehensive platform for wake calculations in wind farm settings. Within this framework, the Bastankhah Gaussian wake model was selected for its balance of computational efficiency and accuracy, particularly important for optimizing turbine spacing in offshore environments. This model incorporates turbine thrust coefficients, ambient turbulence intensity, and downstream distances when calculating wake losses, enabling realistic assessment of turbine interactions. [3]

3.4.3 Optimization Algorithm Configuration

The COBYLA (Constrained Optimization BY Linear Approximation) algorithm was selected for this study based on several practical and technical considerations. COBYLA is readily available as part of TopFarm's "EasyScipyOptimizeDriver" interface, providing easy integration with the existing optimization framework without requiring additional implementation or external dependencies. This out-of-the-box availability was useful given the scope and time constraints of this thesis work.

COBYLA is well-suited for the constraint-heavy nature of offshore wind farm layout optimization. The algorithm handles nonlinear constraints effectively, which is essential for managing the spatial constraints in this study, including minimum turbine spacing requirements, site boundary limitations, and exclusion zones. Additionally, COBYLA is a derivative free method, making it robust when dealing with the potentially noisy objective functions that arise from wake model calculations and economic evaluations.

While TopFarm offers other optimization algorithms such as genetic algorithms and particle swarm optimization, COBYLA provides a good balance between solution quality and computational efficiency for the deterministic optimization approach adopted in this sequential framework. The algorithm's proven reliability with constrained problems and its straightforward parameter configuration made it an appropriate choice for this research scope.

The COBYLA algorithm was configured with a convergence tolerance of 0.001%, meaning the optimization would terminate when the predicted improvement fell below the tolerance of the objective function value. Additionally, a maximum of 1500 iterations was set to ensure practical runtime constraints while allowing sufficient optimization. The maximum iteration limit was established by preliminary testing of the convergence behavior of optimization. Analysis of multiple trial runs showed that significant improvements in the objective function typically plateaued after approximately 1000 iterations, with only small improvements observed beyond this point.

The optimization process follows a systematic approach that begins with random initialization of turbine positions within the boundary constraints. The wake model then calculates AEP for the layout, while the cost model evaluates the economic value of the configuration. The objective function combines these factors, constraints are verified, gradient approximation is performed, and turbine positions are updated based on gradient information. This process iterates until convergence criteria are met or the maximum iteration count is reached.

Three alternative objective functions were implemented for the optimization process: AEP maximization, LCOE minimization, and NPV maximization. Each objective function leverages TopFarm's integrated economic evaluation framework to assess layout performance.

The AEP objective function maximizes energy production without explicit cost considerations according to Equation 2.1

The LCOE objective function minimizes the levelized cost of energy by calculating total lifecycle costs divided by total lifecycle energy production using TopFarm's economic evaluation:

$$\min_{x,y} \text{LCOE}(x, y) = \frac{\text{CAPEX}(x, y) + \text{DEVEX} + \text{ABEX} + \sum_{t=1}^{T} \text{OPEX}_t}{T \times \text{AEP}(x, y)} \tag{3.3}$$

where CAPEX(x, y) includes turbine costs, foundation costs (depth-dependent), and electrical infrastructure, DEVEX represents development expenditures, ABEX represent abandonment expenditures, and OPEX$_t$ are annual operational expenditures. T is the project duration (25 years), and AEP(x, y) is the annual energy production considering wake effects.

The NPV objective function maximizes net present value using TopFarm's cash flow evaluation:

$$\max_{x,y} \text{NPV}(x, y) = -\text{CAPEX}(x, y) + \sum_{t=1}^{T} \frac{\text{CF}_t(x, y)}{(1 + r)^t} \tag{3.4}$$

where the cash flows CF$_t$ are constructed as:

$$\text{CF}_t = \text{AEP}(x, y) \times \text{energy\_price} - \text{OPEX}_t \tag{3.5}$$

with r representing the discount rate (0.0909870634), energy_price set at 80 €/MWh, and T equal to 25 years project duration. This NPV calculation is implemented in TopFarm using the numpy_financial library.

Both economic objective functions depend on turbine positions (x, y) through foundation costs that vary with water depth and energy production affected by wake interactions, enabling the optimization algorithm to balance energy production with infrastructure costs for economically optimal layouts.

3.5 Cable Routing Optimization Framework

The cable routing optimization framework addresses the challenge of designing efficient and feasible electrical collection systems for offshore wind farms. Although TopFarm includes an EDWIN cabling optimization module [9], its limitations in handling exclusion zone constraints and providing flexibility for different network topologies required the development and adaptation of optimization algorithms for this study. This section details the two distinct approaches implemented for cable routing optimization: a genetic algorithm (GA) inspired by the work of Yi et al. (2019) [41] and a Large Neighborhood Search (LNS) approach drawing from the methodology of Cazzaro & Pisinger (2022) [6].

Both algorithms were modified to support both radial and branched cabling topologies. Economic evaluation of the cabling layouts were implemented based on the evaluation of Yi et al [41] using the values presented in their paper. The optimization uses three cable types with different conductor cross-sectional areas: 150 mm^2, 400 mm^2, and 630 mm^2, each with corresponding current capacity and cost characteristics as specified by Yi et al. [41]. Energy price was set at 80 €/MWh. When comparing the results of Yi et al and this paper, it is important to note that the currencies reported in their paper are in pounds, while this paper reports everything in euros.

3.5.1 Visibility Graph Implementation

Both cable optimization approaches utilize visibility graph methodology based on [4] to handle exclusion zones and spatial constraints. The visibility graph connects vertices that have a clear line of sight between them, enabling efficient calculation of shortest paths around obstacles. The implementation begins by segmenting the wind farm area to create a set of vertices that includes all turbine locations, the position of the substation, and the vertices of all exclusion zone polygons.

The edges of the visibility graph represent potential cable connections that have direct line-of-sight without crossing any exclusion zones. The edge determination algorithm checks whether a direct path between any two vertices intersects with exclusion zone boundaries. For each potential vertex pair, the algorithm creates a line segment and tests it against every edge of each exclusion zone polygon. When an intersection is detected, the edge is excluded from the graph.

This visibility graph construction process has a time complexity of $O(n^2m)$, where n represents the number of vertices and m denotes the number of exclusion zone edges. While computationally demanding for complex geometries, this pre-processing step significantly simplifies subsequent path planning operations by transforming the continuous spatial routing problem into a discrete graph search problem.

After constructing the visibility graph, path finding is performed using Dijkstra's algorithm to determine the shortest feasible paths between turbines and the substation that avoid exclusion zones. This approach produces globally optimal paths that respect all spatial constraints. The algorithm minimizes total cable length, directly reducing material costs in the optimization process.

Several special cases required handling to ensure path planning in complex wind farm geometries. Points on exclusion zone boundaries needed special check, as they intersect with exclusion zones but should be allowed in certain contexts. Similarly, connections along boundary edges required specific logic to prevent false positives in intersection testing. Additional checks were implemented to ensure that turbines near exclusion zones could still be connected to the network through valid paths. Using visibility graph also brings special cases of cable crossing that need to be accounted for. These cases are highlighted in study by Yi et al. [41]

3.5.2 Genetic Algorithm based Optimization Approach

The first cable optimization approach implemented the methodology proposed by Yi et al. (2019), utilizing a genetic algorithm to optimize cable connections and types. This approach begins with an initial solution generation phase that employs a greedy algorithm to construct a Minimum Spanning Tree (MST) connecting all turbines. Starting from the substation, the algorithm iteratively connects the nearest unconnected turbine. As each turbine joins the network, cable types are assigned according to capacity requirements determined by the number of upstream turbines.

Following initial solution creation, a genetic algorithm refines the cabling arrangement through an evolutionary process. The genetic algorithm encodes potential solutions as connection sequences that define the network topology, with additional attributes specifying cable types for each connection. This encoding allows the algorithm to explore the solution space efficiently while maintaining feasibility constraints.

The fitness function for the genetic algorithm incorporates comprehensive economic evaluation of each candidate solution. Capital expenditure (CAPEX) includes cable costs based on length and type specifications, along with installation costs that vary according to seabed conditions. Operational expenditure (OPEX) incorporates maintenance costs calculated from failure rate models and energy loss costs determined through power flow analysis.

The genetic algorithm uses tournament selection with a size of 3, balancing selection pressure with population diversity. Crossover operations utilize a modified ordered crossover operator that preserves critical substation connections, ensuring offspring solutions maintain feasible tree structures. Mutation operations include swap mutation with a 0.1 probability, which exchanges the positions of two turbines in the connection sequence, and reconnection mutation with a 0.05 probability, which removes and reconnects a subtree to a different network section.

The algorithm terminates after completing 175000 generations or when convergence is detected through 50000 consecutive generations without improvement. The maximum generation limit was determined based on preliminary convergence analysis. Initial testing showed that substantial cost reductions typically occurred within the first 10000-20000 generations, after which improvements became increasingly marginal. The high iteration limit ensures that the algorithm has sufficient opportunity to explore the solution space thoroughly while incorporating an early stopping criterion (50000 consecutive generations without improvement) to prevent unnecessary computation when convergence is achieved. As shown in the results, the branched topology optimization terminated after 136000 generations and the radial topology after 97000 generations, both before reaching the maximum limit but well after achieving their primary cost reductions.

3.5.3 Large Neighborhood Search Optimization Approach

The second cable optimization approach implemented the methodology proposed by Cazzaro & Pisinger (2022) [6], utilizing a Large Neighborhood Search (LNS) algorithm. The algorithm is then extended to support unbalanced branch topology. While the original algorithm begins with a sweep that orders turbines by the angle of their shortest-path through a visibility graph and then partitions them into equal-sized strings, our modified sweep respects the same angular ordering but slices the sorted sequence into segments of up to the maximum cable capacity, rather than enforcing equal lengths. By randomizing the starting offset on each of several restarts, we generate a diverse set of initial layouts with variations in branch size.

After constructing the initial solution, the LNS approach systematically improves the cable layout through four neighborhood operators (swap, double swap, cycle swap, and repartition). These neighborhood operations are designed to explore different portions of the solution space effectively, balancing local improvements with more substantial network restructuring.

The swap operator, originally an exchange of one turbine from each of two branches, has been modified to support unbalanced branched so that a single turbine may be moved from one branch to another as long as neither branch exceeds its capacity. This modification permits branch-size variation of ±1 in each move. The double-swap operator remains a size preserving exchange of two turbine pairs, but with the size altering swaps, it helps escape local optima that simple one for one moves cannot overcome.

For the cycle swap operator equality constraints were lifted, allowing turbines to cycle among three or more branches without immediate reversal, enabling more global topological rearrangements. Finally, the repartition operator originally split two combined branches into exactly equal halves by using a MIP model to find the best partition. This was modified so that the operator no longer restricts itself to equal halves. Instead, it considers every possible way to split the combined group of turbines into two subsets, with sizes k and n-k, where n is the total number of turbines from the two original branches and k can vary.

The LNS algorithm terminates after a fixed number of iterations or when no improvement has been found for a specified number of consecutive iterations. For this study LNS iterations was set at 175, and early stop at 50 consecutive iterations without improvement. Similarly to the iteration limit for the GA algorithm, the iteration limit for the LNS algorithm was determined based on preliminary convergence analysis. Preliminary runs showed that the LNS method typically achieved significant improvements within the first 50-100 iterations, with subsequent iterations providing only small improvements. Combined with the early stopping criterion (50 consecutive iterations without improvement), this limit balances solution quality with computational efficiency. The results validate this choice, as the branched topology optimization converged after 71 iterations, and the radial topology reached the convergence criteria before the maximum limit.

4. RESULTS

This chapter presents the results obtained from applying the sequential optimization framework to the Baltic Sea case study. The results are organized to first validate the appropriateness of the sequential approach, followed by detailed analysis of layout optimization performance under different objective functions, and concluding with cable routing optimization results comparing different algorithms and network topologies.

4.1 Sequential Optimization Approach Validation

To determine the suitability of a sequential optimization approach, an initial analysis was conducted to assess the sensitivity of cabling costs to variation in turbine layout. The key consideration was whether differences in layout geometry would significantly influence the total LCOE. If the economic impact of cabling across layouts was found to be minor, it would support the use of a two-step optimization procedure, in which turbine layout and cabling are optimized separately.

Five random turbine layouts of equal size (30 turbines) were generated. For each layout, the cable network was optimized using two algorithms: a genetic algorithm (Yi) and a large neighborhood search method (Cazzaro). Both optimizers were configured with identical parameters and used the same set of three cable types with distinct capacities and costs. The results are summarized in Table 4.1.

Table 4.1. *Cabling Optimization Analysis for 5 Random Layouts*

Layout	Optimizer	Layout AEP	Total Layout Cost (M€)	Cable Length (m)	Total Cable Cost (M€)	Total LCOE (€/MWh)	LCOE without Cabling (€/MWh)	ΔLCOE (€/MWh)
Layout 1	LNS	1296	1149	73	170	40.72	35.47	5.247
Layout 1	GA	1296	1149	70	157	40.32	35.47	4.846
Layout 2	LNS	1301	990.9	75	185	36.15	30.47	5.688
Layout 2	GA	1301	990.9	73	160	35.39	30.47	4.919
Layout 3	LNS	1298	1164	74	178	41.35	35.86	5.485
Layout 3	GA	1298	1164	74	162	40.86	35.86	4.992
Layout 4	LNS	1296	1226	73	181	43.42	37.83	5.586
Layout 4	GA	1296	1226	74	159	42.74	37.83	4.907
Layout 5	LNS	1292	902.5	71	175	33.36	27.94	5.418
Layout 5	GA	1292	902.5	68	155	32.74	27.94	4.799
Average	LNS	-	1086	73.2	177.8	39.00	33.51	5.485
Average	GA	-	1086	71.8	158.6	38.41	33.51	4.893
Std Dev	LNS	-	134.5	1.483	5.718	4.122	4.133	0.1677
Std Dev	GA	-	134.5	2.683	2.702	4.173	4.133	0.07368
Coef Var	LNS	-	12.38%	2.026%	3.216%	10.57%	12.33%	3.058%
Coef Var	GA	-	12.38%	3.737%	1.704%	10.87%	12.33%	1.506%

The total LCOE was calculated for each layout, both with and without cabling costs. The difference between these values ΔLCOE was used to quantify the specific economic contribution of the cabling system. The analysis revealed that the coefficient of variation (CoV) in total LCOE was moderate, measured at 10.57% for the LNS optimizer and 10.87% for the GA optimizer. This level of variability reflects differences in how effectively each layout integrates with the cabling solution.

In comparison, the CoV of LCOE values excluding cabling was slightly higher, at 12.33% for both optimizers. This suggests that most of the variation in LCOE is attributable to differences in the layout construction and associated capital expenditures, rather than to cabling design. More notably, the variation in the cabling specific contribution to LCOE was relatively small. The ΔLCOE exhibited a CoV of only 3.06% for the LNS optimizer and 1.51% for the GA optimizer, indicating that cabling costs remain fairly consistent across different layouts.

The standard deviation of ΔLCOE was 0.1678 €/MWh for LNS and 0.0740 €/MWh for GA, with average values around 5 €/MWh. While these differences appear minor, they may still influence project decisions in scenarios where marginal cost savings are critical, such as competitive auctions or strict financing thresholds.

It was also observed that the LNS optimizer tended to yield higher total LCOE values compared to GA. This difference is primarily explained by longer average cable lengths and higher cabling costs, with LNS averaging 177.8 M€ in cable cost compared to 158.6 M€ for Yi. Nonetheless, the difference in ΔLCOE between the two approaches was modest, with LNS averaging 5.48 €/MWh and GA averaging 4.89 €/MWh.

This analysis indicates that the cabling-related portion of LCOE is relatively insensitive to the specific turbine layout under the conditions studied. The small variation in ΔLCOE across the five random layouts suggests that a sequential optimization approach can be applied with minimal loss in overall economic performance. This supports the adoption of a sequential method in this study, particularly given the substantial computational savings it offers. These findings align with previous observations by Cazzaro et al.[5], who reported that while combined optimization can yield improvements, the relative benefit is often outweighed by the increased computational cost.

4.2 Layout Optimization

This section presents the results from the layout optimization phase of the sequential optimization approach. For all optimization scenarios, a wind farm consisting of 30 turbines with 10MW capacity each (300MW total capacity) was configured within the defined Baltic Sea site boundaries, subject to minimum spacing constraints of 800 meters between turbines and the exclusion zones described in Section 3.4.

To address the challenges of potential local minima in complex economic optimization, a two-stage sequential approach was implemented. The process began with optimizing the layout for AEP using the COBYLA algorithm in the TopFarm framework. Following this initial optimization, the resulting AEP-optimized layout served as the starting point for further optimization of economic objectives (LCOE and NPV), helping to avoid suboptimal solutions that might result from directly optimizing the more complex economic metrics from random starting positions.

4.2.1 AEP Optimization Results

The AEP optimization aimed to maximize energy production without explicit consideration of costs. This section presents the results of the primary optimization run, followed by validation through two additional runs to assess the consistency and robustness of the approach.

The optimization process was initialized with a randomly generated layout that satisfied all constraints. This initial configuration produced an AEP of 1295 GWh/year. After completing 1500 iterations of the COBYLA algorithm, the optimization produced a final layout with an AEP of 1320 GWh/year, representing an increase of 1.93% over the initial configuration.

Figure 4.1 shows the convergence history of the AEP objective function throughout the optimization process. The graph shows a rapid initial improvement followed by a gradual plateau. Notably, the convergence started to diminish after approximately 1000 iterations, with only marginal improvements afterwards. This indicates that the selected convergence tolerance of 1e-5 provides a good balance between optimization quality and computational efficiency.

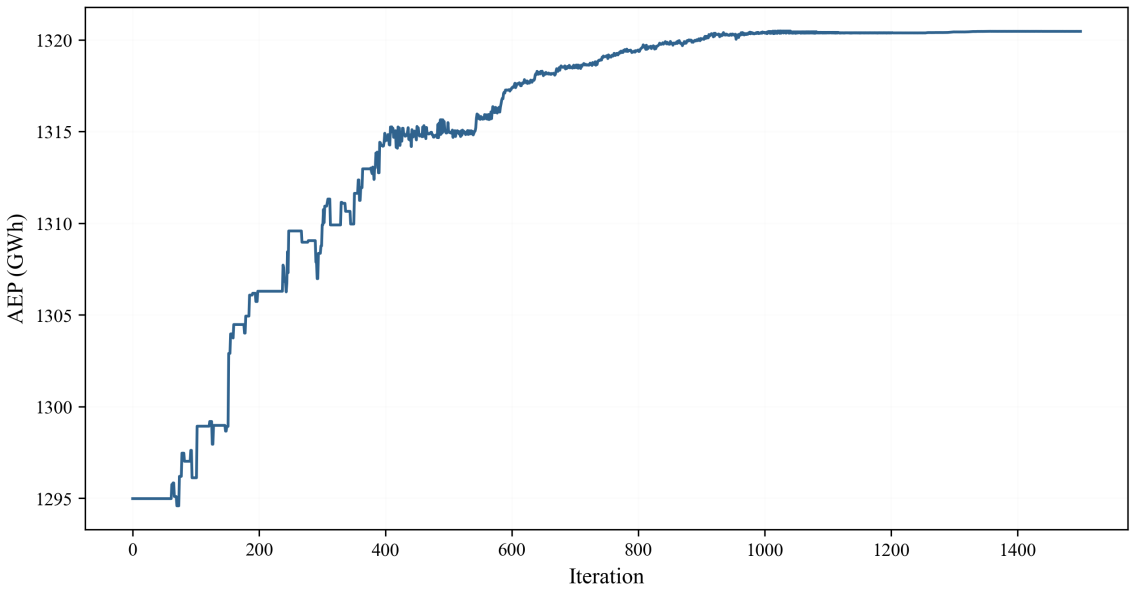

Figure 4.1. *Convergence history of AEP optimization showing rapid initial improvement from 1295 GWh/year to the final value of 1320 GWh/year over 1500 iterations. The optimization shows diminishing returns after approximately 1000 iterations, with most improvements occurring in the first 500 iterations.*

The computational performance was reasonable, with the entire optimization process taking approximately 1500 seconds (25 minutes).

Figure 4.2 shows both the initial random layout and the optimized layout resulting from the AEP maximization. The optimized layout shows how turbines have been repositioned to minimize wake effects, with a clear transformation from random initial distribution to a more spaced layout that maximizes energy production.

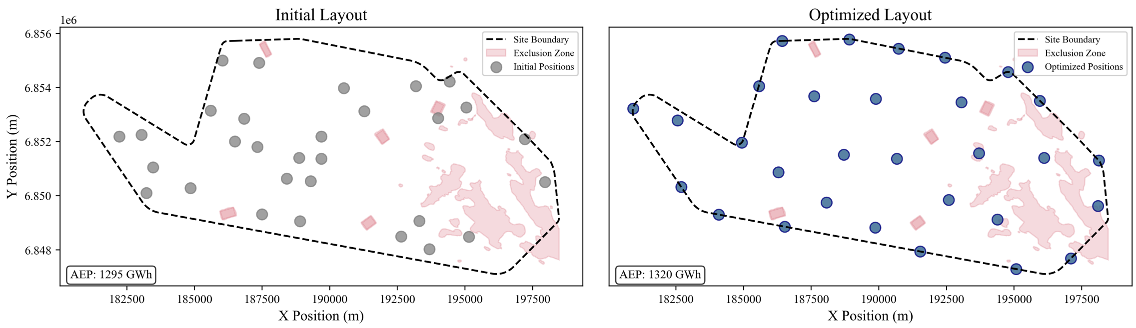

Figure 4.2. *Comparison between the initial random layout (left) and the optimized layout (right) for AEP maximization. The optimization repositioned turbines to minimize wake effects, with notable movement toward site boundaries and increased spacing in the prevailing wind direction (southwest).*

Analyzing the optimization shows few key patterns. Turbines positioned near the edges of the of the farm move right up to the edges. The optimized layout shows increased spacing between turbines in the prevailing wind direction (shown in the wind rose 3.1) while maintaining only the minimum required distance in other directions. The space in the middle of the optimized layout has more evenly distributed turbines.

To validate the robustness of the optimization approach, the AEP optimization was repeated twice more with different random initial layouts. Figure 4.3 presents the initial and optimized layouts for these two additional runs.

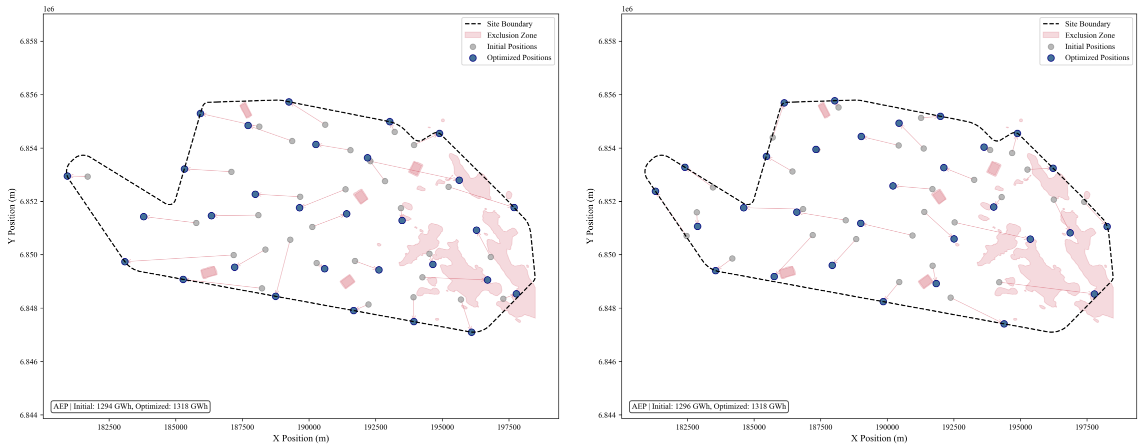

Figure 4.3. *Initial and optimized turbine layouts for validation runs 2 and 3 of the AEP optimization, demonstrating consistent optimization patterns across different random starting configurations.*

The convergence histories for these validation runs are shown in Figure 4.4, demonstrating similar patterns to the primary run despite starting from different initial layouts.

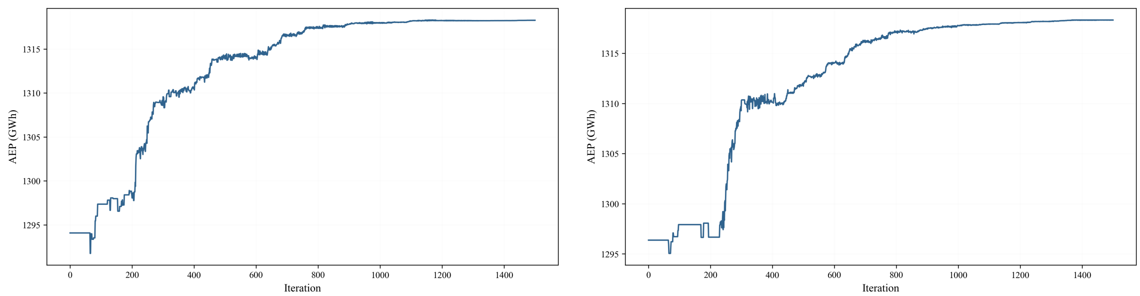

Figure 4.4. *Convergence histories for validation runs 2 and 3 of the AEP optimization, both starting from different random layouts but achieving similar final AEP values. The consistent convergence patterns across multiple runs demonstrate the robustness of the COBYLA optimization approach.*

Table 4.2 presents a comparison of the results from all three independent optimization runs.

Table 4.2. *Comparison of three independent AEP optimization runs*

Run	Initial AEP (GWh/year)	Optimized AEP (GWh/year)	Improvement (%)
1	1295	1320	1.93%
2	1294	1318	1.85%
3	1296	1318	1.70%
AVG	1295	1319	1.85%

The results show consistency across multiple optimization runs, with a mean AEP improvement of approximately 1.85%. This consistency suggests that the optimization approach is robust and capable of finding similar high-quality solutions regardless of the initial configuration. The small variations in final AEP values (1318-1320 GWh/year) indicate that while the algorithm may have converged to slightly different local optima, these solutions are of similar quality. Examining the layouts from all three runs show common patterns in turbine positioning, particularly in how turbines align relative to prevailing wind directions. This behavior across different starting layouts further validates the effectiveness of the optimization approach in identifying advantageous turbine arrangements.

4.2.2 LCOE Optimization Results

After establishing the AEP-optimized layout, a secondary optimization was performed to minimize the LCOE. This sequential approach used the AEP-optimized layout as the starting point rather than a random layout, helping to avoid local minima issues that might happen when directly optimizing LCOE from random layouts.

The optimized layout from AEP run 1 had an LCOE of 28.25 €/MWh with an AEP of 1320 GWh/year and foundation costs of 322 M€. After applying the LCOE optimization process with the COBYLA algorithm, the layout achieved an LCOE of 27.12 €/MWh, representing a further reduction of 4.0%. The optimization ran for 733 iterations before terminating due to reaching the convergence tolerance, indicating that the algorithm had converged to a solution where further improvements were below the specified threshold.

Figure 4.5 presents the convergence history of the LCOE objective function optimization. The left graph shows the complete convergence history with all intermediate evaluation points, showing how the optimization algorithm tests many different turbine layouts, including some that perform worse than previous arrangements. This up-and-down pattern reveals that finding the best economic layout isn't straightforward, as the algorithm must search through many possible solutions with varying performance. The graph also shows that the algorithm continues to find better layouts even after hundreds of iterations, indicating that economic optimization for wind farms requires extensive exploration. The right graph displays only the current best value at each iteration, providing a clearer visualization of the optimization's overall progress toward the final LCOE value of 27.12 €/MWh. The computational run time for this optimiztion was approximately 750 seconds (12.5 minutes).

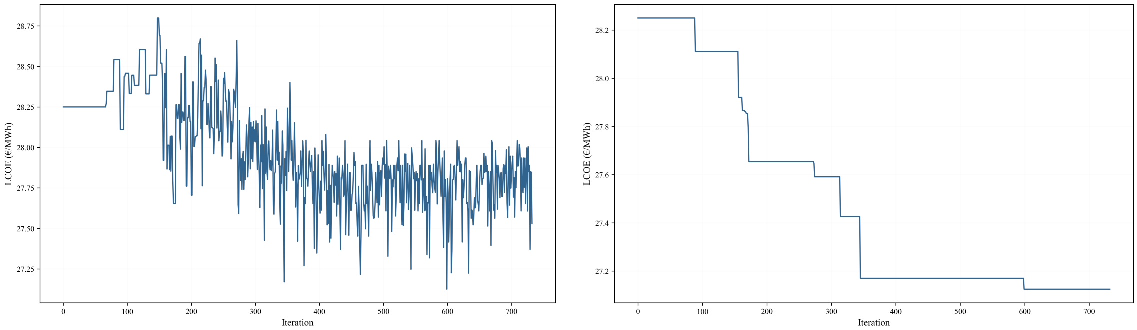

Figure 4.5. *Convergence history of LCOE optimization showing the characteristic 'noisy' behavior of economic objective functions, with the algorithm testing various turbine configurations before converging to 27.12 €/MWh after 733 iterations. The left graph shows all evaluation points while the right graph displays only the current best values.*

Analysis of the optimized layout shows that the LCOE optimization made mostly relatively small adjustments to turbine positions rather than major relocations. As shown in Figure 4.6, the overall pattern of turbine placement remains similar to the AEP-optimized layout, but with small shifts toward shallower water depths. While maintaining the general boundary positioning given by the AEP optimization, turbines were adjusted to more favorable locations that reduce foundation costs. These minor position changes collectively yielded the substantial 12.4% foundation cost reduction while minimally impacting energy production, demonstrating the effectiveness of fine-tuning an already good layout for economic objectives.

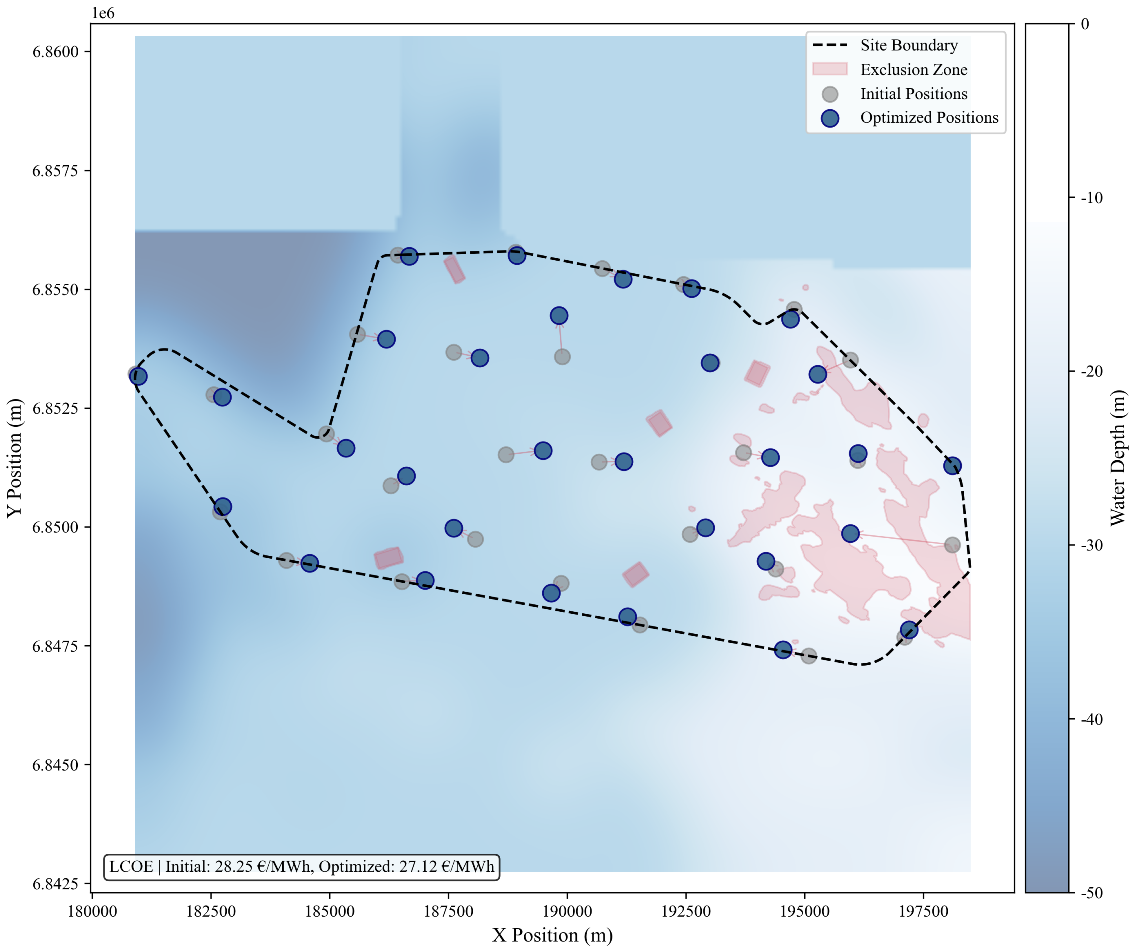

Figure 4.6. *Comparison between AEP-optimized layout (starting point) and LCOE-optimized layout showing relatively minor turbine position adjustments that achieved 4.0% LCOE reduction. The optimization maintained the general boundary positioning from AEP optimization while making small shifts toward shallower water depths to reduce foundation costs.*

Analysis of the cost components shows that the LCOE optimization reduced foundation costs by approximately 12.4% compared to the AEP-optimized layout, while reducing AEP by only 0.3%. This trade-off resulted in the overall LCOE improvement of 4.0%. Table 4.3 presents the metrics before and after the LCOE optimization.

Table 4.3. *Comparison of metrics before and after LCOE optimization*

Metric	AEP-Optimized Layout	LCOE-Optimized Layout	Change (%)
AEP (GWh/year)	1320	1316	-0.3%
LCOE (€/MWh)	28.25	27.12	-4.0%
Foundation Cost (M€)	322.0	282.0	-12.4%

4.2.3 NPV Optimization Results

Following the same approach as in the LCOE optimization, NPV optimization was performed starting from the AEP-optimized layout to maintain consistency in the sequential optimization framework. While starting from the LCOE-optimized layout might yield different results given the similar economic nature of both objectives, beginning from the AEP-optimized layout ensures that both economic optimizations (LCOE and NPV) start from the same baseline, enabling direct comparison of their respective optimization strategies and outcomes. The AEP-optimized layout from the first run had an NPV of 261.1 M€, an AEP of 1320 GWh and foundation cost of 322 M€. After running the NPV optimization with COBYLA, the layout achieved NPV of 296.7 M€, representing improvement of 13.6%. The optimized layout resulted in AEP of 1314 GWh (reduction of 0.45%), LCOE of 27.16 €/MWh (change of 3.9%), and foundation costs of 282 M€ (12.4% reduction).

Figure 4.7 shows the convergence history of the NPV objective during the optimization, with the left graph showing all evaluation points during the optimization and right graph showing the current best value. The computational runtime for this phase was approximately 700 seconds.

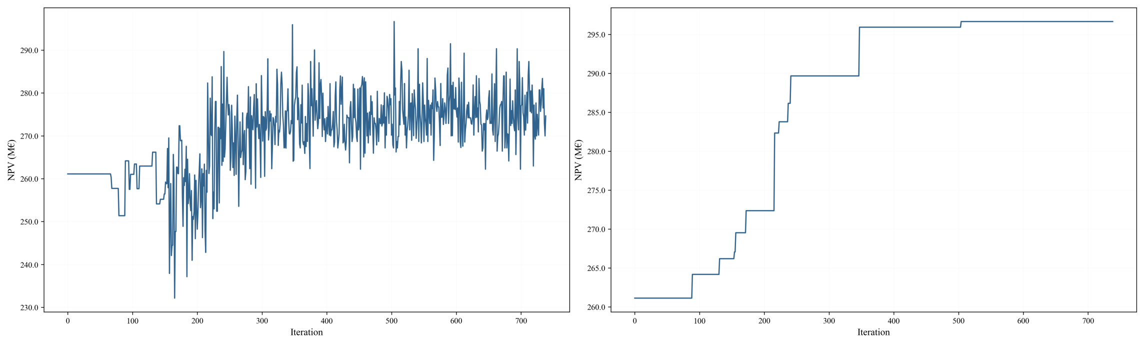

Figure 4.7. *Convergence history of NPV optimization displaying similar noisy convergence behavior as LCOE optimization, with the algorithm achieving 13.6% NPV improvement (296.7 M€) over approximately 700 iterations. The optimization demonstrates that economic objectives require extensive exploration to balance energy production with cost considerations.*

Figure 4.8 presents a comparison between the AEP-optimized starting layout and the final NPV-optimized layout.

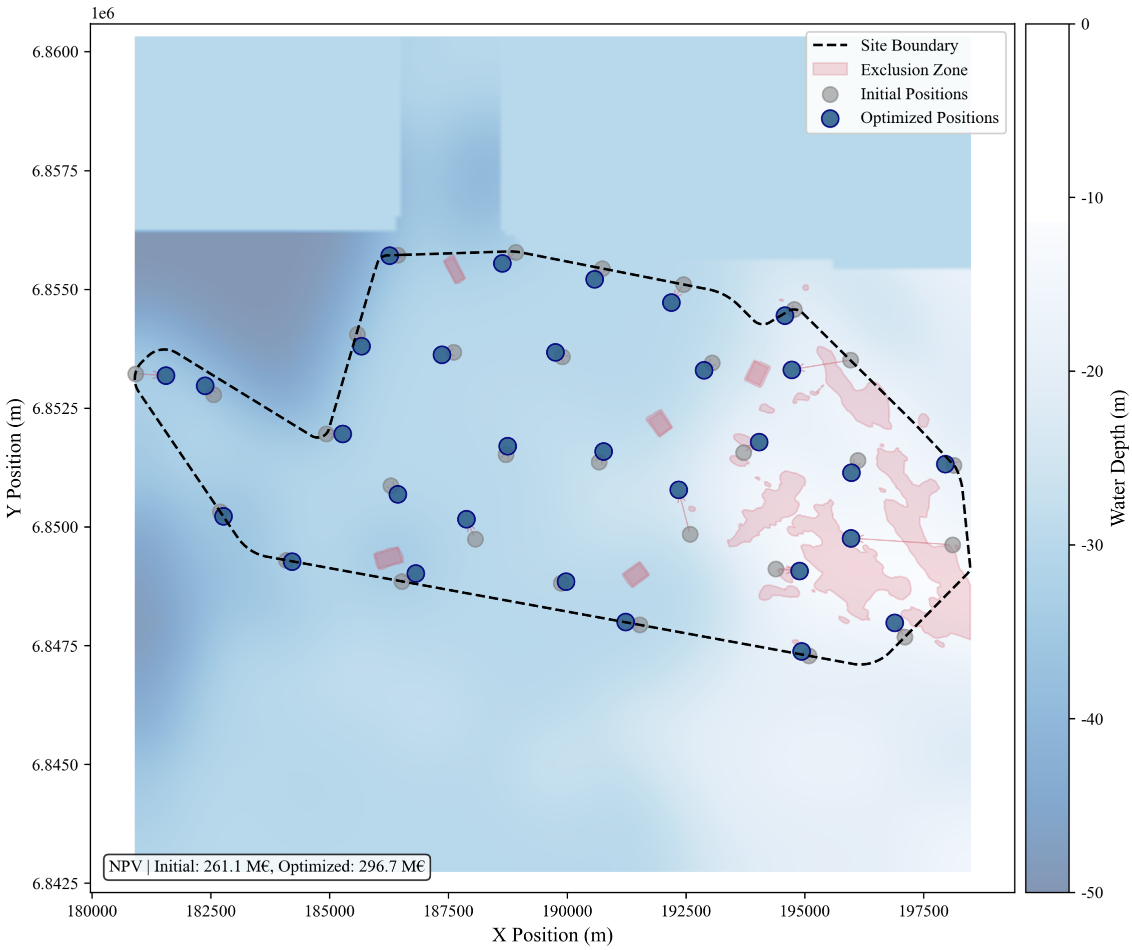

Figure 4.8. *Comparison between the AEP-optimized layout (gray circles) and the NPV-optimized layout (blue circles). The background color represents water depth, with lighter blues indicating shallower areas. Exclusion zones are represented by pink areas, and the site boundary is marked by the dashed black line*

Table 4.4 presents the key metrics before and after the NPV optimization phase.

Metric	AEP-Optimized Layout	NPV-Optimized Layout	Change (%)
AEP (GWh/year)	1320	1314	-0.45%
LCOE (€/MWh)	28.25	27.16	-3.9%
NPV (M€)	261.1	296.7	+13.6%
Foundation Cost (M€)	322.0	282.0	-12.4%

Table 4.4. *Comparison of AEP-Optimized and NPV-Optimized Layouts*

4.3 Cabling Optimization

This section presents the results from the cable routing optimization phase of the sequential optimization. Following the turbine layout optimization, cable routing optimization was performed to determine the most cost-effective inter-array cable network connecting the turbines to the substation. For this optimization, the LCOE optimized layout from Section

4.2.2 was selected as the input layout, as it represents a layout specifically optimized for economic performance.

To thoroughly evaluate different optimization approached and cable network topologies, four different optimization runs were performed. First run is GA with branched topology, second is GA with radial topology, third is LNS with branched topology, and fourth is LNS with radial topology.

This approach allows for comparison between both the optimization algorithms (GA vs. LNS) and the network topologies (branched vs. radial). The analysis of these results will provide insight into the advantages and limitations of each approach when applied to offshore wind farm cable routing.

4.3.1 Genetic Algorithm Results

The GA based cable routing optimization was executed for both branched and radial topologies, using the LCOE optimized turbine layout as the starting point. In the branched topology GA run, the algorithm progressed through 136000 iterations before terminating after approximately 8 hours due to reaching maximum iterations without improvement. The most substantial cost reductions occurred within the first 15000 generations, after which only marginal improvements were observed. Over the course of the optimization, the total cable cost decreased from an initial 370 M€ to a final 153 M€, and the total cable length was reduced from 250 km to 74 km.

Figure 4.9 shows the convergence history of the branched GA run, showing the steep initial decrease in cost followed by a long tail of small incremental gains. The optimized branched cable layout is shown in Figure 4.10, where the improved routing clearly navigates around exclusion zones and balances cable type assignments to achieve the lowest overall cost.

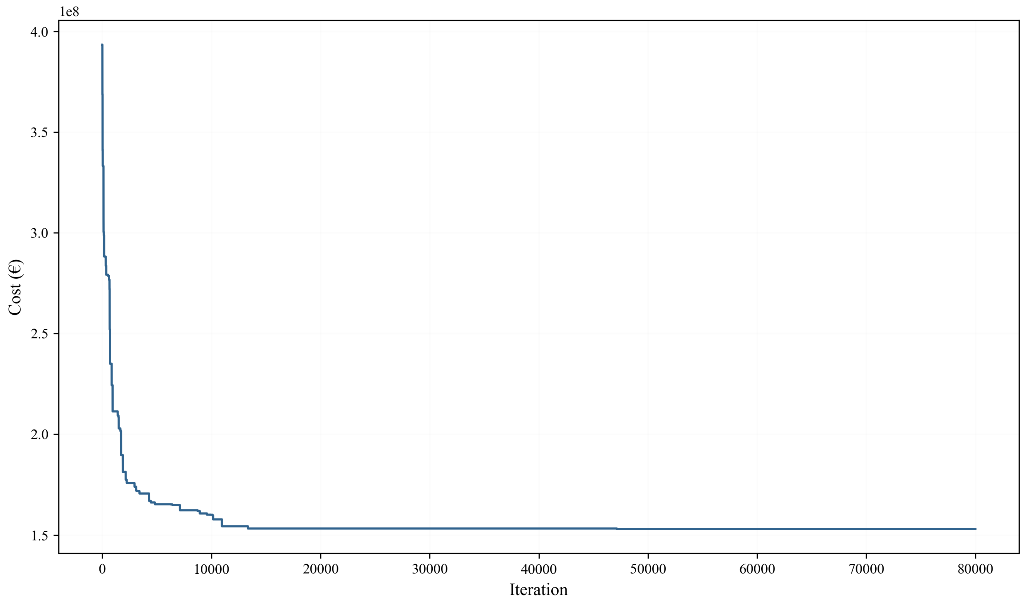

Figure 4.9. *Convergence history for genetic algorithm cable routing optimization using branched topology, showing rapid cost reduction from 370 M€ to 153 M€ within the first 15000 generations out of 136000 total iterations. The optimization demonstrates typical GA behavior with steep initial improvements followed by gradual refinements over extended runtime.*

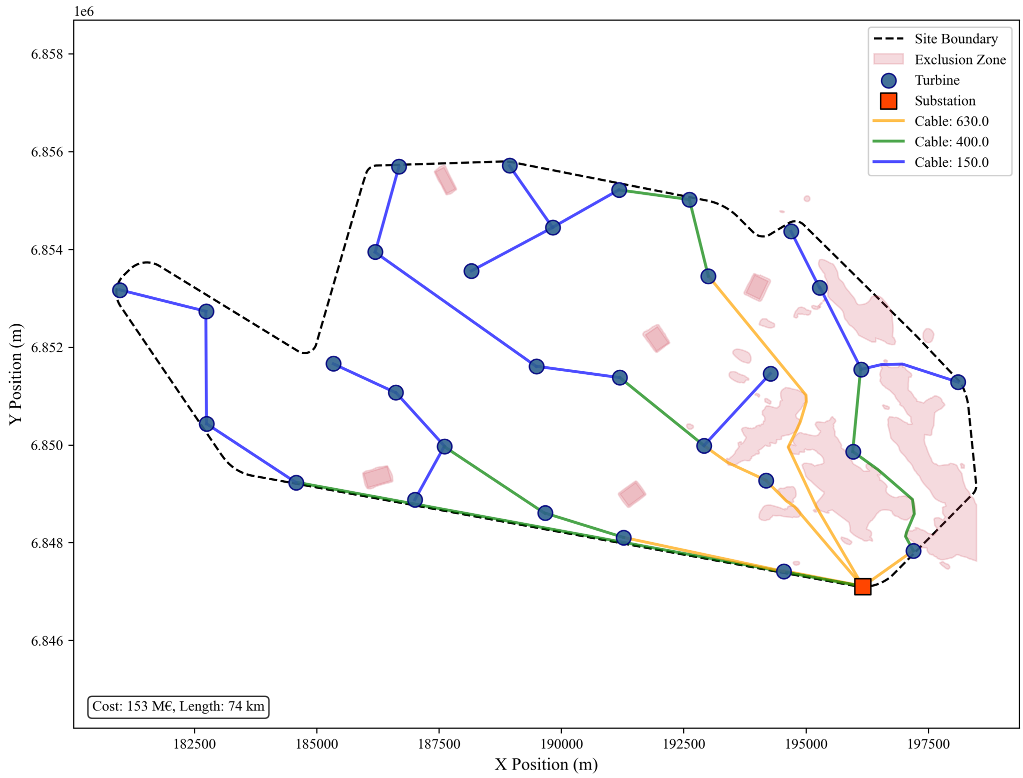

Figure 4.10. *Final branched cable network configuration from genetic algorithm optimization, showing routing around exclusion zones, reducing total cable length to 74.01 km.*

In the radial topology GA run, the algorithm ran for 97000 iterations, completing in approximately 6 hours. As with the branched case, the majority of improvement happened early in the run, within the first 10000 generations, after which very minor improvements were observed. The final radial GA solution reduced the total cable cost from 450 M€ to 155 M€ and shortened the cable length from 250 km to 72 km.

The convergence for the radial GA optimization is presented in Figure 4.11, highlighting both the early rapid improvements and the slower refinements that follow. Figure 4.12 shows the resulting radial layout, where each turbine string is routed independently to the substation with no branching.

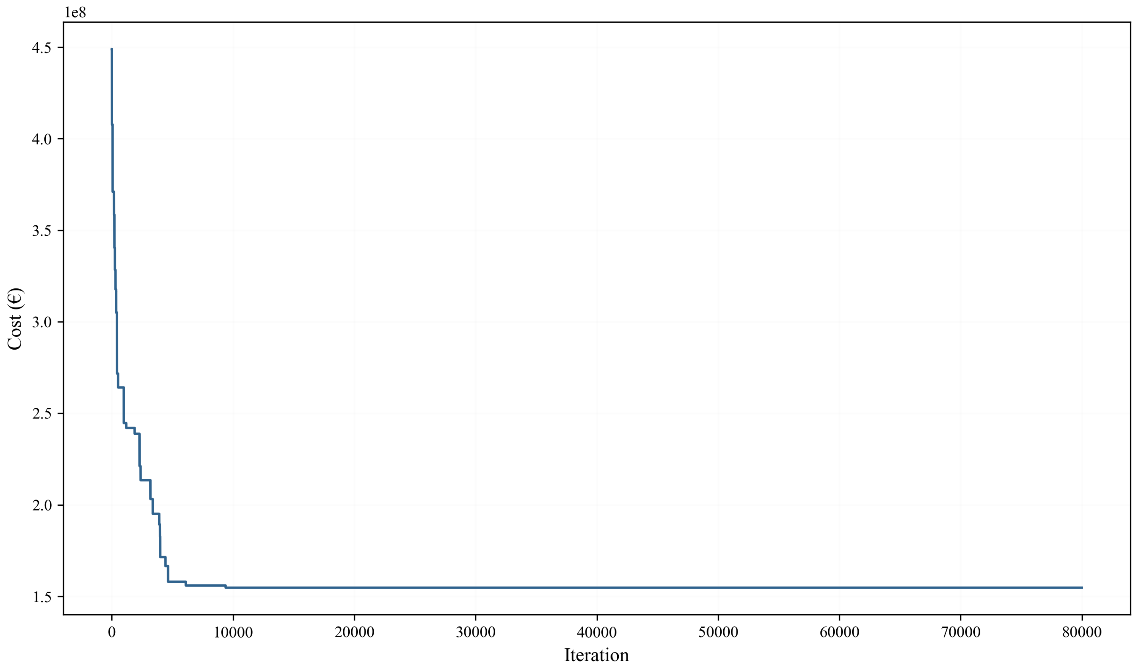

Figure 4.11. *Convergence history for genetic algorithm cable routing optimization using radial topology, reducing costs from 450 M€ to 155 M€ over 97000 iterations with most improvements occurring within the first 5000 generations.*

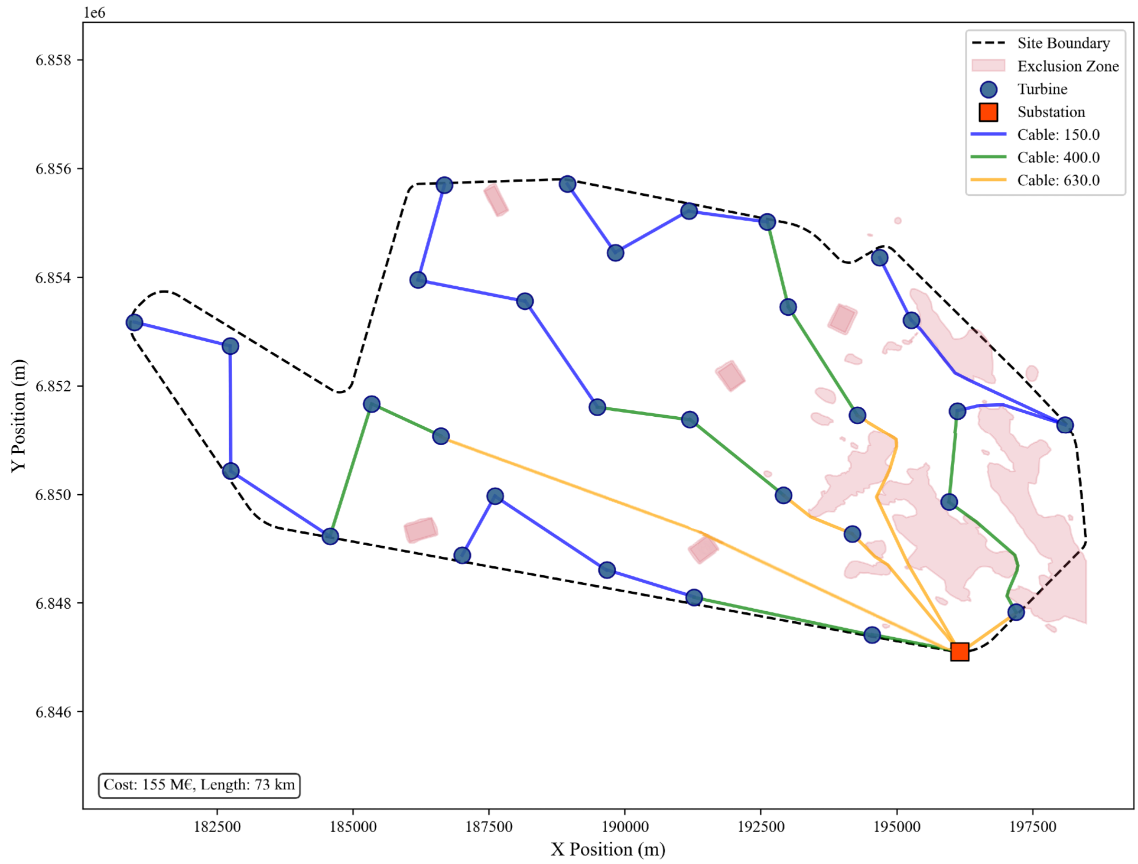

Figure 4.12. *Final radial cable network configuration from genetic algorith run, resulting in 72.89 km total cable length.*

4.3.2 Large Neighborhood Search Results

Identical to the GA runs, two distinct cable routing optimization runs were performed using the Large Neighborhood Search (LNS) method, with one run for the branched topology and another for the radial topology. Both runs used the LCOE-optimized turbine layout as a starting point and applied the LNS method detailed in Section 3.

The first LNS optimization used the branched cable configuration, allowing multiple upstream turbines to be connected into a single turbine node, thus forming branching structures. This optimization terminated after 67 iterations due to the early stopping criterion (50 consecutive iterations without improvement). The total computational runtime for this run was 1075 seconds (approximately 18 minutes), while the last significant improvement was observed at iteration 17, approximately 250 seconds into the optimization process.

The final optimized cable network for the branched topology achieved a total cost of 165 M€ from the initial layout with a cost of 179 M€. The optimized cable layout achieved a total cable length of 69 km, down from an initial length of 78 km. Figure 4.13 presents the convergence history of the branched LNS optimization, illustrating the rapid initial improvement followed by a plateau in later iterations. The optimized branched cable layout is shown in Figure 4.14, showing the cable routing and branching patterns around the exclusion zones.

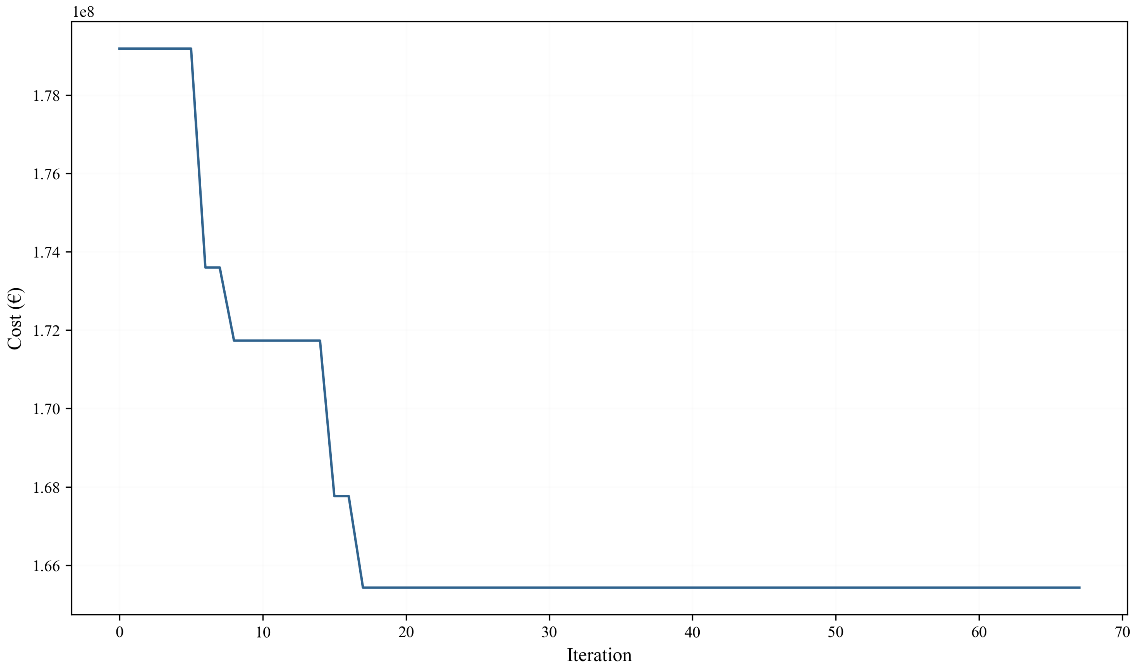

Figure 4.13. *Convergence history for Large Neighborhood Search optimization using branched topology, achieving final cost of 165 M€ after rapid initial improvement within 17 iterations and convergence at 67 iterations. The LNS approach demonstrates faster convergence compared to genetic algorithm but achieves higher final costs.*

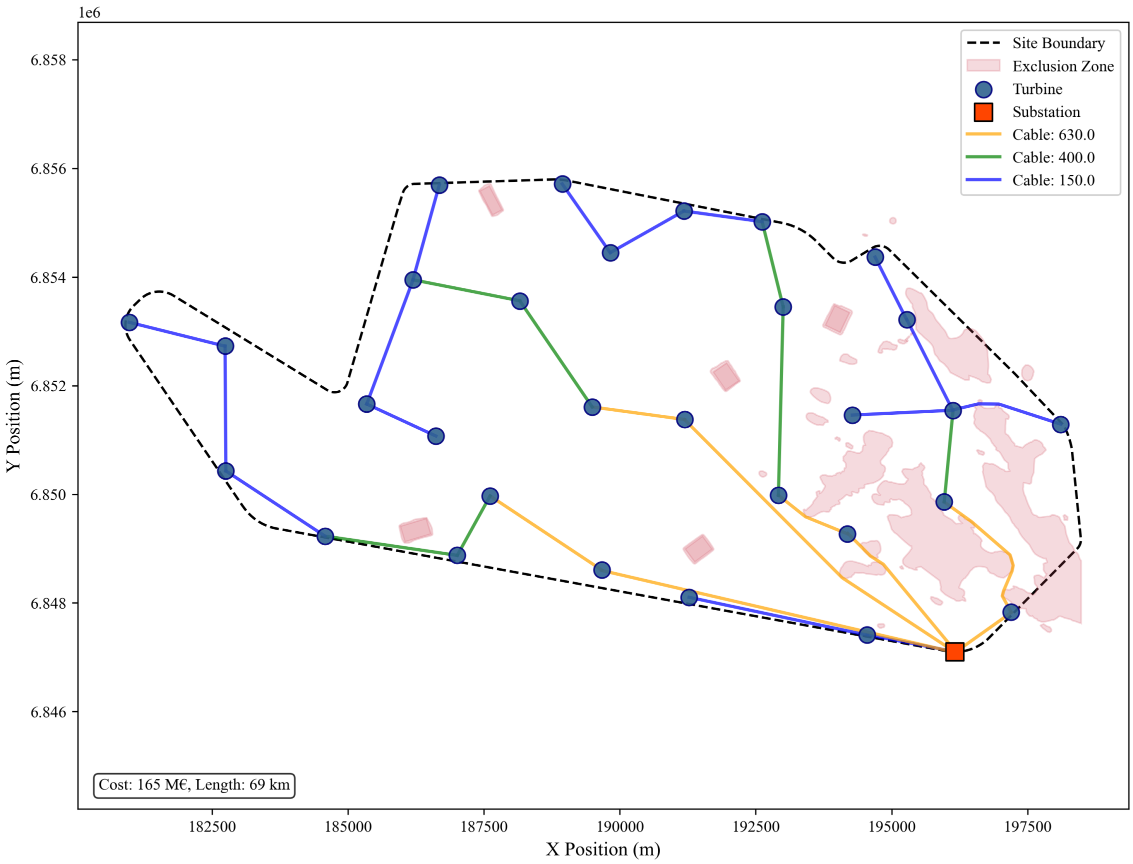

Figure 4.14. *Final branched cable network from Large Neighborhood Search optimization with 69 km total cable length. The LNS approach produces different branching strategies compared to genetic algorithm optimization while maintaining feasible network connectivity.*

In the second LNS optimization run, the radial cable topology was used, restricting each turbine string to connect directly to the substation without intermediate branching points. This optimization run for 140 iterations and terminated due to the early stopping criterion after 50 consecutive iterations without improvement. The total computational runtime was 3156 seconds (approximately 53 minutes), with the final significant improvement observed around iteration 70, at approximately 1500 seconds into the optimization process.

The radial LNS optimization concluded with a total network cost of 168€. Total cable length was reduced to 72 km. The convergence history for the radial LNS optimization, shown in Figure 4.15, shows the optimization process with substantial early improvements and smaller incremental improvements in the mid to late stages. The resulting radial cable layout is shown in Figure 4.16, showing the radial pattern from turbine strings to the substation.

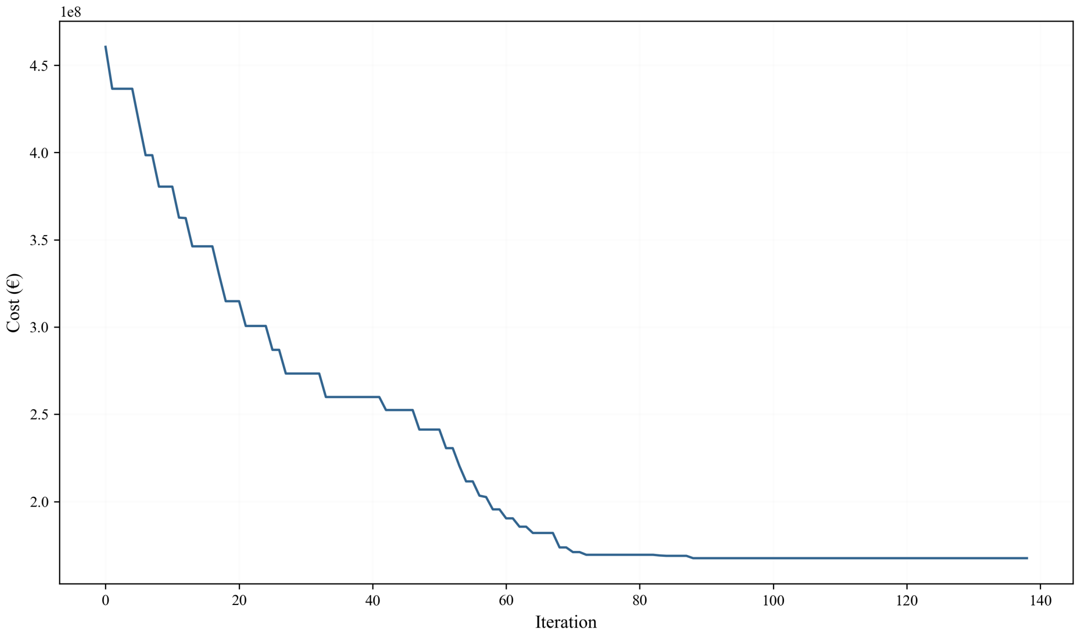

__Figure 4.15.__ Convergence history for Large Neighborhood Search optimization using radial topology, running for 140 iterations with final significant improvement around iteration 70 before convergence.

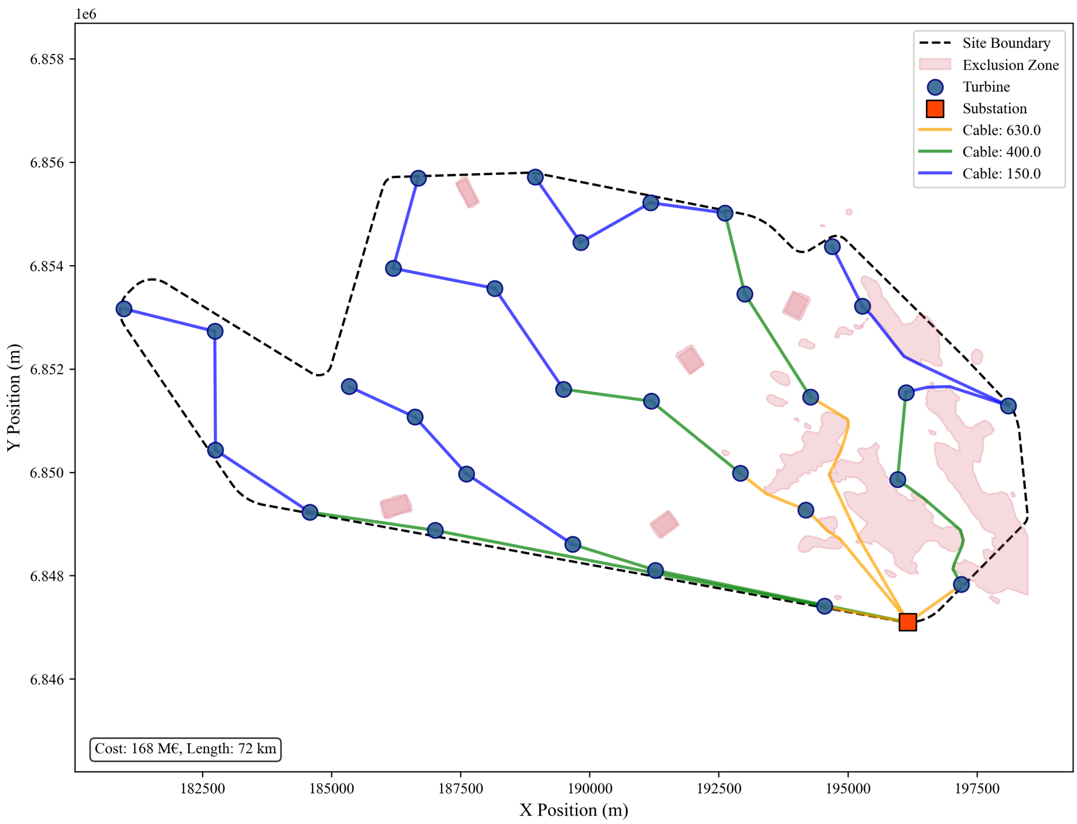

__Figure 4.16.__ Final radial cable network from Large Neighborhood Search optimization with 72.02 km total cable length.

Table 4.5 summarizes the key results of both GA and LNS optimization runs, providing an overview of the optimization performance and outcomes:

Table 4.5. *Cable routing optimization results comparison*

Topology	Algorithm	Total Cost (M€)	Cable Material Cost (M€)	Cable Length (km)	Annual Energy Loss (GWh)	Iterations	Computation Time (s)
Radial	GA	154.7	22.49	72.89	39.32	97147	20495
	LNS	167.5	21.23	72.02	54.81	138	3156
Branched	GA	153.0	22.00	74.01	37.05	136110	28846
	LNS	165.4	22.03	69.25	56.23	67	1075

The analysis of entire results will be discussed in detail in Chapter 5.

5. DISCUSSION

This chapter analyzes the results of the sequential optimization framework developed for offshore wind farm design in the Baltic Sea. The discussion evaluates the effectiveness of the proposed methodology, examines the performance of different optimization algorithms and topologies, presents the integrated final design, and discusses practical implications for offshore wind farm development.

5.1 Validation of Sequential Optimization Approach

The premise of this study, that sequential optimization can effectively balance computational efficiency with solution quality, is validated by the preliminary analysis of random turbine layouts. The analysis of five random layouts demonstrated that the coefficient of variation in cabling-specific LCOE contribution (ΔLCOE) was only 3.06% for the LNS optimizer and 1.51% for the GA optimizer, indicating that cabling costs remain fairly consistent across different layouts.

The standard deviation of ΔLCOE was 0.168 €/MWh for LNS and 0.074 €/MWh for GA, with average values around 5 €/MWh. This low sensitivity justifies the sequential approach adopted in this thesis. While combined optimization approaches can theoretically yield better results by simultaneously considering turbine placement and cable routing constraints, the computational overhead would be substantial for the marginal gains achievable in this specific site context.

It should be noted that this validation is limited and has some critical concerns. Due to the limited scope of this thesis, only five random layouts were examined. The use of only five random layout provides insufficient statistical power to confidently conclude that cabling costs are insensitive to layout variations. A robust validation would require analysis of many more layouts to achieve statistical significance as the small sample size may not capture the full range of layout-cabling interactions possible within the site boundaries. In addition, the random layout generation process may not represent the diversity of layouts that could emerge from different optimization approaches. All random layout were generated using the same constraint set, potentially missing extreme cases where layout cabling interactions would become more distinct. Furthermore, the validation applies specifically to the study case, where water depths and exclusion zones create predictable routing constraints. Sites with more complex bathymetry, exclusion zones, and other constraints might present significantly different layout-cabling sensitivities.

Despite these limitations, the sequential approach enables the use of specialized algorithms for each subproblem: deterministic optimization for layout design and metaheuristic methods for cable routing. This modularity provides flexibility in algorithm selection based on specific project requirements and computational constraints, though it inherently cannot capture all potential synergies between layout and cabling decisions that integrated approaches might identify.

5.2 Turbine Layout Optimization Performance

The layout optimization phase demonstrated effective performance across multiple objective functions. The AEP optimization achieved an Annual Energy Production of 1320 GWh/year for the 300 MW wind farm, corresponding to a capacity factor of 50.2%. When compared to industry benchmarks, the capacity factor seems optimistic but realistic. According to IRENA data, the global average capacity factor for offshore wind was at 41 percent in 2023 [22], while the IEA reports that "new offshore wind projects have capacity factors of 40%-50%, as larger turbines and other technology improvements are helping to make the most of available wind resources" [21]. While the achieved gross capacity factor of 50.2% falls in the upper range of this performance band, few factors suggest this result may be optimistic. The Bastankhah-Gaussian wake model, while more sophisticated than Jensen's model, still has significant simplification of wake interactions. The wind resource data from the Finnish Wind Atlas provides generalized regional conditions but may not capture the specific microclimate effects at the exact wind farm location. The capacity factor calculation does not account for real-world operational constraints including turbine availability or maintenance downtime. More accurate net capacity factor that includes energy losses in cables is calculated in Section 5.4

Economic optimization demonstrated value creation beyond the initial AEP optimization. Starting with the AEP optimized layout, LCOE optimization achieved a 4.0% reduction in levelized energy cost while reducing AEP by only 0.3%. The LCOE-optimized layout achieved an LCOE of 27.12 €/MWh, which is notably lower than literature esitmates of 50-100 €/MWh [17] for offshore wind projects. It should be noted that this calculated LCOE represents only the layout optimization stage and does not include cable routing costs. A more comprehensive analysis of the final project LCOE, including cable routing optimization, will be discussed later in Section 5.4 when the integrated design performance is evaluated.

The LCOE of 27.12 €/MWh is significantly lower than industry benchmarks and raises concerns about the validity of the cost modeling approach. This substantial difference suggests several potential issues: the foundation cost model, while detailed, is based on simplified assumptions about excavation requirements and installation procedures that may not capture the complex logistics, weather dependencies, and site-specific challenges of real-world foundation installation. The economic parameter assumptions, including the fixed electricity price of 80 €/MWh and discount rate, may not reflect current market conditions or project financing realities. Additionally, the LCOE calculation may not fully account for insurance, development costs, grid connection fees, and other project expenses that significantly impact commercial viability. The bathymetric data resolution may not capture small-scale seabed variations that could affect foundation installation costs, and the foundation model assumes relatively homogeneous soil conditions based on surface geology data to 30cm depth, while actual foundation design requires geotechnical data to several meters depth.

The key driver of LCOE improvements was foundation cost optimization, achieving 12.4% cost reductions by positioning turbines in shallower water depths and more favorable seabed conditions. This finding highlights the importance of site specific optimization for projects using gravity based foundations, where water depth significantly impacts installation costs.

Similarly, NPV optimization delivered a 13.6% improvement in net present value with comparable minimal energy production sacrifice (0.45% AEP reduction). The similarity between LCOE and NPV optimization results suggests that both metrics respond to the same cost drivers in this case study application, primarily foundation installation costs related to water depth and seabed conditions. Both economic optimization stages demonstrated that significant value creation is possible through fine-tuning layouts for cost-sensitive parameters while maintaining energy production performance.

The COBYLA algorithm performed sufficiently for layout optimization across all objective functions, though the convergence histories for LCOE and NPV optimization showed characteristic 'noisy' behavior with evaluation histories displaying oscillations around the general trend. This pattern raises concerns about solution quality and robustness, as the oscillations suggest that COBYLA's linear approximation methodology may be inadequate for the complex, nonlinear economic objective functions encountered in wind farm optimization. The noisy convergence indicates potential sensitivity to parameter settings, suggests the algorithm may be trapped in local optima, and raises questions about whether the economic metrics contain numerical noise or discontinuities that affect optimization performance.

5.3 Cable Routing Optimization Analysis

The cable routing optimization results demonstrate clear performance differences between algorithms and topologies that align with and extend findings from previous research.

The genetic algorithm approach achieved superior economic performance compared to the Large Neighborhood Search method, with total costs of 153-155 M€ versus 165-168 M€ for LNS. This finding is particularly significant when considered alongside the work of Yi et al. [41], who demonstrated the effectiveness of genetic algorithms for offshore cable routing optimization. In their study of a 714 MW wind farm with 119 turbines, Yi et al. achieved final costs of £268.6M for branched and £286.8M for radial designs using genetic algorithms, representing a cost difference of £18.2M between topologies. When scaled appropriately for project size, their results show similar cost advantages for genetic algorithm-based optimization.

The computational efficiency trade-offs observed align with broader optimization literature. While GA required 6-8 hours compared to LNS's 18-53 minutes, the economic benefits justify the additional computational investment for commercial projects. Cazzaro et al. [6] noted similar computational challenges in their Large Neighborhood Search implementation, reporting iteration counts of 67-140 for convergence, which is consistent with the LNS performance observed in this study.

The branched topology demonstrated marginal advantages over radial configurations, achieving total costs of 153.0 M€ versus 154.7 M€ for the GA optimization. This 1.7 M€ difference (1.1%) is more modest than the savings reported by Yi et al. [41], who found £18.2M savings (6.3%) favoring branched designs in their larger 714 MW project. The smaller relative benefit in this study may be attributed to the different project characteristics and the 300 MW project scale. The cable length advantages of branched topology (69.25-74.01 km versus 72.02-72.89 km for radial) are consistent with theoretical expectations and previous findings. Yi et al. [41] reported similar patterns with 155 km for branched versus 162 km for radial designs in their demonstration project.

The cable routing results support the validity of the sequential optimization approach adopted in this study. Cazzaro et al. [6] demonstrated that combined layout and cable optimization can achieve up to 12 M€ NPV improvements over sequential approaches, but noted this benefit is most pronounced in low energy density projects. The preliminary analysis in Section 4.1 of this thesis, showing only 1.51-3.06% variation in cabling-specific LCOE across different layouts, suggests that for the Baltic Sea site conditions studied, the potential benefits of combined optimization would be limited relative to the substantial computational overhead.

The genetic algorithm's superior performance in energy loss minimization, while maintaining competitive capital costs, demonstrates that sequential approaches can achieve high-quality solutions when appropriate algorithms are selected for each subproblem. This finding supports the engineering practice of using specialized optimization methods for different aspects of wind farm design, particularly when computational resources or project timelines are constrained. The computational performance comparison reveals important considerations for practical implementation. While LNS achieved reasonable solutions in significantly less time, the GA's superior economic performance (both capital and operational) justifies the additional computational investment for commercial projects. The 6-8 hour optimization time for GA remains practical for the offline wind farm design process, where solution quality typically outweighs computational speed.

These findings contribute to the broader understanding of algorithm selection for offshore wind farm cable routing optimization, providing quantitative comparisons across both economic and computational performance metrics that extend beyond previous literature focused primarily on capital cost minimization.

5.4 Integrated Design Performance

The final wind farm design combines the LCOE-optimized turbine layout with the GA branched cable routing to achieve the most economically optimal solution. This configuration represents the best balance between energy production and total project costs identified through the sequential optimization framework. The integrated design consists of thirty 10 MW turbines connected through a branched cable network with a total length of 74.01 km and annual energy losses of 37.05 GWh. The key performance parameters of the final design are summarized in Table 5.1.

Table 5.1. *Energy Project Specifications*

Parameter	Value
Turbine Configuration	30 × 10 MW turbines
Gross Annual Energy Production	1316 GWh/year
Total Cable Length	74.01 km
Annual Cable Losses	37.05 GWh/year
Net Annual Energy Production	1278.95 GWh/year

The project cost structure is detailed in Table 5.2, which breaks down the total investment across all major cost categories.

The capacity factor analysis shows strong performance for the optimized design. The gross capacity factor, based on turbine energy production without cable losses, reaches 50.2 percent. When accounting for the 37.05 GWh annual cable losses, the net capacity factor becomes 48.7 percent, representing a 1.5 percentage point reduction due to electrical losses. This net capacity factor of 48.7 percent matches more closely to the literature values [21, 22].

The final project LCOE, including both optimized layout and cable routing costs, is calculated as 39.93 €/MWh based on the net energy production of 1278.95 GWh per year and total project cost of 1085.58 million euros over the 25-year project lifetime. This repre-

__Table 5.2.__ Wind Farm Project Cost Breakdown

Cost Category	Cost (M€)
CAPEX	**925.64**
Total Turbine Cost	292.59
Total Foundation Costs	282.09
Cabling Costs	153.00
Balance of Plant	99.00
Substation	67.96
Export Cables	2.80
Onshore Electrical	28.20
OPEX (Annual)	**12.30**
DEVEX	**26.27**
ABEX	**17.06**
Total OPEX (25 years)	**307.50**
TOTAL PROJECT COST (CAPEX + DEVEX + OPEX$_{25}$ + ABEX)	**1276.47**

sents a 12.5 percent increase from the layout-only LCOE of 27.12 €/MWh, demonstrating the significant economic impact of the electrical collection system on overall project economics. While this calculated LCOE of 39.93 €/MWh remains below current industry benchmarks of 50-100 €/MWh [17], several factors contribute to this difference including the use of 2017 cost data in the optimization framework and potential underestimation of real-world project complexities. The final LCOE nevertheless represents a realistic assessment of the optimized design's economic performance under the study conditions and validates the effectiveness of the sequential optimization approach in achieving cost-effective offshore wind farm design for Baltic Sea applications.

5.5 Future Research

This study employed sequential optimization to maintain reasonable computational costs. Future work should investigate combined optimization where layout and cabling are optimized simultaneously, particularly for sites with more varying water depths and complex spatial restrictions that might benefit more from integrated approaches.

The COBYLA algorithm performed fine for layout optimization, but hybrid approaches combining metaheuristics for global search with gradient methods for local improvement could enhance convergence. For cable optimization, developing algorithms that automatically determine optimal topology mixtures rather than requiring predefined choices between radial and branched configurations would be valuable.

A promising research direction for Baltic Sea offshore wind development would be incorporating temporal and seasonal constraints into the optimization framework. The Baltic Sea's seasonal ice formation creates critical time windows for construction, installation, and maintenance activities, fundamentally different from year round accessible sites. Future optimization studies should focus on schedule- and time-constrained optimization rather than purely monetary objectives, incorporating factors such as: weather window availability for foundation installation and turbine erection; seasonal accessibility constraints due to ice formation; vessel availability and scheduling optimization within limited operational periods; and coordinated project phase scheduling to maximize productivity during ice-free months. This temporal optimization approach could significantly reduce project costs and risks in the Baltic Sea region by minimizing weather delays, optimizing vessel utilization during constrained seasons, reducing standby costs during inaccessible periods, and enabling better coordination between multiple offshore projects competing for limited installation resources.

6. CONCLUSION

This thesis successfully addressed the four primary research objectives established in the introduction, demonstrating that sequential optimization provides an effective and computationally practical approach for offshore wind farm design in the Baltic Sea region, though several methodological limitations must be acknowledged alongside these achievements.

The first research objective sought to validate the effectiveness of sequential optimization by analyzing cable cost sensitivity to layout variations under Baltic Sea conditions. This objective was achieved through preliminary analysis of five random turbine layouts, revealing that cabling-specific LCOE contributions varied by only 1.5-3% across configurations. The coefficient of variation in total LCOE was moderate at approximately 10.57%, while the standard deviation of cabling-specific LCOE contribution was merely 0.168 €/MWh for Large Neighborhood Search and 0.074 €/MWh for genetic algorithm approaches. However, the small sample size of five layouts limits the generalizability of these findings, and validation across a broader range of site conditions and layout configurations would strengthen these conclusions. Despite this limitation, the analysis provided sufficient evidence that sequential optimization can be applied to Baltic Sea offshore wind farm design with minimal loss in overall economic performance compared to computationally intensive integrated approaches.

The second research objective focused on developing and integrating a gravity-based foundation cost model within TopFarm to enable realistic economic evaluation for Baltic Sea applications. This objective was successfully accomplished through creation of a comprehensive cost model incorporating site-specific parameters including depth-dependent excavation requirements, soil-type variations, and foundation installation costs. The model's effectiveness was demonstrated through economic optimization results achieving 12.4% foundation cost reductions by positioning turbines in shallower waters and favorable seabed conditions. The successful integration enabled realistic turbine placement decisions reflecting Baltic Sea construction economics, though the model relies on simplified excavation calculations that may not capture all complexities of real-world foundation installation.

The third research objective aimed to implement and compare genetic algorithm and Large Neighborhood Search approaches for both radial and branched network topologies. The genetic algorithm approach demonstrated superior economic performance with total costs of 153-155 M€ compared to 165-168 M€ for Large Neighborhood Search, and substantially better energy loss minimization with annual losses of 37-39 GWh/year versus 55-56 GWh/year. The genetic algorithm required 6-8 hours compared to Large Neighborhood Search's 18-53 minutes, but the superior economic performance justified the additional computational investment. Branched configurations marginally outperformed radial designs, achieving total costs of 153.0 M€ versus 154.7 M€ for genetic algorithm optimization. While these comparisons provide valuable guidance for algorithm selection, the evaluation was limited to a single site with specific characteristics, and performance differences may vary across different offshore environments and project scales.

The fourth research objective sought to demonstrate the sequential framework through a comprehensive case study of a 300 MW offshore wind farm off the coast of Pori, Finland. The case study achieved a final project LCOE of 39.96 €/MWh accounting for both optimized layout and cable routing costs. Layout optimization delivered consistent performance across objective functions, with AEP optimization achieving 1.85% average improvement over random layouts and 50.2% capacity factor. Economic optimization demonstrated substantial value creation with 4.0% LCOE improvement while reducing AEP by only 0.3%, and 13.6% NPV improvement with 0.45% AEP reduction. The cable routing phase resulted in a branched network with 74.01 km total length and 37.05 GWh annual losses, yielding 48.7% net capacity factor. However, the case study represents only a single site with relatively homogeneous conditions, limiting the validation of methodology performance across diverse offshore environments.

Beyond achieving the specific research objectives, this thesis delivered contributions to offshore wind farm optimization by establishing that sequential optimization can achieve high-quality solutions while maintaining computational efficiency for sites where cable costs exhibit low sensitivity to layout variations. The methodology provides a practical framework adaptable to other offshore environments, though several significant limitations must be acknowledged. The economic models utilized 2017 cost data that may not reflect current market conditions, potentially contributing to optimistic LCOE results compared to real-world projects typically ranging from 50-100 €/MWh. The COBYLA algorithm, while effective for layout optimization, exhibited noisy convergence behavior for complex economic objective functions, suggesting that hybrid approaches combining metaheuristics with gradient-based methods might improve performance. The case study focused on relatively homogeneous site conditions, and results may differ substantially for more complex offshore environments with greater spatial variation in constraints and bathymetric conditions.

Future research directions should address these limitations while building upon the established methodological foundation. Investigation of combined optimization approaches would be valuable for sites with complex constraints and varying conditions that might benefit more from integrated decision-making. A particularly promising direction for Baltic

Sea development involves incorporating temporal and seasonal constraints into the optimization framework, as the region's seasonal ice formation creates critical time windows for construction and maintenance activities fundamentally different from year-round accessible sites. Schedule- and time-constrained optimization incorporating weather window availability, seasonal accessibility constraints, and coordinated project scheduling could significantly reduce costs and risks by optimizing resource utilization during constrained seasons and enabling better coordination between competing offshore projects.

This research demonstrates that sequential optimization provides an effective approach for offshore wind farm design that can deliver substantial economic benefits while maintaining solution quality and computational tractability. The successful achievement of all four research objectives validates the methodology's effectiveness for Baltic Sea conditions, though the acknowledged limitations indicate areas where further validation and development would strengthen the approach. The developed framework successfully combines specialized algorithms for layout and cable routing optimization, achieving meaningful cost reductions while providing a solid foundation for offshore wind farm optimization that can be adapted as the industry continues expanding into new regions facing increasing economic pressures.

REFERENCES

[1] Christian Bak et al. “The DTU 10-MW reference wind turbine”. In: *Danish wind power research 2013*. 2013.

[2] R. J. Barthelmie et al. “Modelling and measuring flow and wind turbine wakes in large wind farms offshore”. eng. In: *Wind energy (Chichester, England)* 12.5 (2009), pp. 431–444. ISSN: 1095-4244.

[3] M Bastankhah and F Porté-Agel. “A new analytical model for wind-turbine wakes”. In: *Renewable Energy* 70 (2014), pp. 116–123.

[4] M. de Berg. “Visibility graphs”. In: *Computational Geometry: Algorithms and Applications*. 3rd. Springer-Verlag, 2008, pp. 326–330.

[5] Davide Cazzaro, David Franz Koza, and David Pisinger. “Combined layout and cable optimization of offshore wind farms”. In: *European Journal of Operational Research* 311.1 (2023), pp. 301–315.

[6] Davide Cazzaro and David Pisinger. “Balanced cable routing for offshore wind farms with obstacles”. In: *Networks* 80.4 (2022), pp. 386–406.

[7] Global Wind Energy Council. “GWEC global wind report 2024”. In: (2024).

[8] Alison Duncan et al. *Chapter 5: Project Description*. Environmental Impact Assessment (EIA) Report, Marine Licence Documentation, Renewables - Wind, Post-consent. Environmental Statement - Neart na Gaoithe Offshore Wind Farm. Mainstream Renewable Power Ltd, 2019. URL: https://marine.gov.scot (visited on 04/19/2025).

[9] EDWIN. *Electrical network Design for WINdfarms*. URL: https://gitlab.windenergy.dtu.dk/TOPFARM/EDWIN (visited on 04/01/2025).

[10] Yunus Eroğlu and Serap Ulusam Seçkiner. “Design of wind farm layout using ant colony algorithm”. In: *Renewable Energy* 44 (2012), pp. 53–62.

[11] Finnish Meteorological Institute. *Finnish Wind Atlas*. Finnish Meteorological Institute, 2009. URL: https://en.ilmatieteenlaitos.fi/wind-atlas (visited on 04/24/2025).

[12] Finnish Transport and Communications Agency. *Download and View Service*. Finnish Transport and Communications Agency (Traficom), 2024. URL: https://julkinen.traficom.fi/oskari/ (visited on 04/11/2025).

[13] Martina Fischetti. “On the optimized design of next-generation wind farms”. In: *European Journal of Operational Research* 291.3 (2021), pp. 862–870.

[14] Martina Fischetti and Matteo Fischetti. “Integrated layout and cable routing in wind farm optimal design”. In: *Management Science* 69.4 (2023), pp. 2147–2164.

[15] Martina Fischetti and David Pisinger. “Optimizing wind farm cable routing considering power losses”. In: *European Journal of Operational Research* 270.3 (2018), pp. 917–930.

[16] Martina Fischetti et al. “Vattenfall Optimizes Offshore Wind Farm Design”. eng. In: *INFORMS journal on applied analytics* 50.1 (2020), pp. 80–94. ISSN: 0092-2102.

[17] ISE Fraunhofer. “Study: Levelized Cost of Electricity—Renewable Energy Technologies”. In: *Fraunhofer ISE: Freiburg, Germany* (2024).

[18] Geological Survey of Finland. *Seabed Substrate Classification Data*. Downloaded from Hakku geological data service. Geological Survey of Finland (GTK), 2024. URL: https://hakku.gtk.fi/en (visited on 04/12/2025).

[19] Peng Hou et al. “Optimized placement of wind turbines in large-scale offshore wind farm using particle swarm optimization algorithm”. In: *IEEE Transactions on Sustainable Energy* 6.4 (2015), pp. 1272–1282.

[20] Peng Hou et al. “A review of offshore wind farm layout optimization and electrical system design methods”. In: *Journal of Modern Power Systems and Clean Energy* 7.5 (2019), pp. 975–986. DOI: 10.1007/s40565-019-0550-5.

[21] International Energy Agency. *Offshore Wind Outlook 2019*. International Energy Agency, 2019. URL: https://www.iea.org/reports/offshore-wind-outlook-2019 (visited on 10/06/2025).

[22] International Renewable Energy Agency. *Average capacity factor for offshore wind power worldwide from 2010 to 2023*. Sept. 2024. URL: https://www.statista.com/statistics/1368679/global-offshore-wind-capacity-factor/ (visited on 05/25/2025).

[23] Niels Otto Jensen. *A note on wind generator interaction*. Risø National Laboratory, 1983.

[24] I Katic, J Højstrup, and No O Jensen. “A simple model for cluster efficiency, EWEC’86”. In: *Proc.* Vol. 1. 1986.

[25] Sourabh Katoch, Sumit Singh Chauhan, and Vijay Kumar. “A review on genetic algorithm: past, present, and future”. In: *Multimedia tools and applications* 80 (2021), pp. 8091–8126.

[26] Mojtaba Ahmadieh Khanesar, Mohammad Teshnehlab, and Mahdi Aliyari Shoorehdeli. “A novel binary particle swarm optimization”. In: *2007 Mediterranean conference on control & automation*. IEEE. 2007, pp. 1–6.

[27] K Kalyan Kumar and G Nageswara Reddy. “The sparrow search algorithm for optimum position of wind turbine on a wind farm”. In: *International Journal of Renewable Energy Research (IJRER)* 11.4 (2021), pp. 1939–1946.

[28] National Renewable Energy Laboratory. *Cost of Wind Energy Review: 2024 Edition*. Tech. rep. NREL/TP-6A20-82454. National Renewable Energy Laboratory (NREL), 2024.

[29] G. Mosetti, C. Poloni, and B. Diviacco. "Optimization of wind turbine positioning in large windfarms by means of a genetic algorithm". In: *Journal of Wind Engineering and Industrial Aerodynamics* 51.1 (1994), pp. 105–116.

[30] Mads M. Pedersen et al. "PyWake 2.5.0: An open-source wind farm simulation tool". In: (Feb. 2023). URL: https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake (visited on 04/01/2025).

[31] Kenneth Peire, Hendrik Nonneman, and Eric Bosschem. "Gravity base foundations for the thornton bank offshore wind farm". In: *Terra et Aqua* 115.115 (2009), pp. 19–29.

[32] Juan-Andrés Pérez-Rúa and Nicolaos A. Cutululis. "Electrical Cable Optimization in Offshore Wind Farms—A Review". In: *IEEE Access* 7 (2019), pp. 85796–85811. DOI: 10.1109/ACCESS.2019.2925873.

[33] Arthur Leandro Guerra Pires et al. "Main Trends and Criteria Adopted in Economic Feasibility Studies of Offshore Wind Energy: A Systematic Literature Review". In: *Energies* 15.1 (2022). ISSN: 1996-1073. DOI: 10.3390/en15010012.

[34] S Pranupa, AT Sriram, and S Nagaraja Rao. "A review of wind farm layout optimization techniques for optimal placement of wind turbines". In: *Int J Renew Energy Res* 13 (2023), pp. 957–65.

[35] Riccardo Riva et al. *Welcome to TOPFARM.* URL: https://topfarm.pages.windenergy.dtu.dk/TopFarm2/index.html (visited on 04/01/2025).

[36] Krzysztof Socha and Marco Dorigo. "Ant colony optimization for continuous domains". In: *European journal of operational research* 185.3 (2008), pp. 1155–1173.

[37] Siyu Tao et al. "Joint optimization of wind turbine micrositing and cabling in an offshore wind farm". In: *IEEE Transactions on Smart Grid* 12.1 (2020), pp. 834–844.

[38] Jared J Thomas et al. "A comparison of eight optimization methods applied to a wind farm layout optimization problem". In: *Wind Energy Science* 8.5 (2023), pp. 865–891.

[39] UK Government. *Offshore Wind Industrial Strategy: Business and Government Action*. Tech. rep. Department for Business, Innovation & Skills, 2013.

[40] LJ Vermeer, Jens Nørkær Sørensen, and Antonio Crespo. "Wind turbine wake aerodynamics". In: *Progress in aerospace sciences* 39.6-7 (2003), pp. 467–510.

[41] Xiao Yi, Mircea Scutariu, and Kenneth Smith. "Optimisation of offshore wind farm inter-array collection system". In: *IET Renewable Power Generation* 13.11 (2019), pp. 1990–1999.