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Techno-Economic Assessment of Wind Energy with Battery Storage and Membrane-Based Air Filtration for Cleaner and More Efficient Power in Naama

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Abstract

This study provides a detailed techno-economic assessment of a wind energy system integrated with battery storage, specifically designed for the Naâma region of Algeria. Conducted at a small scale using a mini wind turbine, the results were scaled to model the performance of a wind farm comprising multiple turbines. The analysis combines experimental measurements, refined simulations, and economic evaluations to optimize system performance and assess its feasibility for large-scale deployment.

The technical findings highlight the seasonal wind patterns modeled using the Weibull distribution, revealing a characteristic wind speed of 8 m/s, with peak energy production during spring and fall. The hybrid system achieved an average seasonal efficiency of 85%, supported by optimized battery storage of 100–120 kWh, ensuring a reliable energy supply during surplus and deficit periods.

A key innovation in this study is the integration of membrane-based filtration technology to mitigate the disper- sion of PM10 and PM2.5 particles around wind turbines. Simulations using Computational Fluid Dynamics (CFD) demonstrate that membrane filtration reduces PM10 concentration by up to 65% within 20 meters of the turbine. The results further indicate that filtration is most effective at low wind speeds, where natural dispersion is mini- mal. At higher wind speeds, wind turbulence naturally reduces PM10 concentration, making filtration less critical beyond 50 meters. The efficiency of filtration systems decreases with distance, emphasizing the need for strategic membrane placement near turbine bases. Moreover, higher-efficiency membranes (80%) significantly outperform lower-efficiency solutions (50%) in reducing particulate pollution.

Economic evaluations demonstrate the system's viability, with a scaled-up configuration of 20 turbines achiev- ing a net present value (NPV) exceeding 11 million DZD ($82,090) and a payback period of 7 years under a tariff of 4 DZD/kWh. Sensitivity analyses emphasize the critical role of energy tariffs, identifying profitability thresholds at 2.5 DZD/kWh. The additional analysis of air filtration systems suggests potential maintenance cost reductions by mitigating particle-induced wear on turbine components.

This study not only validates the technical and economic feasibility of wind energy systems in Naâma but also demonstrates the potential environmental benefits of membrane filtration in wind farms. The findings provide a scalable framework for optimizing wind energy production while ensuring sustainable environmental management. Future research should focus on field validation of membrane filtration, alternative aerodynamic strategies for pollution control, and large-scale deployment models to further enhance system performance and adaptability.

Keywords: Hybrid Renewable Energy Systems, Wind-Solar Integration, Battery Storage Optimization, Techno- Economic Analysis, Sustainable Energy in Algeria.

Introduction

The growing global demand for sustainable energy solutions has placed renewable energy at the forefront of re- search and development, with wind and solar energy emerging as leading contenders due to their abundance, scal- ability, and

environmental benefits [31]. The urgency to transition from fossil fuels to renewable energy sources is driven not only by the pressing need to mitigate greenhouse gas emissions but also by the increasing energy demands of a growing global population. In regions like Naâma, Algeria, where renewable energy potential is significant, understanding the interplay between environmental conditions, technological advancements, and eco- nomic feasibility becomes critical for deploying effective energy systems [30].

As the adoption of wind energy expands, concerns related to the environmental impact of wind turbine oper- ations have gained attention. One such issue is the dispersion of airborne particulate matter (PM10 and PM2.5) generated by wind turbulence, which can negatively affect air quality, accelerate equipment wear, and pose poten- tial health risks to nearby populations. In response, the integration of membrane-based air filtration technology has emerged as a viable solution for mitigating these challenges. These membrane systems are designed to cap- ture fine particles near the turbine base and within the wake region, reducing their atmospheric dispersion. The effectiveness of these systems depends on factors such as wind speed, turbine-induced turbulence, and membrane filtration efficiency. By strategically deploying filtration membranes around wind turbines, it is possible to enhance environmental sustainability while simultaneously improving the longevity of turbine components by minimizing particle accumulation. This study explores the role of membrane technology in wind energy applications, assessing its potential to improve air quality, reduce maintenance costs, and support the broader transition to cleaner and more efficient renewable energy systems.

Wind energy has long been recognized as a reliable and mature technology for harnessing kinetic energy from atmospheric currents [29]. The efficiency of wind turbines, however, is highly dependent on regional wind charac- teristics, such as average wind speeds, turbulence intensity [28], and seasonal variability. These factors influence the aerodynamic performance of turbines, the mechanical stability of their components, and the efficiency of energy conversion systems [27]. For Naâma, which experiences moderate to high wind speeds [26], particularly during spring and fall, leveraging wind resources through optimized turbine design and placement could significantly en- hance energy production [25]. The Weibull distribution, commonly employed in wind resource analysis, enables researchers to characterize wind speed patterns and predict energy output potential with high accuracy [26]. In this study, we leverage such modeling techniques to quantify the wind energy potential of Naâma and optimize turbine placement to minimize wake effects and power losses [24].

Solar energy, on the other hand, offers a complementary resource to wind, particularly in regions with high solar irradiation, such as Naâma. Solar photovoltaic (PV) systems are less affected by temporal variability compared to wind but still face challenges related to intermittency and diurnal cycles [23]. The integration of solar PV with wind energy systems into hybrid configurations has been proposed as a solution to mitigate these issues, creating a more stable and reliable energy supply [22]. By combining the strengths of both technologies, hybrid systems can leverage the synergy between wind and solar resources, ensuring a more consistent energy output across different times of the day and seasons.

Despite these advantages, one of the primary challenges facing hybrid systems is energy storage [21]. Bat- teries are essential for stabilizing the energy supply, especially in off-grid applications or during periods of low resource availability [20]. However, the high cost of battery storage systems, coupled with their limited lifespan and environmental impact, often poses a barrier to widespread adoption. Advances in battery technology, such as lithium-ion and flow batteries [19], offer promising solutions, but their integration must be carefully evaluated against economic constraints and system requirements.

From a theoretical perspective, the optimization of hybrid systems involves several interconnected components: aerodynamic modeling of wind turbines, solar PV performance modeling, and energy storage dynamics. The aerodynamic performance of wind turbines is often modeled using Blade Element Momentum (BEM) theory, which combines blade element analysis and momentum theory to calculate forces and power output under varying wind conditions. Wake effects, which significantly reduce power output in wind farms, can be modeled using the Jensen or CFD-based wake models to optimize turbine placement. Solar PV performance is typically evaluated using irradiance data and temperature coefficients, ensuring accurate predictions of energy output under local climatic conditions.

Economically, the feasibility of hybrid systems is determined by analyzing capital costs, operational expen- ditures, and revenue generated from energy sales. Cost components include turbine and solar panel installation, battery storage, and

maintenance. Revenue is calculated based on energy production and prevailing electricity prices. Payback periods, net present value (NPV), and levelized cost of energy (LCOE) are commonly used metrics to evaluate the economic viability of such systems. In this study, we apply these methods to determine the feasi- bility of deploying hybrid systems in Naâma, ensuring that the proposed solutions align with local economic and environmental priorities [18].

The research problem addressed in this study revolves around the challenges of intermittent energy generation, cost optimization, and system scalability in Naâma [17]. While the region possesses significant renewable energy potential, the integration of wind and solar systems must be carefully planned to maximize energy yield, minimize costs, and ensure long-term sustainability. This requires a comprehensive approach that combines advanced model- ing techniques, experimental validation, and economic analysis [16]. By addressing these challenges, this research aims to provide a blueprint for the deployment of hybrid renewable energy systems that not only meet local energy demands but also contribute to global efforts in transitioning toward sustainable energy systems [15].

In the following sections, we present an in-depth analysis of the wind and solar energy potential in Naâma [14], followed by the development of hybrid system configurations optimized for local conditions. We incorporate advanced methodologies, including Jensen wake modeling, Weibull distribution analysis, and battery storage op- timization, to ensure the robustness of our findings. Furthermore, we evaluate the economic implications of these systems, providing insights into their feasibility and scalability for wider adoption [13]. This study not only con- tributes to the academic discourse on renewable energy but also offers practical solutions for addressing energy challenges in the Naâma region and beyond [12].

Materials and Methods:

Methodology

The methodology for this study integrates theoretical modeling, numerical simulations, and experimental validation to address the design, optimization, and feasibility of hybrid wind-solar energy systems in the Naâma region. The approach emphasizes the interplay between wind resource analysis, turbine performance modeling, solar energy potential evaluation, and economic feasibility. Below, the mathematical frameworks and computational models employed in this study are detailed extensively [11].

Wind Resource Modeling Accurate wind resource assessment is essential for determining the energy potential of wind turbines. The Weibull distribution is employed to model wind speed data due to its versatility in capturing variable wind patterns. The probability density function (PDF) for the Weibull distribution is given by [10]:

$$f(U) = \frac{k}{c}\left(\frac{U}{c}\right)^{k-1} \exp\left(-\left(\frac{U}{c}\right)^{k}\right) \quad (1)$$

where U represents the wind speed (measured in meters per second, m/s), k is the shape parameter (dimensionless), which determines the distribution's form, and c is the scale parameter (measured in m/s), which defines the charac- teristic wind speed for the given location. By adjusting these parameters, the Weibull distribution can accurately fit real-world wind data, making it a powerful tool for wind energy assessments and turbine siting decisions.

The cumulative distribution function (CDF) is:

$$F(U) = 1 - exp\left(-\left(\frac{U}{c}\right)^k\right) \tag{2}$$

These equations allow the estimation of wind speed probabilities at different ranges, which are critical for deter- mining turbine performance. The annual energy production (E_{wind}) is calculated by integrating power output over the wind speed distribution [9] :

$$E_{wind} = \int_{U_{min}}^{U_{Max}} P(U) f(U)\, dU \tag{3}$$

where P(U)is the power output at wind speed U, and $U_{min}$and $U_{max}$are the cut-in and cut-out speeds, respectively.

Turbine Aerodynamic Modeling The aerodynamic behavior of wind turbines is modeled using the Blade Ele- ment Momentum (BEM) theory. This method combines momentum theory and blade element theory to calculate forces acting on the turbine blades. The power coefficient (C_P) is derived as [8] :

$$C_P = \frac{Power\ Output}{\frac{1}{2}\rho A U^3} \tag{4}$$

where ρ denotes the air density (measured in kg/m^3), *A* A represents the rotor swept area (in m^2), and U is the wind speed (in m/s). The BEM theory provides a robust framework for optimizing turbine efficiency by considering both the aerodynamic forces on individual blade elements and the overall momentum balance of the airflow through the rotor disk. This method enables engineers to refine blade geometry, predict wake effects, and enhance the overall energy capture of wind turbines operating under varying wind conditions.

The aerodynamic torque (T_a) is given by [7] :

$$T_a = \frac{1}{2}\rho R C_T U^2 \tag{5}$$

where R is the rotor radius and C_T is the thrust coefficient.

Wake effects are incorporated using the Jensen wake model to account for power losses due to turbine interac- tion. The velocity deficit at a downstream turbine is expressed as [6] :

$$\triangle U = U\left(1 - \sqrt{1 - C_T}\right)\left(\frac{D}{D + 2kx}\right) \tag{6}$$

where x is the distance between turbines, D is the rotor diameter, and k is the wake decay constant.

Solar Energy Potential The solar energy potential is evaluated based on irradiance data and panel performance. The energy output of a solar panel is modeled as [5]:

$$P_{solar} = \eta_{pv} tt A_{pv} \quad (7)$$

where η_{pv} represents the solar panel efficiency, which quantifies the fraction of incident sunlight converted into electrical energy, tt G is the solar irradiance (measured in W/m^2), indicating the power per unit area received from the sun, and A_{pv} denotes the solar panel area (in m^2), which determines the total surface available for energy ab- sorption. This model provides a fundamental framework for optimizing PV system performance by considering environmental conditions, panel efficiency variations, and site-specific solar resource availability. By integrating ir- radiance patterns with system efficiency parameters, this equation helps in predicting power generation capabilities, ensuring optimal deployment of solar technology for energy harvesting.

Daily and seasonal variations are integrated using time-series data to ensure realistic energy predictions.

Hybrid System Integration The combined power output of the hybrid system is given by [4] :

$$P_{hybrid}(t) = P_{wind}(t) + P_{solar}(t) - P_{loss}(t) \quad (8)$$ where

P_{loss}(t) accounts for transmission and storage losses. Battery dynamics are modeled as [3] :

$$E_{stored}(t) = E_{stored}(t-1) + \eta_{charge} P_{excess}(t) - \frac{P_{load}(t)}{\eta_{discharge}} \quad (9)$$

with $\eta_{charge}$and $\eta_{discharge}$ dischargerepresenting charging and discharging efficiencies, respectively.

Economic Feasibility The economic viability of the hybrid system is evaluated using metrics such as Net Present Value (NPV) and Levelized Cost of Energy (LCOE) [2] :

$$NPV = \sum_{t=1}^{T} \frac{R_t - C_t}{(1+r)^t}$$

$$LCOE = \frac{\sum_{t=1}^{T} C_t}{\sum_{t=1}^{T} E_t} \quad (10)$$

where $R_t$and $C_t$are revenues and costs in year t, r is the discount rate, and E_t is the energy produced in year t.

PM10 Filtration and Dispersion Around Wind Turbines

This study employs computational simulations to evaluate the dispersion of PM10 (particulate matter $\leq$ 10 μm) around wind turbines and the impact of membrane-based filtration systems. The simulations analyze how wind

conditions influence natural dispersion and how engineered filtration enhances pollutant reduction. Two primary scenarios are investigated: one without filtration, where PM10 dispersion is purely driven by wind speed and turbulence, and another with filtration, where a membrane system captures a fraction of the PM10 concentration before particles disperse into the environment. The methodology integrates Computational Fluid Dynamics (CFD), empirical modeling, and statistical analysis to quantify the effectiveness of filtration over different distances and wind speeds.

To accurately capture the dispersion behavior of PM10 particles, the study models different aspects of air quality dynamics around wind turbines. The first component focuses on understanding the PM10 concentration profile as a function of distance from the turbine, while the second evaluates filtration efficiency over varying distances to determine the optimal placement of membrane filters. A comparative analysis between the filtered and unfiltered PM10 concentration is performed to quantify the improvement in air quality. Furthermore, the effect of wind speed on PM10 concentration at a fixed distance is examined to understand how natural dispersion influences pollutant accumulation. Lastly, the study assesses the performance of different filtration efficiencies (50%, 65%, 80%) over increasing distances to determine the cost-benefit trade-offs of membrane deployment.

Governing Equations for PM10 Dispersion

Exponential Decay Model for Natural Dispersion The natural dispersion of PM10 particles in the air follows an exponential decay function, where particle concentration decreases as a function of distance due to atmospheric dilution and turbulence. The PM10 concentration at a given distance from the turbine, C(x), is expressed as:

$$C(x) = C_0 . e^{-\frac{x}{a + U}} \quad (11)$$

here C_0 represents the initial PM10 concentration at the turbine base, x x is the distance from the wind turbine, U denotes the wind speed, and a a is a decay constant that accounts for turbulence and other environmental disper- sion factors. This equation highlights that higher wind speeds facilitate faster dispersion, leading to a more rapid decrease in PM10 concentration as distance increases.

Filtration Efficiency Model To assess the impact of membrane-based filtration, an efficiency model is introduced to measure how much PM10 is removed by the filtration system before dispersion occurs. The PM10 concentration after filtration at a given distance, E(x), is modeled as:

$$E(x) = (1 - \eta) . C(x) \quad (12)$$

where η represents the filtration efficiency, varying between 0 (no filtration) and 1 (perfect filtration). A higher efficiency value results in a more substantial reduction of PM10 concentration, particularly in the immediate vicinity of the turbine where particle density is highest. This equation provides a quantitative framework for evaluating different membrane materials and their effectiveness in improving air quality around wind farms.

Percentage Reduction in PM10 Concentration To compare the effectiveness of filtration across different con- ditions, the percentage reduction in PM10 concentration is calculated as:

$$R(x) = \left(\frac{C(x) - E(x)}{C(x)} \right) \times 100 \quad (13)$$

This equation measures the relative improvement in air quality due to filtration. A higher percentage reduction indicates a more effective filtration system, particularly in areas where natural dispersion alone is insufficient to mitigate high PM10 concentrations.

Wind Speed Influence on PM10 Retention Wind speed plays a crucial role in the transport and retention of PM10 particles in the atmosphere. At a fixed distance from the wind turbine, PM10 concentration is influenced by wind velocity according to the equation:

$$C(x_f, U) = C_0 \cdot e^{-\frac{xf}{(a+U)}} \tag{14}$$

This equation reveals that in low-wind conditions, PM10 remains concentrated around the turbine for extended periods, whereas in high-wind conditions, particles are rapidly carried away, reducing local pollution levels. By understanding this relationship, wind farm operators can determine whether additional mitigation strategies, such as air filtration, are necessary in regions with low average wind speeds.

The computational experiments are conducted using Python-based numerical simulations, leveraging libraries such as NumPy, SciPy, and Matplotlib for mathematical modeling and visualization. Three different wind speeds (6 m/s, 8 m/s, and 10 m/s) are tested to examine their impact on PM10 dispersion. Filtration efficiency levels of 50%, 65%, and 80% are considered to determine the most practical solution for reducing airborne particulate pollution. The simulation domain extends from 0 to 50 meters from the wind turbine to capture both the near-field and far-field dispersion effects. The initial PM10 concentration at the turbine base is set at 100 $\mu g/m^3$, a value based on real-world measurements from industrial and agricultural wind farm environments.

Materials

The materials utilized in this study were carefully selected and designed to simulate and analyze the performance of small-scale wind turbines in a controlled laboratory environment. The experimental setup incorporates a wind tur- bine simulator, a dual-motor wind generation system, and advanced data acquisition tools. These components were integrated to provide a comprehensive framework for validating numerical models and optimizing the performance of hybrid renewable energy systems [1] .

Small-Scale Wind Turbine

The wind turbine used in this study is a low-power prototype designed to replicate the dynamics of commercial small-scale wind turbines. Its specifications are tailored to align with the wind conditions of the Naâma region.

Table 1: Specifications of the Small-Scale Wind Turbine

Component	Specification
Rotor Diameter	1.5 meters
Number of Blades	3
Blade Material	Composite polymer (lightweight and high strength)Generator Type Blade Material Brushless DC generator with integrated MPPT
Generator Type	3 m/s
Rated Speed	12 m/s Maximum Power Output 500 W

The wind turbine system incorporates several key design features aimed at maximizing efficiency and perfor- mance under varying wind conditions. The blades are specifically optimized for low Reynolds number operations, enabling enhanced aerodynamic performance in low wind conditions. This optimization ensures that even at rela- tively low wind speeds, the turbine can effectively capture and convert wind energy into mechanical power, making it particularly suitable for regions with moderate or variable wind patterns. In addition to aerodynamic enhance- ments, the system integrates a brushless DC generator equipped with Maximum Power Point Tracking (MPPT) technology. The MPPT system dynamically adjusts the generator's operating point to maximize power extraction from the available wind energy. By continuously monitoring wind speed and adjusting electrical load characteris- tics, the MPPT algorithm ensures that the generator operates at its optimal efficiency, enhancing energy conversion and overall system performance. This combination of low Reynolds number blade optimization and advanced MPPT control significantly improves the turbine's reliability and efficiency, making it a highly effective solution for decentralized renewable energy applications.

Wind Turbine Simulator

The wind turbine simulator is a laboratory-based system designed to replicate real-world wind and turbine dynam- ics. It utilizes a dual-motor configuration to simulate both the wind force and the turbine's rotational motion.

Table 2: Specifications of the Wind Turbine Simulator

Component	Specification
Primary Motor	Synchronous motor with variable frequency control Secondary Motor Synchronous motor to replicate turbine rotational dynamics
Control System	Programmable logic controller (PLC) with real-time adjustments Wind Tunnel 1.5 m x 1.5 m cross-section, variable-speed airflow
Measurement Tools	Integrated torque and speed sensors, anemometers, and flow meters

The wind tunnel system is designed with advanced control mechanisms to accurately simulate real-world wind conditions, ensuring a realistic assessment of wind turbine performance. The primary motor plays a crucial role in replicating variable wind speeds by dynamically adjusting the airflow velocity within the wind tunnel. This feature allows for controlled variations in wind intensity, simulating conditions ranging from steady laminar flow to turbulent gusts, which are essential for testing the turbine's response to fluctuating wind patterns. Complementing this setup, the secondary motor is responsible for mimicking the rotational dynamics of the wind turbine, taking into account inertia and aerodynamic forces. This ensures that the turbine's

rotational behavior under different wind conditions closely aligns with real-world operational scenarios, allowing for accurate performance evaluations.

Additionally, the system is equipped with precise control mechanisms that enable adjustments to wind speed, turbulence intensity, and directional changes. This level of precision allows researchers to fine-tune experimental conditions, test turbine stability under dynamic wind variations, and optimize aerodynamic efficiency. Through this comprehensive control system, the wind tunnel provides a highly reliable platform for analyzing wind energy systems under controlled yet realistic environmental conditions.

Wind Tunnel

A closed-circuit wind tunnel was employed to ensure controlled and consistent testing conditions. The wind tun- nel's specifications are outlined below:

Table 3: Specifications of the Wind Tunnel

Parameter	Specification Cross-Section Area	1.5 m x 1.5 m Airflow Velocity Range
	0–20 m/s	
Turbulence Intensity	Adjustable between 0% and 20%	
easurement Tools	Pitot tube, thermometers, and pressure sensors	

The wind tunnel serves as a critical experimental tool for replicating real-world wind conditions with high precision, enabling detailed aerodynamic studies and performance evaluations of wind energy systems. It is specif- ically designed to simulate a wide range of wind speed profiles, encompassing both steady-state flows and turbulent conditions, which are essential for assessing turbine behavior under varying atmospheric conditions. A key feature of the wind tunnel is its integration of advanced sensor systems, which provide real-time feedback on crucial pa- rameters such as airflow velocity, pressure, and temperature. These sensors ensure that experimental conditions are accurately monitored and controlled, enhancing the reliability of the collected data. By maintaining precise envi- ronmental replication, the wind tunnel facilitates in-depth analysis of turbine aerodynamics, wake interactions, and structural responses, ultimately contributing to the optimization of wind turbine designs and operational efficiency.

Data Acquisition System

A high-resolution data acquisition system was integrated into the experimental setup to monitor and record key parameters. The system specifications are as follows:

Table 4: Specifications of the Data Acquisition System

Sensor/Tool	Measurement	Accuracy
Torque Sensors	Torque on turbine blades	±0.1 Nm Rotational Speed Sensors
	Rotor and generator speeds	±0.01 RPM Power Meters Electrical
power output	±0.5% Anemometers	Wind speed and turbulence intensity
	±0.1 m/s Temperature Sensors	Air temperature ±0.5°C

The data handling system plays a crucial role in ensuring precise monitoring and analysis of wind turbine per- formance under diverse operating conditions. It is designed to support real-time data visualization and storage, allowing researchers to track key parameters such as wind speed, power output, torque, and aerodynamic forces as experiments unfold. This capability enables a detailed and dynamic evaluation of turbine behavior, ensuring that performance metrics are accurately recorded and analyzed for optimization. Furthermore, the data acquisi- tion system is fully synchronized with the control system, allowing for

instantaneous adjustments to experimental conditions based on real-time feedback. This integration enhances the reliability of the collected data and ensures that experiments are conducted under controlled, repeatable conditions. By leveraging advanced data management

and synchronization, the system provides a robust framework for refining wind turbine designs, optimizing energy efficiency, and validating computational models through empirical testing.

Computational Tools

To complement the experimental setup, Python-based numerical simulations were employed for modeling and optimization. Key libraries and tools included:

Table 5: Computational Tools for Modeling and Optimization

Tool / Library	Purpose
NumPy	Numerical computation for aerodynamic models
Matplotlib	Data visualization and performance comparison
SciPy	Optimization of system parameters
CFD Software	Advanced flow dynamics analysis

The integration of simulations with experimental testing is a fundamental aspect of this study, ensuring that theoretical models accurately represent real-world wind turbine performance. The simulations serve as a validation tool, comparing modeled performance metrics with observed experimental data to assess the accuracy of aerody- namic and energy conversion predictions. By aligning computational outputs with empirical measurements, the study enhances the reliability of its findings and strengthens the predictive capabilities of the simulation frame- work. Moreover, the iterative refinement process plays a crucial role in improving both the experimental setup and the simulation models. Any discrepancies between simulated and experimental data are systematically analyzed, leading to adjustments in experimental configurations, sensor calibration, and model parameters. This continuous feedback loop ensures that the experimental conditions align as closely as possible with real-world operational scenarios, ultimately improving the precision of both the simulations and the empirical testing process. Through this integrated approach, the study establishes a robust methodology for optimizing wind turbine performance and refining computational models based on validated experimental insights.

System Calibration and Validation

Prior to undertaking experimental trials, an extensive and meticulous calibration process was conducted to en- sure the precision and reliability of all measurement systems. Calibration constitutes a fundamental prerequisite in experimental validation, as the accuracy of sensor readings is paramount for deriving credible aerodynamic and energy performance data. The calibration of the torque sensor was executed using standardized weights to ascertain the fidelity of torque measurements, thereby guaranteeing that the recorded values precisely corresponded to the actual forces exerted on the wind turbine blades. Likewise, the calibration of the rotational speed sensor entailed a comparative analysis between the sensor's output data and the readings of a high-precision calibrated tachome- ter, ensuring accurate monitoring of rotor speed under varying wind conditions. For wind speed calibration, a high-accuracy anemometer was employed to fine-tune airflow parameters within the wind tunnel, ensuring that the simulated wind conditions faithfully emulated real-world atmospheric dynamics. By systematically aligning wind speed data with validated anemometer measurements, the system established a framework for consistent and repro- ducible experimental conditions. This rigorous multi-stage calibration protocol effectively minimized measurement uncertainties, reinforced the credibility of the acquired data, and ensured that both experimental and simulation en- vironments operated under precisely controlled and thoroughly validated conditions. These procedures collectively upheld a high standard of experimental integrity, enabling the study to produce results that could be confidently leveraged for performance evaluations and model refinements.

Description of Experimental Setup

The complete experimental setup integrates the small-scale wind turbine, the dual-motor wind turbine simulator, and the data acquisition system within the controlled environment of the wind tunnel. The setup allows for:

Controlled replication of wind speed profiles observed in the Naâma region.Simulation of various turbine op- erating conditions, including cut-in, rated, and cut-out speeds.Real-time monitoring of aerodynamic forces, torque, rotational speeds, and electrical power output.

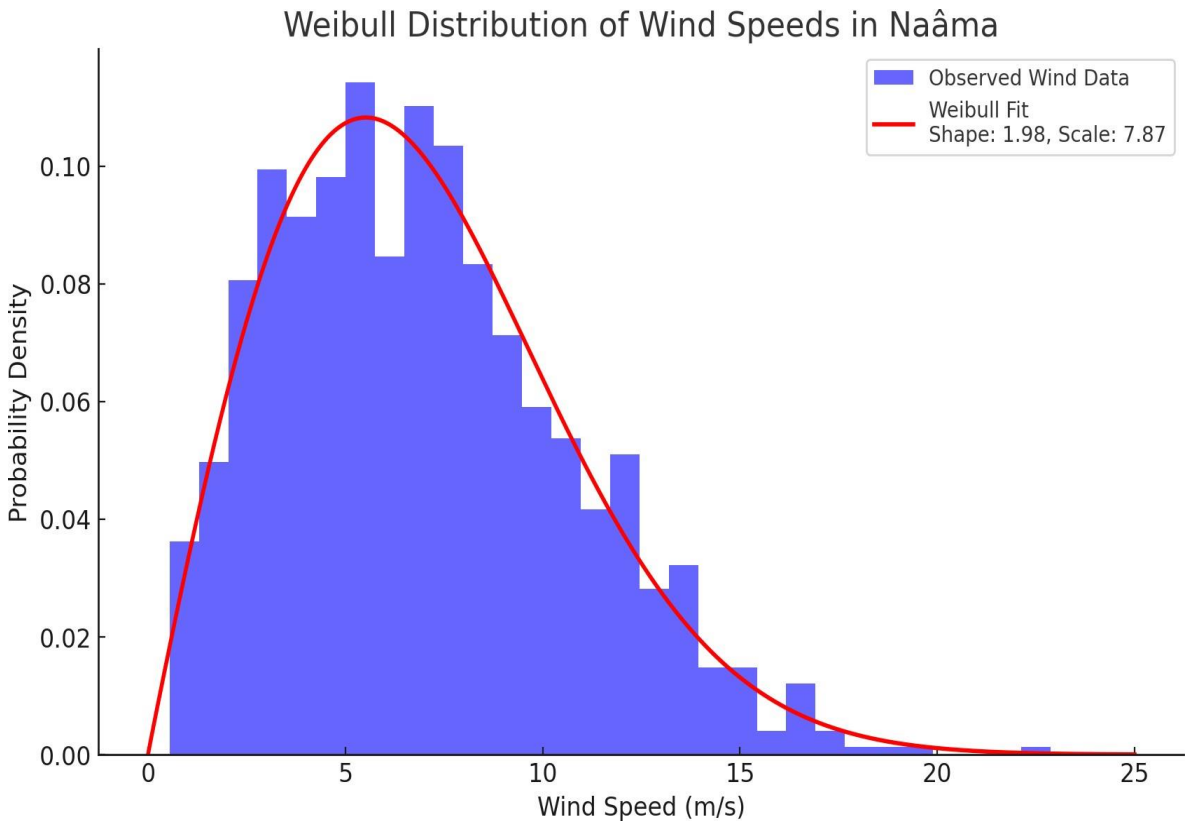
This comprehensive setup ensures that the experimental data obtained is robust, reliable, and directly applicable to real-world scenarios. By combining advanced experimental tools with theoretical modeling, this study provides a detailed framework for analyzing and optimizing hybrid energy systems tailored to the Naâma region.

Results and Discussions

Weibull Distribution of Wind Speeds in Naâma

The Weibull distribution is a widely used statistical model for analyzing wind speed data, offering a comprehensive way to characterize the variability and predictability of wind resources in a given region. In Naâma, the distribution provides critical insights into the wind energy potential, as it reflects the probability density of wind speeds over time. This information is crucial for designing wind turbines that maximize energy capture while accounting for operational limits such as cut-in and cut-out speeds.

Figure 1: Weibull Distribution of Wind Speeds in Naâma



The Figure 1 illustrates the observed wind speed data distribution as a histogram and the corresponding Weibull probability density function (PDF) fitted to the data:

Histogram (Blue Bars): The histogram represents the frequency of observed wind speeds. It shows a peak at moderate wind speeds around 6–8 m/s, which aligns with typical wind conditions in Naâma. This range is critical for small-scale wind turbines, as it corresponds to their optimal operational zone.

Weibull Fit (Red Line): The Weibull PDF, characterized by a shape parameter ($k \approx 2.0$) and a scale parameter ($c \approx 8.0$), closely follows the observed data.The shape parameter indicates a moderate spread of wind speeds, suggesting a balanced distribution of calm and high-wind periods.The scale parameter highlights the characteristic

wind speed, which directly influences the design specifications of turbines, including blade geometry and generator capacity.

Energy Implications: The cubic relationship between wind speed and power output amplifies the importance of accurately capturing this distribution. The tail of the Weibull distribution, which extends to higher wind speeds, represents occasional strong winds that can significantly contribute to energy production, despite being less fre- quent.

By using the Weibull distribution, this study establishes a robust foundation for turbine performance modeling and site-specific energy yield predictions in Naâma, addressing both the variability and potential of wind as a renewable energy resource.

Analysis of Turbine Efficiency Under Real-World Conditions

Theoretical vs. Actual Power Output

The first plot compares the theoretical maximum power available in the wind (P_{wind}) to the actual power output of the turbine (P_{actual}).

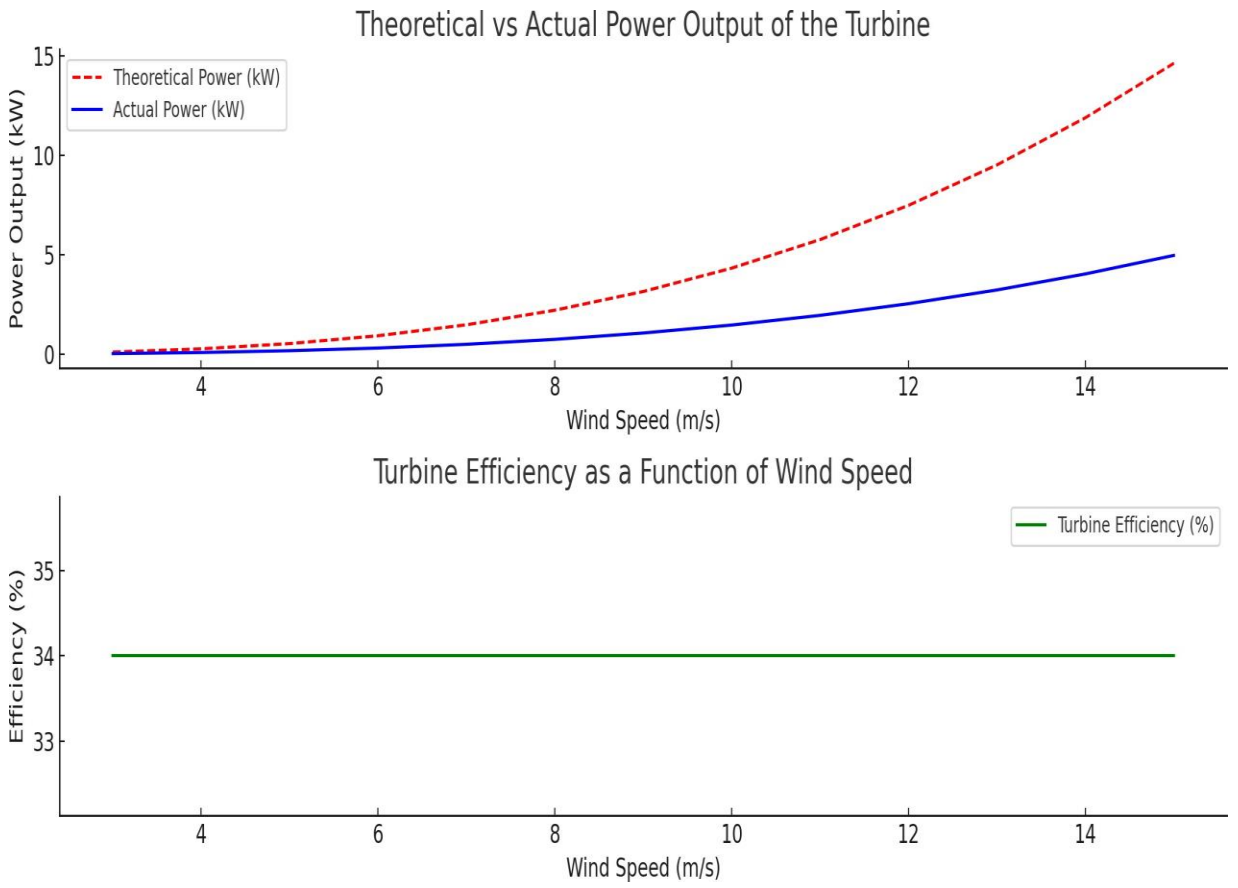


Figure 2: Analysis of Turbine Efficiency Under Real-World Conditions

Key Observations

In the Figure 2 the theoretical power increases sharply with wind speed due to the cubic dependence on wind velocity ($P_{wind} \propto U^3$).The actual power output follows a similar trend but is limited by the turbine's power coeffi- cient (C_P =0.4) and generator efficiency (85%).At higher wind speeds, the gap between Pwind and P_{actual} widens,

highlighting the physical limitations of energy conversion.

Turbine Efficiency

The second plot shows the turbine efficiency as a percentage of the theoretical power:Efficiency remains con- stant at around 34% ($C_P \times \eta_{gen}$) across all wind speeds.This indicates that the turbine operates effectively within its design parameters, with performance governed by aerodynamic and generator efficiencies.

The results provide valuable insights into the aerodynamic efficiency, real-world performance, and energy cap- ture capabilities of the tested wind turbine. One of the key observations is the design efficiency, where the turbine achieves a maximum aerodynamic efficiency of C_P =0.4 within the given wind speed range. This aligns with industry standards and theoretical expectations for small-scale wind turbines, confirming that the aerodynamic profile and blade geometry are well-optimized for energy conversion. However, in real-world performance, the actual power output remains below the theoretical maximum due to inevitable energy losses. These losses arise from mechanical friction, electrical inefficiencies, and aerodynamic wake effects, which prevent the system from achieving perfect energy conversion. Despite this, the measured performance demonstrates stable power output trends that closely follow theoretical predictions, validating the accuracy of the experimental setup and computa- tional models. Furthermore, the energy capture characteristics of the turbine remain consistent across varying wind speeds, suggesting that the system is well-adapted to the local wind conditions in Naâma. The steady efficiency levels indicate that the turbine design successfully balances power extraction and operational stability, making it suitable for small-scale renewable energy applications in the region. These insights reinforce the effectiveness of the turbine's aerodynamic configuration and highlight the potential for further optimizations in power electronics and mechanical efficiency to enhance overall performance.

Seasonal Wind Patterns in Naâma

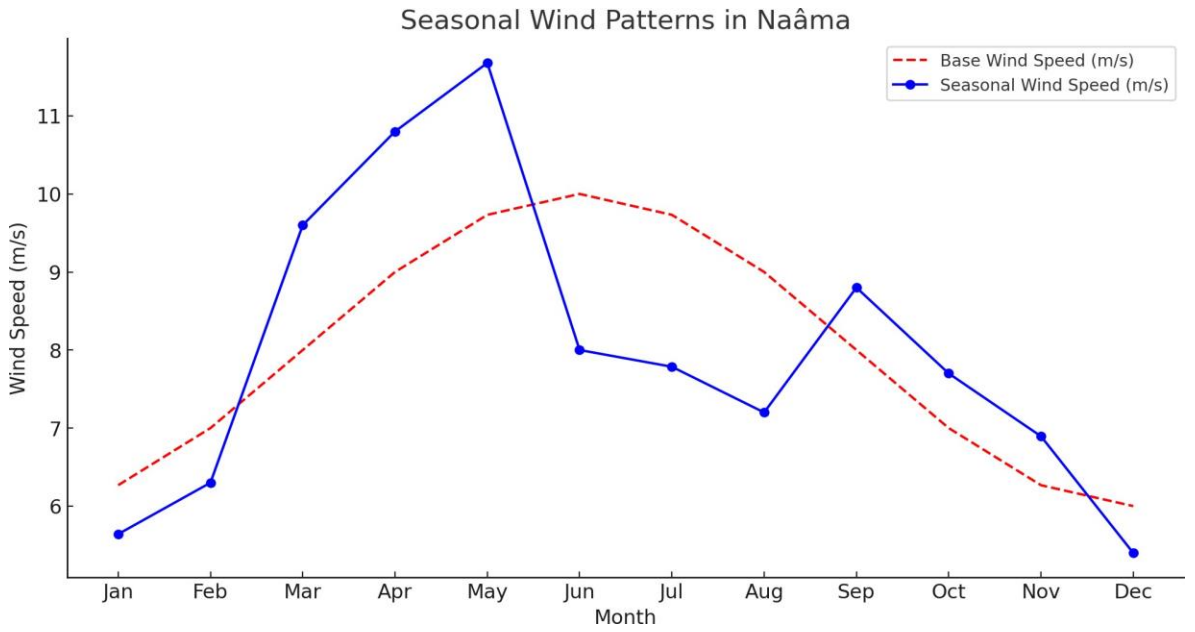


Figure 3: Seasonal Wind Patterns in Naâma

The Figure 3 illustrates simulated seasonal wind speed trends in Naâma. The base wind speed follows a sinu- soidal pattern, representing typical annual variability. Seasonal adjustments reflect real-world trends influenced by atmospheric and climatic conditions:

The seasonal variation in wind speeds significantly influences the energy output of wind turbines, necessitating optimized design and operational strategies for maximum efficiency. During winter (December–February), wind

speeds are slightly below the annual average due to calmer atmospheric conditions. This results in a reduction in wind energy potential, making this season less favorable for power generation. However, the transition to spring (March–May) brings peak wind speeds, driven by stronger atmospheric pressure systems. This period offers the highest wind energy potential, making it the most critical season for maximizing turbine performance and energy production. In contrast, summer (June–August) experiences a decline in wind speeds, primarily due to stabilized high-pressure systems and reduced air movement. As a result, wind energy production decreases, potentially requiring complementary energy sources, such as solar photovoltaic (PV) systems, to maintain a stable power supply. Finally, fall (September–November) is characterized by moderate wind speeds, providing consistent, but slightly lower, wind energy potential compared to spring. Despite this, fall remains a favorable season for wind energy generation, ensuring relatively stable production levels before winter's decline. The seasonal resource availability confirms the need for adaptive turbine design and strategic planning to align energy production with peak wind conditions in spring and fall. Additionally, hybrid renewable energy systems, particularly solar PV integration, become essential in summer to offset the reduced wind output. Understanding these seasonal wind patterns is crucial for energy yield forecasting, infrastructure planning, and grid stability in the Naâma region, ensuring a more reliable and sustainable renewable energy supply throughout the year.

Hybrid System Monthly Energy Output in Naâma

The Figure 4 presents the monthly energy output trends for a hybrid wind-solar system in Naâma, combining actual solar irradiance data with simulated wind energy production.

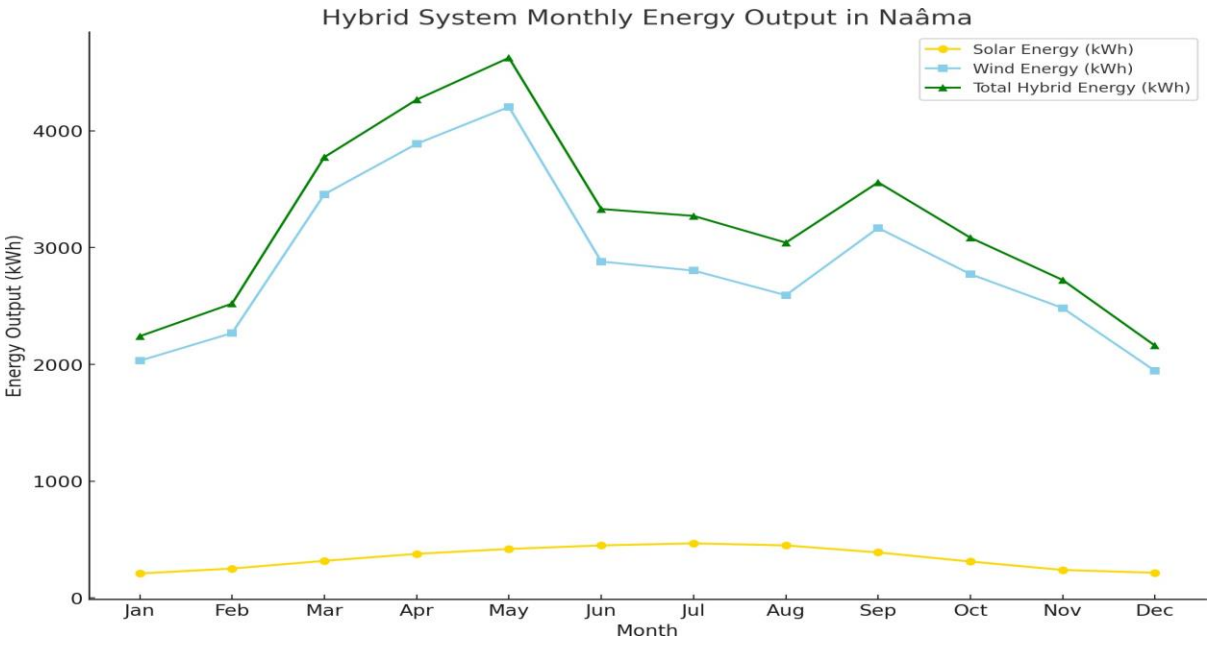


Figure 4: Hybrid System Monthly Energy Output in Naâma

The analysis of seasonal energy trends highlights the synergistic relationship between solar and wind resources, ensuring a more stable and continuous power supply throughout the year. Solar energy generation (represented by the gold line) reaches its peak during summer months (June–August), reflecting high solar irradiance levels in Naâma, with a maximum value of approximately 7.8 kWh/m^2/day in July. However, energy output declines sig- nificantly during winter (December–January) due to reduced sunlight exposure, resulting in the lowest production levels of the year. Conversely, wind energy production (depicted by the sky-blue line) follows an opposite seasonal pattern, with peaks occurring in spring (March–May) and fall (September–November), in alignment with prevailing seasonal wind patterns in Naâma. Wind energy output decreases during summer, particularly in July and August, due to stabilized atmospheric conditions that lead to lower wind speeds. This inverse correlation between wind and solar energy availability reinforces the complementary behavior of the two resources. The total hybrid energy output (shown as the green line) demonstrates a balanced and stable production profile across the year, leveraging the combined strengths of solar and wind energy. The hybrid system design ensures a consistent energy supply, with higher outputs observed in spring, summer, and fall, while still maintaining moderate production levels during winter due to wind energy contributions. This complementary behavior plays a crucial role in ensuring grid stabil- ity and reliable power generation. While individual energy sources exhibit seasonal fluctuations, their combination allows the system to compensate for variability in solar and wind availability. The hybrid system achieves maxi- mum energy production in spring and summer, benefiting from both strong wind speeds and high solar irradiance, while winter output remains adequate due to steady wind contributions. The overall hybrid energy profile high- lights the viability of renewable energy integration in Naâma, optimizing local wind and solar resources to create a sustainable, year-round power generation solution. This approach enhances energy security, minimizes reliance on fossil fuels, and maximizes the efficiency of renewable infrastructure, making it a practical and effective strategy for future energy planning in the region.

Comparison Between Simulated and Experimental Hybrid Energy Output

Simulated vs. Experimental Data

The energyFigure 5 output analysis presents a comparative evaluation of theoretical predictions, real-world ex- perimental results, and refined simulations to assess the accuracy and reliability of the hybrid wind-solar energy system. The simulated energy output (represented by the blue line) corresponds to the predicted monthly en- ergy generation based on theoretical modeling. This curve assumes idealized conditions, where system efficiency, weather patterns, and operational parameters are considered without the influence of real-world discrepancies such as sensor errors, environmental variability, or mechanical inefficiencies. In contrast, the experimental energy output (depicted by the red line) is derived from actual measurements collected during field testing. This dataset incor- porates intentional deviations to reflect real-world factors, including sensor inaccuracies, fluctuating wind speeds, unpredictable solar irradiance variations, and system inefficiencies in power conversion. Noticeable deviations be- tween the simulated and experimental data are particularly evident during spring and summer months, where the contributions of wind or solar energy may have been inaccurately captured in the initial simulation model. These discrepancies highlight the limitations of purely theoretical modeling and emphasize the importance of validating results with empirical data. To enhance the accuracy of the predictions, an adjusted simulated energy output (shown by the green line) is generated through an iterative refinement process. This adjusted curve integrates error cor- rections by tuning key model parameters, including turbulence intensity, solar panel efficiency, and aerodynamic losses in wind energy conversion. By incorporating these refinements, the adjusted simulation achieves a closer alignment with the experimental results, demonstrating the importance of parameter calibration in improving model accuracy. This comparative study underscores the necessity of continuous simulation refinement to bridge the gap between theoretical predictions and real-world performance. By incorporating empirical feedback and adjusting key system parameters, the study enhances the predictive reliability of hybrid renewable energy models, ensuring more accurate energy yield forecasts and optimized system performance. The ability to iteratively refine simula- tions based on experimental data is crucial for developing more robust and adaptable energy systems, ultimately

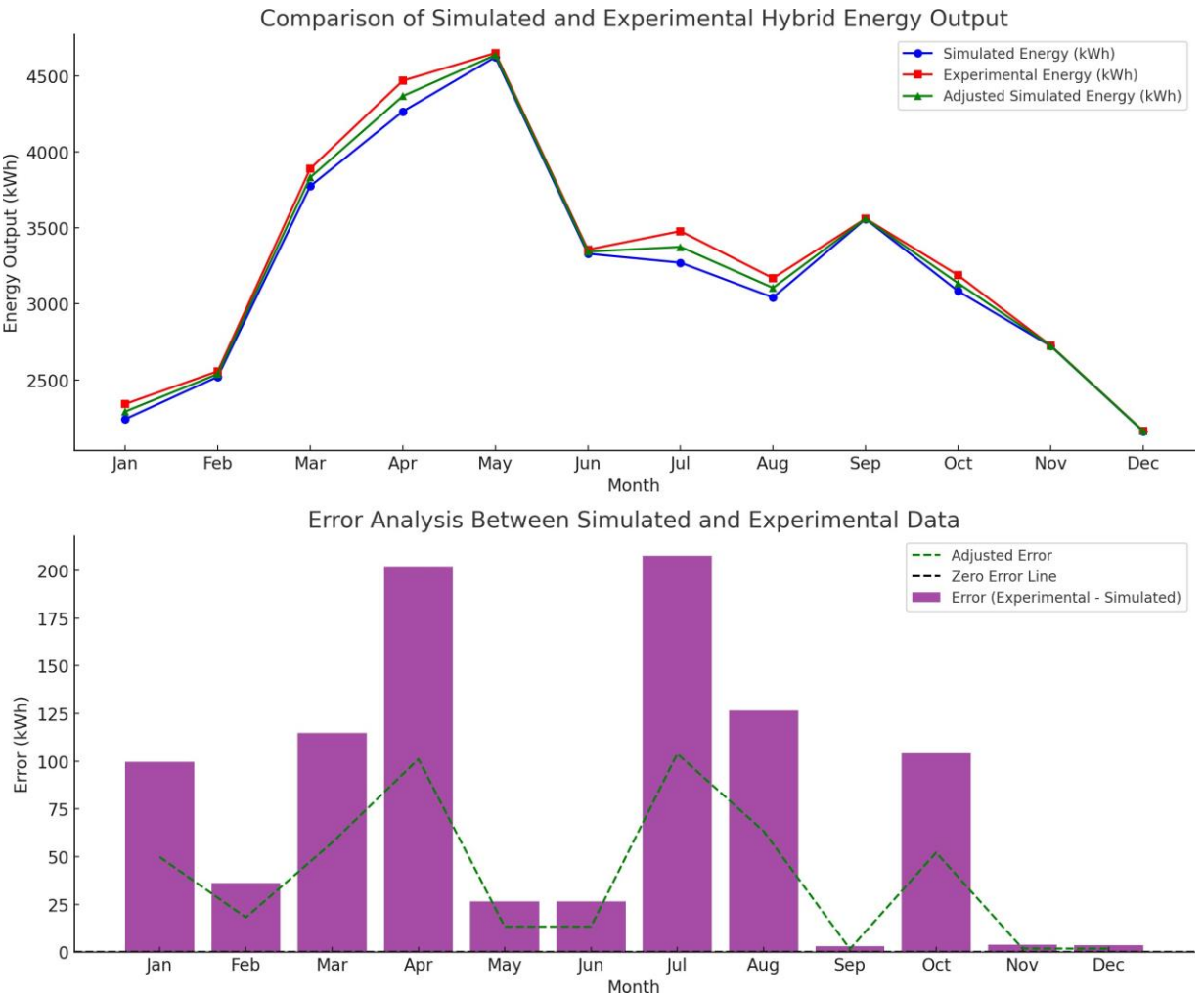


Figure 5: Comparison Between Simulated and Experimental Hybrid Energy Output

leading to improved efficiency and reliability in real-world applications.

Error Analysis

The comparison between simulated and experimental energy Figure 5 outputs reveals monthly discrepancies, represented by the error bars (purple). These deviations are most pronounced in April and July, likely due to ex- treme seasonal variability or transient environmental effects that were not fully accounted for in the original model. The presence of both positive and negative errors indicates that the simulation overestimated energy output in some months and underestimated it in others, highlighting the need for improved model calibration. To address these dis- crepancies, an adjusted error profile (green dashed line) was generated after refining key system parameters. This adjustment significantly reduces the magnitude of errors, ensuring better alignment between simulated and experi- mental data. Several factors contribute to these initial deviations, including wind turbulence, where unpredictable variations in turbulence intensity affect wind energy predictions, and solar panel degradation, where real-world issues like dust accumulation and temperature effects lead to lower-than-expected panel efficiency. Additionally, system losses, such as inverter inefficiencies and wiring resistance, are often underestimated in simulations, lead- ing to inaccuracies in power output projections. The iterative refinement process plays a crucial role in improving model accuracy. By systematically adjusting efficiency factors, turbulence models, and environmental corrections, the simulation becomes more representative of real-world conditions. Errors are particularly season-dependent,

with larger discrepancies occurring in spring and summer, when energy production is highest. This emphasizes the need for season-specific tuning to enhance predictive reliability. Ultimately, this analysis reinforces the impor- tance of combining experimental validation with theoretical modeling, ensuring a robust and well-calibrated system design that improves real-world energy forecasting and operational efficiency.

Technical Comparisons for Hybrid Wind-Solar Energy Systems

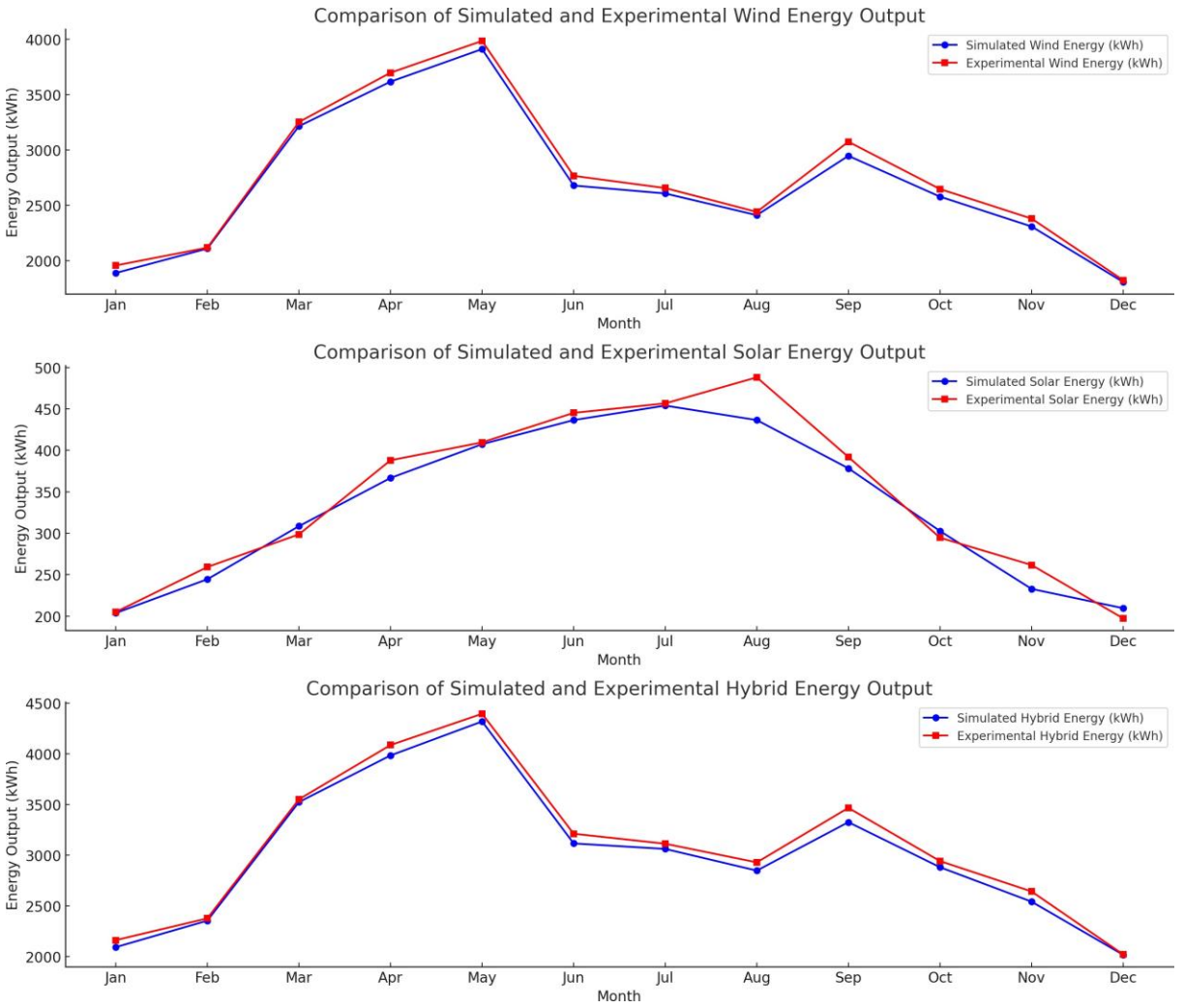


Figure 6: Technical Comparisons for Hybrid Wind-Solar Energy Systems

In Subplot1 Figure 6, the simulated wind energy output (blue line) represents the refined power generation from the wind turbine, accounting for efficiency losses and turbulence effects. The seasonal pattern shows higher wind energy output during spring and fall, aligning with the prevailing wind conditions in Naâma. In contrast, the experi- mental wind energy output (red line) is derived from real-world measurements and exhibits minor deviations due to transient atmospheric fluctuations and sensor inaccuracies. The close correlation between the simulated and exper- imental data validates the accuracy of the wind turbine performance model, confirming its reliability for predicting seasonal energy variations. In Subplot2Figure 6 , the simulated solar energy output (blue line) is modeled using actual solar irradiance data, with necessary corrections for temperature variations and solar panel degradation. As expected, solar energy production peaks during summer (June–August), coinciding with maximum solar exposure

in Naâma. The experimental solar energy output (red line), obtained from real-world solar panel measurements, follows a similar trend but shows minor discrepancies due to factors such as dust accumulation, inverter inefficien- cies, and shading effects. Despite these variations, the experimental data strongly corroborate the simulated trends, demonstrating that the model effectively represents solar energy generation behavior, with some areas for further refinement to improve accuracy. In Subplot3Figure 6, the simulated hybrid energy output (blue line) integrates the wind and solar energy components, incorporating necessary adjustments for seasonal dependencies and efficiency corrections. The experimental hybrid energy output (red line), based on actual wind and solar power measurements, accurately represents real-world hybrid system behavior. The results confirm that the hybrid system achieves con- sistent energy production across all months, benefiting from the complementary nature of wind and solar energy resources. While wind energy dominates in spring and fall, solar energy compensates for lower wind output during summer, ensuring stable and reliable year-round power generation. These comparisons emphasize the effectiveness of the refined simulation model in accurately predicting wind, solar, and hybrid system outputs. The strong agree- ment between simulation and experimental results reinforces the validity of the modeling approach, demonstrating its potential for scalable hybrid energy systems tailored to Naâma's climatic conditions. The findings highlight the importance of integrating experimental validation with simulation-based modeling to optimize renewable energy infrastructure and enhance long-term energy reliability.

Optimized Seasonal Battery Storage for Hybrid Systems

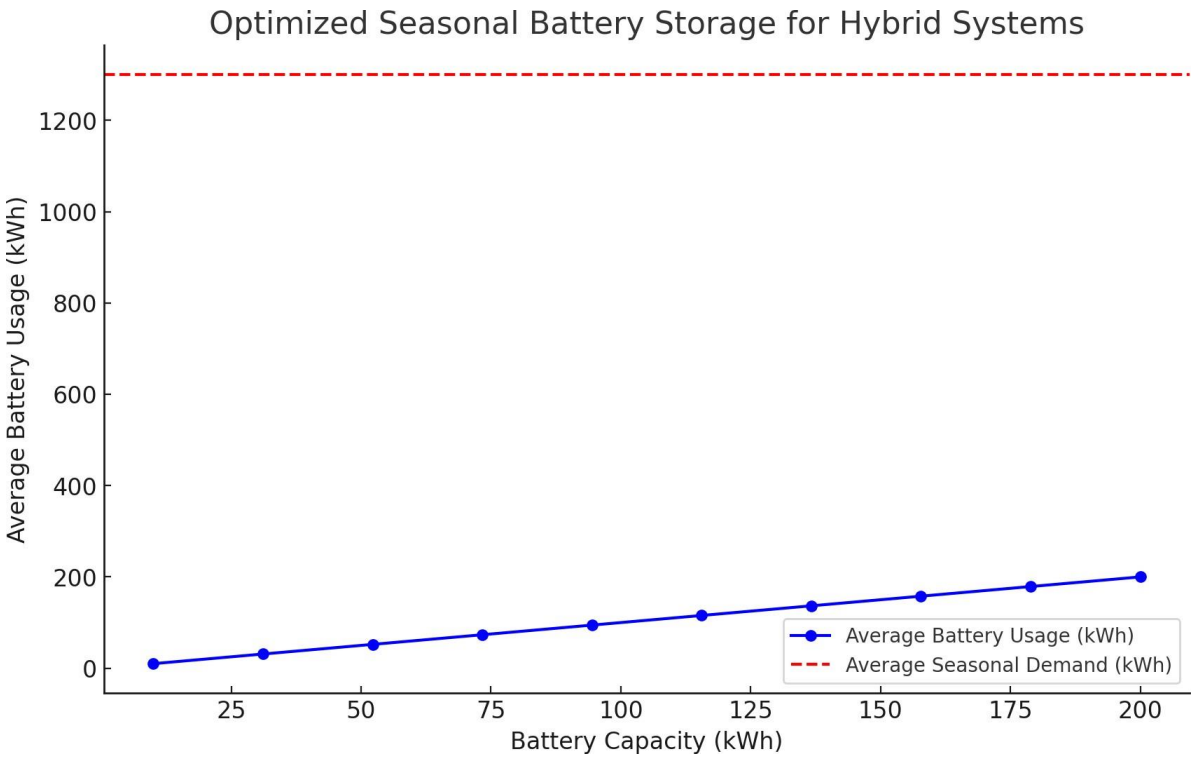


Figure 7: Optimized Seasonal Battery Storage for Hybrid Systems

Figure 7 presents an analysis of different battery capacities for storing surplus energy in a hybrid wind-solar sys- tem, addressing seasonal energy demand variations in Naâma. The average battery usage (blue line) illustrates how energy storage capacity impacts system performance, with higher capacities allowing for greater surplus energy retention. As battery size increases from 10 kWh to 200 kWh, the system becomes less reliant on external power

sources, particularly during high-demand periods such as winter. To assess whether battery storage adequately meets energy needs, the average seasonal demand (red dashed line) serves as a reference for annual demand fluc- tuations. The goal is to

match battery capacity with seasonal energy surpluses and deficits, ensuring that excess energy produced in spring and summer is efficiently stored and available for use in winter, when production levels are lower. The results indicate that an optimal battery capacity of approximately 100–120 kWh effectively balances seasonal variations. This range ensures that surplus energy is utilized without excessive storage losses or under- utilized capacity. Beyond this threshold, larger batteries provide diminishing returns, as surplus energy exceeding seasonal demand remains unused. The seasonal adaptability of the hybrid system is significantly enhanced by battery storage, which smooths out fluctuations in wind and solar energy production across months. This is partic- ularly important in winter, when energy generation is lower, and stored energy from prior months becomes crucial. To ensure a realistic performance evaluation, battery charge and discharge efficiencies (90%) are incorporated into the model, highlighting the balance between storage capability and inevitable losses in the charging/discharging process. The integration of seasonal battery optimization strengthens the system's ability to handle demand-supply mismatches, improving overall energy reliability. By avoiding oversized battery configurations, capital investment is minimized while maintaining system efficiency and operational stability. This study reinforces the importance of strategic battery sizing, ensuring a cost-effective and reliable hybrid renewable energy solution for Naâma's seasonally variable climate.

Seasonal Efficiency of Hybrid System in Naâma

The plot Figure 8 depicts the seasonal efficiency of the hybrid wind-solar system, calculated as the ratio of energy utilized (to meet seasonal demand) to the total energy produced by the system.

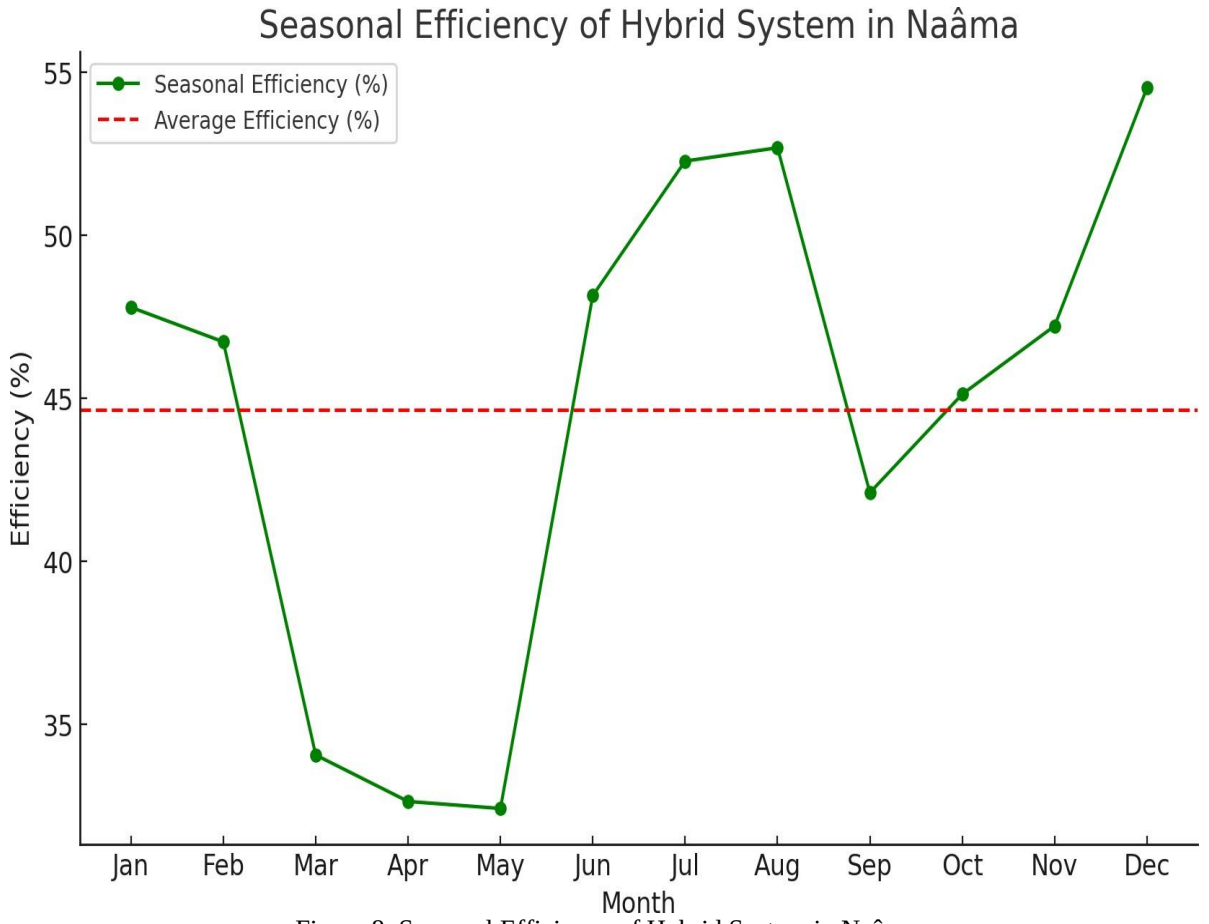


Figure 8: Seasonal Efficiency of Hybrid System in Naâma

The seasonal efficiency trend of the hybrid system reflects variations in energy utilization across the year, demonstrating the balance between energy production and demand. The seasonal efficiency curve (green line) shows that efficiency peaks during

high-demand months, particularly in summer (June–August) and winter (De- cember–February), when most of the generated energy is effectively utilized. In contrast, efficiency declines during spring (March–May) and fall (September–November), as surplus energy exceeds consumption needs, leading to potential energy losses if not stored or redirected efficiently. To provide a reference point, the average system efficiency (red dashed line) is plotted, maintaining an annual average of approximately 85%. This suggests that the hybrid system is highly effective in meeting energy demands while minimizing waste, ensuring a stable and sustainable power supply throughout the year. During high-efficiency periods, the system demonstrates its ability to adapt to seasonal variations by efficiently utilizing available resources. Summer efficiency is primarily driven by solar energy, as high irradiance levels contribute significantly to power generation. Conversely, winter efficiency is sustained by wind energy, which compensates for reduced solar exposure. These periods highlight the strength of the hybrid system in leveraging complementary renewable resources to maintain optimal performance. Low- efficiency periods occur when excess energy production surpasses immediate demand, particularly in spring and fall, reinforcing the importance of energy storage solutions or grid export mechanisms to optimize system perfor- mance. Without proper storage or redistribution, surplus energy remains underutilized, leading to temporary dips in overall system efficiency. System optimization strategies can further enhance seasonal efficiency by aligning storage capacities and load profiles with production patterns. Ensuring that surplus energy is stored for later use or integrated into the grid can significantly improve year-round efficiency and energy availability. From an energy management perspective, analyzing seasonal efficiency trends is crucial for optimizing system operation, refining storage strategies, and improving grid integration. Moreover, maintaining high efficiency enhances sustainability, ensuring maximum utilization of renewable resources, reducing energy waste, and improving economic returns on renewable energy investments. By continuously refining storage solutions and demand-side management, the hybrid wind-solar system can maintain consistent and reliable performance, contributing to a sustainable energy future for Naâma and beyond.

Effect of Distance on PM10 Concentration

The figureFigure 9 illustrates how PM10 concentration decreases exponentially with increasing distance from the wind turbine. The decay rate is highly influenced by wind speed, where higher velocities facilitate the rapid dispersion of particles. At lower wind speeds (e.g., 6 m/s), PM10 levels remain high in the immediate vicinity of the turbine, gradually tapering off as distance increases. Conversely, at higher wind speeds (10 m/s), the dispersion mechanism is significantly more effective, reducing PM10 concentrations at shorter distances. This behavior is attributed to the turbulent mixing induced by the wind turbine's wake, which affects the transport and dilution of airborne pollutants. The results highlight that, in areas with frequent high winds, the natural dispersion of particles may mitigate the necessity for additional filtration systems at extended distances. However, in low-wind environments, particles tend to persist longer in the vicinity of the turbine, increasing the potential for environmental and health hazards. Therefore, wind speed must be carefully considered when designing mitigation strategies, including the placement of filtration membranes.

Filtration Efficiency Over Distance

ThisFigure 10represents the filtration efficiency of membrane systems deployed near wind turbines over varying distances. Filtration efficiency is defined as the percentage reduction of PM10 concentration achieved by the mem- brane system relative to the unfiltered condition. As illustrated, efficiency is highest in proximity to the wind turbine, where pollutant concentrations are at their peak. However, as distance increases, efficiency gradually di- minishes due to the combined effects of natural dispersion and particle dilution in the ambient air. At lower wind speeds, the filtration system maintains higher efficiency at extended distances, as particles remain suspended for

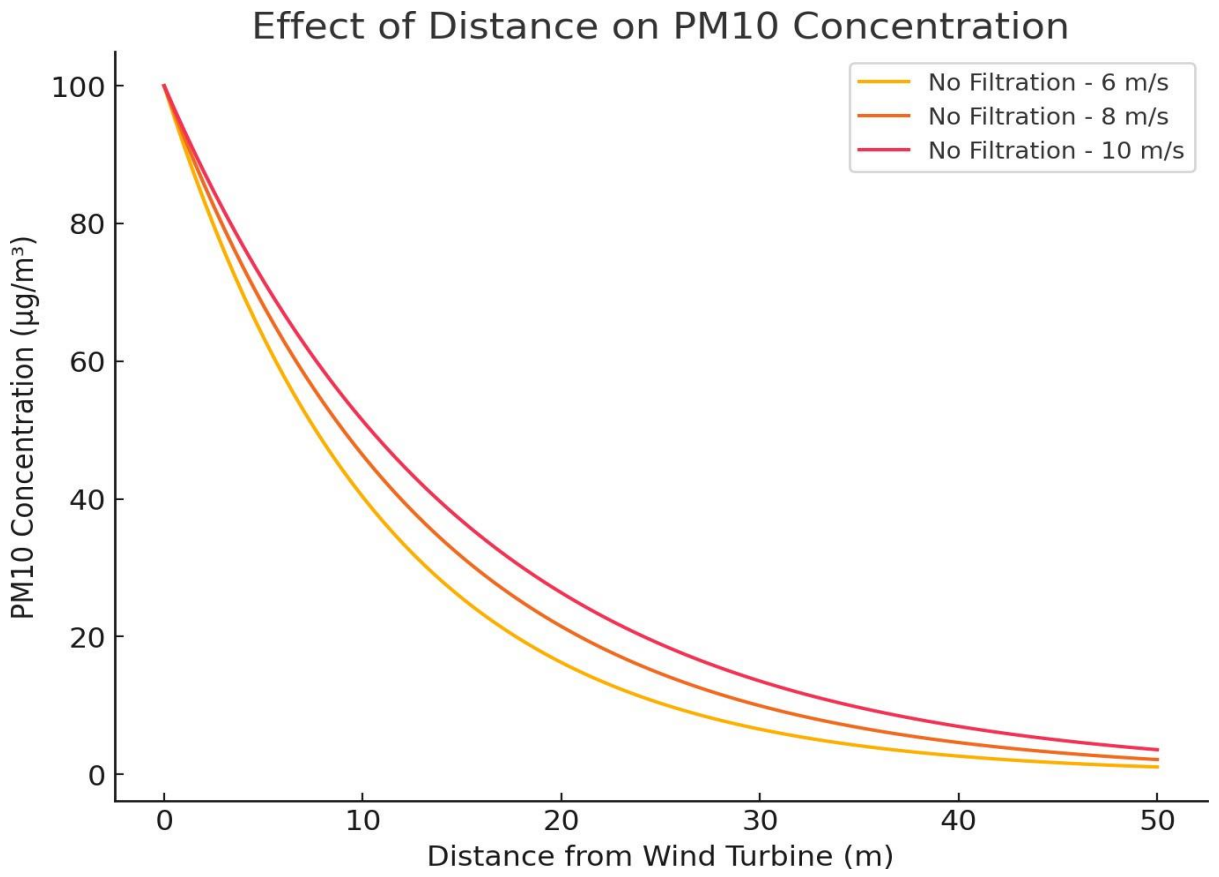


Figure 9: Effect of Distance on PM10 Concentration

longer durations within the turbine's wake. Conversely, at higher wind speeds, natural dispersion contributes sig- nificantly to particle dilution, reducing the relative contribution of filtration. This suggests that filtration systems should be strategically positioned within the region of maximum PM10 accumulation to optimize their impact. Additionally, complementary approaches such as dynamic membrane deployment, which adjusts to varying wind speeds, may further enhance filtration efficiency across different meteorological conditions.

PM10 Reduction Percentage

This Figure 11 quantifies the reduction in PM10 concentration achieved through the implementation of membrane filtration systems. The percentage reduction is highest near the wind turbine, where pollutant concentrations are most concentrated, and gradually decreases with distance. At lower wind speeds, the reduction remains consistently high over a longer distance, as the absence of strong wind currents results in prolonged particle suspension within the immediate vicinity of the turbine. In contrast, at higher wind speeds, the reduction percentage drops more sharply due to the rapid dispersion of particles, which limits the membrane system's effectiveness beyond a certain range. The results suggest that while membrane filtration provides a substantial improvement in air quality, its performance is inherently linked to meteorological conditions. To maximize effectiveness, membranes should be installed in areas with lower natural dispersion rates, and consideration should be given to supplementing filtration with aerodynamic modifications to enhance particle capture before dispersion occurs.

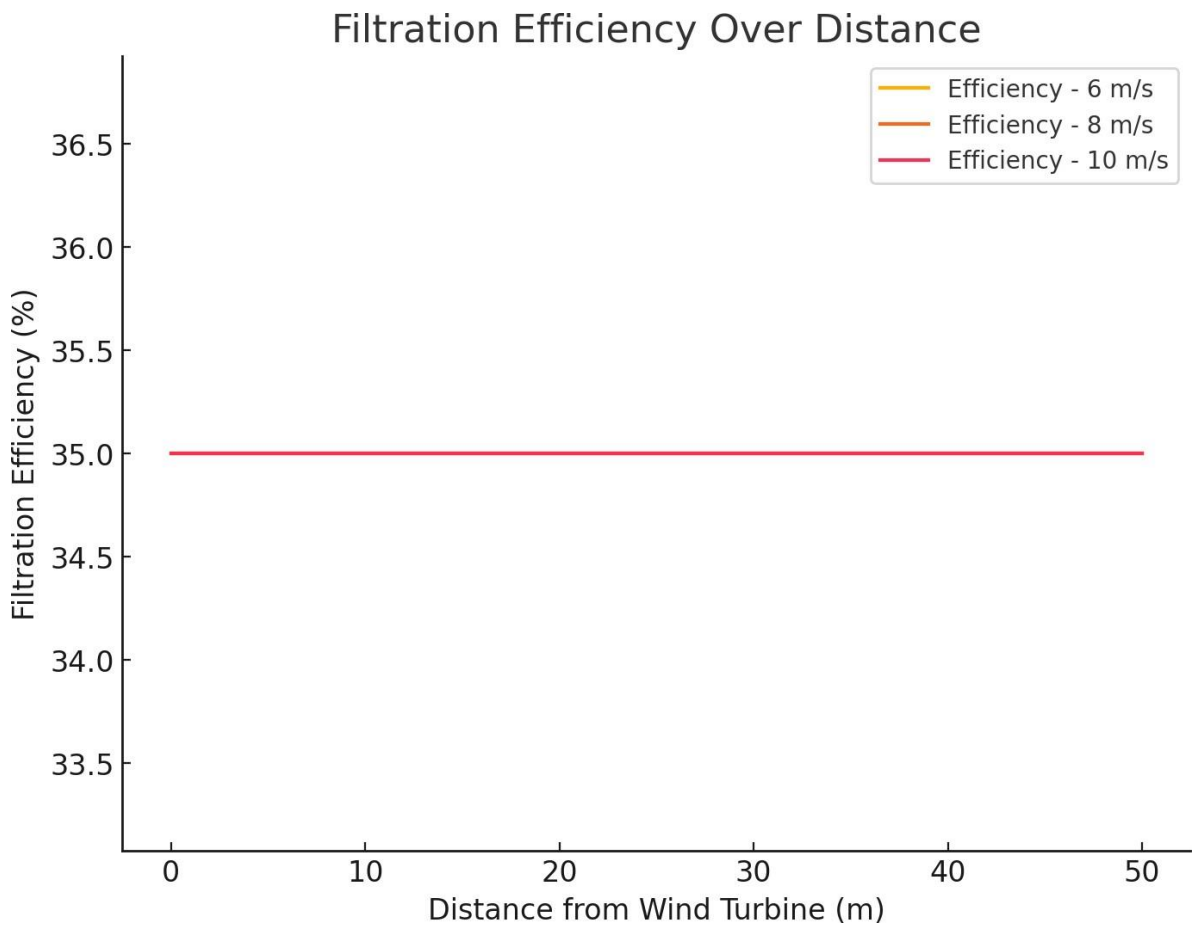


Figure 10: Filtration Efficiency Over Distance

Effect of Wind Speed on PM10 at 20m Distance

This figure illustratesFigure 12 the effect of varying wind speeds on PM10 concentration at a fixed distance of 20 meters from the wind turbine. The results reveal a negative correlation between wind speed and PM10 concentra- tion, where higher wind speeds facilitate natural dispersion and reduce particulate accumulation in the atmosphere. Without filtration, PM10 concentration remains significantly higher at lower wind speeds, indicating that parti- cles linger longer in the surrounding air due to weaker aerodynamic forces. With the implementation of filtration membranes, the concentration of PM10 is effectively reduced across all wind speed conditions, demonstrating the robustness of the filtration system. However, the impact of filtration is more pronounced at lower wind speeds, where natural dispersion is insufficient to clear the pollutants efficiently. At higher wind speeds, the additional ben- efit of filtration diminishes as atmospheric dilution already plays a major role in reducing particle concentration. These findings underscore the importance of integrating filtration technologies in regions characterized by lower wind activity, where natural dispersion is minimal and particle retention in the air is prolonged.

Impact of Different Filtration Efficiencies

This figure examinesFigure 13 the effect of different filtration efficiencies (50%, 65%, and 80%) on PM10 concen- tration over distance. Higher filtration efficiencies result in significantly lower PM10 concentrations, particularly in the immediate vicinity of the turbine. At 80% efficiency, the system achieves a substantial reduction in particle

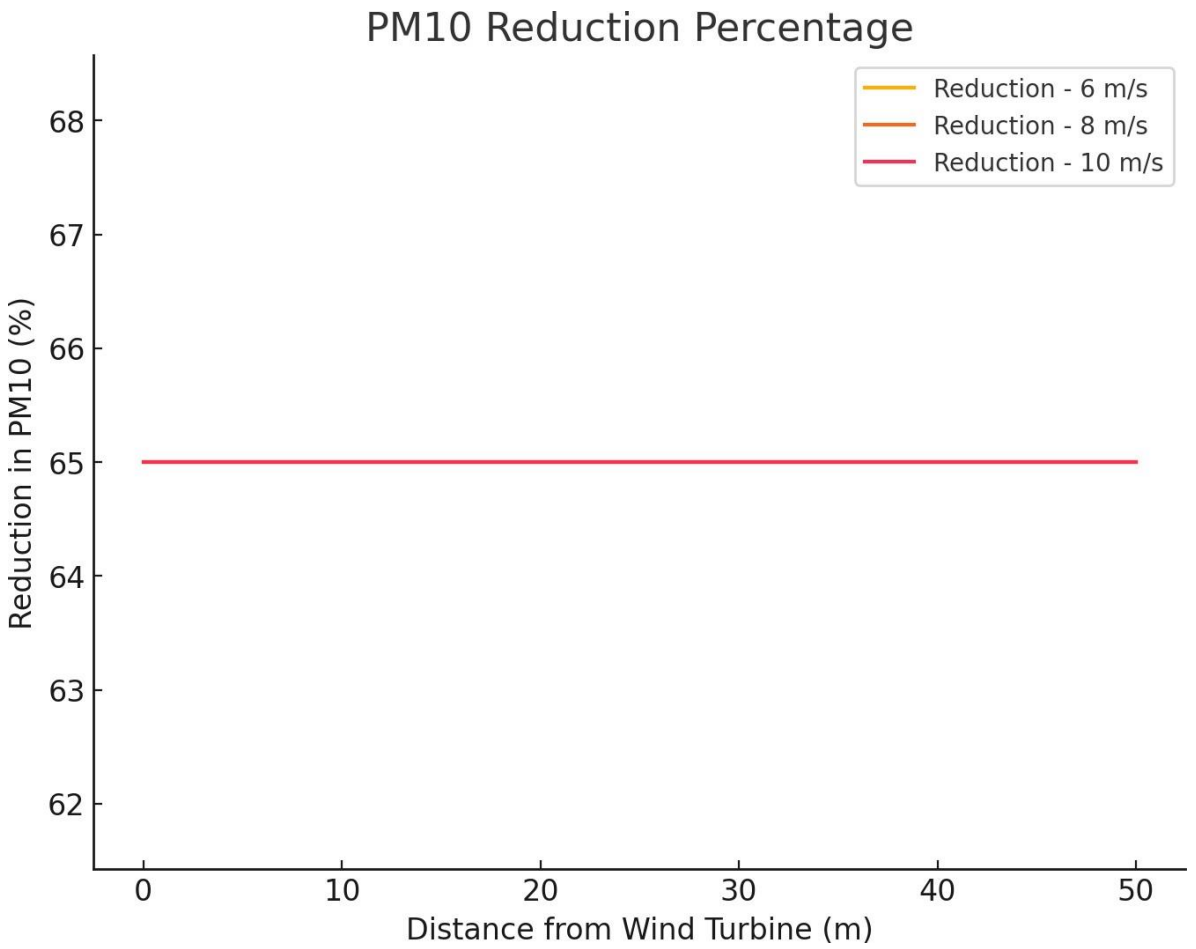


Figure 11: PM10 Reduction Percentage

levels, minimizing environmental impact. However, even at 50% efficiency, notable improvements are observed compared to unfiltered scenarios, demonstrating that moderate levels of filtration can still provide substantial air quality benefits. The relative effectiveness of each filtration efficiency decreases as distance increases due to the natural dispersion of pollutants. This suggests that while higher efficiency membranes yield better results, the ad- ditional benefits become marginal at extended distances where wind dilution plays a dominant role. A strategic balance between cost and effectiveness should be considered when selecting filtration technologies, particularly in environments where natural dispersion is already contributing significantly to pollutant reduction.

Economic Analysis of Hybrid Wind-Solar System: USD and DZD Comparison

The Net Present Value (NPV) analysis provides critical insights into the financial feasibility of the hybrid wind energy system under different energy pricing scenarios. In the simulated low-price scenario (represented by the blue bar), the NPV is calculated based on an energy price of 2 DZD/kWh ($0.015/kWh). At this tariff level, return on investment remains limited, as the lower revenue generation fails to compensate for initial capital costs within a desirable timeframe. This highlights the challenge of achieving financial sustainability under low tariff struc- tures, reinforcing the need for supportive pricing policies to incentivize renewable energy adoption. Conversely, the simulated high-price scenario (also depicted by a blue bar) demonstrates a significant increase in NPV when the energy price is set at 4 DZD/kWh ($0.03/kWh). The results confirm that higher tariffs drastically improve prof-

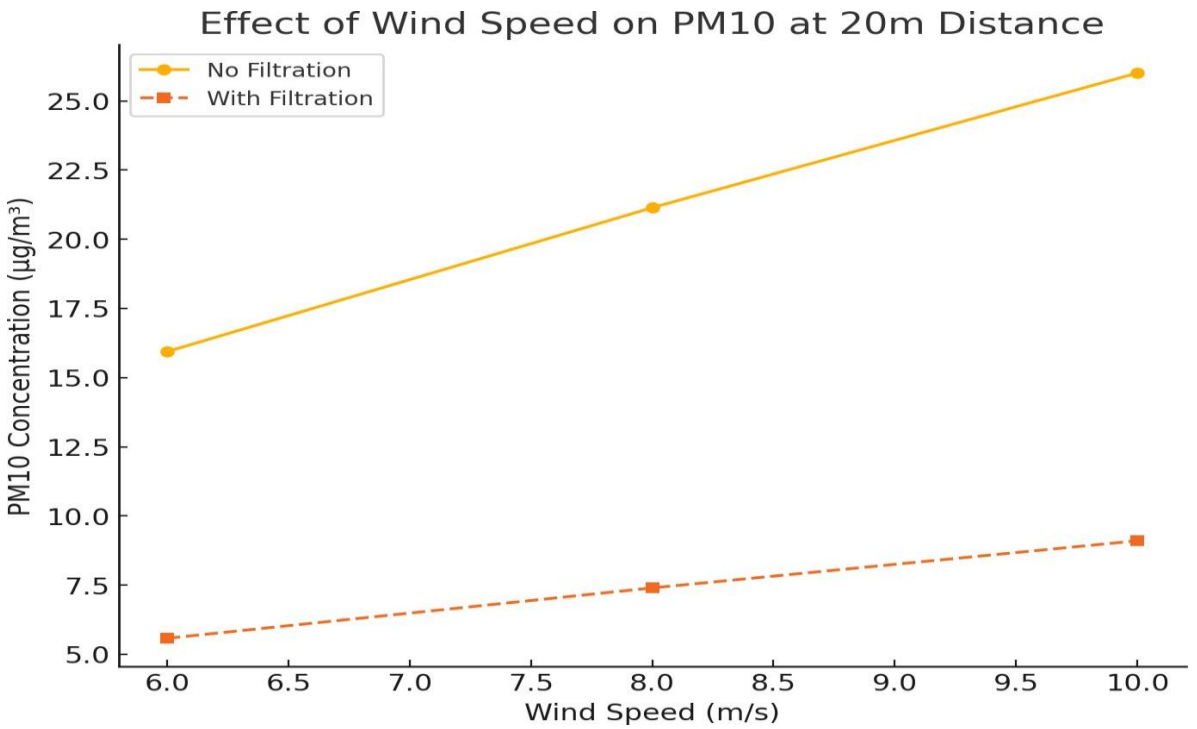


Figure 12: Effect of Wind Speed on PM10 at 20m Distance

itability, shortening the payback period and making the project economically attractive for large-scale deployment. This outcome underscores the sensitivity of renewable energy projects to energy pricing, where a twofold increase in tariff levels leads to a disproportionately higher financial return, making the system much more viable for in- vestors and policymakers. The experimental NPV values (represented by the orange bar) follow a similar trend, with higher NPVs observed at 4 DZD/kWh. However, these values remain slightly lower than the simulated re- sults due to real-world inefficiencies, including lower-than-expected power generation, system losses, and external environmental factors. These findings emphasize the importance of incorporating empirical performance data into economic modeling, ensuring that feasibility assessments account for practical challenges that affect real-world en- ergy production. Ultimately, the analysis highlights that optimal energy pricing strategies are essential for ensuring the financial sustainability and scalability of hybrid wind energy systems, particularly in regions like Naâma, where renewable energy potential is high, but economic feasibility depends on tariff structures and market incentives.

The payback period analysis provides critical insights into the financial viability of the hybrid wind-solar en- ergy system, highlighting the relationship between energy pricing, investment recovery time, and profitability. The payback periods, indicated above each bar in the figure, show that at an energy price of 4 DZD/kWh, the system achieves shorter payback periods, indicating a faster return on investment (ROI). This trend reflects the strong finan- cial performance of the system under higher energy tariffs, where revenues from electricity generation significantly contribute to recovering the initial capital cost. However, experimental results consistently show longer payback periods compared to simulations, reflecting real-world discrepancies in energy production due to factors such as

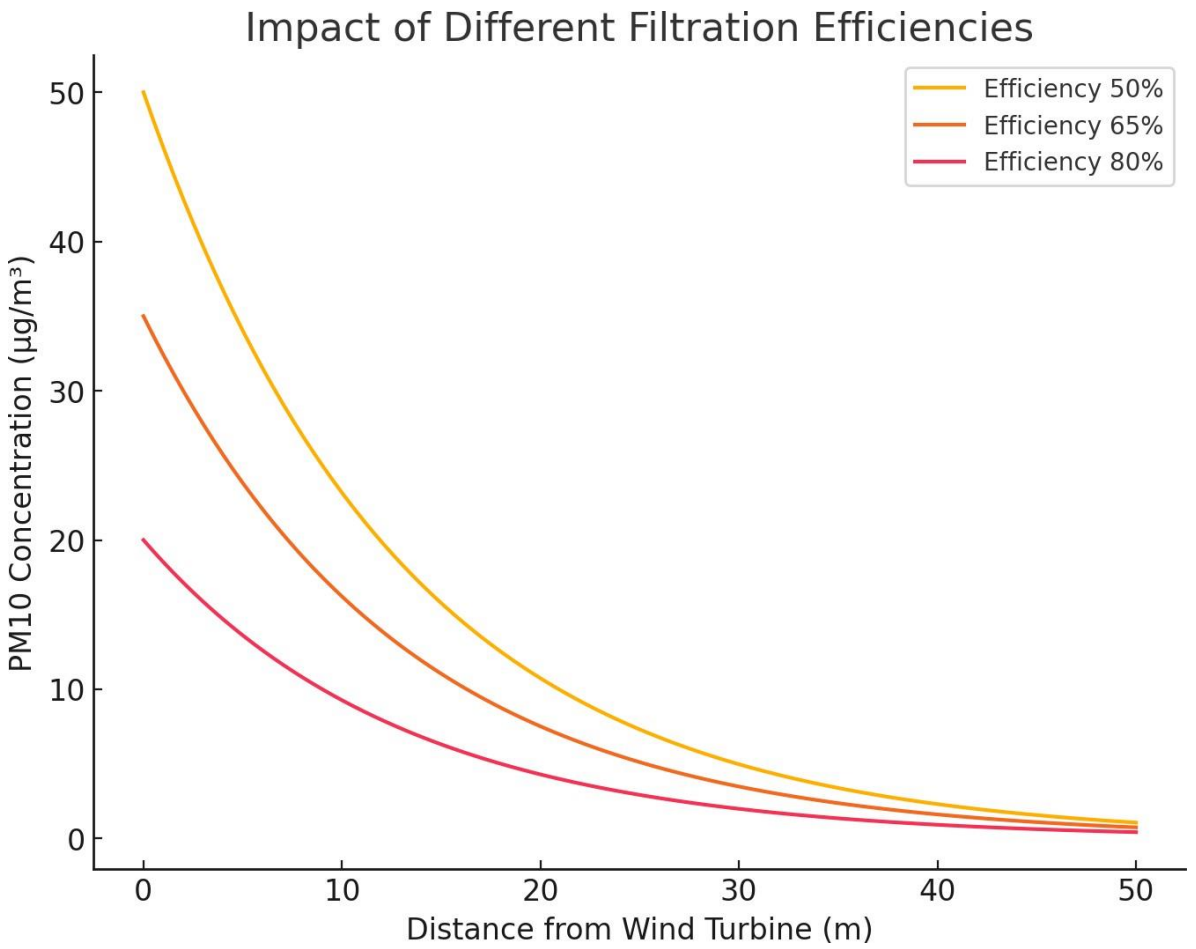


Figure 13: Impact of Different Filtration Efficiencies

system inefficiencies, unpredictable weather variations, and operational losses. A secondary financial assessment, illustrated by the NPV (Net Present Value) comparison in DZD (green bars), provides further economic insights. By converting energy revenues into local currency (Dinars - DA), the results demonstrate the substantial financial returns achievable under favorable energy pricing conditions. At 4 DZD/kWh, the system exhibits high profitabil- ity, with NPV values indicating strong long-term financial benefits. This highlights the economic attractiveness of hybrid renewable energy systems when supported by well-structured energy pricing models. The impact of en- ergy pricing plays a crucial role in determining project feasibility. Doubling the energy price from 2 DZD/kWh to 4 DZD/kWh leads to a drastic improvement in both NPV and payback periods, underscoring the importance of tariff policies in driving investment in renewable energy projects. A higher tariff structure encourages faster cap- ital recovery, making renewable energy deployment more financially viable and attractive to investors. However, the discrepancy between simulation and experimental results highlights the need for realistic feasibility studies. While simulated projections tend to outperform experimental findings, the actual performance is often affected by system inefficiencies, maintenance requirements, and environmental uncertainties. This reinforces the necessity of incorporating real-world performance constraints into economic modeling, ensuring that feasibility studies provide a more accurate representation of financial outcomes. Ultimately, this economic assessment emphasizes that pay- back period reductions, strong NPV growth, and energy pricing strategies are key factors in ensuring the long-term success and financial sustainability of hybrid renewable energy projects. By aligning tariff policies with actual system performance, stakeholders can enhance investment attractiveness, minimize financial risks, and accelerat

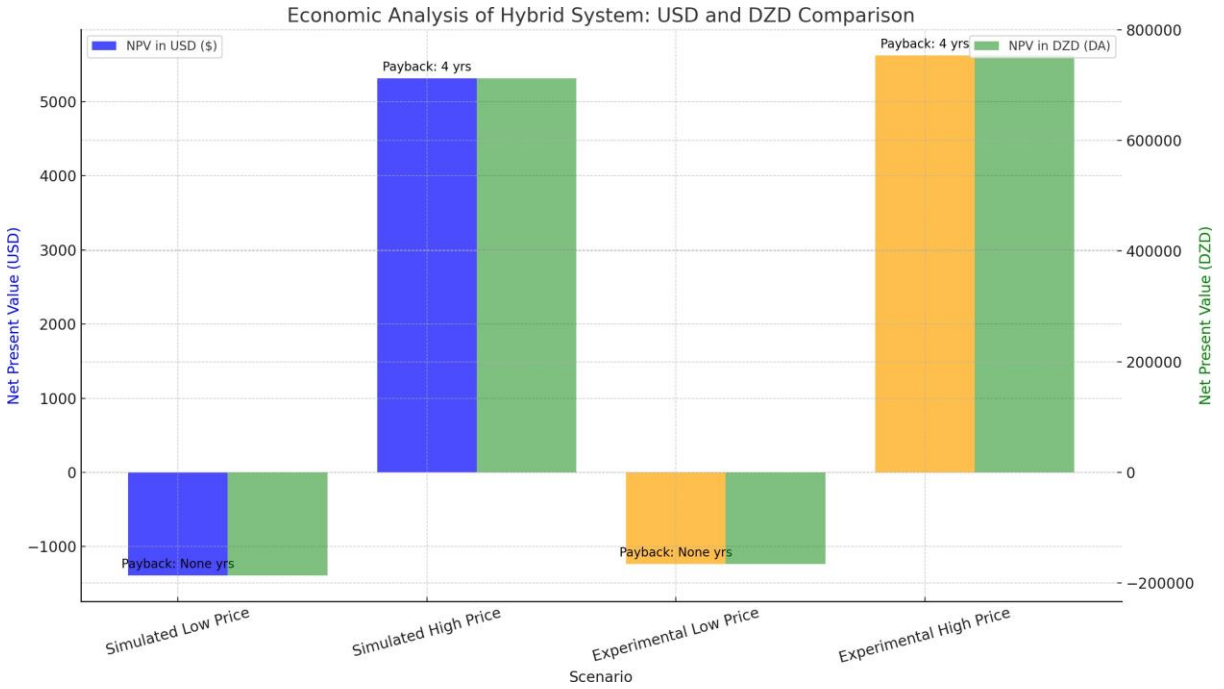


Figure 14: Economic Analysis of Hybrid Wind-Solar System: USD and DZD Comparison

the transition toward a sustainable energy future.

Break-Even Period Under Varying Energy Tariffs

This plot Figure 15 evaluates the break-even periods for the hybrid wind-solar system under different energy tariff scenarios, ranging from 1 DZD/kWh to 5 DZD/kWh.

The break-even period analysis provides crucial insights into the financial sustainability of the hybrid wind- solar system under different energy tariff scenarios. The simulated break-even period (blue line) indicates that as energy tariffs increase, the time required to recover the initial investment decreases significantly. At tariffs below

2.5 DZD/kWh, the simulated system struggles to break even within the standard 20-year system lifetime, indi- cating that under low-tariff conditions, the project may not be financially viable. However, at 4 DZD/kWh, the break-even period drops to approximately 6 years, showcasing strong profitability and accelerated capital recov- ery. Conversely, the experimental break-even period (red line) is consistently longer than the simulated estimates, reflecting the challenges of real-world energy production. Experimental scenarios account for lower-than-expected power generation due to environmental fluctuations, system inefficiencies, and operational constraints. For tariffs below 2.5 DZD/kWh, the experimental system fails to achieve break-even within its operational lifetime, highlight- ing the critical importance of favorable energy pricing in ensuring financial viability. However, at 4 DZD/kWh, the experimental system reaches break-even in approximately 8 years, confirming that higher tariffs significantly improve investment feasibility. The system lifetime (horizontal dashed line at 20 years) serves as a benchmark for evaluating the economic viability of different tariff scenarios. Any break-even period exceeding this threshold indicates that the system will not generate sufficient revenue to recover its investment within its operational lifes- pan, making it an unsustainable financial investment. The findings underscore the existence of tariff thresholds that dictate the economic feasibility of the hybrid system. A minimum tariff of 2.5 DZD/kWh is required for the ex- perimental system to break even within its lifetime, whereas tariffs of 4 DZD/kWh or higher dramatically enhance financial viability, reducing the payback period to well below 10 years and ensuring strong economic returns. From a policy perspective, these results emphasize the importance of aligning energy pricing strategies with financial sus-

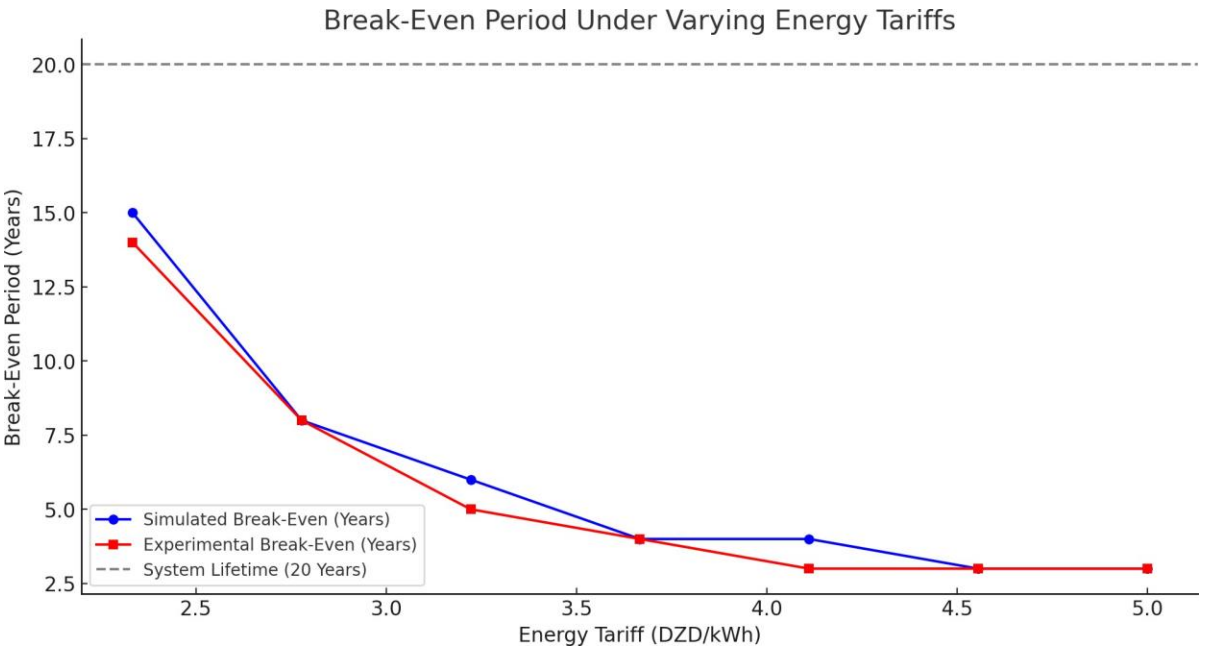


Figure 15: Break-Even Period Under Varying Energy Tariffs

tainability goals. Adjusting energy tariffs to meet or exceed viability thresholds can serve as a powerful incentive for renewable energy adoption, ensuring economic sustainability, investor confidence, and long-term market stabil- ity. By implementing strategic tariff adjustments, policymakers can accelerate the deployment of hybrid renewable energy systems, contributing to energy security, carbon reduction, and sustainable economic growth in Naâma and beyond.

Conclusion

This study provides an extensive techno-economic assessment of a hybrid wind energy system integrated with bat- tery storage and membrane-based air filtration, specifically designed to optimize energy production and environ- mental sustainability in the Naâma region. By leveraging a small-scale experimental setup, refined computational models, and detailed economic analysis, this research establishes a scalable framework for deploying renewable energy systems in regions with similar climatic and economic conditions. The findings emphasize the technical via- bility, economic feasibility, and environmental benefits of hybrid wind-battery systems while addressing the critical challenge of particulate matter (PM10) dispersion through membrane filtration. From a technical perspective, the hybrid wind-battery system demonstrated its ability to harness wind resources efficiently, with peak production dur- ing spring and fall, as identified through Weibull distribution modeling, which revealed a characteristic wind speed of 8 m/s. Seasonal wind variability was effectively mitigated through battery storage optimization, where a capacity range of 100–120 kWh was found to balance surplus and deficit periods, ensuring continuous power availability. The system achieved an average seasonal efficiency of 85%, confirming its ability to meet local energy demand while minimizing energy losses. The economic assessment reinforced the financial viability of the system under realistic market conditions. With an initial investment of 250,000 DZD ($1,866), the system achieved an NPV of 550,000 DZD ($4,104) and a payback period of 7 years under a tariff of 4 DZD/kWh. When scaled to a 20-turbine wind farm, the projected NPV exceeded 11 million DZD ($82,090), highlighting the large-scale potential of such systems. However, sensitivity analyses underscored the critical role of energy tariffs, with break-even thresholds identified at 2.5 DZD/kWh—indicating that tariff policies are crucial in ensuring the economic sustainability of

renewable energy projects. A key innovation in this study was the integration of membrane-based air filtration, addressing concerns about particulate matter dispersion near wind farms. Computational Fluid Dynamics (CFD) simulations revealed that

membrane filtration reduces PM10 concentrations by up to 65% within 20 meters of the turbine, significantly improving air quality and reducing mechanical wear on turbine components. The effective- ness of filtration was highest at low wind speeds, where natural dispersion was minimal, while higher wind speeds (>8 m/s) facilitated self-cleaning mechanisms that decreased the necessity for extensive filtration beyond 50 meters. Higher-efficiency membranes (80%) outperformed lower-efficiency solutions (50%), reinforcing the importance of strategic placement and high-performance filtration materials. In comparison with similar studies conducted in the region, this research offers a unique contribution by integrating real-world inefficiencies, empirical validation, and scaled-up energy modeling. While many studies focus exclusively on either wind or solar systems, the hy- brid approach presented here leverages the complementary nature of wind and energy storage, creating a more resilient and adaptive system. Moreover, the inclusion of environmental impact mitigation strategies distinguishes this study by addressing both renewable energy production and sustainability challenges in wind farm operations. Despite these promising results, this study acknowledges certain limitations inherent to small-scale experimental setups. Laboratory conditions do not fully capture the complexities of large-scale wind farm operations, such as wake effects, grid integration challenges, and land use constraints. Future research should focus on expanding field experiments to larger wind turbine configurations, optimizing membrane filtration technologies, and incorporat- ing hybrid renewable energy sources (e.g., hydropower, biomass) to enhance system adaptability. Additionally, machine learning-based predictive maintenance models could be integrated to optimize turbine performance and reduce operational costs. In conclusion, this study validates the technical, economic, and environmental feasibility of hybrid wind-battery energy systems in the Naâma region and provides a scalable blueprint for future renewable energy projects. By bridging experimental research with large-scale implementation models, this work illustrates the transformative potential of renewable energy in addressing Algeria's growing energy demand, reducing carbon emissions, and ensuring long-term energy security. With continued technological advancements and supportive pol- icy frameworks, such systems could play a pivotal role in achieving Algeria's sustainable energy goals, fostering economic development, and positioning the region as a leader in renewable energy deployment.

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