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Renewable energy-based power generation in Antarctica: Roadmap for optimal sizing, placement and uncertainties prediction using AI-guided technological advances

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Abstract. Antarctica, the most remote and environmentally extreme region on Earth, presents unique challenges for energy generation due to its harsh climate, isolation, and logistical constraints. The continent's research stations, vital for advancing global understanding of climate change, glaciology, ecosystem, and environmental studies, have historically relied on fossil fuels for power, which poses significant logistical and environmental risks, high operational costs, and ethical concerns related to fossil fuel usage in such a pristine environment. This paper provides a comprehensive review of the current landscape of renewable energy adoption in Antarctica, focusing on key research stations such as Princess Elisabeth Station, McMurdo Station, and others that have adopted solar, wind, and hybrid power systems. The paper also discusses the major challenges to widespread renewable energy adoption, including extreme weather conditions, temperature fluctuations, equipment reliability issues, seasonal energy variability, and technological limitations in energy capture and storage systems capabilities. In response to these challenges, the paper explores the potential of advanced computational and artificial intelligence methods to enhance renewable energy system planning in Antarctica. Furthermore, it highlights emerging opportunities for improving renewable energy efficiency and reliability by integrating advanced technologies such as Grey Wolf Optimisation for optimal energy source placement, Random Forest Regression for weather prediction, and innovations in hybrid solar and wind power. The findings underscore the critical need for technological advancements and international collaboration with the Polar Research Institute, Türkiye, to improve energy sustainability, specifically in Horseshoe Island, as well as across the broader Antarctic region. The research concludes by offering recommendations for future research directions, including the implementation of robust data-driven forecasting models and high-performance energy storage technologies. These strategies aim to support the full transition of Antarctica's energy infrastructure to renewable sources, in alignment with urgent global goals to reduce carbon emissions and the imperative to protect one of the Earth's most fragile ecosystems.

Keywords: Antarctica renewable energy, energy efficiency, Grey Wolf Optimisation, Random Forest Regression, solar photovoltaic and wind power, technological innovations

1 Introduction

Antarctica, often regarded as the last pristine wilderness on Earth, presents a unique and challenging environment for scientific research and human activity. With temperatures plunging below –80 °C and winds reaching hurricane force, the continent has some of the harshest weather conditions on the planet (Solomon et al., 2014). While it remains largely uninhabited, numerous research stations established by various countries play a pivotal role in advancing scientific understanding in climate science, glaciology, and marine biology. These stations require reliable energy sources to maintain year-round operations (Aprea, 2012).

Historically, fossil fuels have met the energy demands of these stations due to their high energy density and reliability. However, using them in such a sensitive and remote environment has sparked growing concern. Transporting fuel to Antarctica is complex and costly, requiring specialised icebreakers and aircraft to navigate its harsh conditions. This logistical challenge raises operational costs, increases the risk of environmental disasters such as oil spills, and contributes to carbon emissions in a region already under stress from global climate change (White & McCallum, 2018; Arndt et al., 2020).

A shift toward renewable energy solutions offers a promising alternative. Wind, solar, and hybrid renewable energy systems can provide sustainable power while mitigating the environmental impact of fossil fuel use (Al-Shetwi & Sujod, 2016; 2018a; 2018b). The continent's geographic and climatic conditions present both opportunities and challenges for renewable energy deployment. High wind speeds, particularly in coastal regions, make wind energy feasible, while continuous daylight during summer months offers the potential for solar photovoltaic (PV) power generation. However, the extreme cold, accumulation of ice, and prolonged darkness during winter pose significant obstacles to the consistent generation of renewable energy (Lenky & Davison, 2015).

This review explores the current state of renewable energy-based power generation in Antarctica, examining the challenges and opportunities associated with its implementation. By analysing case studies from research stations such as Princess Elisabeth Station and McMurdo Station, this paper highlights technological advances, best practices, and lessons learned. Additionally, we discuss innovations in energy storage, hybrid systems, and smart grid technologies that are critical for enhancing the efficiency and reliability of renewable energy in Antarctica.

Recent advances in optimal energy planning and uncertainty management can further support the transition to renewables in Antarctica. For example, the Grey Wolf Optimisation framework can be used to determine the appropriate sizing and placement of energy sources (Tyagi et al., 2019; Miao & Hossain, 2020), ensuring that these systems are both efficient. Moreover, the unpredictable weather patterns in Antarctica, which affect both solar irradiance and wind speeds, can be managed using the Random Forest Regression method (Gala et al., 2016; Kim et al., 2019; Huang et al., 2021). This approach leverages recorded weather data to predict the variability in renewable energy generation, helping to ensure a more reliable power supply even in such an unpredictable environment.

Ultimately, this paper aims to outline future directions for research and development in renewable energy, offering strategies to improve system performance and resilience in the harsh Antarctic climate. By leveraging advanced energy management systems and optimisation techniques, Antarctica can serve as a model for sustainable energy infrastructure, aligning with global efforts to reduce carbon emissions and preserve one of the planet's most critical ecosystems.

The paper is organised as follows: Section 2 reviews the current state of renewable energy deployment in Antarctica, highlighting existing installations and their performance. Section 3 discusses the challenges and limitations of renewable energy systems in the harsh Antarctic environment and explores opportunities for renewable

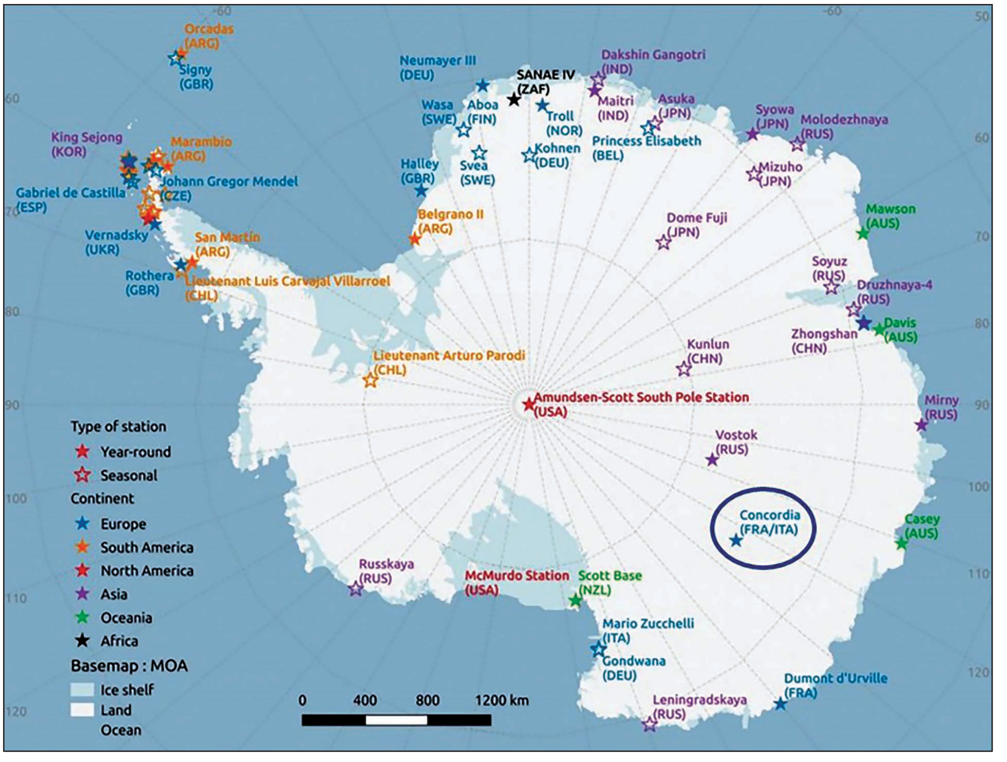

Figure 1. Map of Antarctica Stations (Snels et al., 2021)

energy-based power generation, emphasising the potential benefits and drivers for adoption. Section 4 presents technological innovations and our planned future research, focusing on advanced methodologies such as Random Forest Regression for weather prediction and Grey Wolf Optimisation for optimal sizing and placement of power plants. Finally, Section 5 concludes the paper by summarising the findings and offering recommendations for further research and development.

2 Current state of renewable energy in Antarctica

Antarctica, the coldest, darkest, and least populated continent on Earth, spans approximately 14 million square kilometers, with 98% of its landmass covered by glacial ice (Davies et al., 2025). The continent experiences some of the harshest conditions on the planet, with mean annual temperatures hovering around −50 °C and the lowest recorded temperature, −89.2 °C, registered at Vostok Station (Turner et al., 2009). Governed by the Antarctic Treaty System under the jurisdiction of 28 nations, Antarctica is designated as a "natural reserve devoted to peace and science". Despite the severe environment, many research stations have made significant strides toward adopting renewable energy to support their operations. Figure 1 shows a map of Antarctica, indicating the locations of stations, differentiated by type (year-round or seasonal) and the continent of affiliation. At present, 28 research stations in Antarctica use renewable energy sources, while 63 still depend heavily on fossil fuels, accounting for 69.2% of the total research stations (Vigna, 2022). This reliance on fossil fuels poses environmental risks, such as air pollution and the potential for oil spills, which could have catastrophic effects on the fragile Antarctic ecosystem.

Renewable energy adoption in Antarctica has grown steadily over the past two decades as research stations seek to reduce reliance on diesel fuel and minimise environmental impact. Several stations have successfully integrated solar, wind, and hybrid systems into their energy mix. Table 1 provides an overview of selected Antarctic research stations that utilise renewable energy sources, summarising the type of system, installed capacity, and notable implementation features.

These examples show that hybrid systems combining solar PV and wind turbines (WT) are the most common, often supported by diesel generators and battery storage. The success of these stations informs the approach proposed for the Turkish Antarctic Research Station, which aims to adopt an optimised hybrid renewable energy system tailored to local weather and load conditions.

3 Challenges, limitations, and opportunities for renewable energy-based power generation

Antarctica's extreme environment presents a unique set of technical and operational challenges that impact the design, installation, and performance of renewable energy systems. These challenges must be addressed with appropriate engineering solutions to ensure system durability, safety, and efficiency. Table 2 summarises the key challenges along with their technical implications.

These constraints underscore the need for robust, hybrid systems designed with site-specific parameters in mind. In subsequent sections, we explore technologies and optimisation strategies used to overcome these limitations, with specific attention to the Turkish station.

The shift toward renewable energy in Antarctica presents numerous opportunities. Chief among them is the potential to drastically reduce the continent's carbon footprint, which is essential in the fight against climate change. Hybrid energy systems offer a reliable solution by leveraging the continent's strong wind resources and solar potential during the long summer months (Sanz Rodrigo et al., 2006; de Christo et al., 2016).

The adoption of renewable energy also reduces the need to transport large quantities of fossil fuels to Antarctica, minimising logistical costs and environmental risks. Over time, the high upfront costs of renewable energy infrastructure are offset by lower operational expenses and a reduced environmental impact. The deployment of renewable technologies can also spur technological innovation, opening new pathways for more advanced solutions and driving job creation in the energy sector. Furthermore, these advances improve energy security for Antarctic research stations, which are often isolated and rely on self-sufficient power generation.

Table 1. Overview of renewable energy systems at selected Antarctic stations

Name of Station	Country	Renewable Energy System	Description
Princess Elisabeth	Belgium	Wind + Solar (Hybrid)	First zero-emission station; uses 9 wind turbines and bifacial solar PV panels (Lucci et al., 2022)
McMurdo Station	USA	Wind (Shared with Scott Base)	Part of Ross Island Wind Energy Project; 3 turbines shared with Scott Base (Li et al., 2021)
Scott Base	New Zealand	Wind (Hybrid)	Shares 1 MW wind farm with McMurdo; uses diesel as backup (Baring-Gould et al., 2005)
Mawson Station	Australia	Wind	2 turbines providing up to 80–90% of energy needs (Paterson, 2002)
Zhongshan Station	China	Wind + Solar	Hybrid system integrated with diesel; 1.43 million USD saved annually (Lucci et al., 2022)
Wasa Station	Sweden	Solar	Uses PV panels for electricity and thermal heating (Magill, 2004)

In general, the growing need for renewable energy in Antarctica arises from several key factors:

a) Environmental Preservation

The pristine environment of Antarctica is vital for studying climate change, glacial dynamics, and biodiversity. However, traditional fossil fuel-based energy systems contribute to localised pollution, including black carbon deposition on ice, which accelerates melting and disrupts the albedo effect (Khan et al., 2019). Studies have shown that even snow appearing white to the naked eye can have significantly reduced reflectance due to black carbon accumulation, with potential albedo reductions of at least 25% (Berkowitz, 2017). Transitioning to renewable energy minimises emissions.

b) Operational Challenges of Fossil Fuels

The reliance on fossil fuels in Antarctica is fraught with logistical difficulties. Fuel must be transported across vast distances, often through treacherous sea and ice routes, increasing the cost, complexity, and environmental risk of spills during transportation. Renewable energy, by contrast, leverages locally available resources like solar radiation and wind, reducing dependence on imported fuels.

c) Energy Demand of Research Stations

With the expansion of scientific activities and longer operational seasons, the energy demands of research stations are steadily increasing. Renewable energy offers a sustainable solution to meet these growing demands without exacerbating carbon footprints. For example, solar energy can be harnessed during the austral summer, while wind power remains viable year-round due to Antarctica's strong and consistent winds.

d) Technological Feasibility

Advances in renewable energy technologies make them increasingly viable even in Antarctica's extreme conditions. Innovations in WTs, solar panels, and energy storage systems tailored to cold climates offer reliable and cost-effective energy alternatives. The successful implementation of renewable systems at stations like Princess Elisabeth and Mawson demonstrates their potential and sets a precedent for broader adoption.

e) Global Leadership and Sustainability Goals

Antarctica serves as a platform for international collaboration and scientific exploration under the Antarctic Treaty System. Demonstrating leadership in sustainability through the adoption of renewable energy aligns with global goals, such as those outlined in the Paris Agreement, and reinforces the international community's commitment to combating climate change.

The transition to renewable energy in Antarctica is an environmental necessity and a practical and strategic imperative. By reducing reliance on fossil fuels, improving energy security, and mitigating environmental risks, renewable energy ensures the sustainable operation of research sta-

Table 2. Environmental challenges and the corresponding technical requirements for renewable energy systems in Antarctica (Andrews et al., 2013; Sujod & Erlich, 2013; Andenæs et al., 2018; Anadol & Erhan, 2019; Ghazali et al., 2021)

Environmental Challenge	Technical / Design Implications
Temperatures below −80 °C	Use of low-temperature-tolerant materials in PV modules and batteries
Wind speeds exceeding 300 km · h^{-1}	Reinforced anchoring and structural design for wind turbines and PV
Heavy snow and ice accumulation	Tilted or vertical solar panel installation to prevent snow coverage
Low solar irradiance in winter	Integration with wind power and battery storage for energy reliability
Remote and inaccessible terrain	Modular systems for easier transport and on-site assembly
Logistics and maintenance difficulties	Use of long-lifespan, low-maintenance components; remote monitoring
Limited daylight during polar night	Dependence on wind energy and high-capacity battery storage
Harsh UV and freeze-thaw cycles	Durable coatings and corrosion-resistant materials

Figure 2. Princess Elisabeth Station, with some of the solar PV panels and WTs that power it (Cheek et al., 2011)

tions and upholds Antarctica's role as a global scientific hub.

4 Technological innovations and future research

The adoption of renewable energy in Antarctica has been underpinned by technological advancements that address the unique challenges posed by the continent's environment. WTs and solar panels deployed in research stations are designed to withstand extreme cold, high winds, and ice buildup. For example, the turbines at Princess Elisabeth (Fig. 2) and Mawson stations are built to operate in temperatures as low as –40 °C and wind speeds up to 250 km · h^{-1}. These turbines use advanced materials and low-temperature lubricants to prevent ice accumulation, ensuring longevity and reliability.

Technological innovations in the realm of solar energy include bifacial solar panels, as shown in Figure 3, which capture sunlight from both sides, maximising energy production in high-albedo conditions. Additionally, dynamic solar installations are being tested to optimise energy generation, even when the sun is at low angles or during periods of cloud cover. Battery storage systems, a critical component of renewable energy infrastructure, have also improved. Modern battery technologies provide reliable storage solutions that can maintain power supply during periods of low wind or solar output, which is essential for continuous operation in such an unpredictable environment.

Moreover, intelligent energy management systems are employed to optimise the performance of hybrid energy systems that integrate solar, wind, and battery storage. These systems use real-time data to balance energy loads, maximising the use of available resources and reducing reliance on fossil fuels. By combining renewable generation with storage and smart energy distribution, these stations are moving closer to achieving sustainable and self-sufficient power solutions in Antarctica.

Reducing air pollution while increasing the use of renewable energy for power generation (Tin et al., 2010; Boccaletti et al., 2014) is in line with the global policy towards climate change. The goal is to reduce the reliance on diesel generators for electricity supply and, consequently, to decrease CO_2 emissions. However, power generation from renewable energy sources such as PV and WT is highly dependent on environmental conditions. In Antarctica, the weather changes dramatically with the seasons. The land receives very little sunshine during the winter and experiences rapidly fluctuating wind speeds. These uncertainties in weather data, such as solar irradiance, and load variations significantly impact the reliability of renewable energy power generation systems (Saad et al., 2019a; Mohd Saad et al., 2024), highlighting the need for advanced methods to achieve optimal planning. Artificial intelligence-based methods, particularly Monte Carlo embedded hybrid variant mean–variance, have been successfully used in the case study of tropical environments. Therefore, it is crucial to use an artificial intelligence method for optimal planning (appropriate location and size of renewable energy) in order to minimise mismatch power between power sources and loads and minimise power losses, while residual energy is stored (Ibrahim et al., 2010; Al-Shetwi & Sujod, 2018c; Saad et al., 2018; Akhtar et al., 2022).

In the future, we will analyse PV and WT distributed generation in a microgrid system with expected uncertainty patterns based on one year's

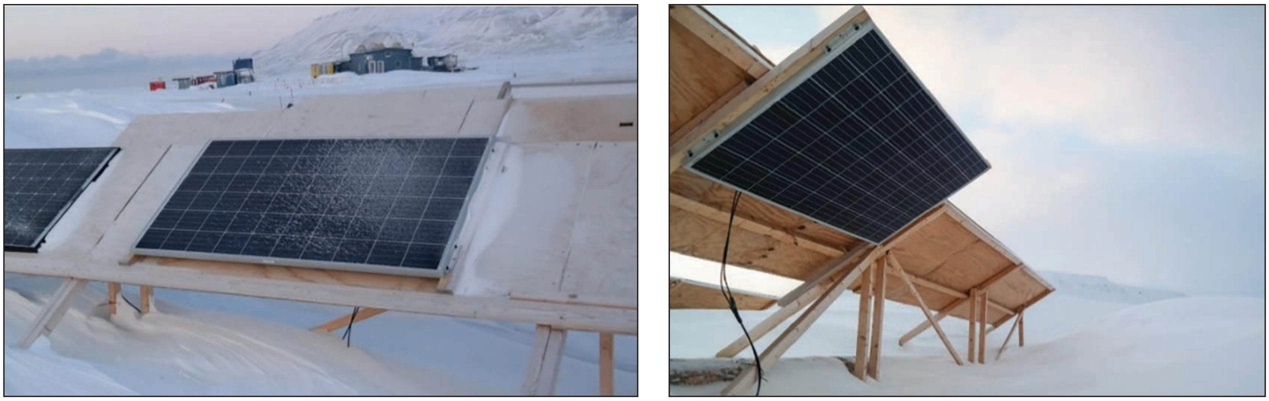

Figure 3. Module installation with a sky-facing module (left) and a ground-facing module (right). The modules are lifted 2 cm from the wooden surface to allow for ventilation (Frimannslund et al., 2021)

worth of environmental data. For distributed generation planning, the optimisation framework using a Random Forest Regression Algorithm (RFR) embedded with a Grey-Wolf Optimiser (GWO) is proposed. The distribution load flow analysis for the radial distribution network will use PV and WT generation fluctuations as input data in 24-time segments. When the variability of PV and WT generation is taken into account in the power flow algorithm, the load flow patterns will be impacted. The method will be tested on the standard IEEE (Institute of Electrical and Electronics Engineers) radial test system before being implemented in an actual microgrid system. The optimal planning using the proposed artificial intelligence framework in the islanded microgrid system will identify the appropriate location and size of the distributed generation while optimising electricity use.

4.1 Random Forest Regression for weather prediction

One commonly used prediction algorithm is Random Forest Regression (RFR) (Hewage et al., 2021; Meenal et al., 2021; Călin et al., 2023). RFR is selected for weather prediction in our planned future research due to its robustness, ability to handle complex datasets, and proven success in renewable energy applications (Khalyasmaa et al., 2019; Sathyaraj & Sankardoss, 2024). RFR is a machine learning method that uses an ensemble of decision trees to model relationships between input variables and target outputs. This approach is particularly effective for predicting weather patterns in Antarctica, where uncertainties in solar irradiance, wind speed, and temperature significantly impact the performance of the renewable energy system.

Compared to other prediction methods, such as linear regression or neural networks, RFR offers several advantages:

a) High accuracy and robustness:

RFR has demonstrated exceptional accuracy in capturing nonlinear relationships and interactions within meteorological datasets. For example:

Solar irradiance prediction: Meenal et al. (2021) applied a random forest machine learning model to predict global solar radiation and wind speed in Tamil Nadu, India. The model outperformed statistical regression models and Support Vector Machines, achieving a mean squared error (MSE) of 0.750 and an R^2 score of 0.97, indicating high accuracy in weather parameter prediction.

Wind speed forecasting: Sathyaraj and Sankardoss (2024) reported that RFR achieved superior performance in wind speed prediction due to its ability to minimise overfitting and generalise well across unseen data.

b) Capability to handle missing and noisy data:

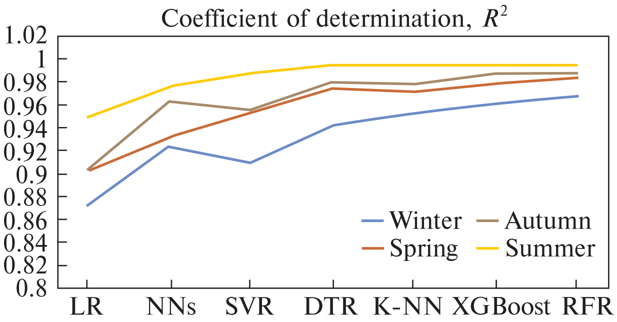

Figure 4. Wind speed forecasting accuracy (Sathyaraj & Sankardoss, 2024)

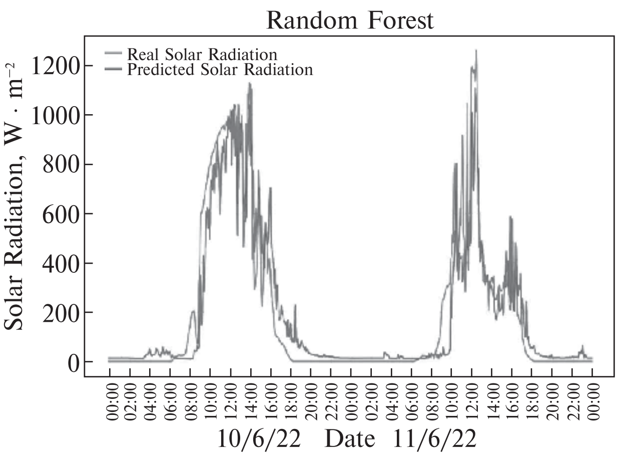

Figure 5. Comparison between real and predicted solar radiation using random forest (Segovia et al., 2023)

Antarctic weather datasets often contain missing values or noise due to extreme conditions and limited measurement infrastructure. RFR is inherently robust to such issues, as it averages results from multiple decision trees, thereby mitigating the impact of anomalies.

c) Feature importance analysis:

RFR provides insights into the relative importance of input features, such as temperature, wind speed, and humidity, enabling researchers to identify key contributors to weather variability. This capability aids in developing more accurate and interpretable prediction models.

d) Scalability and efficiency:

RFR is computationally efficient and scalable to large datasets, making it suitable for Antarctic applications where detailed weather modeling over extended periods is essential.

e) Proven success in renewable energy applications:

The study by Meenal et al. (2021) demonstrates the effectiveness of Random Forest Regression (RFR) in predicting weather parameters such as global solar radiation and wind speed. This highlights RFR's capability to model complex, nonlinear relationships inherent in meteorological data, making it suitable for weather prediction in renewable energy applications.

A study by Sathyaraj and Sankardoss (2024) aimed to investigate wind speed forecasting using the Supervisory Control and Data Acquisition dataset in Turkey and segregated it into four seasonal wind datasets. The wind speed forecasting analysed different machine-learning models, such as neural networks (NNs), linear regression (LR), support vector regression (SVR), decision tree regression (DTR), K-nearest neighbors (K-NN), extreme gradient boosting regression, and RFR. Evaluation metrics, including normalised mean squared error (NMSE), mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) were used to measure the accuracy of the machine learning models. Among these, the RFR model demonstrated lower errors, particularly in RMSE and MAE values, and achieved a higher R^2 score, indicating better predictive accuracy and model fit compared to alternative methods such as SVR and K-NN. For example, RFR showed an R^2 increase of 0.04 over SVR in forecasting winter wind speeds. Figure 4 shows the wind speed forecasting accuracy, where RFR presented the highest accuracy.

Additionally, Segovia et al. (2023) studied the forecasting of meteorological variables using data from the Parque de la Familia Baños meteorological station in Ecuador. The following prediction techniques were tested: multiple linear regression, polynomial regression, decision tree, random forest, extreme gradient boosting (XGBoost), and multilayer perceptron neural network. Random forest presented a better result in R^2, MAE, and RMSE compared with the other prediction techniques for forecasting solar radiation and wind speed variables. Figure 5 shows the comparison between real and predicted solar radiation using random forest.

While methods like artificial neural networks and deep learning excel in handling large and complex datasets, they require extensive training. They are computationally intensive, which may not be practical for Antarctic field applications. Additionally, linear models fail to capture the nonlinear dynamics of weather conditions, reducing their effectiveness. By selecting RFR, this study leverages a proven, efficient, and interpretable machine-learning algorithm to provide reliable weather predictions.

In our planned future research, the required parameters are solar irradiance, wind speed, temperature, humidity, etc. Data collection is done in Antarctica. Data preprocessing handles missing entries, normalises the data, and then adopts feature engineering to combine variables and create time-related features. It selects the features for the model, such as wind speed, solar irradiance, temperature, etc., and eliminates other features. Data is split into training and testing sets. The RFR model is proposed to define the number of trees in the forest (n-estimator) and the maximum depth of the trees and configure the hyperparameters. The model uses the training data to train itself and validates the data by cross-validation techniques to avoid overfitting. The next phase is model evaluation and tuning, where the model's performance is tested on new data using metrics such as RMSE, R^2 score, and MAE to assess its accuracy and reliability. Then, the model fine-tunes hyperparameters, such as random search or grid search, to improve efficiency and performance. The trained model predicts the output parameters of solar PV and WT, such as solar irradiance, wind speed, and power generation. The RFR is for real-time predictions. The RFR model is continuously monitored and updated (Babar et al., 2020; Chauhan et al., 2022). The flow chart of RFR is shown in Figure 6.

4.2 Grey Wolf Optimisation for optimal sizing and placement of power plant

Grey wolf optimisation is a meta-heuristic algorithm that was developed by Mirjalili et al. (2014). Meta-heuristic techniques are bio-inspired optimisation techniques for single- or multi-objective complex nonlinear problems (Jafar-Nowdeh et al., 2020; Shami et al., 2022). GWO promises optimised generation planning for multiple objective functions as compared to other meta-heuristic techniques based on fixed load and renewable energy inputs (Radosavljević et al., 2020; Shadman Abid et al., 2022).

GWO was chosen for this future research due to its effectiveness in handling optimisation problems characterised by nonlinear, multidimensional, and constrained parameters, which are common in renewable energy system design. GWO is inspired by the natural leadership hierarchy and hunting behavior of grey wolves, providing a balance between exploration (global search) and exploitation (local search) of the solution space. This balance is crucial for achieving optimal siting and sizing of renewable energy resources under Antarctica's unique and challenging environmental conditions.

Compared to other optimisation techniques, such as particle swarm optimisation and deep reinforcement learning, GWO has several distinct advantages:

a) Simplicity and fewer parameters:

GWO is computationally less intensive due to its straightforward structure and requires fewer control parameters than particle swarm optimisation and deep reinforcement learning. This makes it particularly suitable for Antarctic applications, where computational resources may be limited.

b) Global search capability:

The leader-following mechanism in GWO allows the algorithm to effectively explore the solution space and avoid premature convergence to local optima, which can be a drawback of particle swarm optimisation.

c) Adaptability and robustness:

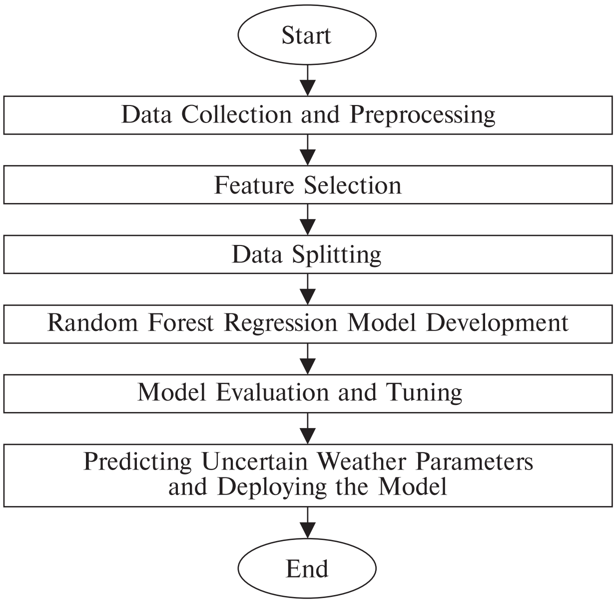

Figure 6. Random Forest Regression flow chart for weather prediction of solar PV and WTs

GWO has been successfully applied in various fields, including renewable energy systems. For instance:

Solar and wind hybrid system optimisation: Research by Mirjalili et al. (2014) demonstrated GWO's efficiency in solving hybrid system optimisation problems, achieving better convergence rates than particle swarm optimisation.

Microgrid design: Studies have shown that GWO is highly accurate in determining the optimal renewable energy mix, outperforming other evolutionary algorithms.

d) Ease of integration with predictive models:

GWO seamlessly integrates with predictive models such as random forest regression, enabling it to account for uncertainties like weather conditions in Antarctica, which is essential for reliable renewable energy deployment.

In contrast, while powerful, deep reinforcement learning requires significant training data and computational resources, making it less practical for this study's scope. Similarly, though widely used, particle swarm optimisation is prone to stagnation in complex optimisation landscapes, which GWO effectively mitigates. By leveraging GWO's strengths, this study aims to ensure efficient and reliable renewable energy generation in Antarctica, supporting both environmental sustainability and energy resilience.

The GWO is proposed for optimal sizing and placement of the solar PV and WTs with batteries energy storage system for minimising total system power losses, distributed generation cost, levelised cost of energy ($/kWh), net present value, and life cycle cost with sensitivity analysis. The process flowchart of the GWO is shown in Figure 7. In this algorithm, A and C represent coefficient vectors that influence the search process. The optimisation process is guided by three "leading wolves" (α, β, and δ), which are responsible for detecting the optimal solution (analogous to prey in nature) and directing the search. The remaining search agents (other "wolves") adjust their positions based on the guidance of these leaders, gradually converging toward the best solution.

Based on the GWO algorithm, the optimisation framework is proposed to minimise the active power loss index under equality and inequality constraints. Standard IEEE radial distribution systems will be employed to test the proposed method. The PVWT generation uncertainty will be investigated using RFR in 33-bus and 69-bus RDN systems for optimally planning the distributed generation in the microgrid islanded mode network for power loss minimisation. Performance evaluations of the proposed method are restricted to voltage stability, power loss minimisation, the active power loss index, and convergence rates. A new optimisation framework will be created based on Figure 8 to optimise power flow for power loss minimisation in radial distribution systems (Saad et al., 2019b).

4.3 Our planned future research — renewable energy-based power generation in Horseshoe Island

In this project, our team from Malaysia has started a collaboration with the TÜBİTAK Polar Research Institute, where a renewable energy-based microgrid power generation system is proposed. The study focuses on Horseshoe Island, which currently has facilities for the Turkish station, including a weather monitoring station and a few camp buildings. The electricity supply is currently generated from diesel generators. Turkey has plans to construct a permanent base on Horseshoe Island, equipped with a renewable energy-based microgrid system, to accommodate approximately 50 people (Varetto, 2021). The goal is to reduce the reliance on diesel generators for electricity supply and, consequently, to decrease CO_2 emissions. However, power generation from renewable energy, such as PV and WT, is highly dependent on environmental conditions. Due to the harsh environment in Antarctica, weather conditions can change dramatically with the seasons. It receives very little sunshine during the winter and experiences rapidly fluctuating wind speeds. Therefore, it is crucial to use an artificial intelligence method for optimal planning (appropriate location and size of renewable energy), to minimise mismatch power between power sources and loads, and minimise power losses while residual energy is injected into storage energy.

The study will analyse distributed generation in a microgrid system with expected PV and WT generation uncertainty patterns based on four years of collected data on solar radiation and wind speed. For planning, the optimisation framework

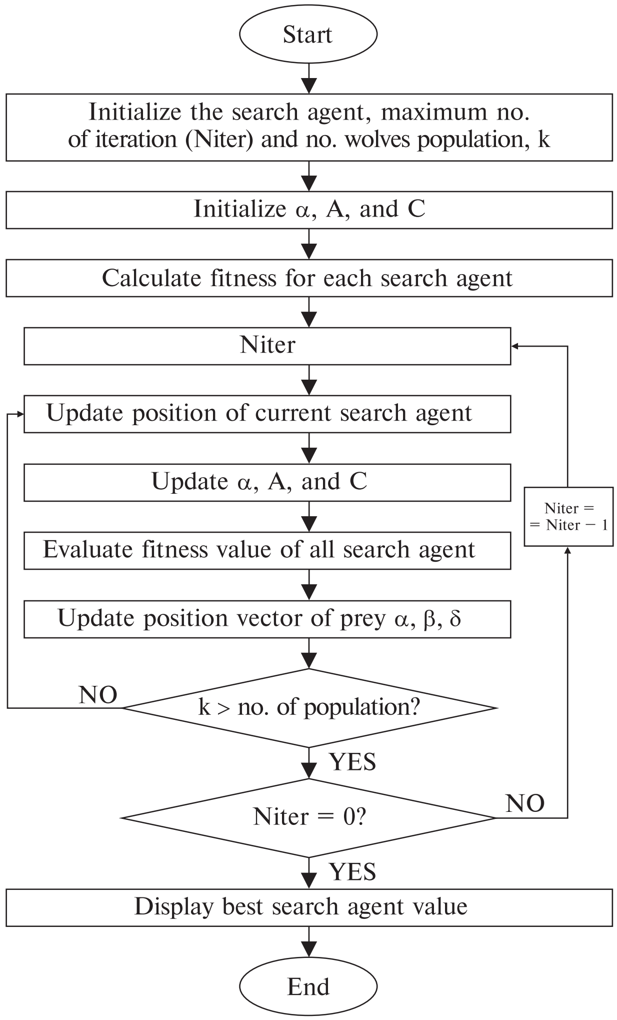

Figure 7. Process flow of GWO

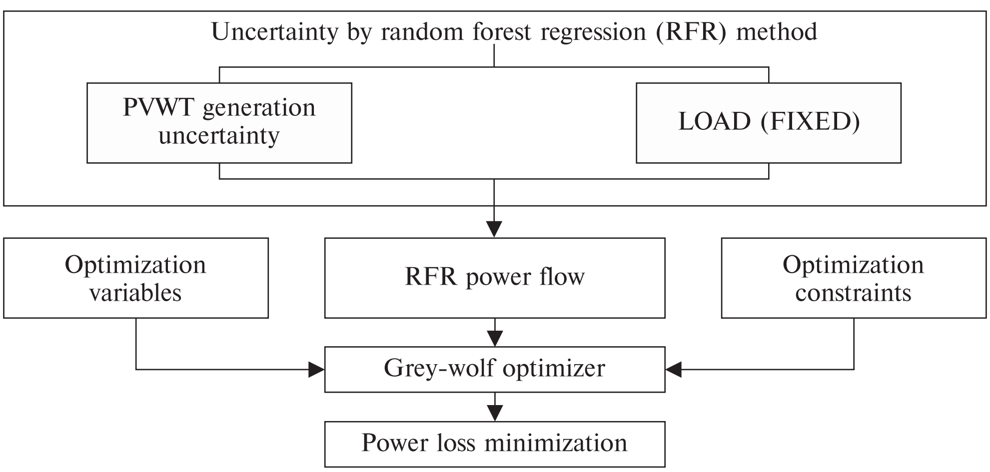

Figure 8. Flow chart of the proposed optimisation methodology

using a Random Forest Regression algorithm with an embedded grey-wolf optimiser is proposed. The distribution load flow analysis for the radial distribution network will use PV and WT generation fluctuations as input data in 24-time segments. When the PV and WT generation variability is considered in the power flow algorithm, the load flow patterns will be impacted. The proposed method will be tested on the standard IEEE radial test system before being implemented in the designed microgrid system. Optimal planning using the proposed artificial intelligence framework in the microgrid islanded system will identify the appropriate location and size of distributed generation while optimising electricity use.

4.3.1 Expected future load profiling at the Turkish Antarctic Research Station

The expected future load profile is required to design the hybrid solar system with battery storage. The expected future load profile for 50 personnel at the station is given in Table 3. The total power demand is 162.1 kW, and the total energy demand is 1404.4 kWh.

4.3.2 Weather data of Horseshoe Island

Wind speed, solar irradiance, and temperature affect the generation supply of solar PV and wind turbines. The station recorded uncertain weather data in the harsh environment at Horseshoe Island for solar PV and wind turbines. The recorded data provided by the Turkish meteorological station is for 4 years (2020–2023). It contains hourly wind speed, wind direction, global solar irradiance, temperature, sunshine hours, humidity, etc.

The solar irradiance, wind speed, and temperatures for 2020, 2021, 2022, and 2023 are plotted and shown in Figure 9.

From the above graphs, the maximum solar irradiance annually is 900 Watts $\cdot$ m^{-2}, and the minimum solar irradiance is 110 Watts $\cdot$ m^{-2}. The maximum average wind speed recorded in a year is 7.5 m $\cdot$ s^{-1}, and the minimum average wind speed is 4.3 m $\cdot$ s^{-1}. The maximum temperature recorded is 4 °C and the minimum is −10 °C. These

Table 3. Expected future load profile for the Turkish Antarctica Research Station

No.	Load Profiling for 50 Persons					
	Appliance Name	Power Rating (W)	Total No. of Appliances' Units	Total kW	Daily Hour Usage	Total Energy in kWh per day
1	Electric Lighting	100	50	5	20	100
2	Microwave	1200	7	8.4	4	33.6
3	Electric stove	1500	7	10.5	8	84
4	Water heaters	2000	12	24	8	192
5	Electric Space Heaters	1300	14	18.2	24	436.8
6	Computers and Laptops	300	50	15	7	105
7	Electric Oven	3000	10	30	7	210
8	Kettle	1500	20	30	6	180
9	Iron	1500	5	7.5	3	22.5
10	Blender	1500	5	7.5	3	22.5
11	Washing Machine	2000	3	6	3	18
Total kW demand		162.1				
Total Energy in kWh demand		1404.4				

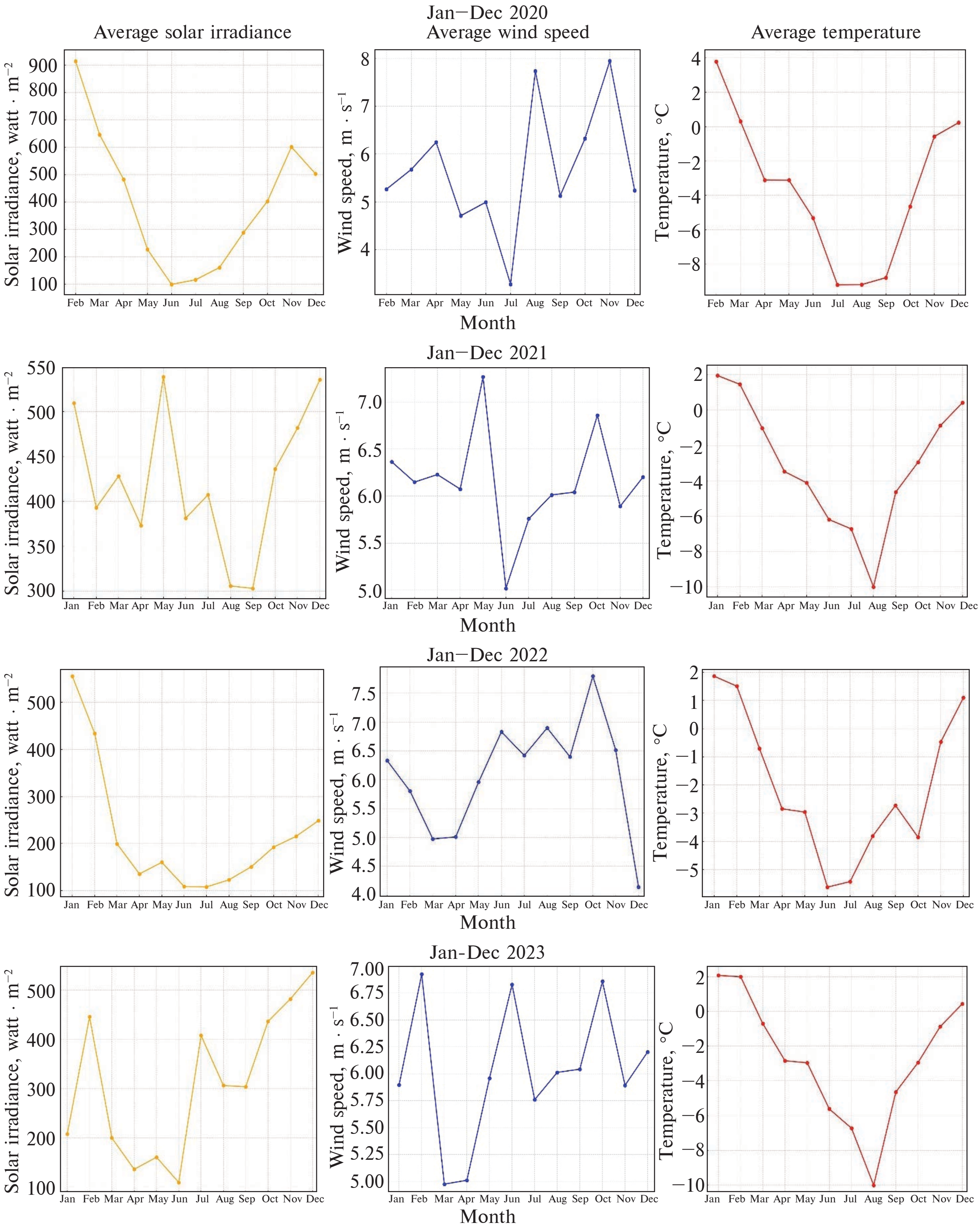

Figure 9. Solar irradiance, wind speed, and temperature at the Turkish Antarctic Research Station (TARS)

weather data indicate the potential for power generation using a hybrid wind turbine and solar PV system. Additionally, an artificial intelligence strategy is employed for optimal planning, ensuring the appropriate location and sizing of the WT and PV, as well as maximising energy utilisation.

Based on initial data analysis, it is required to design at least double the required power/energy in station as per the load profile, 162.1 kW. Because the efficiency of renewable energy mostly depends upon weather conditions, which are uncertain in Horseshoe Island, a comprehensive study is needed to increase the efficiency of the installed renewable energy hybrid system in the region. The solar PV output varies due to shorter daylight hours, lower insolation, snow cover, and temperature. The wind turbine faces ice formation, low wind speeds, or mechanical issues. Furthermore, the battery storage energy must be at least double the output power of solar PV and wind turbines.

Therefore, a hybrid energy system of PVWT supported by a battery energy storage system of 324.2 kW (twice the power demand) is proposed. An example of the design configuration includes 300 kW of wind turbines, 30 kW of solar PV, and a 200-kWh lithium-ion battery energy storage system, providing an 8-hour daily backup. A comprehensive design is essential and will be proposed and discussed in detail in the next article.

5 Conclusion

This review has explored the current landscape of renewable energy deployment in Antarctica, highlighting the critical role of sustainable energy solutions in addressing the region's energy needs. While several research stations have adopted renewable technologies such as WTs and solar panels, fossil fuels still dominate energy generation across much of the continent. The integration of renewables is challenged by Antarctica's extreme weather conditions, logistical complexities, and technological limitations.

Despite these obstacles, technological innovations, including advances in solar panel design, WT engineering, and battery storage, have improved the efficiency and reliability of renewable energy systems. Hybrid energy systems that combine multiple renewable sources with intelligent energy management strategies are emerging as the most promising solution to reduce dependence on fossil fuels.

In addition, optimisation techniques like Random Forest Regression for weather prediction and Grey Wolf Optimisation for optimal sizing and placement of energy sources offer new pathways for overcoming the challenges posed by Antarctica's harsh environment. These methods can significantly improve system design, ensuring that renewable energy systems are tailored to the specific conditions of each research station.

Looking ahead, further research is needed to refine these technologies and develop more resilient energy infrastructures. Expanding renewable energy in Antarctica could not only reduce the carbon footprint of scientific research but also serve as a model for sustainable energy solutions in other extreme environments. With continued innovation, there is potential for renewable energy to eventually replace fossil fuels, aligning with global sustainability goals and preserving the pristine Antarctic ecosystem for future generations.

Data availability. The data that supports the findings of this study are available from the corresponding author upon reasonable request. Weather data for Horseshoe Island were provided by the TÜBİTAK Polar Research Institute and the Turkish State Meteorology Service under data-sharing agreements.

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Відновлювана енергетика в Антарктиді: дорожня карта для розрахунків оптимального обсягу, розміщення та прогнозу невизначеності з використанням ШІ-технологій

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Реферат. Виробництво енергії в Антарктиді, найвіддаленішому від інших місці на Землі з найекстремальнішими природними умовами, обтяжене унікальними складнощами через суворий клімат, ізоляцію та логістичні обмеження. Дослідницькі станції, що є дуже важливими для просування глобального розуміння змін клімату, гляціології, екосистем та довкілля, довгий час повністю залежали від енергії з викопного палива, що створює значні ризики як з точки зору логістики, так і довкілля, дорого коштує та є спірним з точки зору етики використання в такому чистому середовищі. Стаття оглядає сучасне впровадження відновлюваної енергії в Антарктиді; в центрі уваги — станції «Принцеса Елізабет», МакМердо та інші, на яких запровадили енергосистеми, що працюють від сонячної або вітрової енергії або використовують обидва джерела. Обговорення охоплює найбільші перепони на шляху до переходу на відновлювальну енергетику, зокрема, екстремальні погодні умови, коливання температури, проблеми з надійністю обладнання, сезонна мінливість енергії та технологічні обмеження обсягів енергії, яку можна отримати та зберегти. У відповідь на ці виклики стаття досліджує потенціал розвинених обчислювальних та ШІ-методик для підсилення планування подібних енергосистем в Антарктиді. Окрім того, увага приділена новітнім можливостям для покращення ефективності та надійності відновлюваної енергетики шляхом інтегрування просунутих технологій (таких як Grey Wolf Optimisation для розрахунку оптимального місця встановлення виробничих потужностей, Random Forest Regression для передбачення погоди та інновації у гібридних системах, що поєднують сонячну та вітрову енергію). Результати підкреслюють критичну потребу в технологічному поступі та міжнародному співробітництві з турецьким Інститутом Полярних досліджень для покращення енергостійкості в антарктичному регіоні і зокрема на острові Хорсшу. Дослідження пропонує рекомендації для подальших наукових напрямків, включно із запровадженням робастних прогнозних систем, що керуються вхідними даними, та високоефективних технологій зберігання енергії. Ці стратегії націлені на підтримку повного переходу антарктичної енергетичної інфраструктури на відновлювані джерела, що відповідає невідкладним глобальним цілям по зменшенню викидів вуглецю та імперативі захистити одну з найвразливіших екосистем Землі.

Ключові слова: відновлювана енергія Антарктиди, енергоефективність, оптимізація сірого вовка, регресія випадкового лісу, сонячна фотоелектрична та вітрова енергетика, технологічні інновації