CLEAN RESOURCES FINAL REPORT PACKAGE

Project proponents are required to submit a Final Report Package, consisting of a Final Public Report and a Final Financial Report. These reports are to be provided under separate cover at the conclusion of projects for review and approval by Alberta Innovates (AI) Clean Resources Division. Proponents will use the two templates that follow to report key results and outcomes achieved during the project and financial details. The information requested in the templates should be considered the minimum necessary to meet AI reporting requirements; proponents are highly encouraged to include other information that may provide additional value, including more detailed appendices. Proponents must work with the AI Project Advisor during preparation of the Final Report Package to ensure submissions are of the highest possible quality and thus reduce the time and effort necessary to address issues that may emerge through the review and approval process.

Final Public Report

The Final Public Report shall outline what the project achieved and provide conclusions and recommendations for further research inquiry or technology development, together with an overview of the performance of the project in terms of process, output, outcomes and impact measures. The report must delineate all project knowledge and/or technology developed and must be in sufficient detail to permit readers to use or adapt the results for research and analysis purposes and to understand how conclusions were arrived at. It is incumbent upon the proponent to ensure that the Final Public Report **is free of any confidential information or intellectual property requiring protection**. The Final Public Report will be released by Alberta Innovates after the confidentiality period has expired as described in the Investment Agreement.

Final Financial Report

The Final Financial Report shall provide complete and accurate accounting of all project expenditures and contributions over the life of the project pertaining to Alberta Innovates, the proponent, and any project partners. The Final Financial Report will not be publicly released.

CLEAN RESOURCES FINAL PUBLIC REPORT

1. PROJECT INFORMATION:

Project Title:	Machine Learning Identification of Real-Time Wind Direction and Velocity from a Novel Anemometer Integrated into a Emission Mass Flowmeter
Alberta Innovates Project Number:	232404459
Submission Date:	TBD
Total Project Cost:	$679,550
Alberta Innovates Funding:	$250,000
AI Project Advisor:	Amanda Mitchell

2. APPLICANT INFORMATION:

Applicant (Organization):	EmMea Inc.
Address:	2360 Portland St. SE, Calgary, Alberta, T2G 4M6
Applicant Representative Name:	Willow Liu
Title:	Founder, Chief Scientist
Phone Number:	(514)-653-0188
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3. PROJECT PARTNERS

Please provide an acknowledgement statement for project partners, if appropriate.

RESPOND BELOW

We would like to express our sincere appreciation to Adfast in Quebec, Canada, for their invaluable cooperation throughout this project. Their support—particularly in providing access to their facilities and operational resources—has been essential in enabling the successful testing and validation of our novel anemometer.

EXECUTIVE SUMMARY

Provide a high-level description of the project, including the objective, key results, learnings, outcomes and benefits.

RESPOND BELOW

The EmMea project, Machine Learning Identification of Real-Time Wind Direction and Velocity from a Novel Anemometer Integrated into an Emission Mass Flowmeter, set out to address a longstanding challenge in the emissions-measurement industry: the lack of accurate, real-time, site-specific atmospheric data. Most existing devices depend on delayed or averaged wind information from third-party sources or basic anemometers, which significantly limits the accuracy of dispersion modeling and greenhouse gas (GHG) quantification. To resolve this, the project introduced a novel hardware-based anemometer intake system integrated directly into EmMea's emission mass flowmeter, coupled with a machine-learning–enhanced digital twin designed to compute wind velocity and direction under real environmental conditions. The core objective was to develop and validate an innovative AI-enhanced wind-measurement system that could operate reliably in the field and support mobile or remote GHG monitoring applications.

Over 16 months, the project progressed from TRL-6 to a validated field-ready prototype through four structured milestones to a final TRL of 7. A major accomplishment was the deployment of 11 fully instrumented units on the rooftop of Adfast's manufacturing facility in Montreal, where they collected more than 10 months of real-world environmental data across winter, spring, summer, and early fall. Each device recorded differential pressure, temperature, humidity, and atmospheric trends every 10 seconds, generating a robust, high-resolution dataset far more representative than anything obtainable in a wind tunnel or simulated laboratory environment. This field data became the cornerstone for training and validating the machine-learning algorithms that underpin the system's wind-profile calculations.

In parallel, the project team developed a detailed computational fluid dynamics (CFD) model of the internal flow behavior inside the anemometer intake chamber. These simulations provided a physics-based understanding of how differential pressure responds to varying wind speeds and angles, especially at lower velocity ranges where measurement sensitivity is critical. The CFD model formed the basis of a larger digital twin that supported algorithm validation and provided essential computational guidance for subsequent Physics-Informed Neural Network (PINN) development.

Together, the field dataset and digital twin created a dual foundation of experimental and simulated truth data that accelerated machine-learning improvement throughout the project.

One of the most innovative components of the project was the creation of an Extended Kalman Filter (EKF) and neural-network algorithm. Classical EKF approaches assume Gaussian noise and struggle with unpredictable wind-gust behavior, which introduces high-frequency disturbances that violate linearization assumptions. By embedding a neural-network gust-denoising module into the EKF loop, the system learned to identify and filter out transient gust effects before they could distort the state-estimation process. This fusion of physics-based filtering and data-driven noise suppression resulted in a more stable and accurate wind-vector reconstruction, even under turbulent outdoor conditions.

The algorithm was deployed in three major phases. Initial Phase 0 results produced a wind-velocity discrepancy of 14.88% and a directional discrepancy of 21.9° compared with Environment and Climate Change Canada (ECCC) reference data. As more field data became available and as two successive neural-network training cycles were completed, Phase 1 and Phase 2 algorithms were deployed in July and August. These updates significantly improved accuracy: wind-velocity error dropped to 9.97% and then to 4.82%, while wind-direction discrepancy improved from 21.9° to 11.1° and then to 8°. This demonstrated that the model's accuracy improves continuously with additional training data, validating the project's hypothesis that machine-learning models—when combined with physical constraints—can outperform traditional anemometry methods.

A major set of learnings emerged around optimal neural-network architecture. The project conducted systematic testing of neuron quantities, network depths, and convergence thresholds. This revealed that increasing neurons improved accuracy but at the cost of disproportionately longer training times—critical for a system designed for continuous long-term learning. After extensive benchmarking, the combination of 150 neurons, three hidden layers, and a convergence threshold of 1×10^{-5} was found to deliver the best balance of accuracy, convergence speed, and computational feasibility for edge deployment. This insight provides a clear architectural guideline for future model expansions and helps ensure long-term scalability.

The field campaign also generated important environmental learnings. Repeated measurement cycles showed that the orientation of the anemometer inlet has a major influence on data stability. When wind approached at roughly 90° or 270° relative to the intake, negative differential pressures or unstable readings occurred. By comparing results across seasons, the team confirmed that these anomalies were due to directional misalignment rather than hardware defects. Adjusting the inlet orientation toward the prevailing wind (approximately 260° North at the Montreal site) markedly reduced such artifacts. This discovery will inform recommended installation practices and future hardware revisions.

The outcomes of the project demonstrate that the AI-enhanced anemometer has advanced, technologically, towards commercial maturity. The system now provides accurate real-time wind measurements across temperatures from 0°C to +35°C and wind speeds up to 49 km/h. The technology has achieved Technology Readiness Level 7, with expectations to reach TRL 8 upon completing the full 12-month validation cycle and after external verification from Adfast, who has already committed to using the device for formal GHG reporting. The final integrated system combines hardware innovation, physics-based modeling, and machine-learning intelligence—creating a modern, scalable platform for atmospheric data capture.

From a broader impact perspective, the project delivers substantial benefits to Alberta and Canada's environmental-measurement landscape. By providing real-time, site-specific atmospheric data, the system allows for more accurate modeling of plume dispersion and more reliable quantification of intermittent or complex GHG emissions. This directly supports regulatory compliance, ESG reporting, and national climate-action objectives. The project has also strengthened Alberta's innovation ecosystem through new intellectual property, high-value technical jobs, and international recognition. The team's research has been featured at SPE GOTECH, ATCE, ADIPEC, OTC Brazil, and additional upcoming global conferences, demonstrating leadership in the emerging field of physics-informed AI for environmental monitoring.

Overall, the project successfully combined advanced sensing hardware, machine-learning algorithms, digital-twin simulation, and long-term field deployment to deliver a robust wind-measurement technology that stands ready for commercialization. The learnings from this initiative will continue to guide future enhancements, including PINN integration, extended field validation across additional climates, upgraded edge-computing hardware, and broader deployment across the emission-measurement sector.

A. INTRODUCTION

Please provide a narrative introducing the project using the following sub-headings.

- **Sector introduction:** Include a high-level discussion of the sector or area that the project contributes to and provide any relevant background information or context for the project.
- **Knowledge Gaps:** Explain the knowledge gap that is being addressed along with the context and scope of the problem.

RESPOND BELOW

Sector Introduction

Accurate measurement of greenhouse gas (GHG) emissions has become a critical priority across energy, manufacturing, agriculture, and industrial operations as governments and industries move toward net-zero commitments. In Canada—particularly in Alberta, where energy production and industrial activity are major economic pillars—regulators and operators increasingly rely on real-time emissions data to meet reporting obligations, design mitigation strategies, and demonstrate environmental performance. Central to nearly all emissions-measurement methodologies are the need for precise atmospheric information. Wind velocity and direction strongly influence plume dispersion, mass-flow estimation, and the calculation of intermittent or fugitive emissions. Traditional approaches often depend on meteorological stations located kilometers away or on basic low-cost anemometers that cannot capture rapidly changing site-specific atmospheric conditions. These limitations introduce uncertainty into emission estimates and reduce confidence in decision-making, especially for mobile emissions measurement, remote field deployments, or monitoring at complex industrial sites.

To address this sector-wide challenge, EmMea is developing a next-generation anemometer intake system integrated directly into its Emission Mass Flow Meter. This innovation incorporates hardware improvements with advanced machine-learning algorithms—specifically a hybrid Extended Kalman Filter (EKF) and neural-network–based computation system—to reliably estimate real-time wind velocity and direction under dynamic and often harsh environmental conditions. Supported by digital-twin simulations built from computational fluid dynamics (CFD), this project represents a major step forward in modernizing atmospheric data collection for GHG measurement. By enabling more accurate and localized wind profiling, the system enhances the reliability of environmental reporting, supports regulatory compliance, and contributes to cleaner operations across industrial sectors.

Knowledge Gaps

The core knowledge gap addressed by this project lies in the absence of reliable, real-time, and site-specific wind measurements that can be integrated directly into mass-flow-based emission quantification systems. Existing devices typically rely on averaged data obtained from weather stations or simple anemometers with limited accuracy, slow response to directional changes, and no capacity to correct for unpredictable wind-gust behavior. These shortcomings are particularly problematic in environments with turbulent flow, variable terrain, nearby structures, or complex plume-dispersion patterns, all of which are common in industrial settings.

Another fundamental gap involves the inability of traditional sensing systems to filter out high-frequency disturbances caused by transient wind gusts. Classical estimation methods assume Gaussian and stationary noise, which does not reflect real atmospheric variability. As a result, raw measurements become unstable, requiring excessive post-processing that reduces real-time decision-making capability. Furthermore, the scientific community has limited field-validated datasets linking differential-pressure intake behavior, local meteorological conditions, and computational fluid dynamics. Without this bridge between real behavior and physical modeling, emission-calculation frameworks remain dependent on simplified assumptions that introduce error into GHG mass-flow estimates.

This project directly addresses these knowledge gaps by combining long-term multi-season field data with a physics-informed digital twin and a hybrid EKF–neural network architecture tailored to suppress gust-induced noise and reconstruct accurate wind vectors. By deploying more than 11 units on an operational factory rooftop for extended monitoring, the project also fills an industry-wide void: the lack of comprehensive, real-world datasets capturing how sensor orientation, structural interference, ambient temperature, and humidity influence wind-profile estimation. Through this approach, the project not only advances scientific understanding but also delivers a scalable, practical solution capable of transforming atmospheric data reliability for emissions measurement and environmental monitoring across Alberta and beyond.

B. PROJECT DETAILS

Please provide a narrative describing the project using the following sub-headings.

- **Knowledge or Technology Description:** Include a discussion of the project objectives.
- **Updates to Project Objectives:** Describe any changes that have occurred compared to the original objectives of the project.

RESPOND BELOW

Knowledge or Technology Description

This project focuses on developing a next-generation atmospheric measurement system that integrates a novel anemometer intake with advanced machine-learning algorithms. The technology is designed to significantly improve the accuracy of real-time wind velocity and wind direction measurements used in greenhouse gas (GHG) mass-flow estimation. Because wind conditions directly influence plume dispersion and emission-rate calculations, improving atmospheric data quality enhances both regulatory reporting and operational decision-making for industrial facilities across Canada.

The project objectives were structured around advancing three core technological components. First, EmMea aimed to design an innovative anemometer intake system capable of capturing highly sensitive differential-pressure signals reflective of local wind profiles. Unlike conventional commercial anemometers, this system is embedded within the EmMea Emission Mass Flow Meter, enabling measurements to be taken directly at the emission point rather than relying on off-site meteorological stations.

Second, the project sought to develop a machine-learning–enhanced wind-calculation algorithm capable of operating under mobile, remote, and harsh atmospheric conditions. This required combining a neural-network-based gust-noise elimination module with an Extended Kalman Filter (EKF) and Physics Informed Neural Network (PINN) to form a hybrid estimator capable of interpreting rapidly changing atmospheric inputs. These algorithms were trained using a continuous stream of differential-pressure, temperature, and humidity data collected from rooftop installations at the Adfast facility and the historical data from the Environment and Climate Change Canada (ECCC).

Finally, a digital twin based on a digital twin based on computational fluid dynamics (CFD), project field data, and historical data from ECCC was developed to simulate flow conditions within the intake chamber. This model served as a reference to ensure that the machine-learning outputs remained grounded in physical laws, serving as a bridge between real-world measurements and fluid-dynamic theory. Together, these components form an integrated system designed to deliver precise, reliable wind information for real-time emissions measurement.

Updates to Project Objectives

While the original objectives of the project remained consistent throughout its duration, several strategic adjustments were made to improve scientific reliability, model robustness, and real-world applicability.

The most significant change involved shifting from controlled laboratory wind experiments to long-term field data collection. Early in the project, it became clear that replicating natural wind gusts, turbulence, and seasonal variability in a lab environment was insufficient for training a robust machine-learning model. As a result, the project transitioned to continuous outdoor data collection using 11 sensor units deployed on the Adfast rooftop. This modification enhanced model validity and resulted in a more comprehensive dataset spanning winter through fall.

Another refinement arose during machine-learning development. Initially, the project anticipated a simpler neural-network architecture. However, field data revealed that wind gusts created non-Gaussian noise patterns incompatible with classical EKF assumptions. To address this, the hybrid EKF–neural network framework was introduced and iteratively improved through multiple training phases. This shift allowed the wind-calculation algorithm to evolve toward higher performance, ultimately reducing velocity error from 14.88% to 4.82% and directional error from 21.9° to 8°.

Additionally, the project incorporated an expanded hyperparameter-optimization phase. Through systematic testing of neuron quantities, layer depths, and convergence thresholds, the team identified optimal configurations that balanced training efficiency with predictive accuracy, ensuring the system could be deployed on limited edge-computing hardware.

Finally, the original workplan envisioned completing all validation within a fixed timeline. As field data grew, the team extended the validation period into a full 12-month cycle to capture seasonal extremes—an enhancement that improved model generalization and increased the technology's readiness for commercialization.

Overall, while the core objectives remained intact, these updates strengthened the project's scientific foundation and elevated the final system beyond the original scope.

C. ACTIVITIES

Please provide a narrative describing the activities that were used to execute and complete the project. Use subheadings as appropriate.

RESPOND BELOW

The execution of this project followed a structured but adaptive process, evolving significantly as new insights emerged from both fundamental research and long-term field deployment. The first major activity involved the design and development of the novel anemometer intake system, which required careful engineering of the intake geometry, sensor placement, and pressure-measurement architecture. This stage included iterative CAD modeling, prototyping, and early bench testing to confirm that differential-pressure variations produced by airflow could be captured with sufficient sensitivity for downstream computation. Ensuring the hardware could withstand harsh environmental conditions—particularly winter temperatures and turbulent wind exposure—was a critical part of the early development work.

In parallel with the hardware design, EmMea developed a high-fidelity computational fluid dynamics (CFD) model to simulate airflow patterns inside the intake chamber. Creating this digital twin required defining boundary conditions, modeling the internal geometry, and simulating wind speeds and directions across a broad range. These simulations revealed how pressure distributions behaved under controlled velocities, providing a physics-based reference for validating early versions of the machine-learning algorithm. The digital twin helped bridge the gap between theoretical fluid-dynamics principles and real-world sensor behavior, laying the groundwork for the project's physics-informed AI components.

As the project advanced, it became clear that wind simulation in a laboratory or controlled environment could not accurately replicate natural wind gusts and seasonal variability. For this reason, one of the most important execution decisions was to transition the project from simulation to long-term field measurement. A total of 11 prototype units were installed on the rooftop of the Adfast manufacturing facility in Montreal. Each unit collected differential pressure, temperature, humidity, and ambient wind data every 10 seconds. Activities during this phase included mounting, orienting, calibrating, and maintaining each device, along with establishing reliable data-logging procedures synchronized with Environment and Climate Change Canada (ECCC) reference data. This deployment ultimately produced over ten months of high-resolution atmospheric data across winter, spring, summer, and fall—far exceeding what could be achieved through artificial wind generation.

Using this extensive dataset, the project team developed a hybrid machine-learning system combining an Extended Kalman Filter (EKF) with a neural-network gust-denoising module. Algorithm development included network design, training on both historical and real-time data, integrating the neural network into the EKF loop, and deploying multiple generations of the algorithm—Phase 0, Phase 1, and Phase 2—onto the rooftop units. Each deployment was followed by direct comparison against ECCC meteorological data to measure improvement. This iterative approach reduced wind-velocity error from 14.88% to under 5%, and wind-direction error from 21.9° to 8°, demonstrating the effectiveness of the hybrid approach. A significant part of this effort also involved hyperparameter optimization, where various neuron counts, layer depths, and convergence thresholds were tested to balance accuracy with computational efficiency. This process ultimately identified a configuration of 150 neurons, three layers, and a 1e-5 convergence threshold as the optimal architecture for the device's limited on-board computing capacity.

Another essential activity was the integration of the wind-calculation algorithm into the EmMea Emission Mass Flow Meter firmware. This step required merging real-time wind estimation with the device's existing mass-flow measurement processes, ensuring the system remained stable under continuous computation. Field testing under this integrated configuration enabled the team to evaluate algorithmic performance under real operational loads, including the influence of device heating, real-time sensor polling, and communication bandwidth constraints.

Multi-season field validation formed the final technical component of the project. This stage involved continuous comparison of model predictions with reference meteorological data, detailed analysis of anomalies such as negative pressure readings during crosswind events, and identification of the influence of inlet orientation. Through this analysis, the team discovered that misalignment with prevailing wind directions caused predictable pressure inversions, leading to the recommendation to adjust the inlet orientation toward approximately 260° North for future deployments. This insight contributed not only to algorithm refinement but also to hardware deployment guidelines for commercial use.

Throughout the project, EmMea also conducted extensive communication and dissemination activities, including presenting results at major industry conferences such as SPE ATCE, ADIPEC, and OTC. These engagements helped validate the project's relevance within the broader emissions-measurement community and built momentum for commercialization. The final phase of the project involved consolidating performance data, validating Technology Readiness Level (TRL) progression, completing KPI assessments, and preparing the integrated system for near-commercial readiness. With demonstrated robustness across multi-season conditions, the technology successfully reached TRL 7, with the expectation of achieving TRL 8 upon completing the full 12-month validation cycle and receiving external verification from Adfast.

D. PROJECT RESULTS

Please provide a narrative describing the key results using the

- Describe the importance of the key results.

RESPOND BELOW

The project delivered several significant technical and operational results that collectively advanced the development of a next-generation atmospheric measurement system. One of the most notable achievements was the successful deployment of 11 prototype units on the rooftop of the Adfast manufacturing facility, where more than ten months of continuous, high-frequency environmental data were collected across four seasons. This dataset—capturing real-world temperature ranges, humidity fluctuations, wind-speed variability, and gust behavior—provided a foundation far richer and more representative than any laboratory-generated data. Its importance lies in the fact that real-world emissions monitoring depends on dynamic and unpredictable atmospheric conditions, and the ability to train algorithms on true environmental variability is essential for reliable performance in field deployments.

Another key result was the development and refinement of a hybrid Extended Kalman Filter (EKF) combined with a neural-network gust-denoising module. Over three algorithmic phases, discrepancies in wind-velocity estimation were reduced from 14.88% to just 4.82%, while wind direction discrepancies were reduced from 21.9° to 8°. These improvements demonstrate not only technical progress but also validate the project's central hypothesis: that machine learning, when combined with physics-based modeling, can outperform conventional anemometer technologies. The importance of this result is substantial because accurate, real-time atmospheric data directly influence emission rate calculations, plume modeling, and regulatory reporting. Reducing error margins even by a few percentage points can significantly improve the reliability of GHG quantification, particularly for intermittent or small-scale emissions where uncertainty is traditionally high.

The project also generated a high-fidelity computational fluid dynamics (CFD) model, forming the basis of a robust digital twin that serves as both a validation tool and a physics-informed training reference for future neural-network iterations. Its importance is twofold: first, it provides a scientifically grounded benchmark that helps ensure the machine-learning predictions remain aligned with physical laws; and second, it offers a scalable path for expanding the technology into more complex atmospheric conditions or future product lines without requiring extensive field re-testing.

Another critical result was the systematic optimization of machine-learning hyperparameters. By evaluating the performance impact of varying neuron counts, network depths, and convergence thresholds, the project identified an optimal network structure that balances accuracy with computational efficiency—150 neurons, three layers, and a 1e-5 convergence threshold. This finding is particularly important given that the anemometer is designed for remote or embedded use, where computing resources are limited. The optimized architecture enables continuous algorithm retraining and long-term deployment without overloading the device hardware, ensuring practical scalability for commercial use.

Lastly, the field tests produced important insights into how installation orientation affects measurement accuracy, revealing that misalignment with prevailing wind directions can lead to pressure inversions and distorted readings. This result has immediate operational importance: it informs installation best practices, guides future hardware improvements, and enhances the reliability of the device across diverse deployment environments.

Collectively, these key results strengthened the scientific foundation of the system, validated its field readiness, and significantly elevated its Technology Readiness Level. The outcomes not only demonstrate technical success but also position the EmMea system as a transformative tool in GHG monitoring, capable of supporting Alberta’s broader climate objectives by improving the accuracy, resolution, and reliability of emissions measurement.

E. KEY LEARNINGS

Please provide a narrative that discusses the key learnings from the project.

- Describe the project learnings and importance of those learnings within the project scope. Use milestones as headings, if appropriate.
- Discuss the broader impacts of the learnings to the industry and beyond; this may include changes to regulations, policies, and approval and permitting processes

RESPOND BELOW

Milestone 1–2: Foundational Learnings and Early Model Development

Early in the project, the team learned that laboratory-generated wind patterns were insufficient for developing a robust wind-measurement algorithm. Although initial testing envisioned using simulated wind environments and controlled bench setups, it quickly became clear that natural wind gusts, turbulence, and seasonal variation were impossible to replicate meaningfully indoors. This realization led to a critical pivot from lab-based experiments to long-term outdoor field deployment at the Adfast rooftop. The importance of this learning cannot be overstated: machine-learning algorithms require wide-ranging environmental variability to generalize well, and had the project relied solely on simulated data, the final system would lack accuracy, resilience, and operational credibility.

Another important early learning concerned the relationship between wind direction and intake geometry. Field data showed that when wind approached the intake at perpendicular angles—around 90° or 270°—the differential pressure reading could invert, resulting in negative or unstable values. Initially treated as anomalies, these patterns soon emerged as systematic behaviors tied to orientation. This insight underscored the need to consider installation alignment as a critical design parameter. Within project scope, it guided the recommendation to orient the intake toward the prevailing wind direction (~260° North at the test site). Beyond the project, this learning influences hardware deployment guidelines, model compensation strategies, and future structural design considerations.

The development of the digital twin during these milestones also revealed the value of physics-based modeling in constraining machine-learning models. While CFD simulations provided accurate insights into internal flow dynamics, they also highlighted discrepancies between idealized equations and real-world turbulence. This created a foundational lesson: machine-learning models require physical grounding, and physics-based computational models require real-world correction. The digital twin thus became a bidirectional learning tool—informing algorithm design while being refined through field data.

Milestone 3: Machine-Learning Evolution and Environmental Sensitivity

During multi-season data collection, the team learned that real atmospheric noise—especially gust-induced turbulence—does not behave in a Gaussian or stationary manner, as assumed by classical filtering methods. This was a pivotal realization that shaped the development of the hybrid Extended Kalman Filter (EKF) plus neural-network architecture. The neural network proved capable of identifying non-linear gust patterns that the EKF alone could not filter out, leading to significant improvements in accuracy. This learning was essential for the project: without gust-compensation, the wind-direction and wind-velocity measurements would remain noisy and unsuitable for real-time emissions calculation.

Milestone 3 also demonstrated the importance of dataset seasonality. Winter and early-spring wind profiles showed lower variability and weaker gust behavior, while late-spring and summer winds demonstrated higher turbulence and stronger directional shifts. These seasonal differences taught the team that model training should not rely on short-term datasets. For the project, this influenced the decision to extend data collection into summer and fall. For the industry, this highlights a broader need: emissions-measurement technologies must be validated across full annual cycles before adoption in regulatory frameworks.

Milestone 4: Algorithm Refinement, Hardware Constraints, and Optimization

The later milestones introduced deeper learnings about the relationship between computational resource limits and model architecture. As more data was fed into the neural network, hardware constraints became more visible. Real-time processing on embedded hardware forced careful tuning of model size, depth, and convergence thresholds. The discovery that 150 neurons and three layers offered the optimal accuracy-to-efficiency ratio was a direct result of this phase. Within project scope, this learning produced a deployable algorithm suitable for edge devices. More broadly, it reinforces a key principle for industry: advanced AI/ML solutions must be engineered with real-world computational constraints in mind, especially for remote or autonomous environmental monitoring systems.

Another major learning involved the importance of continuous training. As the algorithm evolved from Phase 0 to Phase 2, with accuracy improvements from 14.88% to 4.82% for wind speed and from 21.9° to 8° for wind direction, it became clear that static models would rapidly become outdated in dynamic atmospheric contexts. This validated the design philosophy that the EmMea system should be continuously retrained using live environmental data. For regulators or operators, this highlights a broader shift in emissions monitoring: adaptive, learning-based systems can outperform traditional fixed-parameter sensing tools and may ultimately reshape expectations for accuracy and performance.

Broader Impacts on Industry, Policy, and Regulatory Processes

The learnings from this project have implications far beyond the development of a novel anemometer. One major impact is the potential to enhance the scientific foundation of emissions reporting, particularly for intermittent or fugitive sources where uncertainty is traditionally high. By demonstrating that real-time, localized wind data significantly improves mass-flow estimation, the project supports a shift toward more rigorous atmospheric monitoring in regulatory frameworks.

Moreover, the discovery that intake orientation and structural interference play measurable roles in wind-profile accuracy may influence future equipment installation standards. Regulators may eventually require site-specific atmospheric monitoring rather than relying on distant meteorological stations, particularly for facilities with irregular plume behavior.

In addition, the hybrid EKF–neural-network approach highlights a new frontier for environmental monitoring: AI-augmented atmospheric sensing. As regulators and permitting bodies increasingly adopt digital tools for compliance verification, this project's results may inform future guidelines around how machine-learning models should be validated, benchmarked, and maintained in operational environments.

Finally, by revealing the importance of year-round data collection, the project contributes to a broader industry understanding that climate and seasonal variability must be embedded into emissions-measurement verification processes. This could influence not only emissions reporting but also air-quality modeling, permitting of industrial expansions, and assessments of environmental impact.

F. OUTCOMES AND IMPACTS

Please provide a narrative outlining the project's outcomes. Please use sub-headings as appropriate.

- **Project Outcomes and Impacts:** Describe how the outcomes of the project have impacted the technology or knowledge gap identified.
- **Clean Energy Metrics:** Describe how the project outcomes impact the Clean Energy Metrics as described in the *Work Plan, Budget and Metrics* workbook. Discuss any changes or updates to these metrics and the driving forces behind the change. Include any mitigation strategies that might be needed if the changes result in negative impacts.
- **Program Specific Metrics:** Describe how the project outcomes impact the Program Metrics as described in the *Work Plan, Budget and Metrics* workbook. Discuss any changes or updates to these metrics and the driving forces behind the change. Include any mitigation strategies that might be needed if the changes result in negative impacts.
- **Project Outputs:** List of all obtained patents, published books, journal articles, conference presentations, student theses, etc., based on work conducted during the project. As appropriate, include attachments.

RESPOND BELOW

Project Outcomes and Impacts

The project successfully closed the critical technology and knowledge gaps identified at the outset—specifically, the lack of reliable, real-time, site-specific wind data for emissions measurement. Through extensive multi-season field deployment, advanced algorithm development, and integration of AI/ML with a physics-based digital twin, the project delivered a functional, validated wind-estimation system capable of operating in real environmental conditions.

One of the most important outcomes was the creation of an anemometer system that not only measures wind speed and direction but does so with continuously improving accuracy. Wind-velocity discrepancies were reduced from 14.88% at the start of the project to just 4.82% after Phase 2 training, while wind-direction error declined from 21.9° to 8°. These accuracy gains directly address the knowledge gap surrounding atmospheric variability and its influence on GHG mass-flow calculations. By integrating neural-network gust suppression with an Extended Kalman Filter, the final system is significantly more robust than conventional anemometry—especially under gusty, turbulent, or shifting wind conditions that typically degrade measurement reliability.

The project also generated, for the first time, a real-world multi-season atmospheric dataset collected at high frequency (every 10 seconds). This dataset, covering winter through fall, is invaluable not only for machine-learning improvement but also for broader scientific understanding of rooftop micro-meteorology. The insights gained regarding sensor orientation, crosswind behavior, and turbulence patterns provide operational guidance for future deployments and highlight the importance of site-specific wind monitoring in emissions modeling.

Collectively, the outcomes have elevated the EmMea wind-measurement system to Technology Readiness Level (TRL) 7, with expectations to achieve TRL 8 upon completing the full 12-month validation cycle. This positions the technology on a clear path toward commercialization, adoption by industry partners, and integration into next-generation GHG-measurement platforms.

Clean Energy Metrics

The project outcomes directly advance the Clean Energy Metrics identified in the Work Plan and the Alberta Innovates Investment Agreement. Improved atmospheric measurement accuracy enhances the reliability of real-time emissions quantification, particularly for intermittent, fugitive, or low-volume emission sources where dispersion modeling is highly sensitive to wind variability.

By producing a technology capable of real-time, site-specific wind profiling, the project reduces uncertainty in emission-rate calculations. This directly supports Alberta's goals of enabling precise GHG reporting, improving environmental accountability, and advancing toward carbon-neutral operations. No negative impacts to Clean Energy Metrics were observed, and no mitigation strategies were required.

The primary improvements include:

- Enhanced emission-rate accuracy: Reduction in wind-calculation error improves plume modeling used in emission mass-flow estimation.
- Support for continuous monitoring: Real-time data enables operators to track emissions during operational changes, shutdowns, or maintenance periods.
- Reduction in manual reporting uncertainty: By reducing reliance on outdated meteorological station data, the system supports more accurate regulatory submissions.

The driving force behind these improvements was the transition from lab testing to field-based multi-season data collection, which significantly strengthened the machine-learning models and their real-world relevance.

Program Specific Metrics

The project strongly advances Program Metrics related to AI/ML innovation, technology development, and commercialization readiness.

TRL Advancement:

The system progressed from TRL-6 to TRL-7, with TRL-8 expected following full-year validation. This demonstrates a successful transition from prototype to near-commercial readiness.

Field Pilots:

The deployment of 11 rooftop units at Adfast resulted in successful long-duration testing (10+ months) across diverse weather conditions. This exceeded the planned scope and added robustness to project outcomes.

Collaborators:

Adfast provided the outdoor testing site and committed to future prototype usage in their GHG-reporting workflows. NGIF's planned laboratory facilities were deemed unsuitable for realistic wind simulation, reinforcing the decision to rely exclusively on real-world field conditions.

Job Creation and HQP Retention:

Two full-time programmers were retained through the project to support AI/ML development. The in-kind contributor gained substantial exposure to applied AI in the environmental sector, strengthening Alberta's AI talent base.

New Products and Services:

The EmMea Emission Measurement System with integrated anemometer is now undergoing commercial evaluation by Adfast. This positions the technology for entry into the Canadian emissions-monitoring market and future expansion into North America.

No adverse deviations from Program Metrics occurred, and no mitigation strategies were required.

Project Outputs

The project generated multiple forms of academic and industry-recognized outputs, including conference presentations, accepted papers, and patent filings. These outputs reflect the project's scientific contribution and its relevance to the global energy and emissions-measurement community.

Patents

- United States Patent Application No. 18/596,890
- Canada Patent Application No. 3118874

Patent Title: "APPARATUS FOR MEASURING WIND VELOCITY AND WIND DIRECTION AND RELATED SYSTEMS AND METHODS"

Status: US/CA application published; Canadian Examiner's first action issued with response scheduled.

Conference Presentations & Papers (2025–2026)

- Physics Informed Machine Learning for Multiphase Emission Measurement

– Presented at 2025 SPE GOTECH, April 2025

- Physics Informed Machine Learning for Multiphase Emission Measurement

– Accepted at OTC Brazil 2025

- Virtual Mass MPFM – A Digital Future Enabled by AI/ML & PINN

– Presented at SPE ATCE 2025

- Virtual Mass MPFM – A Digital Future Enabled by AI/ML & PINN

– Presented at ADIPEC 2025, November 2025

- Virtual Mass MPFM – A Secured Digital Future Enabled by PINN

– Accepted for IPTC Summit 2026, Dubai (January 2026)

Pending or submitted for 2026

- 2026 GOTECH (Dubai)
- 2026 Offshore Technology Conference (Houston)

These publications and presentations help disseminate project learnings, strengthen Alberta's leadership in applied AI for clean-technology systems, and support commercialization by demonstrating technical maturity to industry stakeholders.

G. RECOMMENDATIONS AND NEXT STEPS

Please provide a narrative outlining the next steps and recommendations for further development of the technology developed or knowledge generated from this project. If appropriate, include a description of potential follow-up projects. Please consider the following in the narrative:

- Describe the long-term plan for commercialization of the technology developed or implementation of the knowledge generated.
- Based on the project learnings, describe the related actions to be undertaken over the next two years to continue advancing the innovation.
- Describe the potential partnerships being developed to advance the development and learnings from this project.

RESPOND BELOW

The results of this project have positioned the EmMea anemometer and wind-calculation system on a strong trajectory toward commercialization and industry adoption. Building on the technical advancements achieved—particularly the validated EKF–neural network algorithm, the digital twin, and the multi-season field dataset—the next phase will focus on scaling, refining, and integrating the technology into broader emissions-measurement applications. The following narrative outlines the long-term commercialization plan, the recommended actions over the next two years, and the strategic partnerships being developed to advance the innovation.

Long-Term Commercialization Plan

The long-term vision is to commercialize a fully integrated, AI-enhanced Emission Mass Flow Meter capable of delivering real-time, site-specific GHG measurements with embedded wind profiling. The enhanced anemometer system will serve as a core module in EmMea's emissions-monitoring platform and will be offered to industrial operators, energy producers, environmental consultancies, and regulatory bodies.

The commercialization plan will proceed in stages:

1. Completion of 12-Month Validation and TRL Advancement

The system is currently assessed at TRL 7. After completing the full year of field validation and receiving performance verification from Adfast, the technology is expected to reach TRL 8, supporting pilot-scale commercial use.

2. Regulatory and Standards Alignment

The improved accuracy of wind measurements directly supports emissions-reporting requirements under provincial and federal GHG frameworks. EmMea will begin engaging with regulatory bodies to align the technology with reporting standards and to explore opportunities for inclusion in approved quantification methodologies.

3. Productization and Manufacturing Scale-Up

The integration of the anemometer, mass-flow meter, embedded computing, and firmware will be formalized into a production-ready device. This will include supply-chain development, manufacturing partnerships, and hardware optimization for cost, durability, and repeatability.

4. Commercial Deployment and Customer Acquisition

Adfast has already committed to purchasing prototype systems for their GHG-reporting workflows. Additional early adopters will be targeted in the oil and gas, manufacturing, and waste-management sectors. A structured pilot-deployment program will be introduced to accelerate customer onboarding.

Over the long term, the technology will form the basis of a scalable atmospheric-sensing platform that can be adapted to drones, autonomous towers, mobile emission labs, and large-scale environmental networks.

Recommended Actions Over the Next Two Years

Project learnings revealed clear opportunities and priorities for continued development. The next two years will focus on four major technical and operational activities:

1. Completion of Year-Round Dataset and Winter–Spring Extension

Wind profiles demonstrate strong seasonal variability, and full annual representation is essential for model generalization. Additional winter and early-spring data will ensure that the neural-network algorithms remain stable across the entire temperature and wind-speed envelope common in Canadian climates.

2. Algorithm Enhancement Through Expanded Training and PINN Integration

Future work will incorporate:

- increased neuron counts and deeper architectures enabled by upgraded embedded hardware,
- adaptive noise-covariance estimation within the EKF,
- online learning to allow near-real-time model updates, and

- integration of the project's PINN (Physics-Informed Neural Network) model to further constrain predictions using fluid-dynamics principles.

These enhancements will accelerate progress toward <1% wind-velocity error and <5° directional error.

3. Hardware Optimization and Orientation Improvements

Learnings from field testing have shown that sensor orientation has a measurable effect on accuracy. Future iterations will:

- redesign the intake housing for improved crosswind handling,
- incorporate automated or field-adjustable orientation settings, and
- evaluate higher-performance computing modules to support larger neural networks.

4. Expansion of Field Testing to Alberta and Other Climatic Regions

To broaden applicability beyond Quebec's weather patterns, EmMea will initiate deployments in Alberta, where more volatile winds and colder temperatures will help stress-test the model and validate accuracy under harsher conditions.

5. Integration With Full Emission Modeling and Digital-Twin Systems

Next-phase work will connect the validated wind vector calculations directly to mass-flow plume models, enabling complete end-to-end emissions quantification. This integration is core to commercializing the full EmMea GHG-measurement solution.

Future Partnerships and Collaboration Opportunities

Several strategic partnerships are already being developed to support the technology's advancement and commercialization:

Adfast Inc.: As the primary field-testing partner, Adfast will continue to support validation and has expressed interest in adopting the technology for operational GHG reporting. Their involvement will also provide valuable feedback on deployment practices, long-term durability, and performance in industrial settings.

Environmental and GHG-Reporting Organizations: Partnerships with environmental-consulting firms and emissions-verification bodies will support alignment with regulatory frameworks and help accelerate industry adoption.

Academic and Research Institutions: Collaboration with universities—particularly in Alberta—will support advanced CFD modeling, PINN development, and graduate research leveraging the multi-season dataset generated during the project.

Technology Integrators and IoT/Edge-Computing Providers: As the system evolves, hardware partnerships will be explored to integrate higher-performance microcontrollers, neural-accelerator chips, or 5G/IoT connectivity modules into the commercial product.

Energy Sector Operators: Given the importance of accurate emissions monitoring in upstream and midstream operations, potential partnerships with oil and gas producers are being assessed to conduct broader pilots and support field deployment across Alberta and other Canadian provinces.

Potential Follow-Up Projects

Several follow-up initiatives would meaningfully expand on the outcomes of this project:

1. Full Integration of PINNs for Real-Time Atmospheric Flow Prediction

A dedicated project could focus on combining CFD, PINNs, and field data to create a more advanced hybrid model capable of predicting plume dispersion in real time.

2. Development of an AI-Driven Mobile Emissions Measurement Unit

The anemometer system could be adapted into a mobile platform—mounted on drones or vehicle-based labs—to measure wind and emissions across large facilities or difficult-to-access environments.

3. Alberta-Wide Atmospheric Sensor Network Pilot

Leveraging the validated technology, a pilot program could be developed to deploy distributed wind-sensing units across industrial clusters to support regional air-quality monitoring and regulatory enforcement.

4. Integration With Carbon-Capture Monitoring Systems

Future work may explore coupling the technology with carbon-capture leak-detection systems where accurate wind measurement is essential.

H. KNOWLEDGE DISSEMINATION

Please provide a narrative outlining how the knowledge gained from the project was or will be disseminated and the impact it may have on the industry.

RESPOND BELOW

Throughout the project, EmMea has actively disseminated the knowledge generated from the development of the AI/ML-enhanced anemometer and digital-twin–driven emission measurement system. Knowledge sharing has occurred through a combination of peer-reviewed technical papers, international conference presentations, partner collaboration, and detailed technical documentation prepared within the Milestone Reports. These efforts have played a central role in introducing the industry to advanced atmospheric-sensing techniques, novel AI/ML architectures, and the integration of physics-informed modelling within emission-measurement workflows.

A major avenue for dissemination has been EmMea's participation in leading technical conferences. Papers detailing the project's progress—such as Physics Informed Machine Learning for Emission Measurement presented at the 2025 SPE GOTECH Conference and subsequently accepted at OTC Brazil 2025—have communicated foundational knowledge related to PINN-based environmental sensing, digital-twin methodologies, and integration with multiphase flow measurement systems. Additional presentations at SPE ATCE 2025, ADIPEC 2025, and the accepted paper for the IPTC 2026 Summit in Dubai have further extended the reach of the project's outcomes to global operators, researchers, and decision-makers in emissions management and digital oilfield technologies. These technical papers and presentations have been instrumental in raising industry awareness of real-time atmospheric data acquisition and AI-powered wind-profile estimation, demonstrating the potential for significant improvements over conventional methods reliant on delayed or averaged third-party data.

Collaboration with industry partners has been another important dissemination channel. Adfast, a key partner in the project, hosted a large-scale long-term rooftop test installation consisting of 11–12 measurement units, enabling over ten months of real-world environmental data collection. These tests not only validated the hardware and AI algorithms but also provided Adfast with early access to practical system insights, supporting their operational GHG reporting requirements. The test infrastructure, along with shared analysis reports and performance evaluations, has served as a live demonstration platform for potential adopters, accelerating awareness of the technology's practical advantages. These outcomes were documented comprehensively in Milestone Reports for both mid-year and final reporting periods.

Furthermore, the project generated detailed technical documents, including CFD and PINN development notes, EKF-neural network performance analyses, algorithm-training studies, and multi-season atmospheric test reports. These materials provide an in-depth understanding of model behavior, data-processing techniques, and digital-twin integration strategies. Together, they form a valuable body of knowledge that can be used by researchers and engineers seeking to advance AI-driven environmental sensing or replicate similar workflows.

The impact of this knowledge on the industry is expected to be substantial. The project directly addresses a long-standing technological gap: the lack of high-resolution, real-time, locally representative atmospheric data for emission-measurement models. Traditional industry practice relies heavily on coarse, time-averaged meteorological data, which limits the accuracy of plume-dispersion modelling. By demonstrating how an AI-enhanced anemometer—supported by a neural-network-assisted Extended Kalman Filter and physics-informed CFD/PINN modelling—can provide accurate real-time wind velocity and direction, the project introduces a new standard for emissions characterization. Improvements such as reducing wind-velocity discrepancy from 14.88% to 4.82% and wind-direction deviation from 21.9° to 8° across algorithm phases illustrate the tangible potential for operational gains.

The broader impact extends into regulatory reporting, environmental compliance, and digital monitoring strategies across oil and gas, manufacturing, agriculture, landfills, and other emissions-sensitive sectors. By increasing measurement accuracy, the technology can enhance the credibility of GHG reporting and support more precise leak-detection and plume-modelling initiatives. The advancements also help position Alberta as a leader in clean-technology innovation, directly supporting provincial and federal emissions-reduction goals. The knowledge-sharing activities described above contribute to industry readiness, enabling smoother adoption of AI-driven sensing technologies and stimulating continued development of advanced emission-management systems.

In summary, the project has generated significant new knowledge in the areas of atmospheric measurement, AI/ML sensor fusion, digital-twin development, and physics-informed modelling. Through extensive dissemination—via conferences, technical papers, industrial partnerships, and detailed milestone documentation—the project has already influenced both academic research directions and industrial technology strategies. As the system transitions from prototype to commercial readiness, this foundation of shared knowledge will help accelerate adoption across Canada's clean-energy ecosystem and beyond.

I. CONCLUSIONS

Please provide a narrative outlining the project conclusions.

- Ensure this summarizes the project objective, key components, results, learnings, outcomes, benefits and next steps.

RESPOND BELOW

The objective of this project was to develop and validate a novel hardware-based anemometer integrated with the EmMea Emission Mass Flow Meter, supported by advanced machine learning—including an Extended Kalman Filter (EKF), neural-network noise-elimination module, and a CFD-driven digital twin—to enable accurate, real-time measurement of wind velocity and direction for greenhouse-gas emission quantification. Across four milestones and more than ten months of continuous rooftop field testing, the project successfully demonstrated the feasibility, robustness, and accuracy improvements delivered by this integrated AI/ML approach.

Key components included development of the intake-based anemometer, CFD and PINN-supported digital twin modelling, multi-phase neural-network training, and deployment of 11 prototype measurement units at Adfast's Montreal facility. Results showed substantial performance gains: wind-velocity discrepancy improved from 14.88% to 4.82%, and wind-direction error decreased from 21.9° to 8° as algorithms matured through successive training phases. Learnings highlighted the importance of inlet orientation, the strong benefit of neural-network–enhanced EKF filtering for gust suppression, and the need to balance computational efficiency with model complexity for edge-device deployment.

The project delivered meaningful outcomes such as a validated real-time wind-profile algorithm, a functioning integrated GHG flow-measurement prototype, extensive multi-season atmospheric datasets, and multiple international technical publications. Benefits include improved accuracy in emission quantification, expanded capability for real-time plume modelling, and strengthened industry readiness for AI-enabled environmental sensing.

Next steps include completing the full year-long dataset, refining algorithms using expanded seasonal data, upgrading computational hardware for direction estimation, and progressing toward commercial deployment through continued partnerships and validation initiatives.