



Wind speed at light speed

Introducing METICE

Multi-Site Ensemble Turbulence Intensity Cup Equivalent
from ZX Lidars

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UNRESTRICTED





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1 Context: The significance of Turbulence Intensity in wind energy

Turbulence Intensity (TI) is a fundamental metric in wind energy, defined as the ratio of the wind speed standard deviation to the mean wind speed over a 10-minute period. It quantifies how much wind speed fluctuates around its mean, and this variability has critical impacts on wind turbine design, site suitability, certification, energy yield assessments and turbine performance. Turbines are engineered to withstand or respond to certain turbulence levels; higher TI can increase fatigue loads on turbine components and influence extreme load calculations. During site suitability analysis, a project's measured TI is compared against the turbine's design limits (often categorized by IEC turbulence classes) to ensure the selected turbine type and model is appropriate for the site. Likewise, certification bodies require that TI at a project site does not exceed the values used in turbine type certification. Even energy yield assessments (EYA) can be affected by turbulence - for instance, higher TI can reduce turbine power output and increase wake losses, making accurate TI measurement important for predicting annual energy production. In short, accurate TI data is needed to verify that a wind farm's conditions are within safe design parameters and to refine performance estimates.

Despite the significant advances in remote sensing devices, and general acceptance of wind speed measurements from Lidar, TI measurements in industry practice have remained largely “cup-based,” meaning they rely on cup anemometer data. This is largely because much of the historical standards and turbine design calculations are based on cup anemometer TI measurements (denoted TI_{CUP}). A cup anemometer provides a point measurement of wind speed, and by extension TI, at the sensor's location. By contrast, continuous-wave (CW) Lidars measure wind over a conical volume (scanning a laser beam at a range of distances and angles) rather than at a single point. Lidar also samples wind differently in time – a CW Lidar's 50 Hz scanning or averaging pattern differs from the 1 Hz (or higher) sampling of a cup – which can filter or smooth out some turbulence. These inherent differences in spatial sampling and response cause systematic differences between Lidar-derived TI (TI_{CW}) and TI_{CUP} (Kelberlau and Mann, 2019).

Generally, as height increases and a Lidar scans over a larger sampling volume, TI_{CW} underestimates the variance of the wind as spatial averaging smooths out small scale turbulence and acts like a low pass spatial filter (Sathe et al., 2011). This is particularly pronounced for highly stratified conditions (e.g. stable) where the dominant turbulence structures are small and high frequency. It is less noticeable for unstable conditions where TI is dominated by large eddies that are well captured in the probe volume - here the agreement is better.

These nuances have so far meant that the industry continues to treat TI_{CUP} as the reference standard, and any Lidar measurements must be translated into that frame of reference.

Why hasn't Lidar replaced cup anemometers for TI? In short, because trust and traceability are paramount. Wind turbine load models and certification tests have decades of legacy based on cup measurements. Until recently, there was no widely accepted method to ensure a Lidar's TI readings are “cup-equivalent.” If one simply plugged raw Lidar TI data into a turbine design calculation, the loads might be mis predicted or overly conservative. Therefore, the wind industry has insisted on co-locating Lidars with met masts to compare TI_{CW} vs TI_{CUP} , and still often defaults to the cup data for final assessments. Lidar technology's obvious advantages (safety, remote autonomy, higher-height wind measurements, flexibility in deployment etc.) have led to an increasing number of standalone Lidar deployments. The simple lack of any mast and cup data from site have led to more focus than ever being placed on demonstrating a credible, simple, transparent, multi-site approach that allows TI_{CW} to become the new benchmark.

2 The Challenge: Cross-technology validation and standards divergence

Early research identified multiple reasons for the differences between Lidar and cup TI, including the Lidar's probe volume averaging, its circular scanning trajectory, and differing frequency response (a cup has a mechanical response cutoff, whereas a CW Lidar effectively low-pass filters turbulence by averaging across its beam). These factors mean that a Lidar and a cup in the *same wind* may report different TI values. The challenge for the industry has been to develop correction models to adjust TI_{CW} to a cup-equivalent TI (TI_{CE}) that reproduces what a co-located cup would read. Over the past decade, various approaches have been pursued:

- ▲ **Physics-based corrections:** Some methods try to account for the physics of the measurement. Physics-based models can be elegant and universally applicable in theory, and they tend to produce “clean” corrections anchored in known physical differences. Pena et al. (2025) describes the “lidar-turbulence paradox” and attempts solutions concludes that the turbulence tensor cannot be well described from the ground without knowledge of the 3D components. In practice physics-based models are not possible based on current physics.
- ▲ **Probabilistic and analytical models:** Another approach treats the problem statistically. These methods might assume an underlying distribution for true turbulence and model the Lidar's reading as a biased estimator. For example, a Bayesian inference method could estimate the true TI_{CUP} as an unobserved variable with a probability distribution, given the Lidar measurement. The advantage is that such methods can be robust and provide uncertainty quantification on the correction. However, they require careful assumptions about the turbulence distribution and the Lidar's error characteristics. If those assumptions are wrong or overly simple, the model may not generalize well.
- ▲ **Data-driven (machine learning) models:** These learn the relationship between TI_{CW} and TI_{CUP} empirically from co-located data. They can range from simple linear regressions to complex neural networks. The pros of ML approaches are that they are versatile and fast to apply, capturing complex nonlinear relationships if enough data is provided. The cons are dependence on the training data and potential lack of interpretability and generality. A model trained on one site might not work at another if the conditions differ outside the learned patterns – hence generalization is a key concern.

Given these varied approaches, an important effort has been to benchmark and validate them across the industry. Organizations like the Consortium for the Advancement of Remote Sensing (CFARS) have convened working groups to compare techniques. In a recent CFARS initiative, an open-source “*TI Adjustment Comparison Tool (TACT)*” was developed to evaluate more than 15 different TI adjustment techniques side-by-side[1]. Participants (including wind farm owner-operators, consultants, OEMs, and Lidar manufacturers) contributed data from 35+ sites to test how well different corrections bring TI_{CW} in line with TI_{Cup} [2]. This kind of collaborative benchmarking underscores that no single method had been universally accepted, and it aimed to identify best practices.

2.1 Competing Standards: DNV vs CFARS vs OEM Criteria

Because of the criticality of TI for turbine loads, standardized acceptance criteria have emerged to evaluate whether a Lidar's turbulence measurements are "good enough" to use in lieu of a met mast. Notably, in late 2023 DNV published a Recommended Practice DNV-RP-0661 specifically addressing the use of ground-based Lidar TI for wind turbines[3]. This RP was the outcome of a Joint Industry Project and defines two key error metrics for validation:

- ▲ **Mean Relative Bias Error (MRBE):** the mean bias of Lidar vs cup TI, expressed as a percentage of the cup value.
- ▲ **Relative Root Mean Square Error (RRMSE):** the scatter (standard deviation of errors) between Lidar and cup TI, also normalized by the cup TI.

To accept a Lidar's TI for use (in flat terrain onshore or offshore, the scope of RP-0661[4]), DNV specifies that these metrics must be within certain limits. While the RP document is proprietary, it is reported that the acceptance criteria are roughly MRBE within $\pm 5\%$ and RRMSE $\leq 15\%$. In other words, on average the Lidar's TI should not be more than 5% higher or lower than the cup's, and the scatter of differences should be no more than 15%. These are fairly tight constraints – for example, if the true TI is 10%, the Lidar on average should read between 9.5% and 10.5%, with modest variability. This approach is intentionally conservative, aiming to ensure that using Lidar TI will not introduce significant error into either energy or loads estimates. Indeed, one analysis noted that DNV's $\pm 5\%/15\%$ criteria are even more stringent than traditional site suitability requirements in some cases.

Around the same time, CFARS has been developing a complementary set of guidelines focused on site suitability (turbine loading) acceptance. CFARS advocates for using non-relative error metrics – essentially looking at absolute differences in TI, binned by wind speed. Their framework defines "Best Practice" and "Minimum Practice" thresholds for two metrics: the Mean Bias Error (MBE) per bin, and the Representative TI error. The Representative TI is defined as the 90% exceedance threshold (assuming a Gaussian distribution) from a given turbulence distribution, and is designed to describe the more extreme fluctuations. These metrics were applied to the TI estimates for floating lidar systems in a joint work by Fugro and DNV (Kelberlau et al., 2023) to establish the best practice thresholds recorded in Table 1. These thresholds have since been adopted to validate the EOLOS floating TI correction model (Rapisardi et al. 2024). In lieu of onshore specific thresholds for CFARS metrics, these criteria have been adopted for our purpose.

The Fugro and DNV best practice is achieved if the Lidar's mean TI in each wind speed bin is within ± 0.01 (± 1 percentage point) of the cup (MBE $\leq 1\%$), and the representative TI is within ± 0.015 (1.5 points). Minimum Practice loosens those to ± 0.02 and ± 0.03 respectively. Table 1 summarizes these criteria:

Acceptance Metric	Best Practice	Minimum Practice
Binned TI Mean Bias (MBE)	$\leq \pm 0.01$ ($\pm 1\%$ TI)	$\leq \pm 0.02$ ($\pm 2\%$ TI)
Binned Representative TI Error	$\leq \pm 0.015$ ($\pm 1.5\%$)	$\leq \pm 0.03$ ($\pm 3\%$)

Table 1: Fugro and DNV best and minimum practice for offshore TI correction validation (Kelberlau et al., 2023).

These thresholds are broadly in the same spirit as DNV's – limiting bias to a few percent – but the metrics are defined differently. DNV's are relative (%) errors referenced to the cup, whereas CFARS expresses absolute TI differences (e.g. 0.01 TI is 1 percentage point). For a typical mid-range TI of 0.1 (or 10% turbulence), DNV's $\pm 5\%$ relative bias thresholds corresponds to a TI value of ± 0.005 (or 0.5% turbulence), which is stricter than the best practice associated with the CFARS' metrics of $\pm 1\%$. On the

other hand, at very low TI of 0.04 (or 4%), a $\pm 5\%$ relative threshold corresponds to a TI value of ± 0.002 (or $\pm 0.2\%$ turbulence), which might be overly strict. The best practice thresholds stated for the CFARS metrics give a flat $\pm 1\%$ allowance regardless.

The Representative TI criterion in CFARS has no direct analogy in DNV's approach – it is aimed specifically at capturing turbulence peaks that drive loads, ensuring the Lidar not only matches average TI but also the higher-end turbulence distribution within each wind speed bin.

Individual turbine manufacturers (OEMs) have also developed their own acceptance metrics, often tied directly to turbine load effects. For example, Nordex has investigated using the difference in fatigue damage predicted from Lidar vs cup data as a metric. In internal studies, Nordex introduced a “Damage Index” based on turbine S-N fatigue calculations for a reference met mast (RMM) and a temporary met mast or Lidar (TMM). They found that DNV's RRMSE metric, which weights all turbulence fluctuations equally in time, “doesn't correlate well with fatigue-relevant flow properties,” since fatigue damage depends more on the distribution of turbulence over time than on short-term scatter. In some cases, a Lidar dataset could formally meet DNV's criteria yet still produce a significant ($\sim 14\%$ higher) fatigue damage prediction compared to the cup – implying that passing the DNV thresholds doesn't guarantee load equivalence. Conversely, certain datasets might fail a statistic like RRMSE while still yielding negligible differences in cumulative fatigue damage. Because of this, Nordex and some other OEMs lean toward directly evaluating allowable load difference. A common OEM guideline is that using Lidar in place of a met mast should not change the calculated fatigue loads by more than about 5%. This roughly corresponds to a $\pm 5\%$ tolerance on a turbulence-related damage index, which Nordex found many sites already meet even with raw Lidar data, and even more so with corrected data. Such OEM criteria are inherently tied to the specific turbine and its sensitivity to turbulence, but they underscore a practical point: the ultimate goal is not just matching TI for its own sake, but ensuring turbine loads and energy estimates remain accurate.

In summary, while DNV-RP-0661, CFARS, and various OEM internal standards all aim to validate Lidar-derived TI, they differ in focus and stringency. DNV provides a general, conservative statistical envelope for use of Lidar TI (primarily for energy yield and simple terrain site suitability). CFARS focuses on turbine loading applications, introducing slightly different metrics that are arguably more load-relevant (absolute biases, representative turbulence). OEMs may apply even more direct load tests or tighter criteria for their turbines. These discrepancies can lead to confusion or overly restrictive use of Lidar: for instance, a perfectly good Lidar dataset might be “false rejected” because it fails an RRMSE threshold due to random scatter, even though the mean turbulence and loads would have been within an acceptable level. The challenge for the industry is to reconcile these standards and come up with methods (and metrics) that are both physically relevant and not overly prohibitive. Work has begun in this field also within IEA Wind Task 52, a project under the International Energy Agency (IEA) Wind Technology Collaboration Program focused on the Large-Scale Deployment of Wind Lidar.

3 METICE: A new multi-site ensemble approach

ZX Lidars' Multi-site Ensemble Turbulence Intensity Cup Equivalent (METICE) was developed against this backdrop of challenges to provide a robust, generalizable correction model for Lidar TI. In essence, METICE is a machine-learning ensemble transfer function that converts a CW Lidar's turbulence measurements into an equivalent cup reading (TI_{CE}). What sets METICE apart is its novel architecture combining multiple site-specific models with a Bayesian weighting scheme, combined with extensive training and validation data sets that represent the best available tall mast and cup data.

3.1 Ensemble of site-specific neural networks

Instead of training a single global model that attempts to learn all possible conditions, METICE is built as an ensemble of Deep Neural Networks, each one trained on data from a different site. Concretely, if co-located Lidar and met mast data from (say) 15 sites are available, METICE will train 15 separate base models (ZX has used deep multi-layer perceptrons, DMLPs, for each). Each model learns the relationship between TI_{CW} and TI_{CUP} for the conditions at each site, effectively capturing local physics and turbulence response specific to that location. These become a library of “experts.”

The next key ingredient is how METICE uses these experts when faced with new data from a site it has never seen before. This is done through a Bayesian model selection framework using a Gaussian Mixture Model (GMM). The GMM acts as a “regime mapping” tool: it looks at the input features of a new 10-minute period and estimates the probability that the conditions correspond to each of several pre-defined regimes or clusters. In simpler terms, METICE's GMM might recognize patterns like “high wind, unstable atmosphere” or “moderate wind, stable atmosphere” as different regimes. Each of the site-specific neural networks is associated with these regimes to some extent (based on its training data characteristics). The model then assigns probabilistic weights to each neural network's prediction according to how relevant that model is for the current conditions. For example, if the new data shows very high wind shear, and perhaps one of the ensemble models was trained on a site with similarly high shear conditions, the GMM will give that model a higher weight in the ensemble prediction. Conversely, models trained in very different regimes get reduced weight. This approach is akin to a “mixture of experts” where the gating network (the GMM) decides which expert to trust more for each situation.

Through this Bayesian ensemble approach, METICE has and continues to be developed to incorporate several key capabilities. One goal is to enable the framework to account for site heterogeneity: instead of relying on one model to perform well everywhere, it is designed to leverage the diversity of training sites and adaptively select the most relevant model components for new locations. Another focus is on enabling uncertainty quantification. By representing predictions as an ensemble of multiple models - each contributing with a probabilistic weight - the framework can estimate not only a corrected TI value but also provide a measure of confidence or spread in those estimates. Such information would allow users to assess whether a small remaining bias is likely negligible, or warrants further consideration. These enhancements to uncertainty treatment remain an active area of development, with particular emphasis on improving robustness and interpretability for complex sites. Importantly, METICE achieves these benefits with minimal input requirements. It was intentionally developed using basic 10-minute statistics that any Lidar provides. The standard input features are: 10-min mean wind speed, 10-min wind speed standard deviation (i.e. the raw TI components), the measurement height, and a wind shear coefficient. The shear can be calculated from the Lidar's multi-height data (e.g. using two heights' mean winds). These inputs capture the primary factors that affect the TI relationship - wind speed level, turbulence level, height (which correlates with the probe volume size and usually with turbulence scale), and shear (which can be a proxy for stability or terrain-induced gradients). No external meteorological data or mast measurements are required as inputs beyond what the Lidar itself records. This means

METICE can be applied in a stand-alone fashion on any ZX CW Lidar dataset, a critical practical advantage. The output is simply a corrected turbulence intensity time series (TI_{CE}) for each 10-min period, ideally matching what a cup anemometer at the same height and location would have measured.

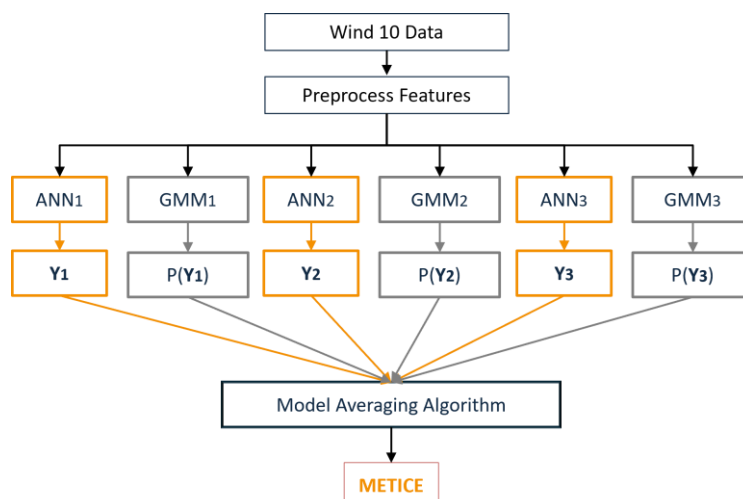


Figure 1: METICE schematic representation showing the Bayesian averaging method applied to an ensemble. The number of ensemble members has been reduced to 3 for the clarity of the schematic. ANN is artificial neural network making prediction Y , GMM is Gaussian mixture model assigning likelihood $P(Y)$.

The METICE model was trained and tuned using a substantial database of co-located measurements. The sites were predominantly simple terrain (to focus on fundamental atmospheric regime differences without complex flow), and data were stratified by wind speed bins and stability classes during analysis. A “leave-one-site-out” cross-validation was employed in validation; that is, each site in turn was treated as an “unseen” site and had METICE models trained on all the other sites applied to it. This tests the generalization capability: the ensemble must adapt to a truly new site each time.

Key advantages of METICE’s architecture can be summarized as follows:

- ▲ **Adaptive to regimes:** By using regime-specific expert models, METICE preserves the “*dynamic, regime-specific, and site-unique physics*” of turbulence behavior. It’s not forced into a one-size-fits-all formula; it can apply different corrections for, say, a stable low-turbulence nighttime period vs. a mid-day convective period, as dictated by the ensemble weighting.
- ▲ **Performance-based weighting:** The Bayesian selection framework essentially weights models based on performance – it “decides what transfers across sites” by emphasizing the models that historically performed best under similar conditions. This means new predictions are influenced most by the training data that is most relevant, reducing the risk of applying a completely off-base correction.
- ▲ **Scalability and maintainability:** The architecture is inherently scalable – new training sites can be added as new ensemble members without retraining from scratch, fitting into a modular design. If a new kind of climate or terrain is encountered (e.g. a tropical site or a complex forested hill), ZX can integrate a new co-located dataset as an additional expert model, thereby expanding METICE’s knowledge base. This also future-proofs the model as the volume of validation data grows.



- ▲ **Robustness to data issues:** The design requirements for METICE included being robust against imperfect or incomplete data. Because it uses only 10-min summaries, it is relatively tolerant of short gaps or sporadic outliers (as those would minimally affect binned statistics). The ensemble approach also means no single model failure will derail the prediction – even if one model misbehaves, its weight can be low. The developers also ensured the model is computationally efficient – a compact ensemble that can be run quickly on large datasets or even in real-time firmware.

In summary, METICE represents a data-driven and probabilistic approach. It leverages the power of machine learning (learning from many sites' data) while embedding domain knowledge via its regime-based weighting. By doing so, it aims to bridge the gap between TI_{CW} and TI_{CUP} in a way that is accurate, general, and transparent in its approach.

3.2 Validation Results: Performance Across Sites and Conditions

A thorough validation of METICE has been conducted to demonstrate its accuracy and reliability. In aggregate, the model has shown excellent agreement with cup anemometer TI across many sites and heights, meeting or exceeding the contemporary acceptance criteria (DNV, CFARS) in nearly all cases.

- ▲ **Multi-site validation:** In the initial validation study, METICE was tested at 16 sites with 64 unique height levels (20 m to 200 m), none of which were used in the training of their corresponding model (each was treated as “new” via the leave-one-out approach). The results were quantified via several metrics:
- ▲ **Orthogonal regression slope:** Plotting METICE's predicted TICE against actual cup TI for each site/height, an orthogonal regression was used to fit a line (slope 1.0 being ideal). The slopes clustered tightly around 1.00 in all height bands, indicating METICE is essentially unbiased. In fact, most fitted slopes were within about $\pm 2\%$ of unity, and nearly all within $\pm 4\%$. This holds true for low heights (<60 m), medium (60–120 m), and high (>120 m) – an important result showing no significant height-dependent bias in the model.
- ▲ **CFARS Binned Mean Bias:** For each wind speed bin (across all sites/heights, totalling 557 bins), the mean error (Lidar-minus-cup) was evaluated. METICE achieved extremely low biases – 553 out of 557 bins (99.3%) fell within the $\pm 1\%$ TI error “Best Practice” bound, and 100% of bins were within $\pm 2\%$ (Minimum Practice). In other words, METICE essentially met the strict CFARS site-suitability bias criterion for virtually all conditions tested.

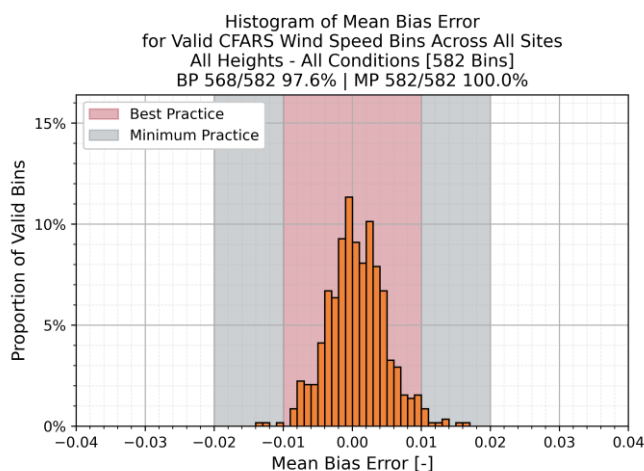


Figure 2: CFARS site suitability histogram showing MBE binned by wind speed for all evaluated sites.

- ▲ **CFARS Representative TI:** Similarly, the Representative TI (roughly the 80th percentile turbulence) was computed for each bin and compared. METICE's predictions were also outstanding here: 551 of 557 bins (98.9%) were within $\pm 1.5\%$ (absolute TI) of the cup value, and all bins were within $\pm 3\%$. This demonstrates that not only does METICE get the mean TI right, it also accurately captures the distribution's spread to remain within 1.5 percentage points of the cup's representative turbulence in ~99% of cases.

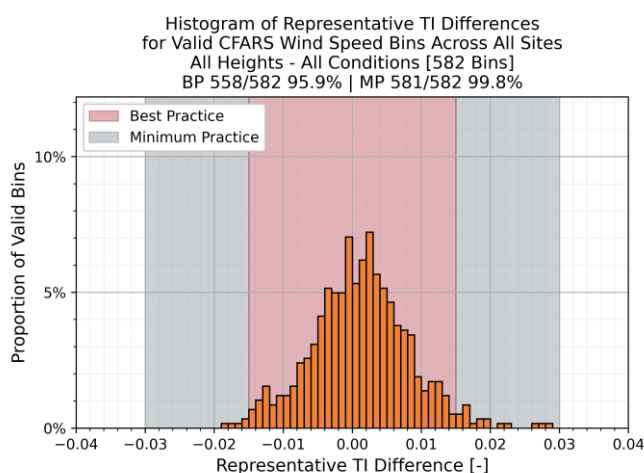


Figure 3: CFARS site suitability histogram showing Representative TI differences binned by wind speed for all evaluated sites.

These results collectively indicate that METICE provides a reliable, unbiased cup-equivalent TI for simple and moderately complex sites, with performance that essentially clears the most stringent industry benchmarks. A visual way to appreciate this is that if one plots the METICE-corrected TI versus the met mast TI, the points lie very close to the 1:1 line, with negligible bias or scatter. In fact, ZX reports the R^2 values of METICE vs mast TI are very high (plots show R^2 close to 1.0 across sites) and

the regression slopes nearly exactly 1.0. Such strong agreement across thousands of hours of data in 557 wind speed bins builds confidence that METICE can generalize well to new “simple” sites.

It is worth noting that METICE’s validation was done using orthogonal regression rather than ordinary least squares, to account for measurement uncertainty on both the Lidar and cup sides. This method avoids bias in slope estimates that can occur if one treats the cup measurements as error-free. The fact that slopes still centre on 1.0 implies METICE is not introducing any systematic bias.

- ▲ **Complex terrain and advanced corrections:** The real test for any TI model is how it handles complex flow conditions – sites with significant terrain variation, forestry, or other factors causing highly non-uniform and non-stationary turbulence. By design, the initial METICE training focused on simpler sites, but ZX Lidars has been actively investigating the model’s application to complex onshore sites. A dedicated study was performed at a very complex site (and a few others with varying complexity) to see how METICE might be integrated with traditional flow corrections.

At a complex hilly, forested site (for example, Project “P1” in ZX’s test dataset, characterized as “*Very Complex – forestry on a hill, slopes >10%*”), a baseline comparison showed the challenges: raw Lidar TI exhibited increasing bias and error with height, often failing to meet DNV’s acceptance criteria at higher levels. This is expected – in complex terrain, the flow differs between the Lidar location and mast, and the Lidar’s volume averaging likely smooths out some small-scale turbulence, especially noticeable higher above the ground. In ZX’s trials, the Mean Relative Bias Error and RRMSE for raw Lidar TI tended to grow with height, sometimes exceeding the $\pm 5\%$ or 15% targets at the upper measurement heights.

To tackle this, ZX applied a two-step correction: first using a CFD-based flow correction, then METICE. The CFD correction provided height- and direction-dependent adjustment factors to account for terrain-induced differences (essentially scaling the Lidar’s wind speed or turbulence to better match what a mast at the exact mast location would see). When the Lidar data was pre-corrected by these CFD factors and then fed into METICE (a configuration termed “CFD + METICE”), the results were impressive. Compared to the raw case (or even simpler corrections), CFD + METICE showed a significant improvement, especially at the complex sites. ZX reported “*significant improvement with respect to the previous corrections and the raw case; less difference with height in the MRBE and RRMSE.*” In other words, the combination largely removed the bias that was growing with height, flattening the error profile.

Quantitatively, one can look at how many wind speed bins fell within the acceptable error thresholds for each method. In an internal analysis, ZX counted the percentage of wind bins that passed certain site suitability (SS) criteria for each correction. The progression was telling: the raw Lidar might have only, say, ~40–60% of bins within requirements at higher heights; the first and second corrections raised that fraction; and METICE with CFD pushed it to near 100% compliance in both site suitability and loads-specific bins. In fact, when considering a turbine loads perspective (e.g. requiring very low bias to protect fatigue life), the CFD+METICE data achieved far more wind bins within a 5% loads-difference tolerance than the raw data did. This aligns with the OEM viewpoint – METICE’s correction was accurate enough that in a Nordex-style comparison of damage equivalent loads, the vast majority of conditions fell within a $\pm 5\%$ band (whereas raw Lidar might have shown some conditions with 10% or more load deviation).

In summary, the validation results confirm METICE’s effectiveness across a broad spectrum:

- ▲ For normal, simple or moderately complex sites, METICE by itself (with basic inputs) produces cup-equivalent TI with negligible bias and scatter, essentially solving the Lidar TI problem for those cases. It meets stringent criteria like the best practice of Kelberlau et al., (2019), for the CFARS metrics ~99% of the time.



- ▲ In highly complex terrain, where additional site-specific factors come into play, METICE can be combined with flow modeling (CFD) to greatly improve performance. In trials, this combination brought even very complex-site Lidar data to within industry-acceptable error margins. This is a crucial finding – it suggests that with the right preprocessing, METICE's learning can extend to complex flows as well, a scenario previously considered very challenging for remote sensing devices.
- ▲ METICE outperformed earlier generation correction models in these tests, especially visible in the reduction of height-dependent errors and in achieving compliance for turbine load evaluations.

These results make a strong case that METICE is an enabling technology for wider use of Lidar in wind projects. By delivering turbine-equivalent turbulence measurements with known accuracy, it addresses the validation gap that standards like DNV-RP-0661 sought to cover, and it provides a path to meet even stricter OEM requirements or future best practices.



4 Use cases and applications for industry stakeholders

With its demonstrated performance, METICE unlocks new possibilities for various stakeholders in wind energy. Different users will find value in METICE's cup-equivalent TI in distinct ways:

- ▲ **Turbine OEMs (Design Load Assessments):** Turbine manufacturers can use METICE-corrected Lidar data to confidently assess site turbulence for load calculations. Traditionally, OEMs require on-site met masts to provide TI data for final load verification of a project. With METICE, a ZX Lidar alone can supply TI data that is equivalent to a cup anemometer, meaning OEMs can trust these measurements for performing fatigue damage analysis and extreme load checks. For example, an OEM could deploy a Lidar at a prospective site, gather turbulence data, apply METICE, and then input that TI_{CE} into their load simulation models (aeroelastic models) to see if the site falls within the turbine's design envelope. The benefit is significant: it reduces the reliance on installing a tall met mast (which is costly and time-consuming) purely for loads measurements. OEMs also gain spatial flexibility – they could instruct a Lidar to measure TI at multiple turbine locations or heights (e.g., hub-height and top-tip) sequentially, which is impractical with single-point mast instruments. Furthermore, METICE's built-in uncertainty estimate allows OEMs to quantify margins. For instance, if METICE indicates a small remaining bias with $\pm 0.2\%$ uncertainty, an OEM can incorporate that small uncertainty into a safety factor for loads. Overall, METICE helps OEMs ensure site compliance with turbine TI limits and can accelerate the site certification process by providing reliable turbulence data faster.
- ▲ **Wind farm developers (Site Classification and Energy Assessment):** Developers planning projects can use METICE to perform site classification and wind resource assessment without full-time met towers. One key early step in project development is determining the site's turbulence category (which affects what class of turbine is suitable or if special conditions apply). With a Lidar deploying METICE, developers can classify a site's turbulence intensity over the project area quickly, by moving the Lidar around or by using multiple Lidars – all the TI data can be corrected to cup-equivalent on the fly. This enables mapping of turbulence across a large site (for example, identifying if ridgelines have higher TI than valleys, etc.), which can inform micro-siting (turbine placement to avoid high-TI spots) and even layout optimization (perhaps spacing turbines differently if turbulence is high to reduce wake interactions). For Energy Yield Analysis (EYA), turbulence plays a secondary but notable role: higher turbulence can reduce turbine power performance slightly and increase wake mixing (which might reduce wake losses). By having accurate TI data, developers can refine the power curve assumptions for the site and improve wake loss models, leading to a more accurate energy estimate. Another benefit for developers is campaign efficiency – deploying a ZX Lidar with METICE means that even without a met mast, they can gather bankable wind data (including turbulence) to satisfy investor or lender technical due diligence. This can shorten the measurement campaign timeline or allow measurements in remote areas where building a mast is infeasible. In short, METICE gives developers a tool to characterize site wind conditions fully (windspeed + TI) with just remote sensors, speeding up development and potentially saving significant met mast costs.
- ▲ **Consultants and Independent Engineers (reducing uncertainty and expanding coverage):** Wind consultants who analyze data for financing or performance guarantees can leverage METICE to reduce the uncertainty in projects that rely on Lidar. Historically, if a project didn't have a met mast for turbulence, consultants would either exclude turbulence from consideration (risky for loads) or apply very conservative assumptions (penalizing the project with uncertainty adders or lower expected life). With METICE, consultants can obtain validated turbulence measurements from



ground-based or even floating Lidars, and thus increase their confidence in stand-alone remote sensing campaigns. For example, an independent engineer could accept METICE-corrected TI data as part of a resource assessment report, knowing it has been validated to industry best practices (e.g., CFARS guidelines). This can make stand-alone Lidar campaigns bankable, a long-sought goal of the industry[5][6]. Additionally, consultants can use METICE to analyze more locations within a site. Instead of just one mast location's turbulence representing an entire site, a consultant might have METICE data from several Lidar positions, allowing a more robust assessment of site-wide turbulence variability. This is especially valuable in complex terrain or large sites where turbulence can vary. It effectively derisks the project by providing a fuller picture of the turbulence environment. Moreover, for operational wind farms, consultants could use METICE with nacelle-mounted or scanning Lidars to measure turbulence across turbine rows (for performance troubleshooting or life extension studies), again getting cup-equivalent data to compare with design assumptions. Overall, METICE enables consultants to provide better advice and tighter uncertainty ranges to clients, backed by data that was previously unavailable without towers.

5 Deployment and implementation guidance

METICE is delivered in a manner that suits different user needs, either embedded directly in the Lidar's firmware or as a post-processing software tool. This flexibility allows METICE to be used in real-time field deployments as well as retrospective data analysis. Below is a high-level workflow and guidance for using METICE in typical project scenarios:

- ▲ **Lidar installation and configuration:** Deploy the ZX ground-based Lidar (e.g., ZX 300 or ZX 300e) at the site of interest. Ensure it's configured to record the necessary 10-minute statistics (mean wind speed, standard deviation, etc.) at the heights of interest. In a firmware-integrated scenario, the Lidar's onboard software would run the METICE algorithm automatically on the 10-min data. If METICE is not running in real-time on the device (e.g., using an older Lidar or one without the firmware update), then the raw 10-minute data should be recorded for later processing using an appropriate version of the ZX ZPH2CSV software.
- ▲ **Site-specific adjustments (if needed for complex sites):** If the site is complex terrain or has unique features, it is recommended to perform a flow analysis to complement METICE. This could involve running a Computational Fluid Dynamics (CFD) model, using a CFD conversion service provider (Meteodyn, WindSim, DNV, Deutsche WindGuard, Ramboll, Natural Power etc.), or a linear flow model (e.g., WRF or WindMap) to compute wind speed and turbulence adjustment factors for the Lidar's location relative to a reference. For instance, a CFD might indicate that at a certain wind direction, the Lidar underestimates turbulence by X% due to a terrain blocking effect. These correction factors can be applied to the Lidar's measured mean wind or sigma before input to METICE. In practice, one might implement this by feeding METICE "adjusted" wind speed and standard deviation values (e.g., sigma multiplied by a factor derived from CFD that varies with height and wind direction). ZX's validation has shown that doing this for very complex sites greatly improves the outcome. For most simple or moderately complex sites, no CFD correction is necessary – METICE can be applied directly to the Lidar data.
- ▲ **METICE processing:** Run the METICE model on the dataset. If using firmware-integrated METICE, this is automatic and continuous – the user will receive T_{ICE} in real time every 10 minutes, just as they would get wind speed readings. If using post-processing, the user would input the recorded data (typically a .zph or database of 10-min stats) into the ZX ZPH2CSV software. The software will apply the ensemble model to each data record and output the cup-equivalent T_I . This process is computationally light (designed to be efficient for potentially large datasets), so even years of data can be processed quickly on a standard PC.

6 Conclusion: Advancing Lidar adoption with METICE

METICE represents a significant advancement in the integration of Lidar technology into mainstream wind resource and site assessment practices. By providing a validated and accurate translation of Lidar-measured turbulence intensity to cup-equivalent values, METICE effectively removes one of the last barriers for replacing or supplementing met masts with remote sensors.

For the industry, the value proposition of METICE is clear: it enables cost-effective, flexible wind measurements without sacrificing the fidelity required for turbine design and certification. Projects in remote or complex locations that once struggled with obtaining reliable turbulence data can now deploy a ZX Lidar and trust that the turbulence data will be on par with a mast. This opens the door to wider deployment of Lidars for site suitability, not just for mean wind speeds as has been common, but for the full suite of design parameters. In doing so, METICE supports the wind industry's drive to reduce costs and timelines – fewer met masts mean lower upfront CapEx and faster project development, and more data from Lidars means potentially better optimized turbine placements and designs.

The collaborative efforts like CFARS underline that the industry is eager for solutions that standardize remote sensing for loads. METICE's performance – meeting 99% of stringent bias targets across hundreds of test cases – demonstrates that a machine learning approach can indeed achieve the level of rigor needed. It essentially provides the “cup anemometer truth” from a Lidar, which can be readily used in commercial energy assessments and load verifications with confidence. This directly de-risks the use of Lidar for site suitability assessment, echoing the CFARS mission to accelerate remote sensing adoption[7].

Looking forward, METICE is not a static solution but a framework that can continue to evolve. Future improvements will likely include:

- ▲ **Broadening the training dataset:** Incorporating data from an even wider range of sites – for example, very complex terrains, offshore wind farms, different climate zones (tropical storms, monsoonal winds, arctic conditions, etc.). As more co-location datasets become available, new ensemble members can be added to extend METICE's applicability. The model's scalable architecture means it can only get better with more data. One can envision a future version of METICE that has “seen everything” – from flat deserts to mountainous forests – and thus can handle any new site with ease.
- ▲ **Offshore and Floating Lidar applications:** While the current METICE has been tested mainly on ground-based Lidars, the principles can apply offshore. Floating Lidars introduce additional complexity (platform motion affecting measured turbulence). Research (e.g., Kelberlau et al. 2023, Rapisardi et al. 2024) has begun addressing floating Lidar turbulence corrections. METICE could be combined with motion compensation algorithms to correct floating Lidar TI data. In fact, the same ensemble approach could learn from floating Lidar vs mast comparisons (some exist from offshore trials) to create a specialized model.
- ▲ **Uncertainty quantification:** Efforts are underway to refine how model uncertainty is represented and propagated through the Bayesian ensemble, ensuring more reliable TI prediction interval estimates under highly variable site conditions. These improvements aim to enhance both the robustness and interpretability of METICE outputs, providing users with clearer insight into model reliability in challenging environments

In conclusion, METICE provides the wind industry with a practical, proven solution for cup-equivalent turbulence intensity from Lidar. It stands at the intersection of meteorology, data science, and wind engineering, translating cutting-edge algorithmic insight into tangible project value. By enabling remote sensing to fully step into roles once reserved for cup anemometers, METICE helps drive the industry



forward into a more flexible and data-rich future. The ultimate vision of “mast-free” wind farm assessments – where all necessary wind characteristics are measured by portable, cost-effective devices – is materially closer thanks to METICE. As the model continues to learn and expand, we can expect even greater confidence and adoption, solidifying Lidar’s place in wind energy from resource assessment through to site certification. The ensemble approach pioneered here may also inspire similar techniques for other measurement translation challenges in wind energy and beyond, where merging physics and machine learning yields powerful results.

7 References

1. Kelberlau, F. and Mann, J., 'Better turbulence spectra from velocity–azimuth display scanning', Atmospheric Measurement Techniques, 2019.
2. Peña, A., Yankova, G. G. and Mallini, V., 'On the lidar-turbulence paradox and possible countermeasures', Wind Energy Science, vol. 10, no. 1, 2025, pp. 83–102.
3. Sathe, A. et al., 'Can Wind Lidars Measure Turbulence?', Journal of Atmospheric and Oceanic Technology, 2011.
4. DNV, 'DNV-RP-0661: Lidar Measured Turbulence Intensity for Wind Turbines', DNV, 2023.
5. CFARS, 'Site Suitability Initiative White Paper', CFARS Publications, 2021.
6. ZX Lidars and NRG Systems, 'Advancing Cup-Equivalent TI from Continuous Wave Lidar', Proceedings of WESC 2025.
8. Nordex, 'Lidar TI Project Presentation: OEM Perspective on Lidar TI and Load-Based Validation', Nordex Group, 2025.
9. Blue Aspirations, 'ZX 300M Lidar on Floating Platform – TI Correction Meets CFARS Best Practice', Blue Aspirations, 2025.
10. Kelberlau, F. et al., 'Assessment of TI Estimates from Floating Lidars', 2023.
11. Rapisardi, G. et al., 'Machine Learning Approach to Correct TI Measured by Floating Lidars', 2024.

8 Links

[1] [2] [5] [6] [7] Publications • CFARS

<https://cfars.github.io/publications/>

[3] [4] DNV issues new recommended practice on Lidar measured turbulence intensity for wind turbines

<https://www.dnv.com/news/2023/dnv-issues-new-recommended-practice-on-Lidar-measured-turbulence-intensity-for-wind-turbines-249937/>

About Us

In 2003 we released the first commercial wind lidar, pooling decades of fibre laser research from the science, security and energy industries. Designed specifically for the wind industry our Lidar has paved the way for many of the remote sensing devices seen in the market today. Our original lidar technology continues to innovate with world firsts such as taking measurements from a wind turbine spinner and being the first to deploy an offshore wind lidar, both fixed and floating. Our Lidars have also now amassed millions of hours of operation across 15,000+ deployments globally spanning two decades of commercial experience. Some of our proudest achievements are listed below; these are the earliest reported examples that we are aware of from open publications.

- 2003** - The first wind lidar to make upwind measurements from a turbine nacelle
- 2004** - The first and original commercially available lidar for the wind industry
- 2004** - The first wind lidar to investigate the behaviour of turbine wakes
- 2005** - The first wind lidar to be deployed offshore on a fixed platform
- 2007** - The first wind lidar to take measurements from a turbine spinner
- 2008** - The first wind lidar to be signed off against an industry-accepted validation process
- 2009** - The first wind lidar to be deployed offshore on a floating platform
- 2010** - The first wind lidar to re-finance and re-power a wind farm
- 2011** - The first wind lidar to be proven in a wind tunnel
- 2012** - The first wind lidar to be used with very short masts and secure project financing
- 2012** - The first wind lidar to be accredited for use with no or limited on-site anemometry for project financing by DNV GL
- 2014** - The largest batch of single-type lidar verifications against an IEC met mast
- 2015** - The first lidar designed specifically for offshore use, with the longest warranty available - 3 years as standard
- 2016** - The first wind lidar to support safe lifting on a jack-up vessel
- 2016** - The first wind lidar SCADA integrated on operational wind farms in replacement of site met masts
- 2017** - The first wind Lidar to be installed across a wind farm on a Lidar-per-turbine basis, uniquely mapping wakes across a wind farm
- 2018** - The first wind Lidar to satisfy all criteria for IEC Classification
- 2019** - The first wind Lidar to take wind measurements from a drone
- 2020** - The first wind Lidar to be accepted for bankable energy assessments in complex terrain standalone (without a met mast)
- 2021** - The first wind Lidar to attract more than £150bn+ of investment into wind energy projects
- 2022** - The first wind Lidar to be fully integrated into a retrofit wind turbine controller for Lidar Assisted Control
- 2023** - ZX Lidars moves to Willow End!
- 2024** - The first wind Lidar with a 5 year warranty and 5 year planned service interval as standard
- 2025** - The first wind Lidar to achieve 21 - 200m IEC Classification and 300m Performance Verifications

Our Products & Services

