Physics-informed Neural Network (PINN)-based component-wise condition assessment approach for floating offshore wind turbines (FOWT) using non-intrusive sensor measurements

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PROPOSAL DETAILS

(CRG/2023/005267)

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Technical Details :

Scheme :	Core Research Grant		
Research Area :	Civil Engineering (Engineering Sciences)		
Duration :	36 Months	**Contact No :**	+918894087002
Date of Birth :	19-Nov-1985		
Nationality :	INDIAN	**Total Cost (INR) :**	47,28,480

Is PI from National Laboratory/Research Institution ? Yes

Project Summary :

India has committed to reducing carbon emissions by 33-35% below 2005 levels by 2030. Wind energy is crucial to achieving this goal, and India aims to increase the share of wind energy in its energy mix to 40% by 2030. Proper maintenance of wind turbines is important for sustained energy production. Floating Offshore Wind Turbines (FOWT) are becoming popular due to issues with land acquisition, aesthetic pollution, and moderate energy yield. The proposal offers a non-intrusive continual targeted CA approach for component-wise health estimation for FOWTs that combines physics-based and data-driven approaches through a physics-informed learning approach. Three subsystems, namely: blades, tower, and mooring lines will be investigated in this attempt. Physics-informed neural networks (PINNs) can revolutionize the structural health monitoring of offshore wind turbines by combining low-fidelity models with sparse high-fidelity real data and especially when that can be employed at the component level while ignoring the rest of the structure. This study proposes the use of non-intrusive sensing and computer vision techniques based on machine learning to extract response information from high-speed video data. The proposed algorithm will address the SHM of FOWTs by estimating location-based health parameters alongside the network parameters, yielding probabilistic measures for the material/health parameters within a Bayesian learning environment. The algorithm will be validated against high-end numerical models and further investigated through noise sensitivity study, model dependency, and parametric analysis to investigate its real-life applicability.

Objectives :

• To develop a non-intrusive continual targeted CA approach for component-wise health assessment of floating-type offshore wind turbines (FOWTs) that combines physics-based and data-driven approaches through a physics-informed learning approach.
• To validate the proposed algorithm for each of the components considered in this study, against high-end numerical models prepared using Openfast open-source software and investigated under non-intrusive sensor measurements using ML-based image processing approaches.
• To investigate the real-life applicability of the proposed algorithm through noise sensitivity study, model dependency, and parametric analysis, leading to enhanced safety, reliability, and optimization of operational costs for offshore wind turbines.

Keywords :
PINN, Wind Turbine, Condition Assessment, ML, FOWT, Component-wise SHM

Expected Output and Outcome of the proposal :

1. A non-intrusive continual targeted CA approach for FOWTs that combines physics-based and data-driven approaches through a physics-informed learning approach. 2. Validation of the proposed algorithm against high-end numerical models prepared using Openfast open-source software and investigated under non-intrusive sensor measurements using ML-based image processing approaches. 3. Investigation of the real-life applicability of the proposed algorithm through noise sensitivity study, model dependency, and parametric analysis, leading to enhanced safety, reliability, and optimization of operational costs for offshore wind turbines. 4. The dissemination of the research findings through a report or a scientific publication. The report or publication could provide details on the proposed non-intrusive continual targeted CA approach for FOWTs, the methodology used, the results obtained, and the conclusions drawn. This would allow other researchers and industry professionals to learn from the research and potentially adopt the proposed approach in their own work.

Any other relevant information:

India is witnessing a rapid shift towards the adoption of renewable energy sources for long-term sustainability. The coastal regions, in particular, are well-positioned to harness the potential of wind energy through the development of offshore wind farms. According to a recent report by the International Renewable Energy Agency (IREA), India, which currently secures the fourth position in the ranks of wind energy harvesters, has the potential to go up to 300 GW by 2030 meeting about 20\% of its energy demand. By realizing this, India could further strengthen its position as a leader in renewable energy and help achieve its long-term sustainability goals.

Suitability of the proposed work in major national initiatives of the Government:

Swachh Bharat, Digital India, Smart Cities

Collaboration Details for last 5 Years :

Planned Collaboration for the proposed work with any foreign scientist/ institution ? No

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Subhamoy Sen, Ph.D.

1 Origin of the proposal

In an effort to curb global warming and meet the 2030 Climate Target Plan, India has pledged to minimize its impact on climate change by setting specific goals. The country aims to decrease its carbon emissions per unit of GDP by 33-35% below 2005 levels by 2030. To achieve this goal, India intends to have 40% of its total power capacity come from renewable sources by 2030, with wind energy playing a key role in reaching this target.

Wind energy, being a renewable, plentiful, and environmentally friendly source of electricity has seen significant growth globally over the past few years. This growth can be attributed to various factors such as decreasing technology costs, heightened worries about climate change, and government initiatives like renewable energy goals and tax incentives. The evolution of more giant and more efficient wind turbines has also paved the way for the growth of offshore wind energy, which is becoming economically more feasible with time.

India is well-suited for wind power generation, with a long coastline, high wind speeds in several regions, and growing energy demand. As of 2021, the global wind energy capacity has exceeded 700 GW, with China, the US, Germany, and India being the top contributors. India had reached a wind energy production capacity of 41.9 GW by December 2022, with a tariff rate as low as 2.77 INR/kWh. The government of India aims to increase the share of wind energy in the country's energy mix to 40% by 2030 and accordingly has introduced various policies to support this goal, such as tax incentives, subsidies, and financial support for wind energy developers, private or public.

As India expands its wind farm infrastructure, older turbines are reaching their end of life and becoming more prone to damage. Proper maintenance is essential to ensure safe and prolonged energy production. The cost of operating and maintaining (O&M) wind turbines (WT) tends to rise over time, but this is offset by the lower cost of energy production compared to other renewables. Despite this, maintaining WTs can be expensive and require extensive research in areas such as design, installation, and operation. Harsh environmental conditions can lead to frequent repairs and replacements, resulting in unscheduled downtime and financial losses. These faults are often caused by exposure to heavy loads, dust, and impacts, with the gearbox, rotor blades, tower, and mooring system being particularly vulnerable. The global market for WT O&M has seen significant growth, accounting for about 30% of the total project cost. This high recurring cost poses a barrier to the growth of wind energy.

Furthermore, in order to avoid the issues originating from land acquisition, aesthetic pollution, and moderate yield in energy for onshore wind turbines, the farms harvesting this renewable energy source focus more on floating-type offshore wind turbines (FOWT). This floating attribute enables towing the structure deep into the sea and positioning it with a set of mooring lines in a zone with high wind velocity. The integrity, stability, and positioning of the FOWT greatly depend on the tower, blades, and mooring lines and possible damage or degradation can severely affect the performance of the FOWT. The current proposal, therefore, focuses majorly on offshore WTs, and the pertinent studies are only discussed in the following.

Determining the condition of FOWT through condition assessment (CA) is a crucial aspect of ensuring its safety, enhancing reliability, and optimizing operational costs [71]. Conventional fault detection methods for FOWT include non-destructive evaluation (NDE) techniques, such as acoustics, vibration analysis, oil analysis, and strain measurement through supervisory control and data acquisition (SCADA). However, recent advancements in computational hardware and data-based methods have made CA more sophisticated and widely used. These methods use operational data to evaluate the health of the system leading to informed maintenance decisions [61, 67]. They are capable of handling uncertainties, including data noise, vague assumptions, and model inaccuracies. However, further investigation is needed in the context of FOWT, as the industry is still developing and limited studies have been conducted.

Currently, the analysis of WTs uses either model-based or data-driven approaches. The model-based WT monitoring uses physics-based models to compare simulated behavior with measured data, but a limited understanding of the physics leads to potential inaccuracies. The data-driven approach uses Machine Learning (ML) models to identify faults from sensor readings but requires a large database of normal and faulty conditions which can be challenging to obtain in real-world scenarios. A recent conceptual framework for data-based approaches uses a "digital twin" concept to improve wind platform design and reliability [5]. Further combining the relative benefits of both approaches may lead to a better solution for FOWT monitoring.

With a broader aim of lessening the unplanned O&M downtime of FOWT towards sustainable harvesting of wind power, the present proposal proposes a non-intrusive continual targeted CA approach that combines the relative benefits of physics-based and data-driven approaches through a physics-informed learning approach. The proposal offers a multi-sensor approach for smart remote CA of FOWT at the subsystem level, suitable for all operational scenarios. To avoid full-scale monitoring and the associated time and cost-intensive abundant instrumentation, a subsystem monitoring approach can be adopted, wherein WT subsystems will be monitored independently for their health while ensuring equivalent proficiency. In turn, this will reduce the reliance on high-dimensional models for a model-based monitoring approach. The uncertainties due to model inaccuracies and measurement noise will be addressed.

2 Review of the status of Research and Development in the subject

2.1 International Status

The dynamic response of FOWT under extreme waves and winds is crucial for evaluating their safety and reliability during operation, as well as for supporting design and feasibility studies [14, 17, 10]. Simulations utilizing the DeepCWind semi-submersible FOWT model from the Offshore Code Comparison Collaboration Continuation (OC4) have investigated the effect of wind turbine aerodynamics on a floating platform behavior [42, 39]. Such forward models have always proved to be helpful to understand the complex dynamics of FOWT systems and accordingly detect anomalies if occur.

Faults in a FOWT can arise in several of its components, including the tower, blades, and mooring lines [66]. The tower is susceptible to corrosion, fatigue, and buckling due to harsh weather conditions and ocean floor movements. The blades are vulnerable to damage caused by external factors such as debris and wear and tear from repeated exposure to wind loads and bending. Mooring lines, which are crucial in securing the FOWT, may experience faults due to corrosion, degradation of materials, and excessive stress from ocean currents and waves. To maintain the safety and reliability of the FOWT, it is crucial to identify and resolve these faults promptly. This proposal focuses on addressing the three key fault-prone areas of wind turbines, namely the rotor blades, tower, and mooring lines with model-assisted approaches.

Moreover, an effective CA system must be able to handle uncertainties originating from model inaccuracies, sensor noise, and unpredictable forces. Inverse stochastic estimation, unlike typical deterministic optimization approaches, is better equipped to address these uncertainties, but it requires repeated simulation, as noted in [65]. Full-scale models of FOWT are typically complex, high-dimensional, and computationally intensive, motivating the adoption of component-wise monitoring approaches [54, 27]. These component-wise monitoring approaches have the potential to reduce computational and instrumental demands while providing quicker and more precise results [39, 55]. Despite this, the subsystems (such as blades, towers, and moorings) are interconnected through complex dynamic interactions [7], requiring accurate information at the interface to ensure reliable monitoring [12].

To mitigate this challenge, the use of machine learning (ML) based approaches in wind structures has been increasing. Neural networks have been employed in various studies for forecasting wind speed, controlling WT power, and diagnosing faults [24, 36]. [29] proposed the use of a multi-scale convolutional neural network for classifying vibration signals and [59] developed a supervised ML algorithm for detecting blade damage. The best-first tree and functional tree algorithms have also been compared for blade monitoring[33]. However, most data-driven approaches concentrate on the supersystem, with only a few studies applying these algorithms for subsystem monitoring. The same has been detailed in the following.

2.1.1 CA approaches for mooring lines

Factors that lead to mooring line damage include fatigue [43, 69], strength capacity [11], tension, durability [8], and environmental loads [23]. Accordingly, five common damage types for FOWT mooring are due to bio-fouling, corrosion, top and bottom segment failure, and fatigue. Biofouling is caused by seaweed and organisms, while corrosion results from salt water and aerobic microorganisms. Top segment failure occurs at the connection with the buoy, and bottom segment failure is due to anchor failure. Fatigue is caused due to prolonged exposure to extreme loading conditions.

Mooring line damage has been found to have a significant impact on the stability of the system [6, 39]. Inverse assessment of mooring damage through the measured response has become popular using fuzzy logic-based damage diagnosis, although it is known to miss small to moderate damages [47, 25, 26]. A fault-tolerant control approach for diagnosis using vibration signals has been proposed, however, it is not suitable for FOWTs with moving parts [18]. Artificial neural networks (ANNs) have also been used to classify mooring damage levels and location [4] and for predicting biofouling [19]. Other methods, such as thermal imaging and acoustic emission monitoring, have been reviewed for cost minimization in operations and maintenance [46, 32].

2.1.2 CA approaches for WT towers

Further, the WT tower, measuring over 80 meters in length, makes it a pliant structure that needs to be monitored under adverse sea conditions [66] to ensure its proper functioning and maintenance [40, 41]. The structural safety of the FOWT tower is primarily determined by two critical indicators: the acceleration at the tower top and the force on the tower root [40]. The conventional method of monitoring the condition of the tower uses modal analysis techniques, however, these methods are often impacted by colored noise, which can interfere with the natural frequency of the tower and make the identification process ineffective [15, 84, 60]. Additionally, the data collected from the SCADA system is inadequate for dynamic analysis and structural parameter feedback due to its low sampling frequency (≤ 0.1 Hz) [40].

[20] introduced a hierarchical identification framework for monitoring of WT towers employing DL networks. [82] compared an auto-regressive dynamic adaptive (ARDA) model-based approach to the LSTM with respect to their performance in real-time predictions of wind power. [13] employed a DL-based approach for numerical optimization and dynamic response prediction of FOWT. Furthermore, [74, 76] investigated the relationship between the force and motion responses of the FOWT towers. To date, few studies have utilized ML/DL-based approaches for monitoring the FOWT towers, offering ample opportunities for further research.

2.1.3 CA approaches for WT blades

The maintenance of large composite WT blades is becoming increasingly complex as time goes on. Inspections of these blades are typically performed when the wind turbine is not in operation. The blades are expensive, accounting for approximately 20% of the overall project cost. Early detection of damage in the blades can significantly reduce the operation and maintenance costs, while also minimizing potential safety hazards. However, instrumenting the blades is challenging [49].

A number of research proposals have been put forward for detecting flaws in wind turbine blades, including Experimental and Operational Modal Analysis (EMA & OMA) [44], thermography [70], Acoustic Emission [70], and strain/load monitoring [16]. However, these methods require extensive instrumentation, making them not practical for real-world applications [16, 28]. Alternative techniques have been suggested, such as photogrammetry [51, 53] and laser vibrometer monitoring [50]. Additionally, the field of wind turbine blade analysis also encompasses signal processing and data mining-based methods, including the Wavelet Transform (WT) [72], Empirical Mode Decomposition (EMD) [3], image processing [58], outlier analysis [73], feature extraction [2, 30] and machine learning techniques [31, 77, 78]. Despite these advancements, the primary challenges of installation and hardware costs, wiring limitations, and experimental restrictions have yet to be resolved.

2.1.4 Non-intrusive sensing for WTs

Furthermore, for floating offshore wind turbine (FOWT) installations in deep-sea environments, the harsh marine conditions can lead to damage or detachment of monitoring sensors [79]. Intrusive vibration sensors, while commonly used, are expensive, prone to noise, intensive to maintain, and may incur damage even during installation [45]. Alternatives such as non-intrusive ultrasonic sensing or thermal imaging may alleviate some of these challenges, but can still result in unwanted downtime and may not detect certain faults [45]. This presents an opportunity to use non-intrusive sensors, such as visual images or video data, which can provide information on structural response through image processing techniques. Camera systems are more cost-effective and can cover large monitored structures, effectively creating a dense virtual sensor network. Techniques such as digital image correlation (DIC), phase-based motion magnification, and optical flow, based on computer vision, have been used to measure mechanical structure displacements, velocities, and other parameters without disrupting system operation [75, 83].

2.2 National status

Compared to the excessive research on the methods of wind turbine health monitoring all around the globe, research in India is still adopting this field. Nevertheless, there have been already some good studies that have been performed [38, 68, 62]. To ensure the safety and efficiency of wind turbines, researchers have examined the potential for catastrophic failures in three stages: the entire turbine system, its sub-components, and individual parts [63]. By employing a Markov Analysis to create system state transition diagrams, researchers were able to identify discrete failure states of wind turbine components over time [64]. Interestingly, these failures were found to be dependent only on the current system state, and not on any previous failure history. [35] demonstrated machine learning techniques to classify wind turbine faults utilizing vibration signals as a measurement signal is a suitable method for detecting and diagnosing blade faults in wind turbines. However, no pertinent literature is available that employs algorithms similar to what has been proposed in this draft.

3 Methodology

SHM is a diverse field involving sensors, signal processing, data analysis, and structural engineering. Sensors, embedded in the critical locations of the structure, collect data to monitor performance and behavior, which is further analyzed to detect damage using physics-based or data-driven methods.

Physics-based techniques rely on the fundamental physics (dynamics) of the structure to identify and locate damage. The spatial correlation between different sensor responses is inculcated in a mathematical model to simulate the structure's response to different loading conditions which can be compared to real-world measurements. Any unexpected deviation can, therefore, be flagged as indicative of damage. While this method provides a comprehensive understanding of the damage's nature and location, it demands a good knowledge of the inherent physics replicated using a meticulous and accordingly costly structural model. To effectively monitor a structure's health over time, it is essential to first comprehend how the same system responds in its healthy state. It is not unlikely that the underlying physics had altogether been misinterpreted and accordingly has been replicated with an inaccurate model, especially for complex systems like FOWT exhibiting rigid as well as flexible body dynamics under uncertain non-stationary forcing due to wind and wave.

Contrastingly, data-driven ML-based approaches employ statistical methods to scrutinize sensor data for irregularities or patterns that may indicate damage. The beauty of this method is that it doesn't require detailed structural models and is often more efficient than physics-based approaches for systems with substantial uncertainties. However, it may not offer the same level of detail regarding the type and location of the damage. Also, the data-driven approaches typically require a considerable amount of training data, which is costly and consequently, there is often a shortage of high-fidelity real-time data pertaining to the different health states of the structure.

In order to overcome the challenges associated with the traditional approaches, such as finite element method (FEM) and data-driven methods, the scientific community has increasingly adopted physics-informed neural networks (PINNs) as a potential solution [56]. The basic concept behind PINNs is to incorporate physical laws, in the form of differential equations, into the neural network training process. The idea of solving differential equations using artificial neural networks was first introduced by [37], who demonstrated that by selecting an appropriate trial solution that satisfies all initial and boundary conditions, this method could effectively solve both ordinary (ODE) and partial differential equations (PDE). Unlike FEM, where the discrepancy between the predicted and actual values at the testing points was typically larger than at the training points, it was observed that the variance at the test points was not greater than the highest deviation at the training points with the PINN approach. This indicated that PINNs showed good generalization performance.

However, the term PINN as well as a rise of subsequent research was initiated by [57]. The authors recommended that deep neural networks be utilized to solve the direct problem of solving differential equations using a set of loss functions that penalizes the loss in physics as well as the departure from the measured response. [48] presented a hybrid PINN approach to integrating ODEs combining both data-driven as well as physics-informed kernels with considerably smaller data compared to typical data-driven neural network models. The rising popularity of PINNs can also be attributed in part to recent progress in deep learning platforms, such as TensorFlow [1] and PyTorch [52], which employ automatic differentiation (AD) to minimize training losses [9]. Prior studies [34, 56] have also showcased the potential success of implementing PINNs for solid mechanics inverse problems, especially when it comes to identifying material parameters using response data. This particular aspect can be beneficial for health assessment approaches.

[80] introduced a general framework for detecting unknown geometric and material parameters for analyzing internal structures and defects. With a similar goal, [21] proposed a multi-network model that utilized displacement and stress data to identify material parameters. Their method was applied to linear elasticity and extended to von Mises plasticity. [22] presented a framework for calibrating constitutive models using full-field displacements and global force-displacement data, demonstrating its effectiveness for hyperelastic material models. Unlike the conventional PINN approach, they enforced physical constraints using the weak form of the PDE. However, this approach relies on a computational grid to integrate the weak form of the PDE and does not fully leverage the potential of PINNs. Furthermore, [81] investigated the identification of heterogeneous, incompressible, hyper-elastic materials using two independent artificial neural networks (ANNs) to approximate the displacement field and the spatially dependent material parameter, respectively.

Compared to typical civil engineering structures, the FOWT is a highly intricate mechanism that involves the principles of structural dynamics, aerodynamics, and hydrodynamics. Modeling the governing physics of such a complex system is challenging. Previous studies have used cost-intensive numerical forward simulations to capture the underlying physics accurately and thereby making the condition assessment unreliable. The present proposal intends to develop a PINN-based approach that combines the low-fidelity model with sparse high-fidelity real data within an ML-based approach and does not demand sampled/simulated data pertaining to the different health states of the structure. This low requirement of real data along with a high-fidelity model can revolutionize the structural health monitoring of FOWT. The complex interaction dynamics, typical for FOWT, will hereby be replicated using finite element models satisfying governing physics instead of using PDEs. Probabilistic approaches will subsequently be employed to estimate the health of the system. The primary schematics of the proposed framework are presented in Figure 1.

The data obtained from sensors is often noisy while the parameters under consideration is also uncertain in nature. It is, therefore, essential to adopt a probabilistic framework to search for an

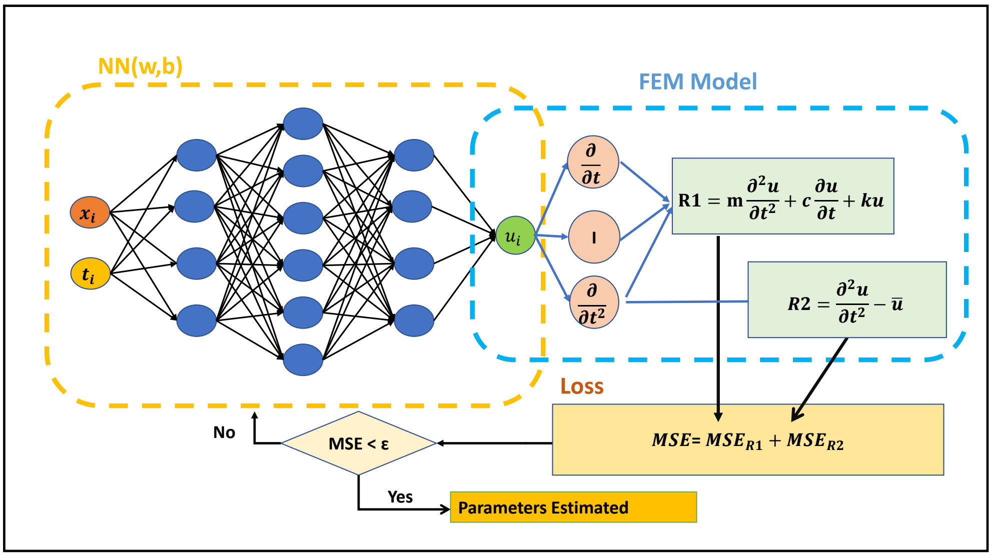

Figure 1: In the training phase, the deep neural network architecture is governed by governing differential equations detailing the physics of the system with a finite element model. At this stage, the parameters are tuned by using x_i (sensor coordinates) and t_i (time index) as inputs and measured response (u_i) as output. The network can then be trained with a set of loss functions (say $\mathcal{L}_1$ and $\mathcal{L}_2$) that penalizes the physics-informed loss as well as the output loss. The network takes the material parameters θ alongside the neural network parameters w, b as the control variable to have an optimal solution.
The presented network gives only a schematic of the actual process.

optimal solution. Herein, to account for the condition assessment of FOWT with a substantially low amount of stochastic high-fidelity data, a novel Bayesian PINN (BPINN) environment is proposed.

BPINNs can be used to estimate posterior parameters $P(\Phi|\bar{\mathbf{u}}, C)$ of the network, $\Phi = (\theta; \mu)$, where $\mu = (c, k_s)$ (model/material parameters), and $\theta = (w, b)$ (network parameters) such that the statistics of the output $\mathbf{u}$ predicted by the network satisfies statistics of the actual data $\bar{\mathbf{u}}$ and governing physics C.

$$P(\mathbf{\Phi}|\bar{\mathbf{u}}, \mathbf{C}) = \frac{P(\bar{\mathbf{u}}, \mathbf{C}|\mathbf{\Phi})P(\mathbf{\Phi})}{P(\bar{\mathbf{u}})P(\mathbf{C})} = \frac{P(\bar{\mathbf{u}}|\mathbf{\Phi})P(\mathbf{C}|\mathbf{\Phi})P(\theta)P(\mu)}{P(\bar{\mathbf{u}})P(\mathbf{C})} \tag{1}$$

Here $P(\bar{\mathbf{u}}, \mathbf{C} \mid \mathbf{\Phi}) = P(\bar{\mathbf{u}} \mid \mathbf{\Phi})P(\mathbf{C} \mid \mathbf{\Phi})$ are the two likelihood functions, the conditional probabilities of data $\bar{\mathbf{u}}$ and physics $\mathbf{C}$ for given parameters $\mathbf{\Phi}; P(\mathbf{\Phi}) = P(\boldsymbol{\theta})P(\mu)$ are the priors, the probability distribution of the network and model parameters θ and $\mu; P(\bar{\mathbf{u}})P(\mathbf{C})$ is the marginal likelihood or evidence; and $P(\mathbf{\Phi}|\bar{\mathbf{x}}, \mathbf{C})$ is the posterior, the conditional probability of the parameters $\mathbf{\Phi}$ for given data $\bar{\mathbf{u}}$ and physics $\mathbf{C}$. The first likelihood function $P(\bar{\mathbf{u}} \mid \mathbf{\Phi})$ evaluates the quality of fit between the model output $\mathbf{u}$ and the observed data $\bar{\mathbf{u}}$ at every i^{th} time step $(\mathbf{u}(t_i))$ as a product of each likelihood function $p_i(\bar{\mathbf{u}} \mid \boldsymbol{\theta})$, for which we can select a normal distribution,

$$P(\bar{\mathbf{u}}|\mathbf{\Phi}) = \prod_{i=0}^{\mathrm{n}} p_i(\bar{\mathbf{u}} \mid \mathbf{\Phi}) \quad \text{with} \quad p_i(\bar{\mathbf{u}} \mid \mathbf{\Phi}) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{\|\bar{\mathbf{u}} - \mathbf{u}(t_i)\|^2}{2\sigma^2}\right) \tag{2}$$

The second likelihood function $P(\mathbf{C}|\mathbf{\Phi})$ evaluates how accurately the model output $\mathbf{u}$ satisfies the physics equation $\mathbf{C} = \mathbf{0}$ at every i^{th} observation as a product of the likelihood functions $p_i(C \mid \mathbf{\Phi})$, for which we can also assume a normal distribution,

$$P(\mathbf{C} \mid \mathbf{\Phi}) = \prod_{i=0}^{\mathrm{n}} p_i(C \mid \mathbf{\Phi}) \quad \text{with} \quad p_i(C \mid \mathbf{\Phi}) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{\|C(t_i)\|^2}{2\sigma^2}\right). \tag{3}$$

For the prior probability distributions $P(\mathbf{\Phi})$, we can select independent low-fidelity informed priors with normal distributions for the two physics parameters, $\mu = \{c, k_s\}$, and normal distributions for the network parameters, $\boldsymbol{\theta} = \{w_k, b_k\}$. This can be done by updating the priors $P(\theta), P(\mu)$ employing the data $\bar{u}$, maximizing the prior-weighted likelihood function $P(\mathbf{\Phi} \mid \mathbf{u}, \bar{C})$.

3.1 Non-intrusive sensing

The proposed study incorporates non-intrusive sensing as another significant aspect. To extract response information from high-speed video data, primarily computer vision techniques based on ML have been planned. To accomplish this, the video data will be discretized based on its frame rate and different image processing approaches can be investigated, such as Digital Image Correlation (DIC), Fourier analysis (in the frequency domain), and optical flow. Some of these approaches will be ML-based, enabling better precision with larger data sets, like object tracking (YOLO, Faster R-CNN, or SSD), convolutional neural networks (CNN), and Gaussian Mixture Models (GMM)-based background subtraction. To further reduce uncertainties in the estimated response data, a motion-tracking approach based on Kalman filters will be utilized. The jerk model will be employed, which is especially effective for rapidly maneuvering objects, to enable precise control over the process of motion tracking. For example, object tracking from video data captured with high-speed cameras is one such application where this approach can be valuable.

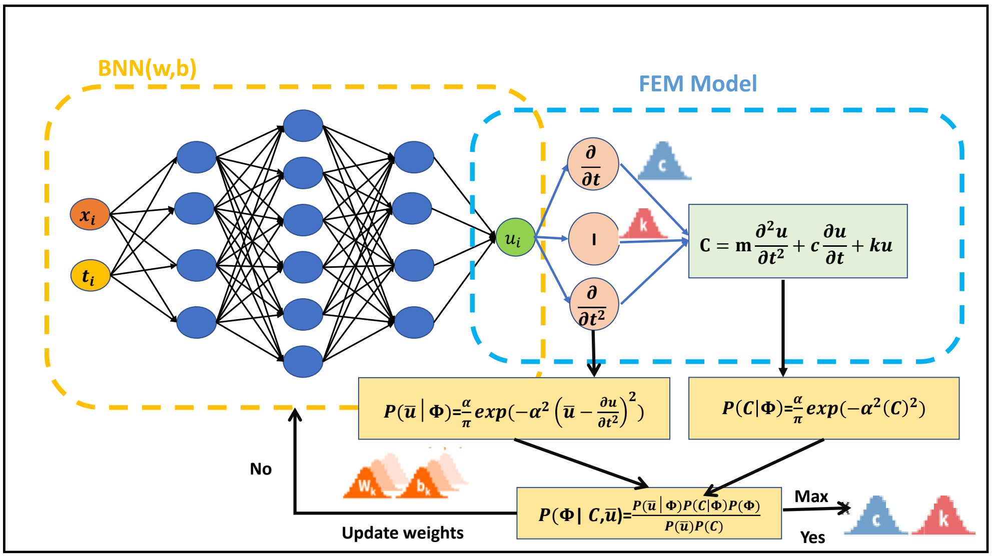

Figure 2: Bayesian Inference maximizes a prior-weighted likelihood function $P(\boldsymbol{\Phi}|\bar{\boldsymbol{u}}, \bar{\boldsymbol{C}})$ that could consist of two terms, the likelihoods $P(\bar{\boldsymbol{u}}|\boldsymbol{\theta})$ and $P(\bar{C}|\theta)$ of data $\mathbf{u}$ and physics C for given parameters θ, to infer distributions of the network parameters $\theta = (w_, b_k)$ and physics parameters $\mu = c, k_s$.

The ML-based computer vision technique proposed for this study is a significant advancement in the field of non-intrusive sensing over traditional intrusive sensing through strain gauges or accelerometers. By using ML-based models, it is possible to extract more accurate and reliable data from high-speed video data. This allows researchers to conduct more precise analyses and make informed decisions based on the results. Moreover, the use of the Kalman filter-based motion tracking approach further improves the accuracy of the estimated response data. The Kalman filter is a widely used algorithm in control systems, and it has proven to be highly effective in reducing uncertainties in motion tracking. This can help researchers better understand the behavior of objects in motion and enable them to make more accurate predictions about their future trajectories.

3.2 Importance of the proposed project in the context of the current status

India is witnessing a rapid shift towards the adoption of renewable energy sources for long-term sustainability. The coastal regions, in particular, are well-positioned to harness the potential of wind energy through the development of offshore wind farms. According to a recent report by the International Renewable Energy Agency (IREA), India, which currently secures the fourth position in the ranks of wind energy harvesters, has the potential to go up to 300 GW by 2030 meeting about 20% of its energy demand. By realizing this, India could further strengthen its position as a leader in renewable energy and help achieve its long-term sustainability goals.

Due to their location in the deep sea, FOWTs face harsh environmental conditions, making it crucial to have robust maintenance processes in place to ensure seamless operation and minimize maintenance and operating costs. To address this, a cost-effective and innovative solution using

DL-based methods has been proposed. The solution involves developing a smart continuous condition assessment framework for wind farms that integrates multiple sensors (both intrusive and non-intrusive). This framework leverages both model-based and data-driven DL networks to monitor key wind turbine subsystems in real-time and automatically detect faults. This will significantly reduce the need for instrumentation and minimize downtime caused by unplanned maintenance visits to the wind turbines.

The alarm system to be developed will feature straightforward indicators that will trigger an alarm if any threshold levels are exceeded. Such simple alarms can also be interpreted even by non-specialists facilitating the smooth operation of the CA approach. By integrating low-cost camera systems into an online network, the proposal will help the Indian wind industry smoothly transition to digital condition assessment (DCA) of its WTs. This will improve the ease of use and accessibility of CA approaches for maintenance and operations. Quick identification of faults will extend the WT lifespan, reducing the need for unnecessary replacement and preserving the environment and ecology. This new technology will promote the adoption of renewable energy resources and contribute to the sustainable development of wind energy by addressing one of the major challenges - the cost of maintenance and operations.

3.3 If the project is location specific, the basis for the selection of location be highlighted

Not applicable

4 Work Plan

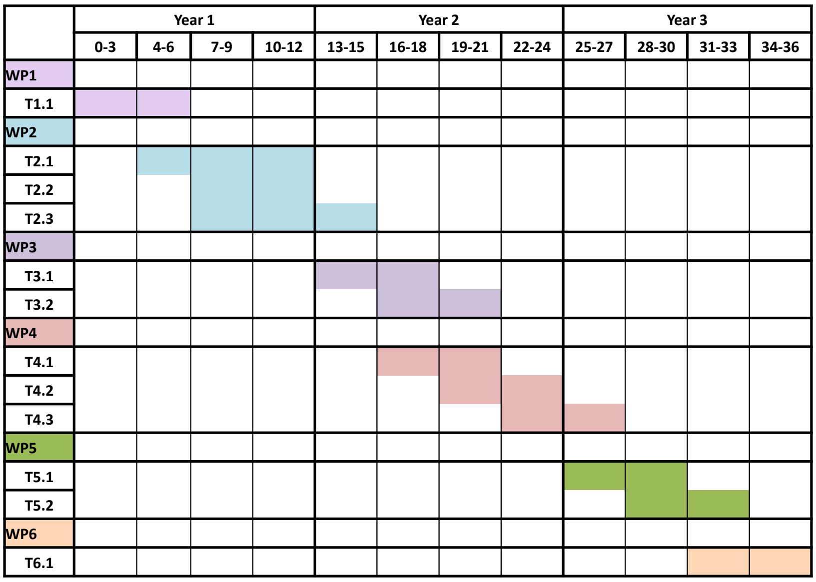

Table 1: Work-plan

WP1		
	T1.1	Literature Survey
WP2		
	T2.1	Development for proposed methodologies (PINN and BPINN) on simple structures such as beam.
	T2.2	Noise sensitivity and parametric analysis
	T2.3	Development of FEM of FOWT
WP3		
	T3.1	Development of PINN and BPINN for CA of blades
	T3.2	Noise sensitivity and parametric analysis
WP4		
	T4.1	Development of PINN and BPINN for CA of tower
	T4.2	Noise sensitivity and parametric analysis
	T4.3	Non intrusive sensing of tower
WP5		
	T5.1	Development of PINN and BPINN for CA of mooring lines
	T5.2	Noise sensitivity and parametric analysis
WP6		
	T6.1	Report writing and dissemination

4.1 Suggested Plan of action for utilization of research outcome expected from the project

The proposal intends to develop an efficient and economical online estimation approach by exploiting the benefits of the substructuring technique and physics-informed neural network architecture. The following plan of action can be considered for the utilization of the research outcome:

- Validate the algorithm's accuracy and efficiency by testing it on a diverse set of wind turbines in various weather conditions.
- Collaborate with manufacturers to integrate the algorithm into their wind turbines during the production process.
- Implement the algorithm in a pilot program in a select region to evaluate the algorithm's effectiveness in a real-world setting.
- Expand the pilot program to additional regions across India to evaluate the algorithm's effectiveness on a larger scale.
- Collect data on the performance of the algorithm in the field and gather feedback from stakeholders, including manufacturers and wind farm operators.
- Use the data and feedback to optimize and refine the algorithm to improve its accuracy and efficiency.
- Promote the algorithm to wind farm operators, investors, and other stakeholders in the wind power industry through marketing and outreach efforts.
- Continue to improve the algorithm based on feedback and advances in technology to ensure that it remains effective and relevant in the rapidly evolving wind power industry.

By following these steps, the research outcome of the proposed PINN-based CA for WT can be effectively utilized to improve the efficiency, profitability, and safety of wind power projects in India.

4.2 Environmental impact assessment and risk analysis

Not applicable

5 Expertise

5.1 Expertise available with the investigators in executing the project

Expertise in three key areas is required for the proposed research: (i) a strong understanding of SHM problems, (ii) experience with machine learning (ML)-based solutions for SHM, and (iii) hands-on experience in experimentation with real systems, including instrumentation, signal processing, and data analysis. My research since completing my Ph.D. has focused on probabilistic SHM approaches for stochastic structural systems. I have developed several SHM approaches both physics-based as well as data-driven while dealing with ambient uncertainties, especially for high-dimensional civil infrastructure systems that pose significant challenges. To concentrate on SHM research for systems with uncertainties, I have established a laboratory (i4s). I have published numerous papers in highly regarded journals, including MSSP, Elsevier, Bridge Engineering, ASCE, SCHM, Willey, and Structural Safety, Elsevier. Additionally, I have worked on six sponsored research projects, funded by SERB, ARDB, Imprint, SJVNL, and IIT Mandi. Two of these projects, completed with positive results, employed ML-based approaches for SHM, resulting in six journal articles. My extensive experience of over fourteen years in SHM research has given me an understanding of the state-of-the-art and critical requirements in this field. Through my research, I have discovered that the lack of a framework to make SHM computationally efficient and precise is the reason these techniques have not been widely adopted despite their rapid development. This realization has motivated the submission of this proposal.

5.2 Summary of roles/responsibilities for all Investigators

Not applicable

5.3 Key publications published by the Investigators pertaining to the theme of the proposal during the last 5 years

1. **Sen, Subhamoy**, Neha Aswal, Qinghua Zhang, and Laurent Mevel, Structural health monitoring with non-linear sensor measurements robust to unknown non-stationary input forcing, Mechanical Systems and Signal Processing, 152:107472, 2021.

2. **Sen, Subhamoy**, Antoine Crini'ere, Laurent Mevel, Frederic Cerou, and Jean Dumoulin, Seismic-induced damage detection through parallel force and parameter estimation using an improved interacting particle-Kalman filter, Mechanical Systems and Signal Processing, 110:231–247, 2018.

3. Neha Aswal, **Sen, Subhamoy**, and Laurent Mevel, Estimation of local failure in tensegrity using interacting particle-ensemble Kalman filter, Mechanical Systems and Signal Processing, 160:107824, 2021.

4. **Sen, Subhamoy** and Baidurya Bhattacharya, Online structural damage identification technique using constrained dual extended Kalman filter, Structural Control and Health Monitoring, 24(9):e1961, 2017.

5. **Sen, Subhamoy** and Baidurya Bhattacharya, Non-Gaussian parameter estimation using generalized polynomial chaos expansion with extended Kalman filtering, Structural Safety, 70:104–114, 2018.

6. Eshwar Kuncham, **Sen, Subhamoy**, Pankaj Kumar, Himanshu Pathak, An online model-based fatigue life prediction approach using extended Kalman filter, Theoretical and Applied Fracture Mechanics, Nov 6:103143, 2021.

7. Smriti Sharma and **Sen, Subhamoy**, Bridge damage detection in presence of varying temperature using two-step neural network approach, Journal of Bridge Engineering, 2021.

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6 List of Projects submitted/implemented by the Investigators

6.1 Details of Projects submitted to various funding agencies

Table 2: List of Projects submitted/implemented

Sl.	Project title	Duration	Agency
1	Study for the optimum height of lift for mass concreting dam structures.	2021-23	SJVNL
2	Vibration-based health monitoring of tensegrity structures incorporating the effects of ambient temperature.	2019-22	DST-ECR
3	Water and energy efficient reliable irrigation system (water-ERIS) (as co-PI)	2019-22	SERB-Imprint
4	Development of damage detection technique for composite laminated structures under varying temperature.	2019-21	ARDB
5	Robust health monitoring of steel bridges under varying environmental and traffic conditions, an application to Victoria Bridge, Mandi H.P.	2018-21	IIT Mandi
6	Digital Twin development employing Bayesian filters with sub-structured predictor models for aerospace application	2021-24	ARDB

6.2 Details of Projects under implementation

Table 3: Projects under implementation

Sl.	Project title	Duration	Fund (in lakhs)
1	Study for the optimum height of lift for mass concreting dam structures (SJVNL)	2021-23	32.4
2	Digital Twin development employing Bayesian filters with sub-structured predictor models for aerospace application (ARDB)	2021-24	39.5
3	Water and energy efficient reliable irrigation system (water-ERIS) (DST-Imprint)	2019-22	74.9

6.3 Details of Projects completed during the last 5 years

Table 4: Projects completed in last five years

Sl	Project title	Duration	Fund (in lakhs)
1	Development of damage detection technique for composite laminated structures under varying temperature (ARDB)	2019-21	23.39
2	Vibration-based health monitoring of tensegrity structures incorporating the effects of ambient temperature (DST)	2019-22	33.71
3	Robust health monitoring of steel bridges under varying environmental and traffic conditions, an application to Victoria Bridge, Mandi HP (IIT Mandi)	2018-21	33.71

7 List of facilities being extended by parent institution(s) for the project implementation

IIT Mandi is a multidisciplinary research-led institution targeting quality research and development. The institution offers a full range of academic programs at the undergraduate, postgraduate and doctoral levels and is located near Mandi town in HP amidst the beautiful landscape in the Himalayan region. Most of the facilities are modern and state of the art.

7.1 Infrastructural Facilities

Sr. No	Infrastructural Facility	Yes/No/ Not required Full or sharing basis
1.	Workshop Facility	✓
2.	Water & Electricity	✓
3.	Laboratory Space/ Furniture	✓
4.	Power Generator	✓
5.	AC Room or AC	✓
6.	Telecommunication including e-mail & fax	✓
7.	Transportation	✓
8.	Administrative/ Secretarial support	✓
9.	Information facilities like Internet/Library	✓
10.	Computational facilities	✓(Basic facilities only. For the rest, fund is requested)
11.	Animal/Glass House	Not required
12.	Any other special facility being provided	Not required

7.2 Equipment available with the Institute for the project

Equipment available with	Generic Name of Equipment	Model, Make & year of purchase	Remarks including accessories available and current usage of equipment
PI & his group	Wireless sensors and gateways	Lord Microstrain	Needs more nodes
PI & his group	Wired accelerometers	TE Connectivity	Need more sensors
PI & his group	Data acquisition system	Dewesoft	Synchroniser is required
PI & his group	MATLAB, ANSYS	2016	Licenses are made available
Other Institute(s)	None	NA	NA

8 Name and address of experts/ institution interested in the subject/outcome of the project

- Dr. Laurent Mevel
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Budget Details

Institution wise Budget Breakup :

Budget Head	Indian Institute of Technology, Mandi	Total
Research Personnel	19,40,400	**19,40,400**
Consumables	1,50,000	**1,50,000**
Travel	1,50,000	**1,50,000**
Equipment	15,00,000	**15,00,000**
Contingencies	1,50,000	**1,50,000**
Other cost	50,000	**50,000**
Overhead	7,88,080	**7,88,080**
Total	**47,28,480**	**47,28,480**

Institute Name : ***Indian Institute of Technology, Mandi***

Year Wise Budget Summary (Amount in INR) :

Budget Head	Year-1	Year-2	Year-3	Total
Research Personnel	6,46,800	6,46,800	6,46,800	**19,40,400**
Consumables	50,000	50,000	50,000	**1,50,000**
Travel	50,000	50,000	50,000	**1,50,000**
Equipments	15,00,000	0	0	**15,00,000**
Contingencies	50,000	50,000	50,000	**1,50,000**
Other cost	30,000	20,000	0	**50,000**
Overhead	4,65,360	1,63,360	1,59,360	**7,88,080**
Grand Total	**27,92,160**	**9,80,160**	**9,56,160**	**47,28,480**

Research Personnel Budget Detail (Amount in INR) :

Designation	Year-1	Year-2	Year-3	Total
Field Worker *The experimentation for this project is extensive and will require a manpower to help the JRF.*	2,37,600	2,37,600	2,37,600	**7,12,800**
Junior Research Fellow *The research fellow will be responsible to execute the idea proposed in this research. S/He will further develop the idea, perform necessary experiments and communicate the outcomes.*	4,09,200	4,09,200	4,09,200	**12,27,600**

Consumable Budget Detail (Amount in INR) :

Justification	Year-1	Year-2	Year-3	Total
A small replica of the wind turbine structure will be fabricated for which consumables will be required. Also, there will be other consumables like stationaries, printer cartridges, etc.	50,000	50,000	50,000	**1,50,000**

Travel Budget Detail (Amount in INR) :

Justification (Inland Travel)	Year-1	Year-2	Year-3	Total
The fund is required for traveling for national conferences, project presentation etc.	50,000	50,000	50,000	**1,50,000**

Equipment Budget Detail (Amount in INR) :

Generic Name ,Model No. , (Make)/ Justification	Quantity	Spare time	Estimated Cost
HIGH SPEED CAMERA DS-CAM-640C (DEWESOFT) *This camera is required to sample images at high speed from the structure. The sampled images are further required to be used to extract response measurements using ML-based approaches described in the proposal.*	1	20 %	**15,00,000**

Contingency Budget Detail (Amount in INR) :

Justification	Year-1	Year-2	Year-3	Total
The contingency fund will be used to support all unanticipated expenses and also for small instruments that are not proposed under the instrument budget.	50,000	50,000	50,000	**1,50,000**

Overhead Budget Detail (Amount in INR) :

Justification	Year-1	Year-2	Year-3	Total
The institute provides the basic amenities, administrative support and licenses for commercial software. Also, the experimentations are performed at nominal rates. The institute charges over head for this.	4,65,360	1,63,360	1,59,360	**7,88,080**

Other Budget Detail (Amount in INR) :

Description/Justification	Year-1	Year-2	Year-3	Total
Furniture The students working on the project will be needing basic furniture.	30,000	20,000	0	**50,000**

SUBHAMOY SEN, Ph.D.

Assistant Professor,
Indian Institute of Technology Mandi, Mandi, HP, India, 175005
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Contact Nos: 0091 1905 267 261; 0091 8894 087 002
Information and Statistics for Stochastic Structural Systems (*i*4S) laboratory
website: https://www.i4siitmandi.com/

Education and work history

May 2017 - till date – **Assistant Professor** *at* School of Engineering, IIT Mandi, HP, India & Team Leader of *i*4S Laboratory, IIT Mandi
Nov 2016 - May 2017 – Post-doctoral fellow *at* I4S team, INRIA, Rennes, France.
2016 (June-August) – Post-doctoral fellow *at* IIT Bombay, SSRR Lab, Civil Engg. Dept.
2011–2016 – Ph.D. *from* IIT Kharagpur, Structural Engineering.
2010–2011– **DAAD Fellow**, Masters thesis *from* Technische Universität Darmstadt, Germany.
2009–2011– Masters of Technology *from* IIT Kharagpur, Specialized in Structural Engineering, 1^{st} Class Honours, Rank–1.

Research interest

Stochastic system estimation, Structural Health Monitoring, Bayesian Filters, Machine Learning, Damage detection, Tensegrity structures.

Awards and Recognition

- **2009** – DAAD Scholarship awarded by Govt. of Germany
- **2004** – Governor Gold Medal, awarded by Governor of West Bengal, India
- **2019** – Overseas visiting Professorship - INRIA, France
- **2022** – Overseas Visiting Scientist - Govt of China

Publications: Journals

1. Aswal, N., **Sen, S.**, and Mevel, L., Switching Kalman filter for damage estimation in the presence of sensor faults, **Mechanical System and Signal Processing (2022)**.
2. Aswal, N., **Sen, S.**, and Mevel, L., Strain-based joint damage estimation approach robust to unknown non-stationary input force, **Structural Control and Health Monitoring (2022)**
3. Tandon, K., **Sen, S.**, and Viswanathan, KS., Integration of machine learning and particle filter approaches for forecasting soil moisture, **Stochastic Environmental Research and Risk Assessment (2022)**
4. E Kuncham, E, **Sen, S.**, Kumar P, Pathak H, An online model-based fatigue life prediction approach using extended Kalman filter, **Theoretical and Applied Fracture Mechanics**, vol – 117, 103143 (2021).
5. Aswal, N., **Sen, S.**, and Mevel, L., Estimation of local failure in tensegrity using Interacting Particle-Ensemble Kalman Filter, **Mechanical System and Signal Processing (2020)**.
6. Sharma, S., **Sen, S.**, Structural damage detection in presence of temperature variability using 2D CNN integrated with EMD, **Structural Monitoring and Maintenance**, vol– 8, issue– 4.

7. Sharma, S., **Sen, S.**, Comparative study on sensitivity of acceleration and strain responses for bridge health monitoring, **Journal of Structural Integrity and Maintenance**, 2021.
8. Sharma, S., Dangi, S., **Sen, S.**,Comparative study on sensitivity of acceleration and strain responses for bridge health monitoring, **Journal of Structural Integrity and Maintenance**, Taylor and Francis, (2022).
9. **Sen, S.**, Aswal, N., Zhang, Q, and Mevel, L., Structural health monitoring with nonlinear sensor measurements robust to unknown non-stationary input forcing, **Mechanical System and Signal Processing (2020)**. vol – 152, 107472.
10. Sharma, S., **Sen, S.** One-dimensional convolutional neural network-based damage detection in structural joints. **J Civil Struct Health Monit (2020)**. doi.org/10.1007 /s13349-020-00434-z.
11. Sharma, S., **Sen, S.**, Bridge damage detection in presence of varying temperature using two-step neural network approach **Journal of Bridge Engineering, ASCE**. doi:10.1061/(ASCE)BE.1943-5592.0001708.
12. Sharma, S., **Sen, S.**, Damage Detection in Presence of Varying Temperature Using Mode Shape and a Two-Step Neural Network, **Recent Advances in Computational Mechanics and Simulations**, Lecture Notes in Civil Engineering, Springer. doi: 10.1007/978-981- 15-8138-0-23.
13. **Sen, S.**, Aswal, N., and Mevel, L., Damage Detection in Tensegrity Using Interacting Particle-Ensemble Kalman Filter **European Workshop on Structural Health Monitoring. Springer, Cham, 2020.**.
14. **Sen, S**, Jianxun H, and K. S. Kasiviswanathan. Uncertainty quantification using the particle filter for non-stationary hydrological frequency analysis. **Journal of Hydrology** 584 (2020): 124666.
15. Sahagun, C, Jianxun He, Kasiviswanathan KS, **Sen, S.**,(201x) Stationary hydrological frequency analysis coupled with uncertainty assessment under nonstationary scenarios **Journal of Hydrology**
16. **Sen, S.**, Crenerie, A., Cereu, F, Demoulin, J. and Mevel, L., Estimation of nonstationary noise processes in a damaged system through Correntropy based IPKF filter, **IFAC papersOnline**, Elsevier, vol–51(24) : 420–427 *doi: 10.1016/j.ifacol.2018.09.611*]
17. **Sen, S.**, Crenerie, A., Cereu, F, Demoulin, J. and Mevel, L., Detection of seismic induced damage through parallel estimation of force and parameter using improved interacting Particle-Kalman filter, **Mechanical Systems and Signal Processing**, Elsevier, vol–110 : 231–247 *doi:10.1016/j.ymssp.2018.03.016.*
18. **Sen, S.** and Bhattacharya, B., Non-Gaussian parameter estimation using generalized polynomial chaos expansion with extended Kalman filtering, **Structural safety**, Elsevier, vol–70 : 104–114 *doi: 10.1016/j.strusafe.2017.10.009.*
19. **Sen, S.** and Bhattacharya, B., Online structural damage identification technique using constrained dual extended Kalman filters, **Structural Control and Health Monitoring**, Wiley (2017), vol–24 (9): 1–12, *doi: 10.1002/stc.1961.*
20. **Sen, S.** and Bhattacharya, B., Progressive damage identification using dual extended Kalman filter, vol–227(8): 2099–2109, **Acta Mechanica**, Springer, *doi:10.1007%2Fs00707-016-1590-9.*
21. **Sen, S.** and Bhattacharya, B., A non-iterative structural damage identification methodology using eigenstructure assignment in state space, **Structure and Infrastructure Engineering**, Taylor & Francis (2017), vol–13(2), 211-222, *doi:10.1080/ 15732479. 2016 .1157825.*
22. **Sen, S.** and Bhattacharya, B., Non-iterative eigenstructure assignment technique for finite element model updating. **Journal of Civil Structural Health Monitoring**, Springer (2015), vol–5(4): 365–375, *doi: 10.1007/s13349-015-0107-x.*

Book Chapter

1. Aswal, N., **Sen, S.**, Design and Health Monitoring of Tensegrity Structures: An Overview, Book Chapter, Reliability, Safety and Hazard Assessment for Risk-Based Technologies, **Springer**, 2019.
2. Sharma, S., **Sen, S.**, Damage detection in presence of varying temperature using mode shape and a two step neural network, **Springer**, 2021
3. Aswal, N., **Sen, S.**, Comparison between joint and dual estimation approaches with Extended and Unscented Kalman filters for the estimation of response states and structural health parameters, Recent developments in structural health monitoring and assessment , ed. Prof. Achintya Halder, **World Scientific**, 2022.

Selected Conferences

1. Aswal, N., **Sen, S.**, and Mevel, L., Estimation of Local Failure in Large Tensegrity Structures via Substructuring Using Interacting Particle-Ensemble Kalman Filter, European Workshop on Structural Health Monitoring 2022, 943-951, Palermo, Italy.
2. Sharma, S., **Sen, S.**, Damage detection in presence of varying temperature through residual error modelling approach with dual neural network, to be presented in EWSHM 2018 Conference, Manchester, UK.
3. **Sen, S.**, Crenerie, A., Cereu, F, Demoulin, J. and Mevel, L., Correntropy based IPKF filter for parameter estimation in presence of non-stationary noise process, to be presented in SAFEPROCESS 2018 (IFAC Conference), Poland.
4. **Sen, S.**, Crenerie, A., Cereu, F, Demoulin, J. and Mevel, L., Estimation of time varying system parameters from ambient response using improved Particle-Kalman filter, Apr 2017, European Geosciences Union, Vienna, Austria.
5. **Sen, S.**, Crenerie, A., Cereu, F, Demoulin, J. and Mevel, L., Seismic induced damage detection through parallel estimation of force and parameter using improved interacting Particle-Kalman filter, presented at IWSHM 2017, California, USA.
6. Hashmi, S., **Sen, S.** and Ghosh, S., Prediction of Flexural Buckling Strength of CFS Members with Local Geometric Imperfection using Stochastic Kriging, presented at ICOSSAR 2017, Vienna, Austria, 2017.
7. **Sen, S.** and Bhattacharya, B., Adaptive nonlinear Kalman filtering technique for parameter identification: an application to Bouc-Wen model, Engineering Mechanics Institute (EMI) International Conference of ASCE on Mechanics for Civil Engineers against Natural Hazards, Kwoloon, HongKong, China, January 2015.

Projects – 1.37 Cr. (as PI) and 94 lacs (as co-PI): Total 2.31 Cr.

- **DST-Imprint 2**- Water and Energy Efficient Reliable Irrigation System (WatErERIS): Solar energy and Cloud-based decision support systems for an automated irrigation system. (₹94 lacs)-**Ongoing**
- **DST-ECR**- Vibration based health monitoring of tensegrity structures incorporating the effects of ambient temperature. (₹34 lacs) – **Completed**
- **SEED-GRANT, IIT Mandi**, Robust health monitoring of steel bridges under varying environmental and traffic conditions: an application to Victoria bridge. (₹9.3 lacs) - **Completed**
- **ARDB Grant-in-aid**, Development of damage detection technique for composite laminated structures under varying temperature, (₹24 lacs) - **Completed**
- **SJVNL**, Study for the optimum height of lift for mass concreting dam structures, (₹33 lacs) – **Ongoing**.
- **ARDB**, Digital twin development using Bayesian filters with substructured predictor model for aerospace application, (₹34 lacs) – **Ongoing**

Research students

PhD Students

- Dr. Smriti Sharma (Graduated on April 2022, Postdoc in BCAM, Spain)
- Ms. Neha Aswal (Submitting PhD in January)
- Mr. Eshwar Kuncham (Submitting PhD in January)
- Mr. Kshitij Tandon (Joined PhD on August 2021)
- Mr. Maninder Singh (Joined PhD on December 2021)

MS Students

- Mr. Yeturi Pramod Kumar Reddy (Graduated MS on May 2022, pursuing Ph.D.)
- Mr. Sumeet Kumar (Joined MS on December 2021)

Facilities developed

- Laboratory i4S (https://www.i4siitmandi.com/)
- State-of-the-art laboratory dealing with vibration based SHM and uncertainty quantification
- Graduated one PhD (employed as postdoc in BCAM, Spain) and one MS student
- Current students: Four (4) PhDs, 1 MS, 1 MTech student
- Handled project worth 2.08 Cr. and consultancy of worth 20 lacs

Credentials

- Courses taught: Rigid Body Mechanics, Structural Dynamics, Design of Steel Structure, Civil Engineering Drawing (Teaching feedback - very good)
- Leadership roles: Coordinator of Centre for Himalayan Studies, Coordinator for flagship course, Design Practicum for three consecutive years
- Administrative roles: Member of Purchase committee, Entrepreneurship cell, Disciplinary committee, warden-ship, Faculty advisor etc.
- Organised workshop as coordinator on composite health monitoring (103 participants)
- Organised workshop to teach school students the basics of vibration (under DST social responsibility scheme)
- Organised symposium in collaboration with AR&DB, DRDO.
- Co-coordinated ICCMS conference in IIT Mandi and several other workshops.

Dr. Venkata Krishnan M.Sc., Ph.D.
Dean, Sponsored Research, Industrial Consultancy
& International Relations (SRIC & IR)

Endorsement Certificate from the Head of Institution

This is to certify that:

1. Institute welcomes participation of Name: **Dr. Subhamoy Sen**, Designation: **Associate Professor** as the Principal Investigator for the project titled "**Physics-informed Neural Network (PINN)-based component-wise floating offshore wind turbines (FOWT) condition assessment approach using non-intrusive sensor measurements**" and that in the unforeseen event of discontinuance by the Principal Investigator, the Principal Co-Investigator will be identified, who will assume the responsibility of the fruitful completion of the project with due information to SERB.
2. The PI, **Dr. Subhamoy Sen** is a permanent or regular employee of Indian Institute of Technology (IIT)-Mandi and has **28 years** of regular service left before superannuation
3. The project starts from the date on which the University/Institute/ Organization/College receives the grant from SCIENCE & ENGINEERING RESEARCH BOARD (SERB), New Delhi.
4. The investigator will be governed by the rules and regulations of University/ Institute/Organization/College and will be under administrative control of the University/ Institute/Organization/College for the duration of the project.
5. The grant-in-aid by the SCIENCE & ENGINEERING RESEARCH BOARD (SERB), New Delhi will be used to meet the expenditure on the project and for the period for which the project has been sanctioned as mentioned in the sanction order.
6. No administrative or other liability will be attached to SCIENCE & ENGINEERING RESEARCH BOARD (SERB), New Delhi at the end of the project.
7. The Institute (IIT-Mandi) will provide basic infrastructure and other required facilities to the investigator for undertaking the research project.
8. The Institute (IIT-Mandi) will take into its books all assets created in the above project and its disposal would be at the discretion of SCIENCE & ENGINEERING RESEARCH BOARD (SERB), New Delhi.
9. The Institute assumes to undertake the financial and other management responsibilities of the project.

Seal of

V. Krishnan

Dean SRIC
IIT Mandi
Kamand - 175005.
H.P., India

Signature
Head of the Institute

University/
Institute/Organization/College
Date: 21st Feb, 2023

SCALING THE HEIGHTS

Certificate from the Investigator

Physics-informed Neural Network (PINN)-based component-wise condition assessment approach for floating offshore wind turbines (FOWT) using non-intrusive sensor measurements

It is certified that

1. The same project proposal has not been submitted elsewhere for financial support.

2. We/I undertake that spare time on equipment procured in the project will be made available to other users.

3. We/I agree to submit a certificate from Institutional Biosafety Committee, if the project involves the utilization of genetically engineered organisms. We/I also declare that while conducting experiments, the Biosafety Guidelines of Department of Biotechnology, Department of Health Research, GOI would be followed in toto.

4. We/I agree to submit ethical clearance certificate from the concerned ethical committee, if the project involves field trails/experiments/exchange of specimens, human & animal materials etc.

5. The research work proposed in the scheme/project does not in any way duplicate the work already done or being carried out elsewhere on the subject.

6. We/I agree to abide by the terms and conditions of SERB grant.

Subhamoy Sen, Ph.D.
Name and signature of Principal Investigator:
Date: 14th March 2023
Place: IIT Mandi, HP

Undertaking by the Principal Investigator

To

The Secretary
SERB, New Delhi

Sir

I Dr. Subhamoy Sen, Associate Professor, IIT Mandi, HP

herby certify that the research proposal titled Physics-informed Neural Network (PINN)-based component-wise condition assessment approach for floating offshore wind turbines (FOWT) using non-intrusive sensor measurements submitted for possible funding by SERB, New Delhi is my original idea and has not been copied/taken verbatim from anyone or from any other sources. I further certify that this proposal has been checked for plagiarism through a plagiarism detection tool i.e. Turnitin approved by the Institute and the contents are original and not copied/taken from any one or many other sources. I am aware of the UGCs Regulations on prevention of Plagiarism i.e. University Grant Commission (Promotion of Academic Integrity and Prevention of Plagiarism in Higher Educational Institutions) Regulation, 2018. I also declare that there are no plagiarism charges established or pending against me in the last five years. If the funding agency notices any plagiarism or any other discrepancies in the above proposal of mine, I would abide by whatsoever action taken against me by SERB, as deemed necessary.

Signature of PI with date

Name / designation

Dr. Subhamoy Sen
Associate Professor
IIT Mandi, HP