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EDITORIAL

The issue opens with the article “Towards Smart Solar Panel System Development: Case Study from Cleaning System Design and Algorithm Development Using Data-Driven Method”, which combines mechatronic design with data-driven control for photovoltaic maintenance. The authors design and experimentally evaluate two fixed cleaning mechanisms for PV panels—a multi-arm wiper system and a single-axis rail system—instrumented with panel and cleaning-power metering. Building on a carefully constructed image dataset that reflects local soiling conditions (soil, sand, leaves, shade, wet/dry states), they compare hand-engineered feature extraction against convolutional models for dirt detection, from binary “clean/dirty” classification to 3x3 zonal assessment. The study demonstrates that a compact SVM fed by dark-channel and contrast-based features can outperform heavier CNN architectures in accuracy–latency–power trade-offs on embedded hardware, while multi-zone detection still favors learned features. This work shows how targeted dataset design, hardware-aware model compression, and explicit performance metrics can turn PV cleaning from heuristic scheduling into a quantitatively optimized control problem.

The second paper, “Empowering Smart Grids: An IoT and LoRa-Based Approach for Energy Monitoring and Theft Detection”, addresses one of the most persistent operational challenges in modern distribution systems: reliable and scalable detection of non-technical losses. The authors propose an IoT- and LoRa-based architecture that pairs two ESP32-based units, installed at the pole and the customer premises, to measure voltage and current, compare upstream and downstream currents, and flag discrepancies as potential theft events. Using ZMPT101B voltage and SCT013B current sensors, with cloud logging via Google Sheets and Google Apps Script, the system achieves long-range, low-power communication suited for rural and peri-urban grids. Experimental campaigns with no-load, nominal-load and emulated theft conditions show robust discrimination based on a simple current-mismatch threshold, with an average current-measurement error around 2.33. Packet-loss and delay characterization demonstrate that LoRa provides sufficiently reliable telemetry for near real-time supervision, offering a low-cost platform that can be extended with advanced analytics and stronger cybersecurity.

The third contribution, “Statistical Failure Analysis and Reliability Indices Estimation in a Medium-Voltage Distribution System”, turns to reliability assessment of existing distribution infrastructure, using historical outage and maintenance records from a medium-voltage network to quantify performance trends and investment needs. Despite data limitations arising from asset renaming, grouped event reporting and a sizable fraction of unclassified fault causes, the authors show that the dataset is sufficient to compute statistically meaningful indicators such as SAIDI, SAIFI and mean time between failures. Over the observation period, these indices reveal a clear improvement in continuity of supply, confirming the impact of previous revitalization measures. Spatial-temporal analysis highlights specific feeders and segments where recurring faults cluster, guiding targeted reinforcement and condition-based maintenance. The study also points to emerging correlations between local meteorological stressors and failure rates, underscoring the value of integrating weather telemetry and more granular asset-health data into reliability planning.

The fourth article, “Individual Phase Current Control Algorithm for Load Unbalance Compensation in Grid-Connected Three-Level Inverters Operating in Islanding Mode”, is a control-oriented study focused on maintaining power quality during islanded operation of grid-connected three-level NPC inverters under severe load imbalance. It introduces an individual phase current control algorithm that couples a DQ-frame outer voltage loop with an ABC-frame inner current loop, and augments it with per-phase load-current feed-forward and automatic reconfiguration between three- and four-wire modes via a static switch. By injecting measured phase load currents directly into the natural-frame current reference, the controller achieves fast per-phase tracking, current errors below 2%, and threefold reductions in settling time for 100% and 50% single-phase load steps. Simulation results show a substantial improvement in power quality, with current THD reduced from 13.18% to 3.64% and the voltage imbalance factor VUF dropping from above 8% to below 1%, in line with IEEE 519 limits. The design also demonstrates robustness to $\pm 20\%$ filter-parameter variation, making it attractive for practical islanded microgrid implementations.

The fifth article, “Potential Assessment and Techno-Economic Analysis of Offshore Wind Farm in Croatia”, broadens the issue towards long-term system planning and the Croatian energy transition. It assesses the technical and energy potential of bottom-fixed offshore wind in the Adriatic Sea and couples this with a detailed techno-economic evaluation of a reference 150 MW project in the northern Adriatic. The authors first develop an integrated spatial-technical screening of the Croatian maritime area, combining wind resource, bathymetry, seabed properties, existing concessions, environmental constraints, maritime traffic and visual impact to identify realistically usable zones. They then link these zones with planned transmission developments, emphasizing the Istria Program and the future 400/110 kV Vodnjan substation as key enablers for grid integration. Using high-resolution wind data and an IEA 10 MW reference turbine, the paper quantifies energy yield, losses, LCOE, NPV and IRR, and performs sensitivity analyses on electricity price and CAPEX, showing that financial viability of the first Croatian offshore project critically depends on moderate price support and cost reductions. The conclusions highlight offshore wind as a promising but capital-intensive option whose realization requires coordinated regulatory reform, transmission expansion and dedicated measurement campaigns in the Adriatic.

Igor Kuzle
Editor-in-Chief

Towards Smart Solar Panel System Development: Case Study from Cleaning System Design and Algorithm Development Using Data-Driven Method

Ganghee Jang, Cameron Robinson

Summary — In general, solar power is generated by solar panels, but their efficiency depends on panel conditions, which are affected by environmental factors. To consider the variation, we need a smart cleaning mechanism. In this work, we used a data-driven approach to develop a control algorithm that accounts for the wide range of dirty-surface conditions on solar panels. As another essential design space was the budget, various feature development methods were considered to identify more power- and performance-efficient approaches. Two cleaning systems — a wiper-based and a rail-based system — were designed and used to evaluate the developed algorithms. In our experiment, the wiper-based system outperformed the rail-based system in both cleaning speed and power efficiency. Algorithms based on hand-engineered features can reduce algorithmic size and inference time while maintaining competitive performance. However, the algorithms with learned features showed consistently decent performance and development time.

Keywords — Solar panel, cleaning, data-driven control algorithm, hand-engineered features, dark channel, dataset.



Fig. 1. Solar panel arrays covered with snow.

I. INTRODUCTION

Solar panels are a popular renewable energy source. However, the performance of each solar-powered system can be affected by the condition of its solar panels' surfaces in many ways. If the solar panel system has a goal of making a profit, it can be severely hindered by poor weather conditions. Power generation can also be interrupted when the surfaces of the solar panels is covered. For example, sandstorms in the Middle East can reduce power generation efficiency or even cause total power loss, resulting in financial losses for power plants, as studied in [1].

Sometimes, solar panels can get damaged by dirt. Uneven heating from sticky materials, such as organic waste, moss, etc., can cause damage to the panels over time [2]. Therefore, the timing of cleaning is essential. Dirty panels should be cleaned before the

dirt has solidified. In the case of light snow, it would be better to clean the surface when the snow stops. However, as in the example shown in Fig. 1, cleaning a snow pile requires significant effort, and sometimes even snow removal by hand. If cleaning were performed while it was snowing, the solar panels would be ready for power generation right after the snow stopped.

The decision to clean and the timing of the action can vary depending on the type of dirt and weather conditions. Also, as climates differ by region, dirt types and weather will vary. So, data-driven algorithm development is a necessary design direction.

Running algorithms from the data-driven approaches tends to require more computing power, however, power and performance efficiency for the target embedded system should be considered. We approached our designs from two different feature development methods: hand-engineered, and automatically generated features.

To test the cleaning algorithm, we developed fixed types of cleaning mechanisms for the design exploration. There has been related research activities in the domain of fixed cleaning mechanisms for solar panels. Still, only a small amount of attention has been given to the development of controller algorithms. On-time cleaning requires smart identification of dirt species - soil, sand, snow, leaves, etc.

The contribution of our work is as follows:

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- Development of the training dataset for the development of a control algorithm using a data-driven approach. The dataset development reflects local weather conditions.
- Exploration of design space for realistic cleaning workloads. For this purpose, we design cleaning test procedures to numerically compare two different cleaning systems.
- Exploration of algorithm design spaces for better performance and power efficiency.
- Development of two different solar panel cleaning systems and comparison of their performance using the test procedures.

In Chapter II, we discuss similar research to contrast the different approaches we took. Then, we explain our approaches — dataset, hardware cleaning mechanisms, and dirt detection algorithms — in Chapter III. The performance measures for the hardware mechanisms and algorithms are listed in Chapter IV. Lastly, the conclusion and future work are discussed in Chapter V.

II. RELATED WORKS

Renewable energy investment has increased, especially in photovoltaic electricity, which was expected to account for about 20% of global energy demand by 2050 [1]. Given the importance of photovoltaic (PV) electricity, the cleaning and protection of solar panels has attracted researchers' attention.

It is obvious that dust accumulated on solar panels would reduce the amount of solar energy absorbed and converted into electricity. Energy lost from dust or dirt was reported between 7% and 50% [3]. If cleaning is necessary, the next question is how we can apply an efficient cleaning methodology.

In [1], the authors classified commonly-used mechanisms into Brush Cleaning System (BCS), Electrostatic Cleaning System (ECS), Heliotex Cleaning System (HCS), Robotic Cleaning System (RCS), and Coating Cleaning System (CCS). The classification is somewhat uncertain; for example, RCS can also have brushes to clean dust. Also, soiling can be prevented with immediate cleaning. In other words, specific cleaning methods depend on the chosen cleaning strategy. BCS systems are the least expensive in terms of hardware, so they are the most cost-efficient among the systems categorized in [1].

Many BCS systems have been suggested. One of the most common choices is to move a wiper with a silicone brush or roller in a single direction on the rails [2], [4], [5], or a two-dimensional rail system to clean multiple solar panels aligned on the same rails [6]. Using two sets of rails has clear benefits over a single-rail cleaning system. In [6], the y-axis movement wipes down a single solar panel while the x-axis rails move the wiper to the neighboring solar panels. The two-axis implementation was utilized to expand the cleaning system to cover an array of solar panels. A single motor is used for each axis, and rollers are used to slide the wiper. Rollers are kept in the E-shaped channel to hold the brush against the solar panel securely. This system lacks intelligent dirt detection, so soil can be compacted on the surface. Some systems have water sprinklers to handle this issue.

The previous works listed above failed to use standardized metrics or common standards to compare with other designs. Habib et al. [5] compared many different blade materials with the amount of scratches after cleaning with varying cleaning loads. Still, the discussion of the definition of the dirt species was weak, and no numerical measure of the amount of sand used in the experiments was provided.

To trigger the cleaning action on time, dirt detection algorithms and mechanisms are required. The algorithm depends on the mo-

dality of the input data or characteristics; the choice of sensors is critical for the design of dirt-detection mechanisms.

Between the choices, non-imaging sensors would be less complex than imaging sensors in terms of data and computational complexity. Manish's work [6] is one of the simplest yet efficient approaches. The author used an infrared sensor to determine day/night shifting, overheating, etc., and to make cleaning decisions together with temperature and power generation measures. However, power generation depends on seasons and weather conditions, and this work did not fully account for these performance sensitivities. Habib et al. [5] addressed this issue by adding an LDR (light-dependent resistor) to determine whether dust covers the panels. Still, coverage of variations was minimal, as only sand was used to determine the threshold value for triggering cleaning.

To consider seasonal variation, Rupin, et al. [2] used a temperature sensor while [4] utilized a color sensor, a humidity sensor, and a temperature sensor. However, thresholding was still used to trigger actions without discussion of long-term performance. This solution mainly focuses on soil dirt on the solar panel, which turns the panel's color gray. Cleaning was performed based on a threshold of color sensor values. However, this method cannot handle many different kinds of dirt or dirt spots. Rupin et al. [2] employed similar rail-based mechanisms, with a temperature sensor and a humidity sensor, to detect dirt on the solar panel surface. This is one of the rare works that measured cleaning time as a performance metric. It took 300 seconds to finish a single cleaning process, moving the wiper from one side to the other. A spiral roller brush improves cleaning efficiency.

To handle wide variety of dirt species and seasonal change, data-driven algorithm development should be considered. Deep Neural Networks (DNNs) are technically mature and widely adopted, so if we have a proper dataset, developing a high-performing algorithm is easily achievable, even by a hobbyist or blogger [7]. Convolutional Neural Networks (CNN) [8] have demonstrated their effectiveness for identification and classification by automatically learning features. However, algorithms using CNNs require higher computational complexity than the methods we discussed above, so we should carefully assess their usefulness when designing systems under a tight power and cost budget. For example, Hu et al. [9] used an imaging modality to detect dirt on solar panels, but they handengineered their algorithms using image processing methods such as histogram equalization, gray-level concentration, edge detection, etc., rather than using more automated features with CNNs.

We can probably use image processing operators to generate features, and then apply clustering or classification using supervised machine learning methods such as Support Vector Machine (SVM) [10]. These methods will be more timeefficient during development than fully hand-engineered algorithms when working with complex multidimensional data. At this point, we had a design question whether handengineered features would work better than learned or automatically generated features. In terms of development or design time, learned features such as convolutional layers of CNNs will be more efficient. However, in terms of performance, many researchers are still debating the comparison between the two approaches, as in [11], [12]. In the literature, authors agreed that methods using learned features have been outperformed in many domains; however, handengineered features can improve performance when combined with learned features.

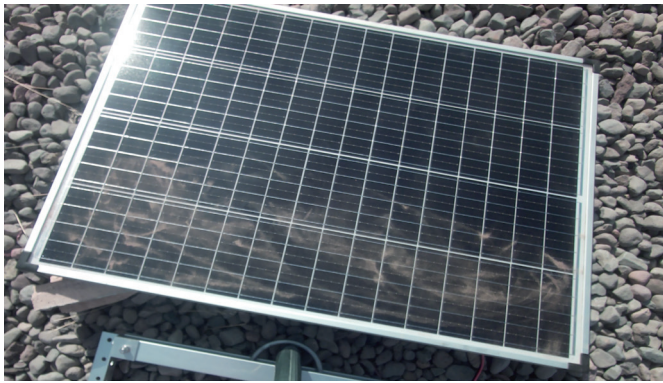
For high-computational-complexity data, hand-engineered approaches had an edge over methods with learned features, but were later surpassed, as in the example of [13]. Therefore, there may be some domains where hand-engineered approaches are more efficient.

III. SUGGESTED METHODS

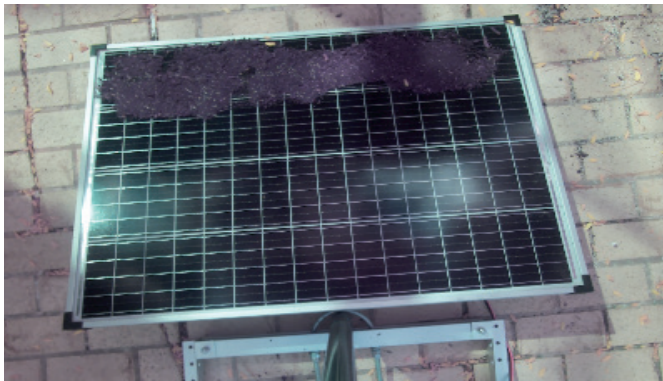
A. DATASET DEVELOPMENT FOR A SMART CONTROL ALGORITHM

The system's intelligence should stem from the careful design of a dataset, as unseen events are not easily handled in data-driven algorithm development. Therefore, developing a dataset that reflects the weather conditions at the target installation site is essential for comparing the efficiency of cleaning mechanisms.

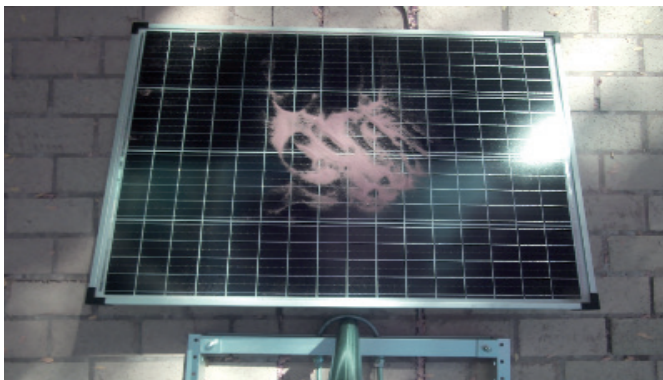
Each dirt species was selected based on Oregon's weather. The types of species are soil, sand, and leaves. For the soil, we used garden topsoil, and for the leaves, we used a collection of dried leaf litter. We used two different types of sand: orange sand with medium-sized granules and fine brown dust we sifted from sand and small rocks. Other variations we added include camera angle, camera distance, date, and time. Shade, dry, and wet conditions of



(a) Sample Dust Image - Label: 000-000-111



(b) Sample Soil Image - Label: 111-000-000



(c) Sample Red Sand Image - Label: 000-010-000

Fig. 2. Sample images from solar panel training dataset. labeled 0 – 8 from left-to-right top-to-bottom

the dirt species were applied for further variation. With the type of species, the ground truth also carries information about dirty (1) and clean (0). The areas of dirt within the three-by-three division of the solar panel were encoded in the image name, as shown in Fig. 2. For example, the image of Fig. 2 (a) has a file name with a label, 000-000-111, which means the bottom row is covered with the dirt specie.

TABLE I
IMAGE DATASET SPECIES COUNT

Species	Image Count
Soil	96
Sand	200
Leaves	180
Clean	64

The three images show the camera angle variation (max skewed position, slight variation, and normal position from top to bottom), dirt specie variation (dust, soil, and red sand), and covered area variation. Data collection was conducted during the summer, and solar panel mechanism tests were conducted during the winter. A layer of snow was tested during the cleaning hardware tests, but was neither included in the dataset nor used during the performance evaluation of the trained model.

With the setup, we collected up to 540 images, and the detailed species and counts are listed in Table I. One thing to note is that we have 246 images out of 540 with the extra label “shade” to check whether the trained algorithm can distinguish between shaded and dusty surfaces.

The images were collected using a Raspberry Pi 4B and a Raspberry Pi Camera Module 3 with a 120-degree lens. An image has a resolution of 4096 x 2592 and is saved in the TIFF format. The data collection system was reused as the controller for the cleaning mechanisms.

B. CLEANING MECHANISMS: WIPER SYSTEM AND RAIL SYSTEM

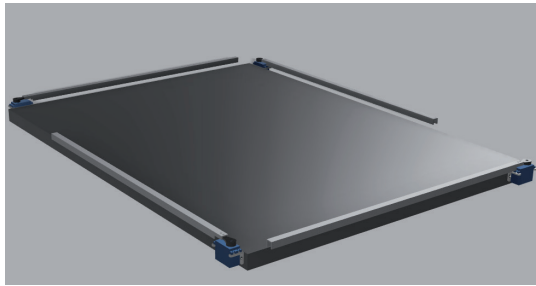
As discussed in Chapter II, the cleaning system without a dirt detection mechanism should be run periodically. This type of solution can cause two issues. The system can clean even when there is little dust on the panel, resulting in wasted power. On the other hand, dust piled on the panel can solidify, requiring more cleaning power or even additional mechanisms, such as water spray, as discussed in [6]. With a dirt-detection mechanism, the cleaning system can be more power-efficient and designed with less powerful motors.

Here, the question is how to evaluate whether the cleaning system has adequate power. To answer the question, we designed two different cleaning systems with power measurement circuitry (Fig. 7). The power measurement for system power consumption compares the power used by the two different cleaning mechanisms we developed. Even though we added an additional circuit for monitoring panel power generation, the study on optimization of current power generation is left as future work.

The two cleaning systems developed are a wiper system and a single-axis linear rail system. Both systems used cleaning arms fitted with rubber windshield wiper blades. Each system was installed on a 100 W single-panel monocrystalline solar panel. The dimensions of the solar panels are 91.4 cm x 68.6 cm with a thickness of 3.56 cm.

For the wiper system, we used four 61 cm cleaning arms, each attached to a corner of the solar panel and operated by a servomotor, as shown in Fig. 3. Each arm can move 90 degrees clockwise and counter-clockwise. We ordered arm movement to ensure the best cleaning efficiency. A single run takes 15.3 seconds on average. To ensure that the wipers did not get in each other's way when cleaning, they were run in the following order (relative to Fig. 3.(a)):

1. Right motor rotates 90-degrees clockwise (CW)
2. Front motor rotates 90-degrees CW
3. Left motor rotates 90-degrees CW and then 90-degrees counter-clockwise (CCW)
4. Front motor rotates 90-degrees CCW
5. Right motor rotates 90-degrees CCW
6. Left motor rotates 90-degrees CW
7. Back motor rotates 90-degrees CW and then 90-degrees CCW
8. Left motor rotates 90-degrees CCW



(a) Wiper System - Angled



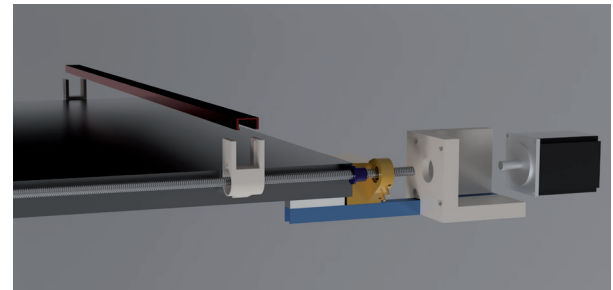
(b) Wiper System - Top Down

Fig. 3. CAD Model of Rail System

The servo motor has a maximum torque of 3.43 N·m, and all four motors are controlled by a Raspberry Pi board circuit shown in Fig. 4. The components shown in the circuit diagram, from left to right and top to bottom, are the voltage divider, current sensor, Raspberry Pi, analog-to-digital converter (ADC), solar panel, charging station, 12 V to 6.6 V buck converter, camera (not used), and four servomotors.

The rail system has one cleaning arm attached to two lead screws on each side of the solar panel, as in Fig. 5. The lead screws were rotated using two NEMA 23 stepper motors with a maximum torque of 1.85 N·m controlled by a Raspberry Pi board circuit as in Fig. 6. A single run moves the arm from one side to the other. As the lead of the screw is very dense (2 mm), a single run takes around 200 seconds.

Fig. 6 is the circuit diagram for the rail system. From left to right, top to bottom, the components shown in the diagram are the voltage divider, current sensor, Raspberry Pi, ADC, solar panel, charging station, limit switches, camera (not used), stepper motor driver, and two stepper motors. The entire system is powered by a 12 V output from the charging station. The Raspberry Pi and other



(a) Rail System - Side



(b) Rail System - Top Down

Fig. 5. CAD Model of Rail System

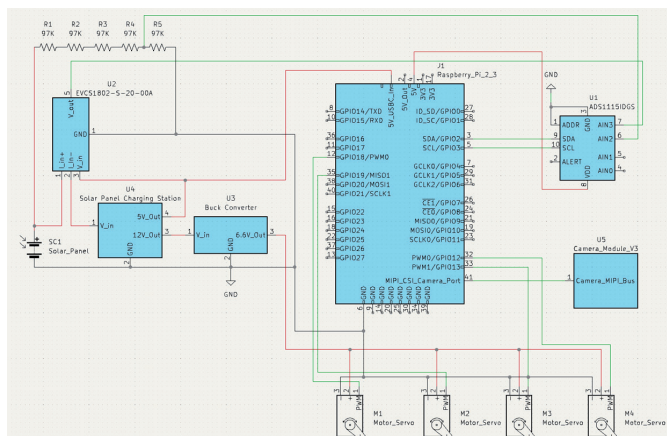


Fig. 4. Circuit for Wiper Cleaning System

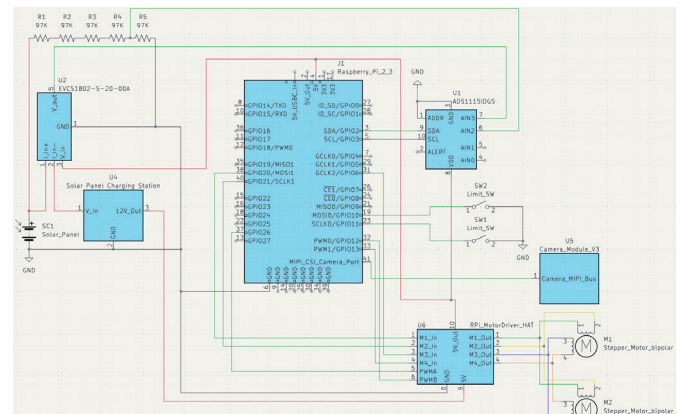


Fig. 6. Circuit for Rail Cleaning System

sensors are powered by 5 V, while the motors are powered by 12 V.

As mentioned earlier, to measure the system's power consumption, we connected an additional current sensor between the charging station's power output and the cleaning system, exactly as we did between the solar panel and the charging station's power input. This power measurement system is outlined in Fig. 7, where we measured and collected data from both the solar panel and cleaning systems. The power measured from the panel was power generated by the system, while the power measured from the cleaning systems was power consumed by the system.

C. DATA-DRIVEN CONTROLLER ALGORITHMS

The developed cleaning mechanisms could clean every dirty solar panel setting (we will discuss further hardware performance in the next chapter) with fixed counts of run(s); we did not utilize dirt species labels for the algorithm development. The developed algorithms are to identify dirty solar panels and areas with dirt to evaluate their dirt condition. The overall pipeline of the dirt detection mechanism is explained in Fig. 8.

To explore the design space of power and performance efficiency, we approached algorithm development from two different perspectives. We tried both hand-engineered and automatically generated features for algorithm development. In general, automatically generated features take less time to develop and, in many cases, outperform hand-engineered features due to advances in technologies such as hardware accelerators. However, hand-engineered features can yield more power-efficient algorithms when developers correctly interpret the problem.

When developing our models, we focused on two main types of models: single-label binary classification models that indicate whether the entire panel is clean or dirty, and multilabel binary classification models that classify individual 3x3 grid segments of the panel. These are the same segments as illustrated in Fig. 2.

Fig. 8 is a system block diagram showing the integration of the cleaning algorithms with our cleaning mechanisms.

1) *Approach using hand-engineered features:* As we can see in

Fig. 2, from some distance, dust looks similar to the hazy or blurry effect on images. This observation drove us to start with hand-engineered features from haze detection and degree estimation [14].

$$I^{dark} = \min_{(i,j) \in \Omega(x,y)} \left(\min_{c \in r,g,b} \frac{I^c(i,j)}{A^c} \right) \quad (1)$$

$$C_{RMS} = \sqrt{\frac{1}{MN} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} (I_{ij} - \bar{I})^2} \quad (2)$$

Dark channel can be expressed in a mathematical formula as in Equation 1. $\frac{I^c(i,j)}{A^c}$ means the removal of atmospheric light A^c from the original image I^c . Then, select block-wise (patchwise) minimum. Another feature set, RMS contrast values can be calculated with Equation 2. The indices, i and j are to indicate a pixel, and I_{ij} is the intensity of the pixel pointed by (i,j) , and $\bar{I}$ is the average intensity value in a patch.

We followed the empirical approach to select dark channel values, as suggested, and used the same method for patch-wise contrast values.

In both cases, the RMS contrast or dark channel was calculated for each pixel in the 256x400 BGR images, which were then flattened and sorted (after removing the now duplicate second and third image channels). We then extracted values from each vector at select indices. The dark channel values were selected as a part of the feature set at 50%, 25%, 10%, 5%, and 1% of the overall length of the vector from the whole patches (e.g., if the overall dark channel vector was 100 elements, then the 50th element was selected for the 50% value). The RMS contrast features were selected from the shorted patch-wise values at the 100%, 95%, 90%, 85%, 50%, and 10% locations.

The 11 selected features were used to train algorithms using a support vector machine (SVM). We set the regularization parameter to 900 and the gamma to 12.0, and used a polynomial kernel of degree 3 during training, as these values worked best in our experiment. The SVMs were trained using k-fold cross-validation on

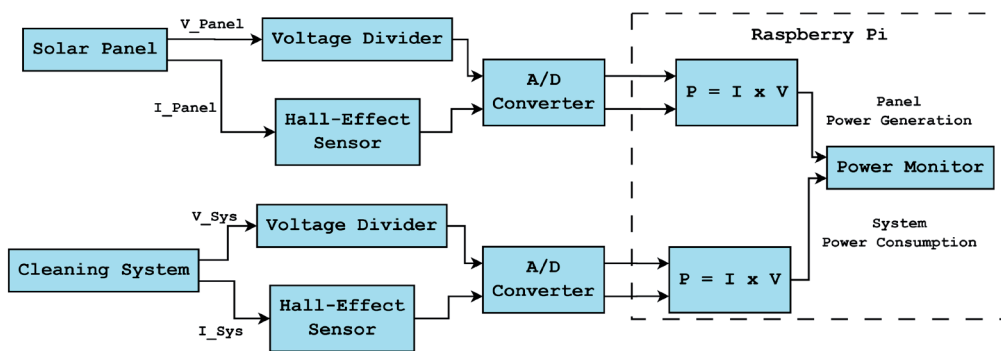


Fig. 7. Power Measurement Block Diagram

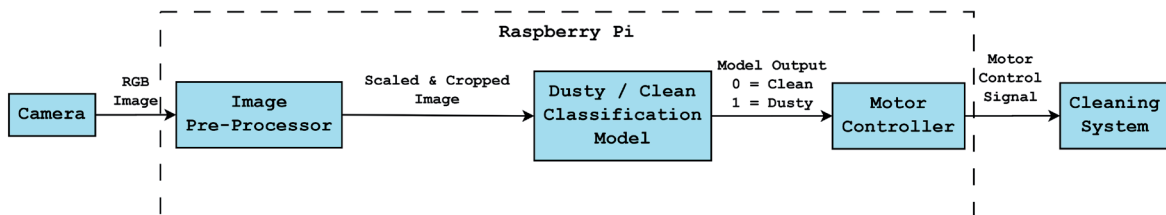


Fig. 8. Cleaning Decision Block Diagram

80% of the dataset, while the other 20% was used for the final test.

For training the feature-based deep-learning models, we split the original dataset, using 80% for training, 10% for validation, and 10% for testing. We applied random brightness adjustments to the images in the training set. In total, we had 54 images in the test and validation datasets, and 880 images in the training dataset. At runtime, the input images were further split into nine segments and individually passed into the models for inferences. Unweighted binary-cross-entropy (BCE) loss, like that in Equation 3, was used for training.

2) *Approach using automatically generated features:* When we began training the deep-learning models, we had no prior knowledge of the newly developed dataset. Therefore, we selected various neural networks of different sizes.

Our architecture exploration was focused on convolutional neural networks (CNNs). CNNs are well-known for their high performance, thanks to automatically generated features from convolutional layers. At one extreme of this class of neural network architectures, there are Fully Convolutional Networks (FCNs), such as U-Net [15]. We can interpret the architecture as a combination of an autoencoder and a decoder [16], with skip connections between the corresponding pairs of the encoder and decoder in a U-shaped architecture. This design enables the model to efficiently find a feature map without using fully connected layers, thereby reducing memory usage significantly. Since we need a prediction about the presence of dirt, fully connected layers were added to flatten the feature map and convert it into a probability of dirt presence. From the experiment, four layers for both the down- and up-sampling performed well. The overall model architecture is in Fig. 10; the larger model is for the 3x3 segment model we trained while the smaller version is for the binary model.

ResNet [17] used the skip connection in a different way to avoid degradation in deeper networks. The skip connection is in the residual building block in the forward direction. We used ResNet50 and ResNet101 as the baseline and modified the fully connected layer to get output logits indicating the probability of dirt on the panel (nine logits for multiclass, one for binary). The overall model architecture is depicted in Fig. 9.

Lastly, we trained customized LeNet [8] based models, such as in Fig. 11. We prepared three other size variations from the CNN1 model shown in the figure. The size variations mostly came from fully-connected layer blocks. The fully-connected (FC) layers' input and output sizes of CNN2 are 51200 in, 13 out; 13 in, 9 out; and 9 in, 9 out. The FC layers' sizes for CNN3 are 12800 in, 9 out; 9 in, 9 out; and 9 in, 9 out. Lastly, the FC layers' sizes for CNN4 are 12800 in, 8 out; 8 in, 9 out; and 9 in, 9 out. These are all for the first, second, and third FC layers, respectively. CNN2 also uses a 2x2 average pool kernel, while CNN3 and CNN4 use 4x4 kernels. To create a model smaller than CNN4 we decided to remove all but one fully-connected layer resulting in the model illustrated in Fig. 12.

The binary and 3x3 segment models were trained on 256x400 BGR images (resized and cropped from the original dataset). Since we wanted the model to learn to segment the panel relative to the image, we minimized augmenting the dataset with methods that changed the panel's orientation within the image, such as reflections and rotations. Instead, we used techniques such as brightness and contrast adjustments, region segmentation, blur, and edge segmentation, but ultimately decided to train the final models with random brightness adjustments and some random Gaussian blur.

We split the original dataset, using 80% for training, 10% for validation, and 10% for testing. Augmentations were applied to the training data after the split, which resulted in 54 images in both the validation and test sets, and 5,616 images in the training dataset.

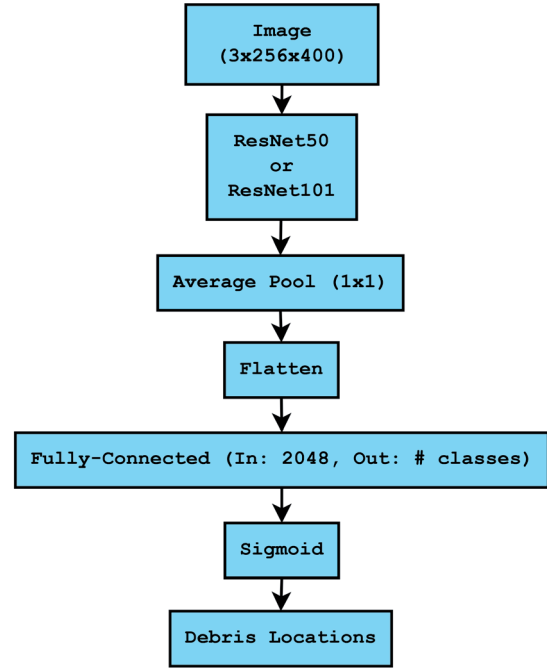


Fig. 9. ResNet Model Diagram

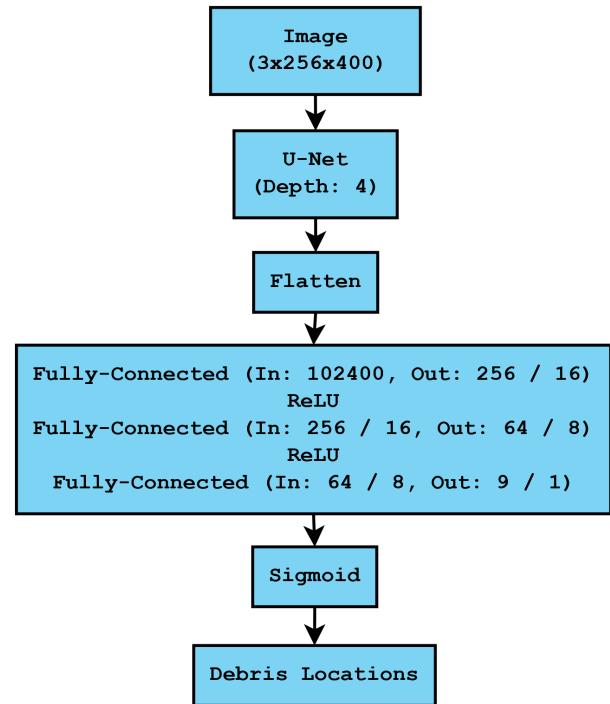


Fig. 10. U-Net Model Diagram

Equation 3 is the loss function used to train the deep learning models. When training binary models, we did not weight either class, but when training the 3x3 segment models, we added more weight to the positive class (dirty).

In the equation, W_p is the weight for the positive class, while W_n is the weight for the negative class. y_n and p_n are the labels and predictions for each panel section, respectively. The sum of the loss for each segment is averaged to get the total loss for the input image.

$$BCE\ Loss = \frac{1}{N} \left(\sum_{n=1}^N - (W_p y_n \ln(p_n) + W_n (1 - y_n) \ln(1 - p_n)) \right) \quad (3)$$

We used PyTorch [18] for the algorithm development. The system specification of the machine used for the model development is as follows:

- CPU: Intel(R) Core(TM) Ultra 9 i85H 2.3 GHz
- GPU: NVIDIA RTX 2000 Ada Generation Laptop GPU (8 GB Dedicated, 16 GB Shared)
- SSD: BG6 KIOXIA 1014 GB
- RAM: 32 GB 5600 MT/s

We further explored model compaction using optimization methods of ONNX [19] and pruning [20] to optimize for the target embedded system. Nine variations were created from the trained models discussed above. The variations were from combinations of four different operations: converting the PyTorch model to ONNX, pruning the PyTorch model, preprocessing the ONNX model, and performing static quantization on the ONNX model.

The pruning method is an unstructured pruning [21], which sets 20% of the lowest weights over the entire trained model to zero. Preprocessing is an ONNX method intended to prepare and optimize a model for quantization by determining tensor shapes, adjusting the model computation graph, and combining model layers [22]. Lastly, quantization from 32-bit floatingpoint numbers to 8-bit signed integers is performed using ONNX static quantization optimization. We tested various combinations of these optimization methods in order to determine which resulted in a small and fast model that does not compromise too much on accuracy.

IV. EXPERIMENT RESULTS

A. SYSTEM CLEANING MECHANISMS TEST RESULTS

Comparison of cleaning performance between the two systems, wiper and rail, shows steady trends. Fig. 13 compares power consumption over time between the two systems. The wiper system graph shows two runs to clean dry leaves and has a spikier graph, which explains the higher standard deviation of the wiper system results in Table II.

The total power consumption is proportional to the multiplication of average power, single run time, and count of cleaning runs (clean runs). The rail system consumes roughly six times more power for the same cleaning performance. As the rail system moves the wiper arm with two stepper motors, power consumption is less varied for different dirt species during the cleaning. The wiper system's average power consumption varies from 4.5792 W/s to 11.6426 W/s, while the rail system's average power consumption ranges from 6.0932 W/s to 6.9821 W/s.

There are two things that should be considered for the generalization of the comparisons. First, we used only soiltype dirt with moisture variations. The wiper system can consume more power than with other dirt types, such as heavier-grained or stickier dirt. Secondly, the wiper arm's moving speed on the rail system can be improved by using a longer thread distance for the lead screws. However, the power consumption rate will be different, so further experiments are required.

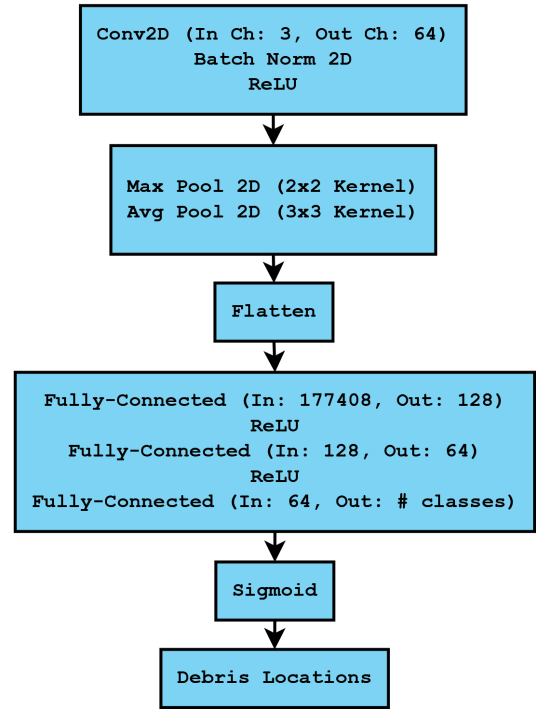


Fig. 11. CNN1 Model Diagram

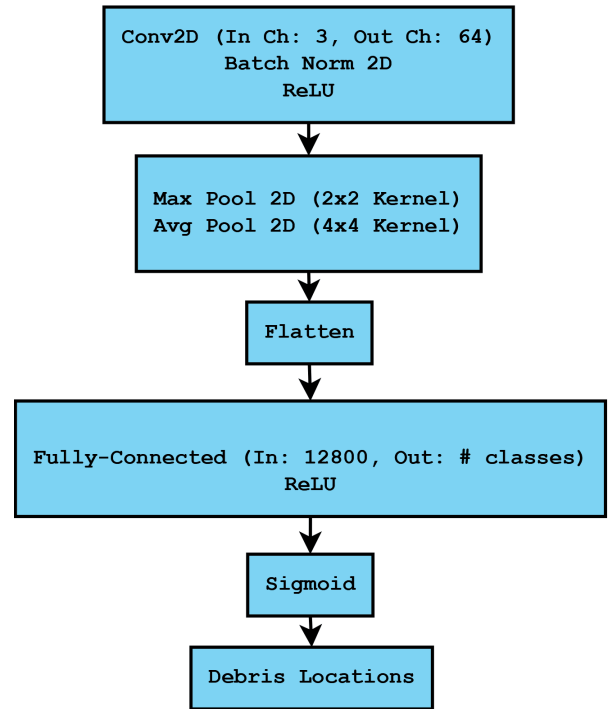
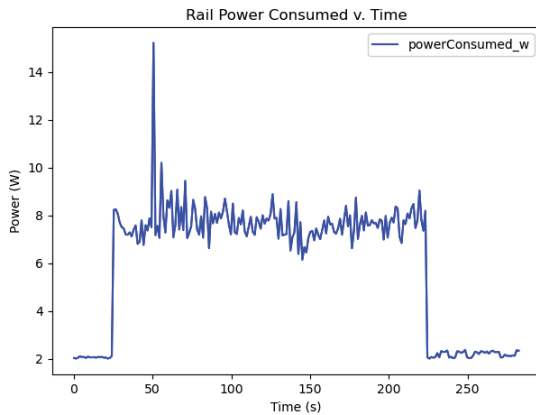


Fig. 12. CNN5 Model Diagram

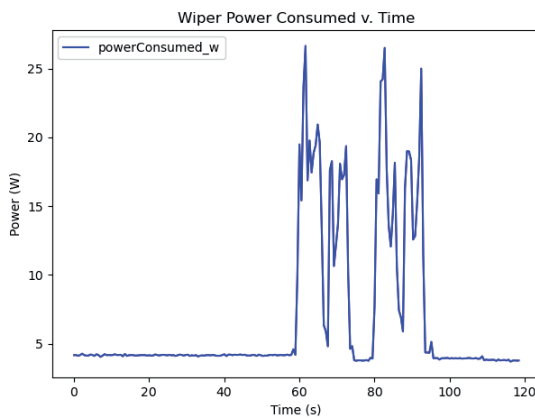
TABLE II
CLEANING SYSTEM COMPARISON RESULTS

System	Material	Avg. Power (W/s)	Power Std. Dev. (W/s)	Single run time(s)	Clean runs
Rail	Dry Dirt	6.1233	2.7381	200	1
Rail	Wet Dirt	6.0932	3.1191	199	1
Rail	Dry Leaves	6.9821	2.6381	201	1
Rail	Wet Leaves	6.1671	2.8639	200	1
Rail	Wet Leaves & Dirt	6.4994	3.0711	199	1
Rail	Snow	6.6529	2.6850	187	1
Wiper	Dry Leaves	6.6444	3.4261	15.3	2
Wiper	Dry Dirt	11.6426	4.6877	15.4	2
Wiper	Wet Dirt	4.5792	3.1269	15.4	2
Wiper	Wet Leaves	6.3422	4.6570	15.3	2
Wiper	Wet Leaves & Dirt	5.0517	3.4346	15.3	2
Wiper	Snow	5.4972	3.7457	15.3	2

Both systems are powerful enough to handle the designed dirty panel setups. The rail system needs only a single cleaning cycle, as the blade is securely down-forced, while the wiper system requires two runs of four arms to clean the remainder due to the openness at the end of each arm. Fig. 14 shows each system under cleaning action.



(a) Rail System Power Consumption



(b) Wiper System Power Consumption

Fig. 13. Cleaning System Power Consumption Graph with Dry Leaves



(a) Rail system in action.



(b) Wiper system in action.

Fig. 14: Rail system cleaning wet leaves, while wiper system cleaning snow.

The rail system's cleaning speed could be improved by increasing the screw leads. The one we used is a lead screw that moves the carriage 2 mm every rotation. If the rotation speed of the stepper motors is maintained, the carriage will move twice as fast with a twice-as-long lead screw. The design update and power/performance measurements on the updated system are left for future work.

B. BINARY DUST-DETECTION ALGORITHMS AND MODEL VARIATIONS

We developed and compared a variety of algorithms from two approaches: hand-engineered features and automatically generated features. The approaches from generated features, using convolutional neural networks, were developed relatively quickly and showed decent performance overall. Algorithms developed with hand-engineered features took much longer to develop and showed relatively better memory efficiency, but performance was inconsistent and sometimes much worse.

Table III summarizes the overall experiment. the first nine models in the first box are trained for binary classification: the decision on whether the panel is clean (0) or dirty (1). The best performance and power efficiency was from when we used hand-engineered features. As in Table III, the binary SVM model size is about 4.5 KB, and the inference time takes just 0.0034 seconds on average on the Raspberry Pi 4B board. It was developed as described in Section III.C.1., with 11 features as explained. We will discuss hand-engineered features further in the following subsection.

The overall most accurate models were the ResNet models, which got 100% accuracy on the test set. U-Net, and CNNs 1 - 4 all got 98.15% accuracy. Our smallest model, CNN5, performed the worst of the binary deep neural networks with 94.44% accuracy, but is still about 50 KB, which is almost 10 times larger than SVM (binary).

We also performed tests on the impact of model compaction in Fig. 15. Static quantization had the largest effect, reducing model size to a quarter of its original size (32-bit floating point to 8-bit integer). For the larger models, static quantization also tended to significantly decrease inference time, with CNN1's inference time decreasing by 40%. On the other hand, CNN2-CNN5 all showed a slight increase in inference time. For the smaller models, the most significant decrease in inference time came from converting them to ONNX variants, which sped them up by at least 50%.

Pruning did not have consistent results. In some cases, such as the base PyTorch (i.e., Torch) ResNet101, ONNX ResNet101, and Torch ResNet50, pruning decreased inference time slightly. In other cases, such as ONNX ResNet50 and Torch CNN5, pruning increased inference time.

ONNX preprocessing was similarly inconsistent. At times, preprocessing decreased the models' inference times, while at other times, it increased them. Interestingly, the difference is not

consistent even between static quantization models and preprocessed static quantization models: five architectures saw a decrease in inference time, while the others saw an increase.

The best binary deep learning models depend on the application. If accuracy is more important than real-time performance, the preprocessed static-quantization ResNet50 model works well, achieving 100% accuracy with an inference time of about half a second and a memory footprint of 22.58 MB. If a balance between inference time, size, and accuracy is needed, any of the ONNX (and further) variations of CNN2-CNN4 are good options. To pick one, however, the preprocessed static quantization CNN4 strikes a good balance with about 98% accuracy, a 110 KB model size, and 12.8 ms inference time. Overall, a classifier using hand-engineered features - SVM (binary) achieved the best performance with the smallest size and the shortest inference time.

The convergence of developed algorithms is shown in Fig. 16.

C. THREE BY THREE ZONED ALGORITHM DEVELOPMENT

In a larger deployment, we can group multiple solar panels and monitor them with an imaging sensor. In this scenario, multi-zoned detection is necessary to clean only dirty panels. We performed three-by-three zoned dirt detection to explore algorithm deve-

	Torch	Pruned Torch	ONNX	Preprocessed ONNX	Static Quantization	Preprocessed Static Quantization ONNX	Pruned ONNX	Pruned Preprocessed ONNX	Pruned Static Quantization ONNX	Pruned Preprocessed Static Quantization ONNX
ResNet101	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
ResNet50	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
U-Net	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%
CNN1	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%
CNN2	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%
CNN3	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%
CNN4	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%	98.15%
CNN5	94.44%	94.44%	94.44%	94.44%	94.44%	94.44%	94.44%	94.44%	94.44%	94.44%

(a) Accuracy vs Model Variation

	Torch	Pruned Torch	ONNX	Preprocessed ONNX	Static Quantization	Preprocessed Static Quantization ONNX	Pruned ONNX	Pruned Preprocessed ONNX	Pruned Static Quantization ONNX	Pruned Preprocessed Static Quantization ONNX
ResNet101	162.74	162.73	161.98	161.99	40.84	40.84	161.98	161.99	40.84	40.84
ResNet50	89.99	89.99	89.61	89.61	22.58	22.58	89.61	89.61	22.58	22.58
U-Net	124.65	124.65	124.65	124.65	31.25	31.25	124.65	124.65	31.25	31.25
CNN1	86.67	86.67	86.67	86.67	21.67	21.67	86.67	86.67	21.67	21.67
CNN2	2.55	2.55	2.54	2.54	0.64	0.64	2.54	2.54	0.64	0.64
CNN3	0.45	0.45	0.44	0.44	0.12	0.12	0.44	0.44	0.12	0.12
CNN4	0.40	0.40	0.39	0.39	0.11	0.11	0.39	0.39	0.11	0.11
CNN5	0.05	0.05	0.05	0.05	0.02	0.02	0.05	0.05	0.02	0.02

(b) Model Size (MB) vs Model Variation

	Torch	Pruned Torch	ONNX	Preprocessed ONNX	Static Quantization	Preprocessed Static Quantization ONNX	Pruned ONNX	Pruned Preprocessed ONNX	Pruned Static Quantization ONNX	Pruned Preprocessed Static Quantization ONNX
ResNet101	2.7843	2.7805	2.1269	2.2004	0.9497	1.0916	2.2936	2.1605	1.1065	0.9925
ResNet50	1.6509	1.6292	1.0891	1.0951	0.5923	0.4901	1.1228	1.1427	0.5027	0.5212
U-Net	8.5416	9.1728	8.4413	8.9373	3.5343	4.9123	8.1550	7.3005	3.6509	4.7601
CNN1	0.3796	0.3796	0.0936	0.1027	0.0615	0.0608	0.1003	0.1116	0.0549	0.0650
CNN2	0.0317	0.0367	0.0113	0.0108	0.0134	0.0161	0.0162	0.0116	0.0182	0.0145
CNN3	0.0280	0.0268	0.0111	0.0114	0.0145	0.0139	0.0112	0.0122	0.0176	0.0142
CNN4	0.0266	0.0275	0.0114	0.0125	0.0136	0.0128	0.0117	0.0158	0.0171	0.0144
CNN5	0.0247	0.0320	0.0123	0.0116	0.0135	0.0132	0.0128	0.0171	0.0143	0.0135

(c) Avg. Inference Time (s) vs Model Variation

Fig. 15. Model Variation Comparison Charts

lopment for the up-scaled applications.

The SVM kernel we used could not perform multi-label classification. So, our approach was to train a single SVM kernel that takes a single region of a solar panel. As it requires expensive pre-processing time of processing patches to get the feature values and then running the model nine times, the inference time increased significantly, as we can see the results value for SVM (Segment)'s total average execution time in Table III. Even the single run time increased since we increased the kernel size for feature calculation to improve performance. Overall, we failed to find a consistent set of feature indices that yielded the best performance during this project. The best we achieved was 87.4% accuracy while testing.

We tried different classifiers, including fully connected layers (Multilayer Perceptron, MLP) and Recurrent Neural Networks (RNN) [23], to determine whether we could achieve better performance with hand-engineered features. In the case of MLP, we ended up with seven fully connected layers with ReLU [24] and batch normalization [25] for each layer, which significantly increased the size and inference time compared to the SVM (segment). Still, it failed to achieve an accuracy above 91%.

Next, we selected an RNN to improve accuracy on our one-dimensional feature series. A combination of CNNs and RNNs is a common approach to improve performance [26]. We applied a recurrent layer to the input feature vector, followed by five fully connected layers. We could achieve marginal success, maintaining similar performance while having a smaller memory footprint than MLP.

Unlike in binary classification, most of our success in 3x3 classification came from classifiers with automatically generated features. The models we found performed best include ResNet101, ResNet50, U-Net, and CNN1. The multilabel variants of these models differ in their output shapes, as shown in the model diagrams in the previous sections. The exception to this is the U-Net model, where we observed better performance after increasing its fully connected layer sizes.

TABLE III

FEATURE EXPLORATION MODEL RESULTS. THE SEGMENT SVM, MLP, AND RNN MODELS PERFORM NINE SEPARATE INFERENCE, ONCE FOR EACH SEGMENT, WHILE 3X3 MODELS RUN ONCE TO GET DIRT DETECTION RESULTS FOR THE NINE SUB-AREA.

Model	Accuracy (%)	Size (MB)	Inference Time (s)
ResNet101	100.00	162.74	2.78
ResNet50	100.00	89.99	1.65
U-Net	98.15	124.65	8.54
CNN1	98.15	86.67	0.380
CNN2	98.15	2.55	0.0317
CNN3	98.15	0.45	0.0280
CNN4	98.15	0.40	0.0266
CNN5	94.44	0.05	0.0247
SVM (Binary)	100.00	0.0045	0.0034
ResNet101 (3x3)	99.59	162.74	3.06
ResNet50 (3x3)	97.27	89.99	1.77
U-Net (3x3)	91.15	218.46	10.23
CNN1 (3x3)	92.18	86.67	0.408
MLP	91.0	3.08	0.66 (total: 5.9)
RNN	90.4	2.36	0.60 (total: 5.4)
SVM (Segment)	87.4	0.77	0.199 (total: 1.8)

Unlike the segment SVM, feature MLP, and feature RNN, the 3x3 deep learning models do not need to split the image into segments and then perform binary classification on each one separately. Both ResNets and CNN1 outperformed the feature models in both accuracy and total inference time. The ResNet models in particular achieved higher accuracies with reasonable inference times compared to the other 3x3 classification models.

Fig. 17 and Fig. 18 show convergence via the loss versus epoch graphs for each of the 3x3 segment classification and feature classification deep learning models.

V. CONCLUSIONS AND FUTURE WORKS

Data-driven controller design is better suited to account for different types of dirt under various weather conditions. However, the hardware requirements for running data-driven algorithms tend to be higher; it is essential to optimize their performance to meet the target performance and power efficiency.

To develop a power-efficient algorithm using a data-driven approach, we first developed a dataset and hardware systems for algorithm development and testing. We used the dataset for the development and performance evaluation of selected algorithms. The definition of the dirt species in the dataset was used to set up performance comparison experiments for two different cleaning

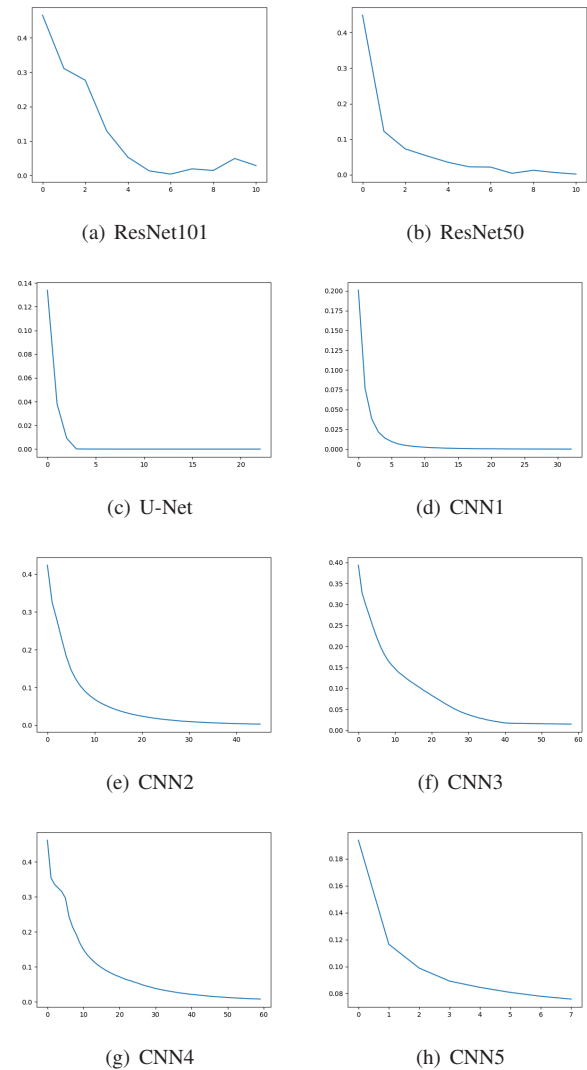


Fig. 16. Loss vs. Epoch Graphs for Binary Models

mechanisms. We could assess that both systems were powerful enough to be used and select the best algorithms for our purpose among the chosen algorithms.

Then, we developed and compared algorithms from two perspectives: hand-engineered and automatically generated features. The algorithm using hand-engineered features outperformed in terms of power efficiency and inference time, while maintaining comparable performance for detecting dirt on the panel.

However, the development of the multi-zoned dirt detection took significant development time, and we failed to achieve the better performance than 91% of accuracy. On the contrary, the methods based on automatically generated features showed a relatively consistent trend across model size, inference size, and performance.

Admittedly, there are still many dirt species and surface conditions from other weather conditions in Oregon and other US areas. We need further study to determine whether the algorithms based on hand-engineered features remain useful as the dataset becomes more complex. We plan to update the dataset further, conduct the study, and make it publicly available.

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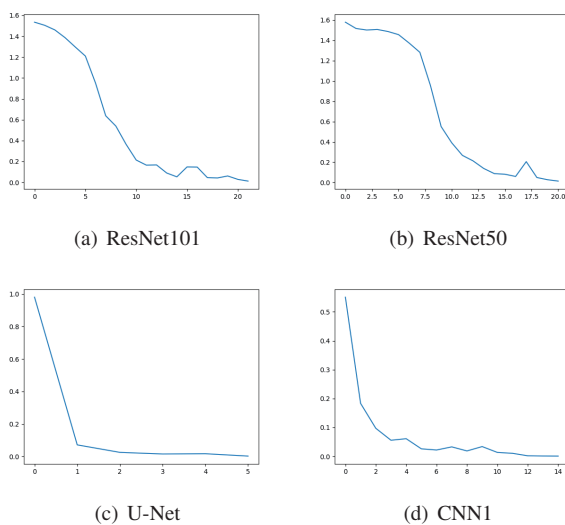


Fig. 17. Loss vs. Epoch Graphs for 3x3 Segment Models

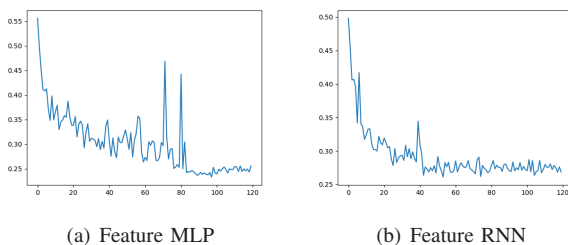


Fig. 18. Loss vs. Epoch Graphs for Feature Models

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Individual Phase Current Control Algorithm for Load Unbalance Compensation in Grid-Connected Three-Level Inverters Operating in Islanding Mode

Mohammed Moyed Ahmed

Summary — Grid-connected inverters must maintain a stable power supply to critical loads during islanding operation when grid faults occur. Imbalanced loads make it difficult to sustain balanced three-phase voltages and can seriously impair sensitive three-phase equipment. This paper proposes an individual phase current control algorithm for load imbalance compensation in grid-connected three-level inverters operating in islanding mode. The method uses a dual-loop control architecture: a D–Q frame voltage controller handles overall voltage regulation, while an ABC frame current controller provides per-phase current management. A key innovation is feedforward compensation using real-time load current measurements, combined with a static switch that enables flexible switching between three-wire and four-wire configurations. When a power-based detection algorithm identifies significant load imbalance, the system automatically transitions to four-wire mode, where independent control of each phase current is possible without the zero-sum constraint. The voltage controller operates at a 5–6Hz bandwidth in the D–Q frame; the current controller operates at a 1kHz bandwidth in the ABC frame for fast per-phase tracking. Simulation results show accurate current tracking—a 1.76A increase under a 100% load step and a 1.02A decrease under a 50% load reduction—while maintaining balanced voltages and reducing total harmonic distortion (THD) from 13.18% to 3.64%. The distinct novelty of this work lies in the tight integration of ABC-frame per-phase feedforward with automatic three-/four-wire reconfiguration, which avoids the coordinate-transformation overhead inherent in existing approaches and achieves a settling time two to three times faster than conventional D–Q-only methods.

Keywords — Grid-connected inverter, individual phase current control, load imbalance compensation, three-level inverter, islanding mode, dual-loop control, feedforward compensation, static switch.

I. INTRODUCTION

Grid-connected inverters are central to modern power systems, particularly for integrating renewable energy sources such as photovoltaic and wind power systems.

[1], [2]. These inverters operate in two distinct modes: grid-connected mode during normal conditions and standalone (islanding) mode when grid faults occur [3]. During islanding, the inverter must maintain power quality independently for critical loads that require uninterrupted operation [4].

The increasing penetration of distributed energy resources has intensified challenges in power quality and load management [5], [26]. Critical loads—hospitals, data centers, essential industrial processes—demand tightly regulated voltages with minimal frequency deviation [6]. Although these loads are predominantly designed for balanced three-phase conditions, the integration of singlephase loads and the inherent asymmetry in practical load distribution create significant voltage imbalance during islanding [7], [27].

Load imbalance is among the most significant challenges in islanding mode [8]. When the inverter supplies both critical three-phase loads and single-phase or imbalanced major loads, the resulting power asymmetry directly affects the three-phase voltage balance at the point of common coupling (PCC) [9]. Recent studies have shown that imbalanced grid conditions lead to double-line-frequency power oscillations, which worsen DC-link voltage ripple and stress DC-link capacitors [10], [28]. This voltage imbalance causes reduced efficiency, overheating, and potential equipment failure [11].

Conventional control strategies primarily rely on synchronous reference frame (d-q) methods, which assume balanced three-phase quantities [12], [13]. These approaches demonstrate significant limitations under imbalanced conditions, leading to steady-state errors and poor dynamic response [14], [15], [16]. Recent efforts include advanced low-voltage ride-through strategies [17], proportional-resonance controllers [18], and disturbanceobserver-based decoupled current approaches [19]. Fourleg voltage source inverters with space-vector hysteresis controllers have been applied in the $\alpha\beta 0$ frame [20], and multi-functional grid-connected systems using $\alpha\beta c$ coordinates have been proposed for imbalanced loads [21].

State-feedback controllers using linear quadratic regulators have also been investigated [22]. More recently, model-predictive control [29], virtual synchronous machine strategies [30], and deep-learning-aided imbalance compensation [31] have been explored.

Despite these advances, existing solutions often suffer from complex coordinate transformations, poor performance under severe imbalance, or inability to control individual phase currents independently [23], [24], [25].

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This paper proposes an individual phase current control (IPCC) algorithm that differs from existing approaches in three concrete ways.

1. **ABC-frame per-phase feedforward:** existing D–Q-only controllers generate current references in the synchronous frame and transform them to the natural frame; any per-phase load disturbance appears only after propagating through the voltage loop. The proposed algorithm injects the measured per-phase load current directly into the natural-frame current reference, providing instantaneous feedforward that the D–Q path cannot supply.
2. **Automatic three-/four-wire reconfiguration:** a power-deviation detection algorithm monitors perphase power in real time. When imbalance exceeds the threshold, a static switch closes to establish the neutral path, lifting the zero-sum constraint on phase currents without manual intervention or modeswitching transients. Returning to three-wire mode is equally automatic when balance is restored.
3. **Bandwidth-separated dual-loop architecture:** the outer voltage loop (5–6Hz bandwidth, D–Q frame) and the inner current loop (1kHz bandwidth, ABC frame) are designed with a 10–20× frequency separation, which provides stability guarantees absent in single-loop or same-bandwidth dual-loop designs.

Together, these features yield settling times two to three times shorter, current tracking errors below 2%, and THD compliant with IEEE 519, even under 100% single-phase load steps.

The remainder of this paper is organized as follows. Section II presents the system configuration and mathematical model. Section III describes the imbalance detection algorithm. Section IV details the proposed IPCC algorithm. Section V provides stability analysis and controller design. Section VI describes the simulation setup. Section VII presents and discusses simulation results. Section IX addresses practical implementation considerations. Section X concludes the paper.

II. SYSTEM CONFIGURATION AND MODELING

A. GRID-CONNECTED THREE-LEVEL INVERTER CONFIGURATION

The proposed system uses a three-level neutral-pointclamped (NPC) inverter connected to the utility grid through an L-C output filter. Compared with a two-level inverter, the three-level NPC topology offers lower harmonic distortion, reduced switching losses, and improved power quality [12]. The system operates in both gridconnected and islanding modes with seamless transition on grid fault detection.

The output filter comprises inductor L_f and capacitor C_f chosen to attenuate voltage ripple while preserving dynamic performance. Critical loads (sensitive three-phase equipment) and major loads (single-phase or imbalanced three-phase loads) both connect at the PCC. The static switch enables reconfiguration between three-phase threewire and four-wire operation; it remains open underbalanced conditions and closes once significant imbalance is detected.

B. LOAD CONFIGURATION

Critical loads represent sensitive three-phase equipment—industrial motors, precision instruments, and critical infrastructure—that requires tightly regulated, balanced voltages. *Major loads* include single-phase or imbalanced three-phase loads that genera-

te asymmetric power consumption and are the primary source of system imbalance. In three-wire mode the neutral is isolated, constraining the sum of phase currents to zero. In four-wire mode the static switch establishes a neutral path, allowing each phase current to be controlled independently.

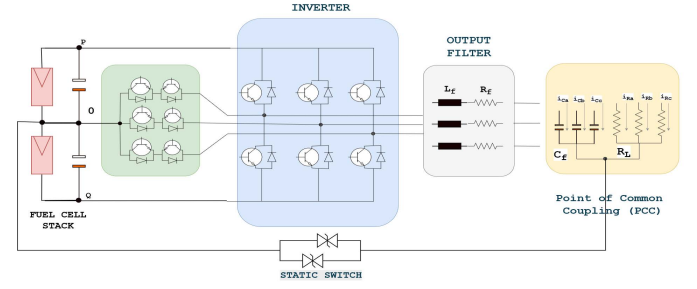


Fig. 1. Overall system configuration.

C. MATHEMATICAL MODELING

The three-level NPC inverter produces phase output voltages

$$v_{inv,abc} = S_{abc} \cdot \frac{V_{dc}}{2}, \quad (1)$$

where $S \in \{-1, 0, +1\}$ is the per-phase switching function and V_{dc} is the DC-link voltage. Equation (1) shows that the controller must synthesize the desired output voltage through the switching function; the maximum achievable phase voltage is $V_{dc}/2$.

The filter inductor dynamics that underlie the current control loop are

$$L_f \frac{di_{L,abc}}{dt} = v_{inv,abc} - v_{C,abc}, \quad (2)$$

where $i_{L,abc}$ are the filter inductor currents (the quantities tracked by the inner loop) and $v_{C,abc}$ are the filter capacitor voltages (the quantities regulated by the outer loop). The capacitor node equation is

$$C_f \frac{dv_{C,abc}}{dt} = i_{L,abc} - i_{R,abc}, \quad (3)$$

where $i_{R,abc}$ are the per-phase load currents. Equation (3) reveals the load current as a disturbance input to the voltage loop; feedforward of $i_{R,abc}$ is the key mechanism that decouples load changes from voltage regulation.

D. THREE-WIRE VERSUS FOUR-WIRE OPERATION

In three-wire operation the instantaneous current constraint

$$i_{La} + i_{Lb} + i_{Lc} = 0 \quad (4)$$

prevents independent control of individual phase currents and limits the effective compensation of severe imbalance. When the static switch is closed, this constraint is lifted:

$$i_{La} + i_{Lb} + i_{Lc} = i_n \neq 0, \quad (5)$$

where i_n is the neutral current. The value of i_n quantifies the severity of imbalance and is monitored after switch closure to confirm four-wire operation. This transition is reflected in the control model by removing the constraint (4) and replacing it with (5), after which three independent current references i_{La}^* , i_{Lb}^* , i_{Lc}^* can be issued without any coupling.

E. SYSTEM PARAMETERS

Filter inductance L_f is chosen to limit current ripple to below 10% of rated current at the switching frequency, while preserving sufficient current-control bandwidth. Filter capacitance C_f is sized to provide reactive power support during load transients. The switching frequency balances switching losses against harmonic

performance. DC-link voltage V_{dc} is set to maintain adequate modulation headroom across the required output voltage range. Numerical values are given in Table II.

III. LOAD IMBALANCE DETECTION AND ANALYSIS

A. IMBALANCE METRICS

Imbalance manifests as asymmetric power consumption, leading to unequal current magnitudes and phase displacements. Under four-wire operation, the neutral current i_n from (5) provides a direct measure of imbalance severity. Two standard metrics quantify imbalance. The current imbalance factor (CUF) is defined as

$$CUF = \frac{\max(|I_a - I_{avg}|, |I_b - I_{avg}|, |I_c - I_{avg}|)}{I_{avg}} \times 100\%, \quad (6)$$

where $I_{avg} = (I_a + I_b + I_c)/3$ and I_a, I_b, I_c are the RMS phase currents. The voltage imbalance factor (VUF) is

$$VUF = \frac{V^-}{V^+} \times 100\%, \quad (7)$$

where V^- and V^+ are the negative- and positive-sequence RMS voltages, respectively. Threshold values for CUF and VUF, together with the power-deviation criterion below, trigger the four-wire control mode.

B. POWER-BASED DETECTION ALGORITHM

Per-phase instantaneous power provides better sensitivity to imbalance than current-only or voltage-only approaches because it captures both magnitude and phase distortions simultaneously. Per-phase power is computed as

$$P_\phi = V_{C\phi} I_{L\phi} \quad \phi \in \{a, b, c\}, \quad (8)$$

where $V_{C\phi}$ and $I_{L\phi}$ are the RMS filter-capacitor voltage and inductor current for phase ϕ . The maximum power deviation across phases is

$$\Delta P_{\max} = \max(|P_a - P_{avg}|, |P_b - P_{avg}|, |P_c - P_{avg}|), \quad (9)$$

where $P_{avg} = (P_a + P_b + P_c)/3$. Imbalance is flagged when $\Delta P_{\max}$ exceeds a threshold, typically 10–20% of rated power depending on load sensitivity.

C. STATIC SWITCH CONTROL LOGIC

When imbalance is detected, the static switch transitions the system from three-wire to four-wire mode. A hold-off period (100–500ms) prevents nuisance switching. The neutral voltage and system fault status are verified before the switch closes. Switch closure is synchronized to the zero-crossing of the neutral current to minimize switching transients. After closure, neutral current is monitored to confirm successful four-wire operation. Switch opening follows the same logic in reverse, reverting to three-wire mode when the CUF and VUF return below threshold.

IV. PROPOSED INDIVIDUAL PHASE CURRENT CONTROL ALGORITHM

A. CONTROL ARCHITECTURE OVERVIEW

The outer (voltage) loop operates in the synchronous D–Q frame to maintain balanced three-phase capacitor voltages. The inner (current) loop operates in the natural ABC frame for per-phase tracking with high bandwidth. The combined structure is shown in Fig. 2.

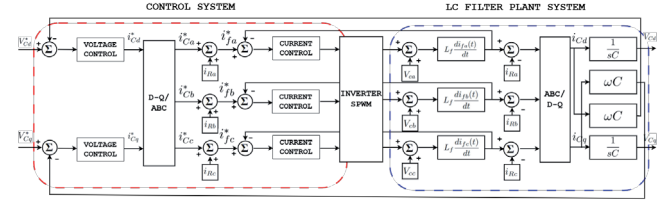


Fig. 2. Dual-loop control architecture: D–Q frame voltage controller (outer loop, red dashed boundary) and ABC frame current controller (inner loop) with load-current feedforward compensation.

The key design choices are: (i) D–Q frame voltage control for inherently balanced regulation; (ii) ABC frame current control for independent per-phase management without the zero-sum constraint of (4); (iii) explicit crosscoupling cancellation in the voltage controller; (iv) loadcurrent feedforward via (3) to improve transient response; and (v) bandwidth separation of at least 10:1 between the two loops.

B. D–Q FRAME VOLTAGE CONTROLLER

Applying the Park transformation to (3) yields the D–Q frame capacitor dynamics:

$$i_{Cd} = C_f V_{Cd} + \omega C_f V_{Cq}, \quad (10)$$

$$i_{Cq} = C_f V_{Cq} - \omega C_f V_{Cd},$$

where ω is the angular grid frequency and the crosscoupling terms $\pm \omega C_f V_{Cq,d}$ arise from the frame rotation. A PI controller with explicit cross-coupling cancellation generates the D–Q current references:

$$\begin{aligned} i_{Cd}^* &= \left(k_p V + \frac{k_i V}{s} \right) (V_{Cd}^* - V_{Cd}) + \omega C_f V_{Cq} \\ i_{Cq}^* &= \left(k_p V + \frac{k_i V}{s} \right) (V_{Cq}^* - V_{Cq}) - \omega C_f V_{Cd}. \end{aligned} \quad (11)$$

With cross-coupling cancelled, the closed-loop voltage dynamics reduce to two decoupled second-order systems:

$$C_f \dot{V}_{Cd,q} = \left(k_p V + \frac{k_i V}{s} \right) (V_{Cd,q}^* - V_{Cd,q}). \quad (12)$$

12

C. ABC FRAME CURRENT CONTROLLER WITH FEEDFORWARD

The current reference for each phase is obtained by inverse-Park transforming the D–Q references and adding the measured load current as a feedforward term derived from (3):

$$i_{L,abc}^* = \mathbf{T}_{dq \rightarrow abc}^{-1} [i_{Cd}^*, i_{Cq}^*]^\top + i_{R,abc}, \quad (13)$$

where $\mathbf{T}_{dq \rightarrow abc}^{-1}$ is the inverse Park transformation matrix. The feedforward term $i_{R,abc}^*$ makes the current reference respond immediately to load changes without waiting for voltage error to develop, which is the mechanism behind the fast settling times reported in Section VII.

A per-phase PI controller then tracks this reference:

$$v_{inv,\phi}^* = \left(k_{pI} + \frac{k_{iI}}{s} \right) (i_{L\phi}^* - i_{L\phi}) + v_{C\phi}, \quad \phi \in \{a, b, c\} \quad (14)$$

where the capacitor voltage $v_{C\phi}$ acts as a voltage feedforward to decouple the current loop from load-voltage disturbances. In four-wire mode, (14) is applied to each phase independently with no coupling between phases, as permitted by (5).

V. STABILITY ANALYSIS AND CONTROLLER DESIGN

A. SMALL-SIGNAL MODELING

The linearized closed-loop voltage-loop transfer function, obtained from (12), is

$$G_v(s) = \frac{\Delta V_{Cd}(s)}{\Delta V_{Cd}^*(s)} = \frac{k_{pV}s + k_{iV}}{C_f s^2 + k_{pV}s + k_{iV}}. \quad (15)$$

The linearized current-loop transfer function for each phase, from (2) and (14), is

$$G_i(s) = \frac{\Delta i_L(s)}{\Delta i_L^*(s)} = \frac{k_{pI}s + k_{iI}}{L_f s^2 + k_{pI}s + k_{iI}}. \quad (16)$$

Both transfer functions share the standard PI-controlled second-order form, which facilitates gain selection through pole placement.

B. CONTROLLER PARAMETER DESIGN

Matching the denominator of (15) to a desired natural frequency ω_{nV} and damping ratio ζ_V gives

$$k_{pV} = 2\zeta_V \omega_{nV} C_f, \quad k_{iV} = \omega_{nV}^2 C_f. \quad (17)$$

The natural frequency ω_{nV} is set to achieve a closed-loop bandwidth of 5–6 Hz. This value is chosen conservatively: it is high enough to regulate voltage against 50 Hz fundamental load variations, yet low enough to attenuate switching-frequency ripple and to remain well below the current-loop bandwidth, satisfying the stability separation requirement. A critical damping ratio $\zeta_V = 0.707$ ($1/\sqrt{2}$) is selected because it minimises settling time without overshoot, which is important for protecting sensitive loads [12].

Applying the same procedure to (16) yields the current controller gains:

$$k_{pI} = 2\zeta_i \omega_{nI} L_f, \quad k_{iI} = \omega_{nI}^2 L_f. \quad (18)$$

The current-loop bandwidth ω_{nI} is set to 1 kHz (approximately 6283 rad/s). This value is selected to be 10–20× greater than the voltage-loop bandwidth, satisfying the bandwidth-separation criterion that ensures the inner loop tracks its reference before the outer loop generates a new one [13]. At 1 kHz, the current loop is also well below the 20 kHz switching frequency, avoiding excitation of

switching-frequency resonances. The same critical damping ratio $\zeta_i = 0.707$ is applied for consistency and to prevent resonant current peaking.

To verify robustness to filter parameter uncertainty, the gains are evaluated at nominal values and at $\pm 20\%$ of both L_f and C_f as detailed in Section V-D.

C. STABILITY UNDER THREE-/FOUR-WIRE TRANSITION

When the static switch closes and (4) is replaced by (5), the per-phase current controllers become fully decoupled. Since each phase controller (14) has the same structure and gains, stability is preserved across the transition and the only change is removal of the zero-sum coupling. The voltage controller (11) continues to operate unchanged in the D–Q frame; it sees the transition only as a load disturbance, which the feedforward path (13) immediately compensates.

D. ROBUSTNESS TO PARAMETER VARIATIONS

To quantify robustness, the closed-loop poles of $G_v(s)$ and $G_i(s)$ are evaluated when L_f and C_f deviate from their nominal values by $\pm 20\%$, representing manufacturing tolerances, temperature drift, and ageing. Table I summarises the resulting closed-loop bandwidth and phase margin for each case.

TABLE I:
CLOSED-LOOP BANDWIDTH AND PHASE MARGIN UNDER FILTER
PARAMETER VARIATIONS ($\pm 20\%$ OF NOMINAL L_f AND C_f).

Case	L_f (mH)	C_f (μ F)	BW _i (kHz)	PM _i (°)
Nominal	1.26	4.50	1.00	52
$L_f - 20\%$	1.01	4.50	1.25	49
$L_f + 20\%$	1.51	4.50	0.83	55
$C_f - 20\%$	1.26	3.60	1.00	52
$C_f + 20\%$	1.26	5.40	1.00	52
$L_f + C_f + 20\%$	1.51	5.40	0.83	55
$L_f - C_f - 20\%$	1.01	3.60	1.25	49

All cases maintain a phase margin above 45°, confirming adequate stability margin across the expected parameter range. The bandwidth-separation ratio between voltage and current loops remains above 10:1 in all cases. These results show that the proposed control design is robust to typical filter parameter uncertainties without requiring adaptive gain scheduling.

VI. SIMULATION SETUP

A. SYSTEM PARAMETERS

All simulations were performed in PSIM with a detailed model comprising the three-level NPC inverter, L–C filter, proposed control algorithms, and load variations. Table II lists the simulation parameters.

TABLE II
SIMULATION PARAMETERS.

Parameter	Value	Parameter	Value
V_{dc}	700[V]	C_f	4.5[μF]
R_L	30[Ω]	f_{PWM}	20[kHz]
L_f	1.26[mH]	P_{rated}	250[W/phase]
k_{pV}	0.0119	k_{iV}	0.0178
k_{pI}	11.21	k_{iI}	49.87 10^3

B. TEST SCENARIOS

The system was implemented in three-phase four-wire configuration with the static switch short-circuited to allow per-phase current control throughout. Load variations were applied only to the R-phase to isolate the controller response to a single-phase disturbance while the other two phases remained undisturbed. Two scenarios were tested: (1) a 100% load increase (R-phase resistance halved at $t = 0.5s$) and (2) a 50% load decrease (R-phase resistance doubled at $t = 0.5s$).

VII. SIMULATION RESULTS AND PERFORMANCE EVALUATION

A. LOAD INCREASE SCENARIO

1) *Without feedforward compensation:* Fig. 3 shows the system response without feedforward. Despite the load doubling, current increased by only 0.8A, well below the 1.76A required to match the new load. The resulting Rphase voltage drop created visible three-phase voltage imbalance while the other two phases remained near nominal.

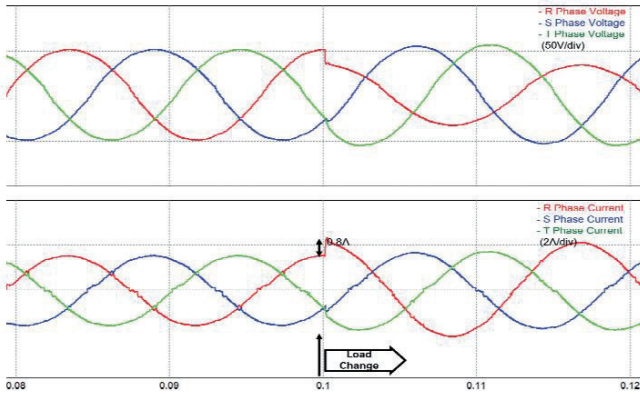


Fig. 3. Capacitor voltage and inverter current *without* feedforward: 100% load increase on the R-phase.

2) *With feedforward compensation:* Fig. 4 shows the compensated response. Current increased by 1.76A, closely matching the doubled load. The feedforward term supplied the current reference before voltage could deviate appreciably. All three phase voltages remained balanced, and steady-state conditions were re-established within approximately three fundamental cycles.

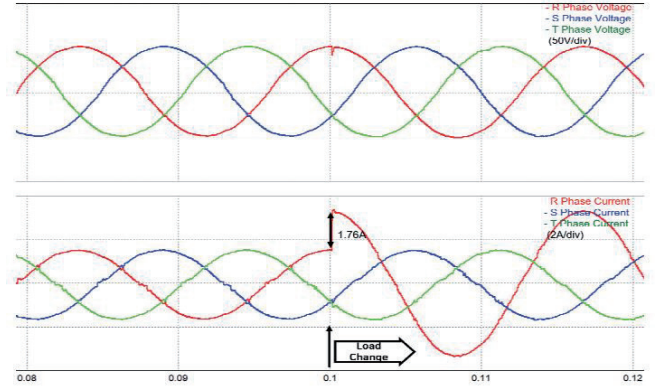


Fig. 4. Capacitor voltage and inverter current *with* feedforward: 100% load increase on the R-phase.

B. LOAD DECREASE SCENARIO

1) *Without feedforward compensation:* Fig. 5 shows the response to a 50% load decrease without compensation. Current reduced by only 0.5A while the load required a 1.02A reduction. The excess current caused the Rphase voltage to rise, introducing imbalance and potential overvoltage stress.

2) *With feedforward compensation:* Fig. 6 shows the compensated response. Current decreased by 1.02A, accurately matching the reduced load, and peak-to-peak ripple fell by approximately 40%. All three phase voltages relationships. The system settled within roughly two fundamental cycles.

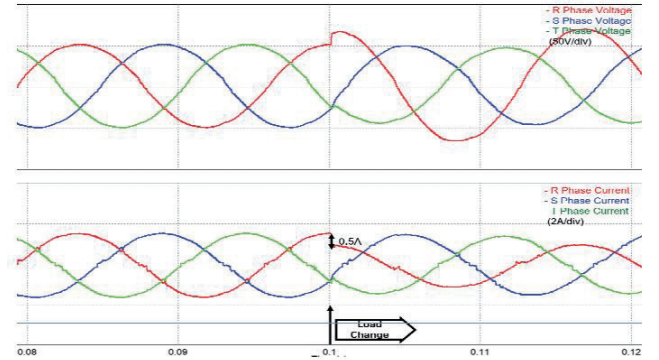


Fig. 5. Capacitor voltage and inverter current *without* feedforward: 50% load decrease on the R-phase.

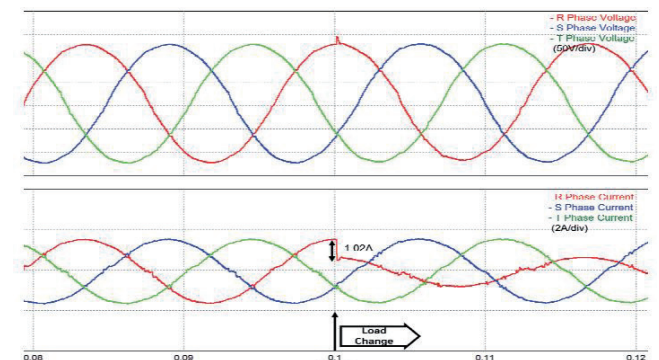


Fig. 6. Capacitor voltage and inverter current *with* feedforward: 50% load decrease on the R-phase.

C. HARMONIC DISTORTION ANALYSIS

Fig. 7 shows the inverter output current spectrum from DC to 3kHz (up to the 50th harmonic at 60Hz fundamental).

Without compensation, THD reached 13.18%, exceeding the IEEE 519 limit of 5%. Pronounced low-order harmonics were present: the 3rd at 8.5%, 5th at 6.2%, and 7th at 4.8% of the fundamental. With compensation, THD dropped to 3.64% (a 72.4% reduction), satisfying the IEEE 519 requirement. The 3rd, 5th, and 7th harmonics fell to 2.1%, 1.5%, and 1.0%, respectively.

Beyond THD, Table III reports three additional distortion indices to provide a more complete picture of power quality.

The crest factor (CF), defined as the ratio of peak to RMS current, falls from 1.81 to 1.43 with compensation, indicating a more sinusoidal waveform with lower peak stress on switching devices. THD_i (current THD referenced to the fundamental component rather than to the total RMS) follows the same trend as THD. The VUF, computed from (7), drops from above 8% to below 1%, confirming that the proposed algorithm effectively restores voltage balance in addition to reducing harmonic content.

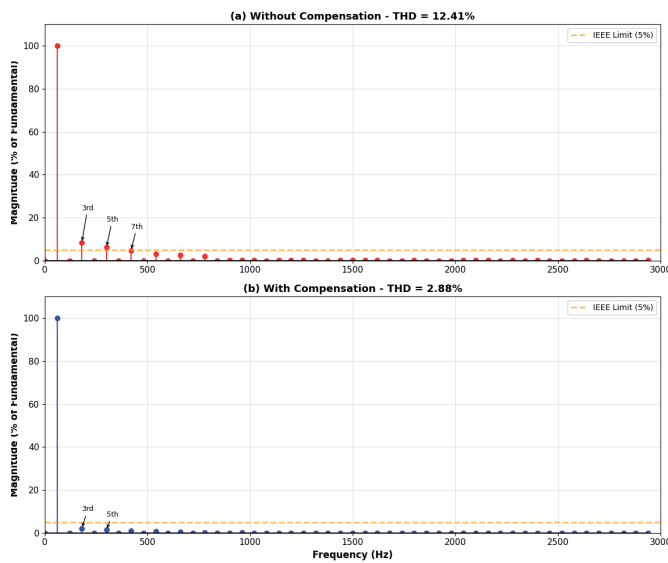


Fig. 7. Inverter output current harmonic spectrum: (a) without compensation (THD=13.18%), (b) with compensation (THD=3.64%). The orange dashed line indicates the IEEE 519 limit of 5%.

TABLE III:
HARMONIC DISTORTION INDICES: WITHOUT VS. WITH FEEDFORWARD COMPENSATION.

Index	Without comp.	With comp.
Total harmonic distortion (THD)	13.18%	3.64%
Total harmonic distortion of current (THD_i , fundamental-referenced)	12.95%	3.51%
Crest factor (CF)	1.81	1.43
Voltage imbalance factor (VUF)	>8%	<1%

VIII. COMPARATIVE PERFORMANCE EVALUATION

Table IV summarises the main performance differences between the uncompensated and compensated methods.

The compensated system achieves current tracking errors below 2%, VUF below 1%, and settles approximately three times faster than the uncompensated approach. The per-phase feedforward, enabled by four-wire reconfiguration, allows each phase to be adjusted independently without disturbing the other phases—a fundamental capability that conventional three-wire D–Q methods cannot replicate.

IX. PRACTICAL IMPLEMENTATION CONSIDERATIONS

Several aspects deserve attention when moving from simulation to hardware. The feedforward path requires high-bandwidth current sensors with low phase delay to keep load current measurements accurate at the 1kHz current-controller bandwidth. Anti-aliasing filters must suppress measurement noise without introducing phase shift that could destabilise the current loop. A DSP or FPGA with sufficient throughput is needed to execute both coordinate transformations, the three PI controllers, and the feedforward calculation within each sampling interval; a sampling rate of at least 10–20kHz is recommended.

The static switch must be rated for the expected neutral current and capable of efficient continuous operation in four-wire mode. Gate drivers should provide fast, reliable switching synchronised with the imbalance detection output. The control software should incorporate overcurrent detection, overvoltage monitoring, and thermal management, along with graceful degradation strategies if a sensor or computational resource becomes temporarily unavailable.

TABLE IV
PERFORMANCE COMPARISON: UNCOMPENSATED VS. COMPENSATED CONTROL.

Metric	Without compensation	With compensation
Current tracking error (load increase)	>60%	<2%
Current tracking error (load decrease)	>50%	<2%
Voltage imbalance factor (VUF)	>8%	<1%
THD	13.18%	3.64%
Crest factor (CF)	1.81	1.43
Settling time	8–10 cycles	2–3 cycles
Ripple current reduction	—	40%

X. CONCLUSIONS

This paper proposed an individual phase current control (IPCC) algorithm with load-current feedforward compensation for maintaining stable, balanced voltages during islanding under severe imbalanced loading. The dual-loop architecture separates voltage regulation (D–Q frame, 5–6Hz bandwidth) from current tracking (ABC frame, 1kHz bandwidth), combining the symmetry advantages of synchronous-frame control with the per-phase flexibility of natural-frame control.

The explicit novelty—ABC-frame feedforward combined with automatic three-/four-wire reconfiguration—removes the zero-sum constraint in three-wire mode and allows each phase current to be updated instantaneously on a load disturbance, before

voltage error can develop. This mechanism reduces tracking error from over 50–60% to below 2%, reduces THD from 13.18% to 3.64% (satisfying IEEE 519), and reduces settling time from 8–10 cycles to 2–3 cycles. Robustness analysis confirms phase margins above 45° across $\pm 20\%$ filter-parameter variations.

Future work will address experimental validation on a hardware prototype, performance under mixed resistive–inductive and nonlinear loads, adaptive gain scheduling for varying load compositions, and coordinated protection schemes for fault scenarios during extended islanding.

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Statistical Failure Analysis and Reliability Indices Estimation in a Medium-Voltage Distribution System

Marion Jan, Antonin Meunier, Karlo Kobešćak, Igor Kuzle, Igor Bujan, Mladen Modrovčić

Summary — This paper presents a statistical failure analysis of data obtained from the DISPO system for the purpose of evaluating the reliability and maintainability of a medium-voltage distribution network. Failure occurrences and outage durations are analyzed using statistical methods to model reliability behavior and downtime characteristics. Based on the processed data, key reliability and maintainability indicators are determined. Emphasis is placed on maintainability assessment through the evaluation of repair times and their influence on system availability. Standard distribution system performance indices are calculated, including the System Average Interruption Duration Index (SAIDI), the System Average Interruption Frequency Index (SAIFI), Mean Time Between Failures (MTBF), and Mean Time To Repair (MTTR). These indicators enable the identification of critical components and network sections with the greatest impact on overall system performance. The obtained results support condition-based maintenance planning and targeted reliability improvement measures. The proposed approach demonstrates how historical outage records can be systematically utilized to enhance operational decision-making and improve the reliability performance of distribution systems.

Keywords — Failure statistics, Reliability assessment, Distribution network performance, Maintainability modeling.

I. INTRODUCTION

Ensuring high reliability of electric power distribution networks is a central objective of modern power system planning and operation, as interruptions at distribution level directly affect end-users and the wider economy. Regulatory frameworks in many countries explicitly link utility performance incentives or penalties to continuity of supply, which is monitored through standardized reliability metrics [2]. At the same time, increasing integration of dispersed generation, aging infrastructure, and evolving customer expectations are making distribution networks more complex to operate and more exposed to stochastic failure mechanisms. In this context, quantitative assessment of reli-

ability is essential not only for regulatory reporting, but also for asset management, network planning, and optimization of maintenance strategies in medium-voltage (MV) distribution systems.

Distribution system reliability is commonly evaluated using continuity indices such as the System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI). However, to obtain unbiased and statistically meaningful reliability indices, utilities must rely on structured, complete and consistently coded outage data collected over several years. This requires dedicated information systems that integrate operational event recording with network topology and customer data, as implemented for example in the Croatian DISPO (Distribucijska Pouzdanost) - Information System for Identification and Monitoring of Distribution Reliability.

A substantial body of literature addresses statistical analysis of failures and estimation of reliability indices in MV distribution networks using historical outage databases [3], [4], [5], [6]. Many early and contemporary works focus on calculating SAIDI, SAIFI and related indices from recorded outages to characterize performance of specific feeders or substations, often in the form of case studies on real distribution utilities [7], [8]. These studies typically classify outages by cause and voltage level, and then compute annual customer- and load-oriented indices to identify critical feeders or regions with systematically poor reliability. More recent contributions emphasize statistical modeling of failure processes and restoration-related times in MV networks, moving beyond simple index calculation. Clavijo-Blanco et al. provide a detailed statistical characterization of key reliability parameters such as time between failures, time to locate the fault, switching time and repair time, using MV outage data from a European distribution system operator and fitting appropriate probability distributions to each parameter [3]. Building on this, a later work by the same research group introduces an integrated Monte Carlo-based algorithm for statistical characterization of reliability indices in real MV networks, explicitly accounting for the probabilistic distribution of SAIDI and SAIFI and their economic implications via penalty-based schemes [4]. Other authors propose methodologies to estimate component failure rates for overhead lines, underground cables and transformers directly from large incident databases, showing that utility-specific failure rates can significantly deviate from generic handbook values and thereby improve prediction of future interruptions and reliability indices [9]. Recent analyses of MV and LV distribution grids highlight that adverse weather conditions, equipment faults and operational interventions are major contributors to unplanned outages and to the deterioration of SAIDI and SAIFI [10].

In the Croatian setting, works presented at HRO CIGRE and HO-CIRED have used DISPO-based outage statistics to compare reliability performance across different distribution areas, dem-

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onstrating significant differences in SAIDI and SAIFI levels and pointing to the impact of planned outages and maintenance practices on overall continuity of supply [11]–[13]. Authors in [1] discuss distribution reliability and quality of supply in Croatia, with emphasis on continuity indices, regulatory requirements and use of operator databases for reliability monitoring and planning.

II. DATASET DESCRIPTION

The dataset used in this study originates from the DISPO information system, which is employed for recording, monitoring, and analyzing operational events in Croatian power distribution networks. DISPO represents a centralized outage management and reliability tracking platform integrating event logging, classification, and performance indicator calculation within a unified relational database environment. Operational events are entered manually into the system by authorized personnel following the occurrence or completion of an outage. The accuracy and consistency of the dataset therefore depend on standardized reporting procedures and predefined classification catalogues embedded within the system. Each recorded event is uniquely labeled and associated with detailed technical and operational descriptors, enabling traceability and structured analysis. Outages are categorized according to predefined event types. The classification of outage types used in this study is summarized in Table I, where planned outages (Type A) and forced outages (Type B) are distinguished. This categorization allows separate evaluation of reliability and maintainability indicators in accordance with established power system reliability assessment methodologies. The system architecture supports hierarchical aggregation across organizational units, plants, voltage levels, feeders, and components, enabling multi-level performance analysis.

The analyzed dataset consists of approximately 57,000 recorded events covering the period from 2006. to 2024. The records span multiple voltage levels and organizational units within the distribution system.

Each dataset entry contains the following attributes:

- Label – unique event identifier
- Organizational Unit – responsible operational entity
- Plant – substation or supply facility
- Field – network section identifier
- Type – outage classification
- Voltage – operating voltage level
- Start – outage start timestamp
- Duration (min) – interruption duration in minutes
- Pmax (kW) – maximum interrupted power
- ENS (kWh) – Energy Not Supplied
- Affected Customers – number of impacted customers
- Customer Minutes – aggregated outage duration across all affected customers
- Description – textual event description
- Cause – categorized failure cause
- Fault – fault type classification
- Fault Location – specific equipment location
- Unit – operational unit designation
- Component – affected network component

- Feeder Type – feeder classification
- Entry Date – data entry timestamp

A schematic representation of the dataset structure and parameter interrelations is presented in Fig. 1.

Raw data showed trailing commas in the final row and string types with comma decimals; these were fixed by artifact removal, comma-to-dot replacement, and type conversion (float/int for numerics). Sustained outages (>3 min) were filtered, preparing data for reliable index estimation and statistical analysis.

A specific subset of records associated with so-called EKVI fields was excluded from the analysis. EKVI fields were used in the early stages of DISPO implementation, when measurement points were not yet properly linked to individual low-voltage (LV) feeders within medium-voltage/low-voltage (MV/LV) substations. At that time, the total number of customers was distributed across substations and feeders proportionally according to installed transformer power, in order to approximate customer allocation. Consequently, customer counts associated with EKVI records represent estimated rather than actual values, introducing significant uncertainty in SAIDI and SAIFI calculations. Following the introduction of the Informator system and subsequently the SAP Informator platform, measurement points were progressively linked to specific and accurately defined LV feeders. As a result, feederlevel customer counts are now largely accurate. Remaining discrepancies are primarily due to incomplete or inaccurate customer address data and represent an estimated error margin below 5%. A small number of measurement points remain unassigned, but their impact on aggregated reliability indicators is negligible. Due to the inherent uncertainty of EKVIbased allocation, approximately 12,000 records ($\pm 20\%$ of the original dataset) were removed from the analysis to ensure statistical consistency. A total of 151 records (less than 0.3% of the dataset) were removed due to corrupted CSV formatting or encoding-related anomalies.

TABLE I:
DISPO FAULT TYPES

Code	Type	Description
A1	Planned	Elimination of fault consequences
A2	Planned	Regular maintenance
A3	Planned	Construction of facilities/network
A4	Planned	Construction of facilities/connections
A5	Planned	Fault consequences (force majeure)
A6	Planned	Fault consequences (third parties)
A7	Planned	Maintenance of third-party facilities
A8	Planned	Construction third-party network
A9	Planned	Construction third-party connections
A10	Planned	Supply network
B11	Forced	Distribution generator
B10	Forced	Supply network
B14	Forced	Malfunction
C13	Outage by order	By NDC (OPS) order
C12	Outage by order	By Supply order

III. METHODOLOGY

The simplified architecture of the Distribution System is presented in Fig. 2. The methodological framework adopted in this study consists of data preprocessing, event filtering, location-based aggregation, and reliability index computation. For reliability and availability assessment, only Type B outages are considered, as

Label	Organizational Unit	Plant	Field	Type	Voltage	Start	Duration (min)	Pmax (kW)	ENS (kWh)	Affected Customers	Customer Minutes	Description	Cause	Fault	Fault Location	Unit	Component	Feeder Type	Entry Date
0 2264/25	ELEKTRA BJELOVAR-POGONSKI URED VELIKO GRĐEVAC	TS 10/0.4 kV DONJA KOVAČICA	1-DRAŽICA	B11	0.4	2025-11-02 17:16:00	82.0	4.0	5.24	1.0	82.0	NEMA FAZE	-	-	-	-	-	N	2025-11-02 18:56:00
1 2262/25	ELEKTRA BJELOVAR-SJEDIŠTE	TS 20/0.4 kV MALE SREDICE	2-BREZOVAC	B11	0.4	2025-11-02 08:47:00	71.0	8.0	9.08	1.0	71.0	NEMA FAZE	-	-	-	-	-	K	2025-11-02 10:01:00
2 2261/25	ELEKTRA BJELOVAR-SJEDIŠTE	TS 10/0.4 kV PRESPA - CIGLENA	2-PRESPA-ZIDANA	B14	0.4	2025-11-01 07:26:00	56.0	4.0	3.58	1.0	56.0	NEMA STRUIJE	TU6-prolazan kvar	NVO OO 25A U KPOMO-U.	zračna dionica - priključak (priključni vod, L)	ZD	PRKV	N	2025-11-01 08:21:00
3 2260/25	ELEKTRA BJELOVAR-SJEDIŠTE	TS 10/0.4 kV BJELOVAR 1	10-M BOGOVIĆA	B11	0.4	2025-10-31 19:43:00	40.0	4.0	2.56	1.0	40.0	NEMA FAZE	-	-	-	-	-	K	2025-10-31 20:23:00
4 2258/25	ELEKTRA BJELOVAR-POGONSKI URED VELIKO GRĐEVAC	TS 10/0.4 kV BEDIENIK 1	1-PREMA BEDIENIKU 2	B14	0.4	2025-10-31 17:28:00	65.0	4.0	4.16	1.0	65.0	ZASTOI NA OMM-0600802425 - nema jedne faze	TU5-preopterećenje	zamjenjen nvo 00 25a u kpmou	zračna dionica - priključak (priključni vod, L)	ZD	PRKV	N	2025-10-31 18:34:00
5 2259/25	ELEKTRA BJELOVAR-SJEDIŠTE	TS 10/0.4 kV PREDAVAC - CENTAR	4-PREDAVAC 2	B11	0.4	2025-10-31 16:22:00	198.0	4.0	12.66	1.0	198.0	NEMA STRUIJE	-	-	-	-	-	N	2025-10-31 19:40:00
6 2257/25	ELEKTRA BJELOVAR-POGON KRIŽEVCI	TS 10/0.4 kV MARINOVAC 2	2-PREMA KLETIMA	B11	0.4	2025-10-31 13:16:00	143.0	4.0	9.14	1.0	143.0	NEMA FAZE	-	-	-	-	-	N	2025-10-31 15:39:00
7 2256/25	ELEKTRA BJELOVAR-SJEDIŠTE	TS 10/0.4 kV DONJA NARTA	1-GORNJA NARTA	B14	0.4	2025-10-31 11:50:00	52.0	8.0	6.65	10.0	520.0	NEMA STRUIJE	TU6-prolazan kvar	ZAMJENJEN VU 50A U SEKCUSKOM PANCERU	zračna dionica - selektivni osigurač	ZD	SOSG	N	2025-10-31 12:42:00
8 2255/25	ELEKTRA BJELOVAR-SJEDIŠTE	TS 20/0.4 kV TAD 1	TP-TRAFO POLJE	A2	20.0	2025-10-31 09:15:00	65.0	173.0	178.15	33.0	2145.0	MAJERIĆ, UGRADNJA SUMARNOG BROJILA	-	-	-	-	-	K	2025-10-31 09:15:00
9 2253/25	ELEKTRA BJELOVAR-POGON KRIŽEVCI	TS 10/0.4 kV ZRINŠČINA	EKVITP-EKVITP	A2	10.0	2025-10-31 09:05:00	66.0	35.0	36.18	56.0	3696.0	VRENEŠIĆ, UGRADNJA SUMARNOG BROJILA	-	-	-	-	-	N	2025-10-31 09:05:00

Fig. 1. Sample DISPO dataset.

they represent stochastic failure events. Maintainability assessment includes both Type A and Type B events. Fig.3 shows the distribution of fault types.

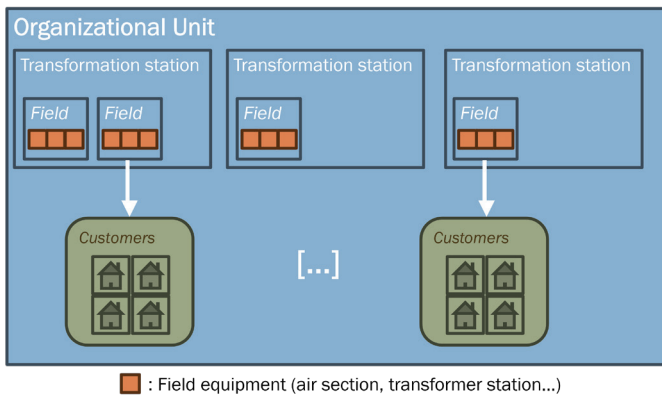


Fig. 2. System architecture of power distribution.

A. FAULT LOCATION AND FIELD ANALYSIS

1) *Most Frequent Failure Locations*: The identification of the most frequent locations of unplanned interruptions represents a primary step in reliability assessment. Failure locations were analyzed primarily according to the attribute Field. In the majority of cases, the field name contains the designation of a street, settlement, or geographically identifiable area, enabling spatial grouping of events at a meaningful operational level. This approach allows aggregation of interruptions by geographically coherent network segments and facilitates the identification of critical areas contributing most significantly to system reliability degradation.

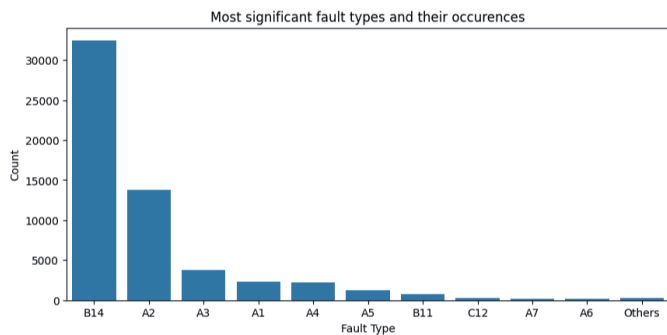


Fig. 3: Distribution of fault types (A: Planned, B: Forced, C: By order) in DISPO dataset (N=57k records).

2) *Equipment Distribution per Location*: Since each location comprises multiple components, it is necessary to examine the failure frequency of individual elements within the most critical locations. If a single component dominates failure occurrences at a given site, corrective actions such as equipment replacement, enhanced monitoring, or intensified preventive maintenance should be considered to improve operational performance.

B. RELIABILITY ANALYSIS

Reliability evaluation requires the exclusive consideration of forced outages (Type B faults), as these represent unplanned disruptions directly affecting system performance. Two standard performance indicators are used: the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI). A high SAIDI combined with low SAIFI indicates infrequent but long-lasting outages, suggesting repair inefficiencies. Conversely, low SAIDI with high SAIFI reflects frequent but short interruptions, implying good repair capability but poor reliability. Simultaneously high SAIDI and SAIFI values indicate inadequate system reliability and maintainability.

1) *SAIDI*: SAIDI represents the average outage duration experienced by a customer:

$$SAIDI = \frac{\sum_{i=1}^N U_i \cdot N_i}{N_{tot}} \quad (1)$$

where U_i is the duration of the interruption event i [min], N_i is the number of customers affected by the interruption i , N_{tot} is the total number of customers in the observed system, and N is the total number of interruption events in the observed period.

2) *SAIFI*: SAIFI represents the average interruption frequency per customer:

$$SAIFI = \frac{\sum_{i=1}^N N_i}{N_{tot}} \quad (2)$$

where N_i is the number of customers affected by the interruption i , N_{tot} is the total number of customers, and N is the total number of interruption events.

C. MAINTAINABILITY ANALYSIS

Maintainability analysis includes both planned (Type A) and unplanned (Type B) outages. Two key indicators are evaluated: Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR).

1) *MTBF*: MTBF represents the average operational time between consecutive failures:

$$MTBF = \frac{T_{op}}{N_f} \quad (3)$$

where T_{op} is the total system operating time during the observation period [h], and N_f is the total number of forced outages (failures). If constant failure rate is assumed:

$$\lambda = \frac{1}{MTBF} \quad (4)$$

2) *MTTR*: MTTR represents the average repair duration per failure:

$$MTTR = \frac{T_{rep}}{N_f} \quad (5)$$

where T_{rep} represents the total repair time associated with failures [h].

IV. RESULTS AND DISCUSSION

A. FAULTS ANALYSIS

The spatial distribution of recorded failures is presented in Fig. 4, which illustrates the number of outages aggregated by settlement (based on the Field attribute). Since field names typically correspond to street names or residential areas, this aggregation provides a geographically meaningful representation of failure concentration within the observed distribution network.

The results indicate a non-uniform distribution of failures across settlements. A limited number of locations account for a disproportionately large share of total interruptions, suggesting localized reliability weaknesses. Such concentration may be attributed to aging infrastructure, environmental exposure, network topology characteristics, or higher load density.

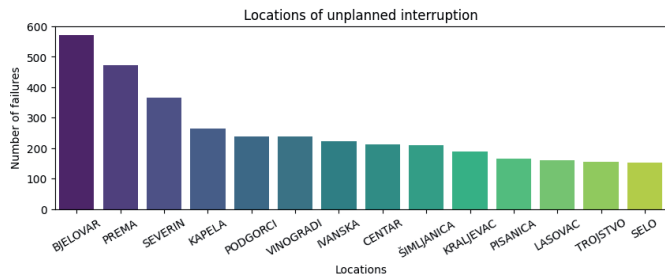


Fig. 4. Most common fault locations.

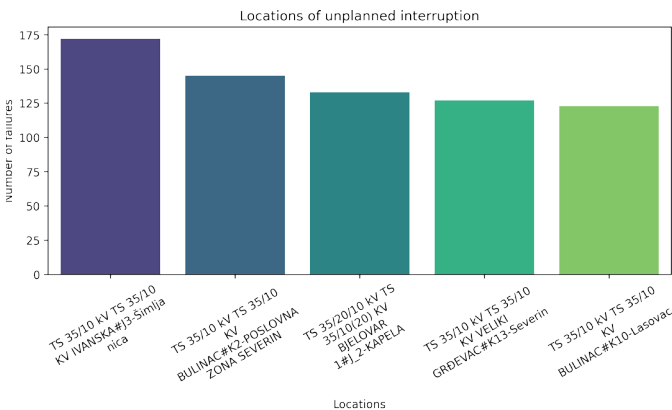


Fig. 5. Most common fault Fields.

To further refine the analysis, Fig. 5 presents the three fields with the highest number of recorded failures over the observed period. These locations represent the most critical network segments from a reliability perspective. The dominance of these fields in total outage count confirms the need for targeted maintenance and potential infrastructure reinforcement in these areas.

Equipment with the most failures in three locations is presented in Fig. 6.

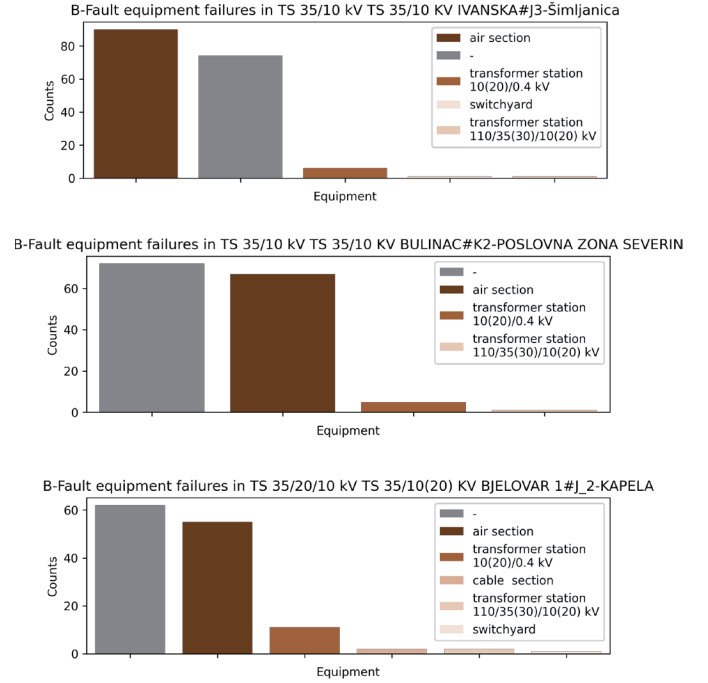


Fig. 6. Most common equipment failure.

The identified critical fields were subsequently analyzed in terms of their contribution to global reliability indices.

B. RELIABILITY INDICES

The temporal evolution of failures is shown in Fig. 7, where outages are aggregated by year and month. The results reveal seasonal variations in interruption frequency, with noticeable peaks during specific periods. These peaks may be associated with adverse weather conditions, increased loading, or operational stress factors typical for distribution systems.

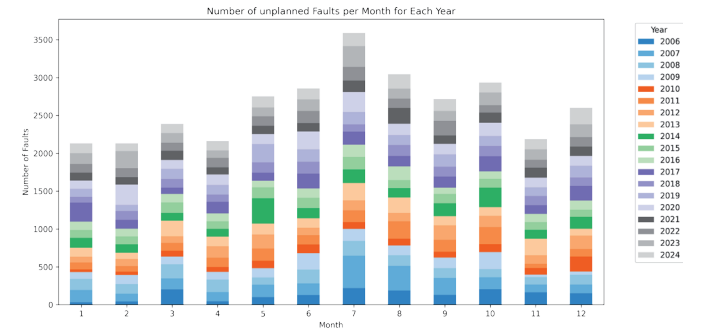


Fig. 7. Failures per month.

It can be observed that the majority of failures occur during the summer months. This seasonal concentration may be associated with the predominant failure mechanisms identified in the dataset.

In particular, air sections represent one of the most frequent fault locations, which suggests a possible correlation with elevated ambient temperatures and associated thermal stress. Higher temperatures can increase conductor sag, mechanical stress, and the likelihood of insulation degradation, thereby contributing to a higher interruption rate during summer periods. The reduced number of failures during the winter period is primarily driven by climatic factors, such as a lower frequency of atmospheric overvoltages and vegetation dormancy, concurrently accompanied by a decrease in construction activities and general operational workloads during the winter months. The distribution infrastructure of Croatia is exposed to highly diverse environmental stressors due to its distinct climate zones. The continental interior—encompassing the Bjelovar distribution area—is characterized by a moderate continental climate. In this zone, the primary meteorological threats to overhead line reliability include seasonal lightning activity, severe summer windstorms, and winter ice loading events.

The calculated system-wide SAIDI and SAIFI are presented in Fig. 8 and Fig. 9. It can be observed from the temporal analysis of the reliability indices that both SAIFI and SAIDI exhibit a general decreasing trend over the analyzed years. This trend indicates an overall improvement in the continuity of supply and reliability performance of the distribution network. Such positive development can be attributed to systematic investments in network modernization, enhanced maintenance planning, replacement of aging infrastructure, and the implementation of condition-based maintenance practices that resulted from the structured reliability assessment enabled by the DISPO system. Among the concrete measures implemented, the transition to a 20 kV operating voltage is particularly prominent. Consequently, as part of the preparation and retrofitting of the network for 20 kV operation, obsolete equipment is systematically replaced, thereby minimizing the long-term duration and frequency of electricity supply interruptions [14].

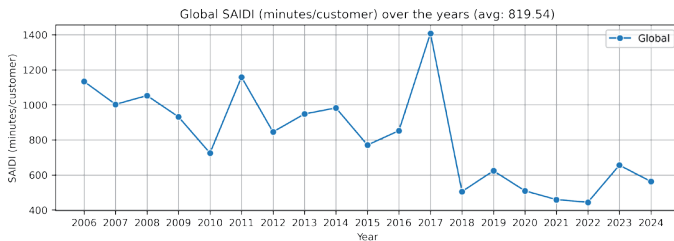


Fig. 8. System wide SAIDI evolution.

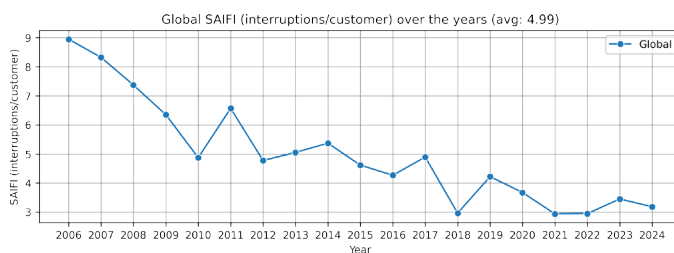
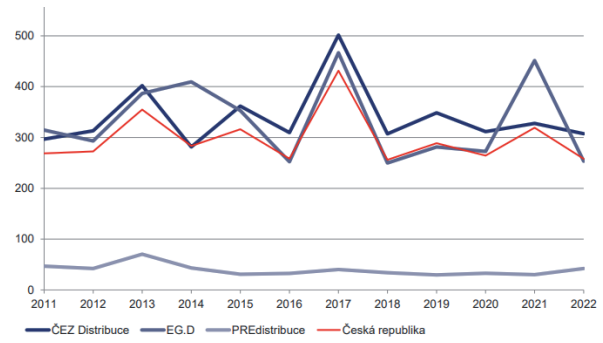


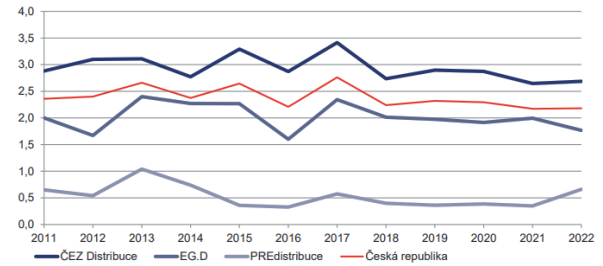
Fig. 9. System wide SAIFI evolution.

A notable exception to this trend occurred in 2017, where both SAIFI and SAIDI values show an elevated deviation relative to the surrounding years. This anomaly corresponds to an exceptionally warm summer in Croatia, which has been climatologically characterized as extremely warm with seasonal temperature anomalies reaching up to approximately 4.0 °C above the long-term average at several monitoring stations, including Bjelovar [15].

To facilitate a benchmarking evaluation, Fig. 10a and 10b display the historical reliability trends of the Czech distribution grid via SAIDI and SAIFI metrics.



(a) SAIDI



(b) SAIFI

Fig. 10. SAIDI and SAIFI for the Czech DSO [16].

The comparative analysis highlights the steady-state nature and high stability of the Czech power system. Concurrently, data from the Bjelovar distribution area demonstrate a pronounced trend of technological and operational advancement, characterized by a steady reduction in both interruption duration and frequency. The projection of this observed trend suggests an imminent performance convergence of the Bjelovar grid with the reference Czech indicators, thereby validating the efficacy of the implemented network modernization measures.

C. MAINTAINABILITY INDICATORS

For the three locations with the highest number of faults, the annual MTTR and MTBF were calculated. The results are presented in Fig 11 and Fig 12, illustrating the comparative reliability and maintenance performance at the selected sites.

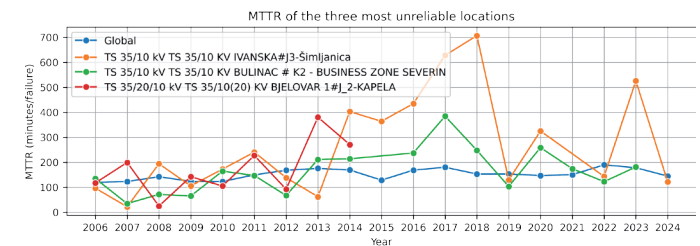


Fig. 11. Annual MTTR for the three locations with the highest number of faults.

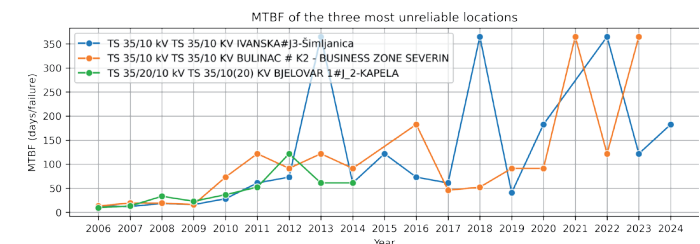


Fig. 12. Annual MTBF for the three locations with the highest number of faults.

Fig 13 shows the distribution of faults and maintenance activities across the months of the year.

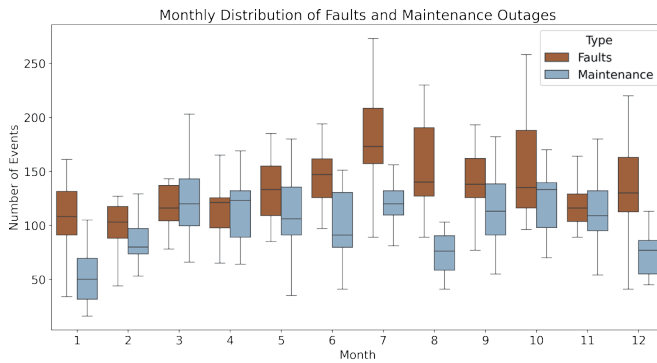


Fig. 13. Distribution of faults and maintenance activities per month.

As can be seen, the highest number of faults occurs during the summer months, while maintenance activities are reduced in August, likely due to annual holidays. Lower maintenance levels are also noticeable in winter, which can be attributed to both public holidays and adverse weather conditions. The box plot representation highlights the variability, median, and outliers for each month, providing insight into seasonal trends in network reliability and maintenance workload.

V. CONCLUSION AND FUTURE WORK

Although the analyzed dataset exhibits certain limitations—such as historical gaps due to asset renaming during network revitalization, a 20% omission rate in manual records resulting from equivalence grouping, and a high proportion of unclassified fault causes designated as null values—it nevertheless provides a statistically sound foundation for validating grid performance. The empirical trends established over the analyzed period demonstrate a positive trajectory, characterized by a continuous increase in the Mean Time Between Failures and a concurrent reduction in both SAIDI and SAIFI indices, thereby confirming a measurable improvement in overall system reliability. Furthermore, the spatial-temporal distribution of recurring faults has successfully isolated specific grid segments requiring prioritized capital investment and infrastructure revitalization. Concurrently, preliminary evaluations reveal correlations between localized meteorological stressors and fault occurrences. To build upon these findings, substantial scope remains for future research, particularly regarding the quantification of Energy Not Served (ENS) and the evaluation of associated macroeconomic losses. While data-driven methodologies are increasingly vital for modern distribution systems, the fidelity of the generated insights remains inherently constrained by data quality. Consequently, integrating automated data acquisition pipelines with multi-dimensional operational parameters—such as realtime weather telemetry and advanced asset health metrics—is imperative to enhance the robustness of predictive analytics. Ultimately, this study demonstrates that even in the presence of partial data constraints, structured reliability monitoring yields highly actionable insights that effectively guide targeted investments, optimize maintenance scheduling, and enhance grid performance.

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Empowering Smart Grids: An IoT and LoRa-Based Approach for Energy Monitoring and Theft Detection

Samandar Khan Afridi, Yasir Ali, Raja Masood Larik, Zeeshan Ahmad Arfeen and Tuseef Ahmed Khan

Summary — In today's world, as electricity demand continues to rise, one of the major challenges faced by power utilities is power theft. This not only results in significant revenue losses but also strains the power infrastructure, leading to inefficiencies and potential outages. Addressing this issue has become a critical priority for utility companies and governments. This project develops an IoT-enabled, LoRa-based power theft detection system that monitors electricity usage in real-time to identify unauthorized consumption. The system uses two ESP32 microcontrollers, two SCT013B current sensors, a ZMPT101B voltage sensor, and LoRa communication modules. These components are deployed in two setups: the Pole Side Setup and the Home Side Setup (Rx). The Pole Side Setup, placed at the electricity pole, includes an ESP32 microcontroller, an SCT013B current sensor, and a LoRa module. It measures the current flowing through the electrical line and wirelessly transmits this data to the Home Side Setup. The Home Side Setup, located at the consumer's premises, uses another ESP32, an SCT013B current sensor, a ZMPT101B voltage sensor, and a LoRa module. This setup compares the pole's transmitted current with the local current and voltage readings to detect discrepancies that might indicate theft. If unauthorized consumption is identified (e.g., when the pole's current exceeds the home's), the system logs the event and transmits the data to a Google Spreadsheet for easy monitoring. This provides utility companies with real-time alerts and detailed logs for quick response and analysis. The LoRa technology ensures long-range, low-power communication, making this system especially suitable for rural or remote areas where wired communication is impractical. The solution reduces manual inspections and operational costs by automating theft detection and offering real-time insights into electricity usage. In the future, the system can be enhanced by improving data security, integrating with smart meters, and expanding its coverage. The project represents a scalable, cost-efficient approach to combating electricity theft and optimizing power distribution.

Keywords — ESP32 microcontroller, Internet of Things (IoT), LoRa communication, Smart energy metering, Voltage sensor, Current transformer, Power theft detection, Real-time monitoring

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I. INTRODUCTION

The energy sector in Pakistan plays a crucial role in supporting national economic development and ensuring societal well-being. However, the sector continues to face persistent challenges, including inadequate infrastructure, supply-demand imbalances, and inefficiencies in energy consumption. These issues have created a pressing need for modernized energy management solutions that enhance operational efficiency and promote sustainability. Conventional energy metering systems have proven insufficient in addressing these challenges due to several inherent limitations. Traditional meters generally lack the capability for real-time monitoring, detailed data acquisition, and remote accessibility [1], which restricts the ability to analyze consumption trends and respond promptly to irregularities [2]. Manual meter reading further introduces human error, leading to inaccurate billing and inefficient energy utilization [5]. The maintenance and large-scale deployment of these systems are both resource-intensive and costly.

Pakistan's energy distribution network also experiences significant losses due to transmission inefficiencies, technical faults, and widespread electricity theft [4]. These issues reduce the financial sustainability of utility providers and compromise overall grid reliability. To address these problems, the implementation of advanced technological solutions has become essential.

This section reviews prior work relevant to IoT-based energy metering, long-range wireless telemetry, and automated power-theft detection. Each cited work is described succinctly to highlight methods, technologies, and findings that motivated the present prototype.

In [1], an ESP32-based electric energy consumption meter is presented; the work demonstrates feasibility of low-cost microcontroller platforms for real-time measurement and cloud-enabled logging of voltage, current, active power, and cumulative energy. In [2] reports an IoT energy-monitoring prototype that leverages a Wi-Fi microcontroller and MQTT-style data forwarding to achieve remote accessibility and basic dashboarding for voltage and current metrics. The prototype in [3] implements a postpaid electricity and water usage monitoring system, showing practical integration of utility metering with remote billing and monitoring workflows. In [4], an IoT prototype for smart home automation is presented, illustrating how distributed sensors and actuators can be integrated into a single management framework for residential energy control. Work in [5] develops a smart energy meter that compares grid and solar generation, demonstrating multi-source metering and cost-analysis capabilities for hybrid energy systems. The comparative study in [6] analyses the working principles of the ESP32 and other low-cost microcontrollers, providing perfor-

mance and suitability guidance for embedded IoT metering applications. Reference [7] document software tooling and IDE usage (Arduino IDE) for rapid firmware development and deployment in embedded IoT projects.

Long-range, low-power telemetry and its application to energy monitoring are addressed in several studies. In [8], a LoRa-based IoT system for industrial energy consumption monitoring is described, emphasizing reliable long-distance telemetry in harsh environments. The viability of LoRa-based networks for theft detection and wide-area monitoring is further examined in [9], which evaluates LoRa network design and performance metrics specific to energy-theft applications. The benefits of integrating LoRa with IoT sensing for enhanced power monitoring are discussed in [10], focusing on improved coverage and resilience. LoRa-based frameworks for rural energy monitoring are developed and benchmarked in [11] and [12], where network architecture and deployment trade-offs are explored. Multi-hop LoRaWAN designs for urban energy monitoring are proposed in [13], demonstrating methods to extend coverage in built-up areas.

Automated theft detection and analytics using IoT data streams are explored in [14] and [15]; these works outline system architectures and microcontroller-based detection mechanisms that reduce reliance on manual inspection. Challenges and taxonomy of the theft-detection problems are summarized in [16], which identifies practical obstacles and operational constraints faced by utilities. Machine learning and deep-learning approaches for anomaly detection in energy consumption are surveyed and demonstrated in [17] and [18], where feature extraction and classifier design are used to improve detection accuracy and reduce false positives. Real-time analytics architectures for smart grids that incorporate streaming data processing and anomaly detection are presented in [19].

Security, data integrity, and tamper-evidence are addressed by blockchain and secure-framework studies. In [20], a blockchain-enabled smart energy meter architecture is proposed to provide tamper detection and immutable logging of meter readings. The combination of LoRa with blockchain for secure, decentralized energy monitoring is explored in [21], showing how distributed ledgers can augment trust in wide-area IoT deployments. Fog and edge computing strategies to reduce latency and enhance local detection while preserving cloud connectivity are discussed in [22], which proposes architectures that place computation closer to the meter for faster theft detection and reduced network load.

Reviews and infrastructure-level perspectives complement system-level studies. An overview of advanced metering infra-

structure (AMI) and smart-grid communication requirements is provided in [23], framing interoperability and scalability challenges. Integration of next-generation cellular (5G) connectivity with IoT for low-latency energy monitoring is analyzed in [24], highlighting potential gains in responsiveness for critical grid applications. Finally, comparative and implementation-focused works such as [11], [12], and [10] collectively provide practical guidance on selecting radio hardware, network topology, and deployment strategies for large-scale monitoring.

The surveyed literature collectively demonstrates that low-cost microcontrollers (ESP32/ESP8266), LoRa/LPWAN communications, cloud analytics, and ML-based anomaly detection form a viable technology stack for scalable energy monitoring and theft detection. However, gaps remain in (i) practical end-to-end prototypes that combine non-invasive sensing, LoRa telemetry, cloud logging, and real-time ML inference in a single, field-tested package; (ii) lightweight yet secure data-integrity mechanisms suited to constrained LoRa payloads; and (iii) systematic field evaluations that quantify detection accuracy, communication reliability, and power/maintenance trade-offs across rural and urban deployments. These gaps motivate the current work, which integrates ESP32-based sensing, LoRa RA-02 telemetry, cloud logging (Google Sheets), and rule-based theft detection into a compact prototype aimed at validating feasibility, range, and detection performance under realistic conditions.

In Pakistan, the effective management of energy resources poses significant challenges due to outdated monitoring methods and inefficient data-handling processes. Traditional approaches to energy meter data monitoring often involve manual entry, leading to inaccuracies, delays, and limited insights into energy consumption patterns. This manual approach hampers decision-making processes and undermines efforts to optimize energy usage, reduce costs, and promote sustainability.

A. COMPARATIVE ANALYSIS WITH EXISTING IOT-BASED POWER THEFT DETECTION SYSTEM

To evaluate the significance and practical contribution of the proposed system, a comparative analysis was conducted with previously reported IoT- and LoRa-based power theft detection approaches available in the literature. Table 1 summarizes the comparison in terms of communication technology, cloud integration, theft detection capability, monitoring functionality, deployment suitability, and overall system complexity.

TABLE: I
COMPARATIVE ANALYSIS OF PROPOSED SYSTEM WITH EXISTING APPROACHES

Reference	Communication Technology	Cloud Monitoring	Theft Detection Method	Real-Time Monitoring	Long-Range Communication	Deployment Cost	Key Limitation
Ref. [9]	LoRa	No	Current threshold comparison	Partial	Yes	Moderate	Limited cloud integration
Ref. [14]	Wi-Fi	Yes	Smart meter monitoring	Yes	No	Moderate	Short communication range
Ref. [15]	GSM/Wi-Fi	Partial	Raspberry Pi-based monitoring	Partial	Limited	High	Higher system complexity
Ref. [17]	Smart Grid Network	Yes	Deep neural network	Yes	Depends on infrastructure	High	Computational complexity
Ref. [18]	Smart Grid Network	Yes	Deep reinforcement learning	Yes	Depends on infrastructure	High	Requires large datasets
Proposed System	LoRa + Wi-Fi	Yes	Dual-side current comparison	Yes	Yes	Low	Fixed-threshold limitation

This research contributes directly to several United Nations Sustainable Development Goals (SDGs) by promoting innovation, sustainability, and transparency in energy management. It supports SDG 7 (Affordable and Clean Energy) by enhancing the accuracy and efficiency of energy metering to minimize losses due to theft, and SDG 8 (Decent Work and Economic Growth) through the creation of opportunities in the technology and energy sectors. The integration of IoT and LoRa technologies aligns with SDG 9 (Industry, Innovation, and Infrastructure) by fostering resilient and intelligent energy systems, while SDG 11 (Sustainable Cities and Communities) is addressed through improved access to reliable electricity and efficient urban energy management. Furthermore, the system promotes SDG 12 (Responsible Consumption and Production) by encouraging efficient energy use, and SDG 16 (Peace, Justice, and Strong Institutions) by ensuring transparency, accountability, and fairness in energy distribution and monitoring.

Main objective of the research:

- To develop an IoT-based system for monitoring energy meter data.
- To implement a theft detection mechanism.
- To test and verify the complete prototype system.

The present research introduces an Internet of Things (IoT)-based energy monitoring and theft detection system designed to overcome the limitations of conventional metering infrastructure. The proposed framework employs an ESP32 microcontroller integrated with current and voltage sensors to facilitate real-time data acquisition, analysis, and remote accessibility. The system utilizes secure communication protocols and data encryption techniques to ensure accurate, reliable, and tamper-resistant energy monitoring. This approach provides an efficient, low-cost, and scalable solution aimed at improving transparency, optimizing energy usage, and mitigating electricity theft in Pakistan's power sector.

II. RESEARCH METHODOLOGY

The research methodology is designed to ensure a systematic, structured, and efficient execution of each project phase to meet the defined objectives. The process began with the system design phase, where the overall architecture was developed to enable real-time monitoring of electrical energy consumption and wireless transmission of data to a centralized cloud platform using Google Sheets. The architecture incorporated core components, including the ESP32 microcontroller, SCT013B current sensors, ZMPT101B voltage sensor, LoRa RA-02 communication modules, and a cloud-based data storage interface for real-time analysis and visualization. Component selection was carried out based on factors such as performance efficiency, compatibility, cost-effectiveness, and reliability. The ESP32 microcontroller was chosen for its powerful dual-core processing capabilities, built-in Wi-Fi and Bluetooth functionalities, and seamless interfacing with analog and digital sensors. The LoRa RA-02 module was selected for its long-range, low-power communication characteristics, making it ideal for wide-area monitoring and data transmission in distributed energy systems. The SCT013B current sensors and ZMPT101B voltage sensor were integrated for accurate, non-invasive measurement of current and voltage, ensuring safety and ease of installation.

Following the design and selection stages, hardware development was carried out by assembling all components onto a custom-designed printed circuit board (PCB). The current and voltage sensors were interfaced with the ESP32 microcontroller for continuous data acquisition, while the LoRa module facilitated long-distance wireless communication between the pole-side and home-side units. To protect the components from environmen-

tal exposure and mechanical damage, the assembled circuit was enclosed in a weather-resistant casing. Software development was conducted using the Arduino Integrated Development Environment (IDE), enabling efficient communication between the sensors, microcontroller, and cloud database. The ESP32 microcontroller was programmed to read real-time current and voltage data, process the acquired measurements, and transmit them via the LoRa module to the receiver unit. The receiver unit, also based on the ESP32, was configured to receive the transmitted data, perform comparative analysis between the pole and home readings, and upload the processed information to Google Sheets through Wi-Fi connectivity. This configuration enabled automatic cloud logging, remote monitoring, and theft detection based on discrepancies between transmitted and received data.

Upon successful integration of hardware and software components, the complete prototype underwent comprehensive testing and validation to ensure functional accuracy and system reliability. The system was evaluated under multiple operational scenarios, including no-load, normal load, and simulated theft conditions. The performance of the prototype was compared with conventional energy meters to validate accuracy and consistency. The communication performance of the LoRa modules was examined by varying the distance between transmitter and receiver units to confirm long-range stability and data integrity. The testing phase provided valuable feedback for refining system calibration, optimizing sensor response, and improving transmission reliability.

The data collected during experimental testing were analyzed to identify anomalies, communication delays, or measurement deviations. Based on the analytical results, iterative adjustments were implemented in both the hardware and software to enhance precision, reduce latency, and improve real-time responsiveness. The processed data also provided meaningful insights into energy consumption behavior, supporting efficient load management and theft detection strategies. The adopted methodology ensured the development of a robust, scalable, and cost-effective IoT-based prototype capable of real-time monitoring and automatic detection of unauthorized energy consumption. The integration of LoRa-based communication, cloud data management, and non-invasive sensing technologies resulted in a reliable solution for enhancing transparency, operational efficiency, and sustainability within modern energy distribution networks.

A. WORKING PRINCIPLE

The working principle of the IoT-based Reading Monitoring and Theft Detection Mechanism is grounded in the seamless integration of real-time energy monitoring, wireless communication, and advanced theft detection technologies. The system operates by continuously collecting data from electrical circuits using specialized sensors connected to an ESP32 microcontroller. These sensors, which measure both current and voltage, are strategically positioned to monitor energy consumption across various circuits. The ESP32 microcontroller acts as the brain of the system, processing the incoming data to calculate power usage. But this system doesn't just stop at monitoring; it's also designed to detect any anomalies that might indicate unauthorized energy use. By analyzing fluctuations in current and voltage, the system can identify patterns that suggest theft, such as sudden spikes in energy consumption or irregular power draws that deviate from normal usage. Once the data is processed, it's prepared for transmission through a LoRa RA-02 module, chosen for its ability to send data over long distances with minimal power consumption. This wireless transmission capability is crucial for ensuring that the data reaches a centralized server or cloud platform, where it can be securely stored and accessed by users in real time. The system's design allows for a responsive approach to theft detection; if any suspicious activity is

detected, an immediate alert is generated and transmitted as a priority signal. This proactive feature ensures that users can respond quickly to potential energy theft, minimizing losses and enhancing overall security. On the receiving end, another ESP32 microcontroller is responsible for processing the incoming data and uploading it to a Google Spreadsheet cloud via a Wi-Fi connection. This cloud-based storage solution not only secures the data but also makes it accessible from virtually anywhere, allowing users to monitor their energy consumption and any potential theft attempts through a web interface, smartphone, or laptop. The system's user interface is designed to be intuitive, providing clear visualizations of energy usage patterns and highlighting any detected anomalies. Furthermore, the system is built with scalability in mind. It can be easily expanded to monitor additional circuits or integrated with other IoT devices, making it versatile enough to adapt to different environments, whether residential or commercial. This flexibility is complemented by the system's robust data handling capabilities, with cloud storage ensuring that even large volumes of data can be managed efficiently. In essence, this IoT-based mechanism not only empowers users with real-time insights into their energy consumption but also equips them with the tools needed to detect and prevent energy theft, ultimately contributing to more efficient and secure energy management practices.

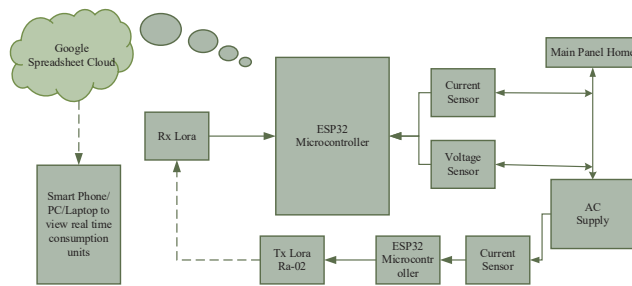


Fig. 1. Block diagram of the Prototype Development Project

Figure 1 is the block diagram of the prototype development of the project. The main controller is ESP32 with sensors that help with reading monitoring and detecting theft.

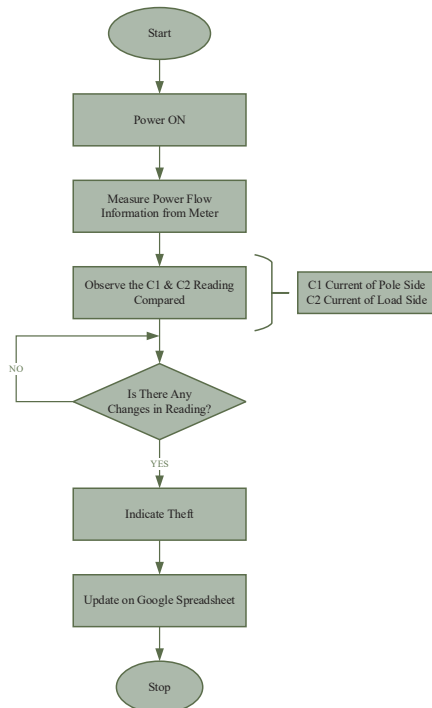


Fig. 2. Project methodology flow chart

The flowchart in Figure 2 outlines the process of detecting energy theft in an IoT-based monitoring system. It begins with powering on the system, which then measures the power flow from the meter by capturing the current values on both the pole side (C1) and the load side (C2). These readings are continuously observed and compared to detect any discrepancies. If the system finds no significant difference between C1 and C2, it continues monitoring without further action. However, if a change is detected, indicating a possible theft, the system flags this as a theft event. The incident is then logged and updated on a Google Spreadsheet for remote monitoring and record-keeping. The process is designed to loop continuously, ensuring real-time monitoring and quick detection of unauthorized energy use.

B. ESP32 MICROCONTROLLER

The ESP32 microcontroller (shown in Figure 3) functions as the core processing unit, handling data collection from connected sensors and wireless communication. The sensors are connected to GPIO pins 33 and 34, where they continuously monitor parameters like current and voltage. Pin 34 is designated for reading the voltage sensor data, while Pin 33 captures readings from the current sensor.

The dual-core Tensilica Xtensa LX6 processor within the ESP32 efficiently handles multitasking, allowing it to process the incoming sensor data and manage communication protocols simultaneously. The built-in Wi-Fi is used to transmit data to cloud storage or a local network, enabling real-time monitoring. The Bluetooth functionality is available for low-power communication with nearby devices when required. In Table 1 shows specification of ESP32 microcontroller.

The ESP32 communicates with LoRa modules to send sensor readings wirelessly over long distances, making it essential for energy monitoring and theft detection.

TABLE I.
SPECIFICATIONS FOR ESP32 MICROCONTROLLER

Specification	SCT-013 Input Current
Input Current 0-30A AC	0-5A AC
Output Signal	DC 0-1 V
Non-linearity	2-3 %
Built-in sampling resistance (RL)	62 Ω Turn Ratio
Turn Ratio	1800:1 G
Resistance Grade	Grade B
Working Temperature	25 °C~+70 °C
Dielectric Strength	1000 V AC / 1 min 5 mA



Fig. 3. ESP32 Microcontroller

C. SCT-013 CURRENT TRANSFORMER

The SCT-013 (shown in Figure 4) is a non-invasive AC sensor that plays a key role in this project. It is used to measure up to 5A of alternating current (AC) by utilizing its split-core design, which allows it to clamp around live or neutral wires without the need for high-voltage rewiring. The current transformer (CT) in the sensor converts the AC flowing through the primary winding into a small, safe-to-handle current that flows through the secondary winding. In this project, the SCT-013 sensor is connected to the ESP32 microcontroller via GPIO pins 33. The specifications are mentioned in the Table 2.

The sensor continuously measures the AC current flowing through the monitored power lines, providing real-time data that the ESP32 processes and transmits wirelessly via LoRa to the monitoring system. The sensor's data is crucial for calculating energy consumption and detecting potential energy theft by analyzing current patterns.

TABLE II.
SPECIFICATIONS FOR SCT-013 CURRENT TRANSFORMER

Specification	Details
Operating Voltage	2.2 to 3.6 V
GPIO Ports	3
ADC Ports	14
DAC Ports	2
Flash Memory	16 Mbyte
SRAM	250 Kbyte
Clock Speed	Up to 240 MHz
Wi-Fi	2.4 GHz
Sleep Current	2.5 μ A



Fig. 4. SCT-013 Current Transformer

D. ZMPT101B AC VOLTAGE SENSOR

A high-precision ZMPT101B (shown in Figure 5) voltage transformer is the foundation of the ZMPT101B AC Single Phase voltage sensor module, which is used to detect precise AC voltage. With an ESP32 can be measure AC voltage quite effectively using this method. The analog output of the ZMPT101B sensor can be adjusted in response to the sensor's ability to measure voltage up to 250V AC. The specifications are mentioned in table 3. The module contains a multi-turn trim potentiometer for calibrating and adjusting the ADC output, and it is simple to use. In the prototype, the voltage signal is being measured and sent to the ESP32 microcontroller.

TABLE III.
SPECIFICATIONS FOR ZMPT101B SENSOR

Specification	ZMPT101B Sensor
Output Signal	0-5v
Operating Voltage	DC 5V-30V
Measure within	250V AC.
Rated input current	2mA
Size	49.5 mm x 19.4 mm
Operating temperature	40°C ~ + 70°C

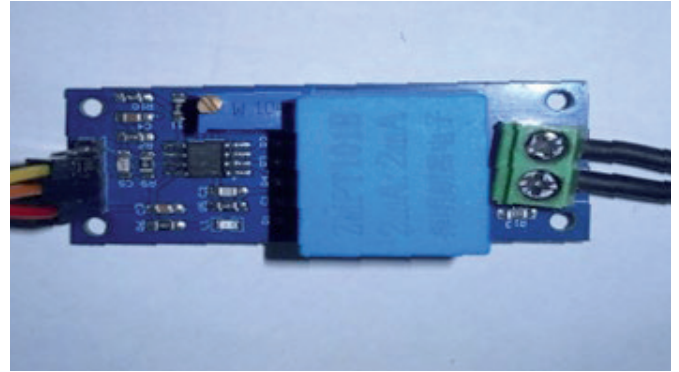


Fig. 5. ZMPT101B Sensor

E. LM2596 BUCK CONVERTER

The LM2596 (shown in Figure 6) power supply module is a step-down (buck) DC-DC converter designed to regulate voltage. It can efficiently handle loads of up to 3A while ensuring consistent regulation even when dealing with changes in input and output conditions. This module is available in different variants, offering fixed output voltages like 3.3V, 5V, and 12V, and it also includes an adjustable output version for flexibility. Notably, the LM2596 series operates at a switching frequency of 150 kHz, making it a versatile and adaptable choice for various applications. The characteristics are shown in Table 4. In this project, it has been used to convert 12V DC to 5V DC to give an input source to the desired components, such as relay module, BTS7960, esp32nodemcu controller, proximity sensor, and limit switches. The operating voltage of the system is 12V DC, so a converter is required for those components that can only operate at 5V to convert the input from 12V to 3.3V to provide a power source. Specifications of buck converters are given below.

TABLE IV.
SPECIFICATIONS OF THE LM2596 BUCK CONVERTER

Specification	Value
Model	LM2596 Buck Converter
Input Voltage Range	3.3V to 40V
Output Voltage Range	1.25V to 37V (adjustable)
Output Current	Up to 3A
Switching Frequency	150 kHz (typical)
Efficiency	Up to 92%
Output Ripple	50mV to 100mV (depending on load)
Load Regulation	$\pm 0.5\%$
Voltage Regulation	$\pm 2\%$
Operating Temperature	-40°C to +125°C
Dimensions	45 mm x 20 mm x 14 mm

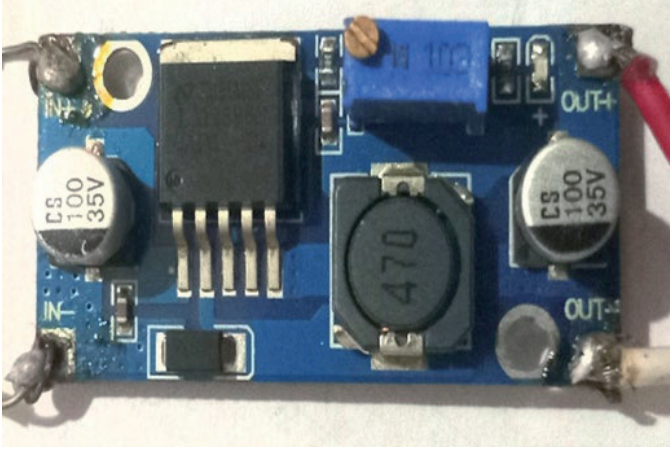


Fig. 6. Buck converter

F. RA-02 LORA MODULE

The LoRa RA-02 (shown in Figure 7) module was utilized to enable long-range, low-power wireless transmission of current and voltage data from the energy meter to the central monitoring system. LoRa, an abbreviation for Long Range, is a low-power wide-area network (LPWAN) communication technology that facilitates data transmission over several kilometers, making it well-suited for distributed energy monitoring applications. The specifications are describes in Table 5. The RA-02 module serves as the primary medium for collecting data from the sensing units and transmitting it to the receiver node for analysis. This configuration provides continuous updates on energy usage and supports the detection of anomalies indicative of potential energy theft.

TABLE V.
SPECIFICATIONS OF THE LORA RA-02 MODULE

Specification	Value
Module Model	Ra-02
Frequency Range	410-525MHz
Communication Range	Up to 10 km (in open areas)
Modulation	Lora Modulation Technique
Interface	SPI
Programmable bit rate	300Kbps
Antenna	IPEX
Max Transmit Power	18±1dBm
Power(Typical Values)	433MHz:TX:93mARX:12.15mAS- tandby:1.6mA 470MHZ: TX:97mARX:12.15mASandby:1.5mA
Power Supply	2.5~3.7V Typical3.3V
Operating Temperature-	-40°C to +85°C
Weight	0.45g

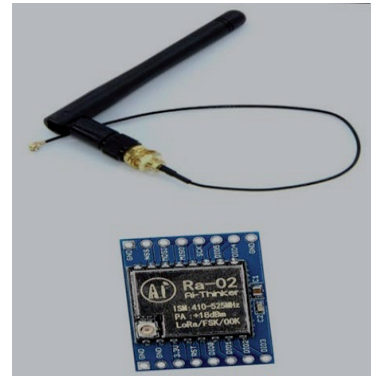


Fig. 7. Lora ra02 Module with Antenna

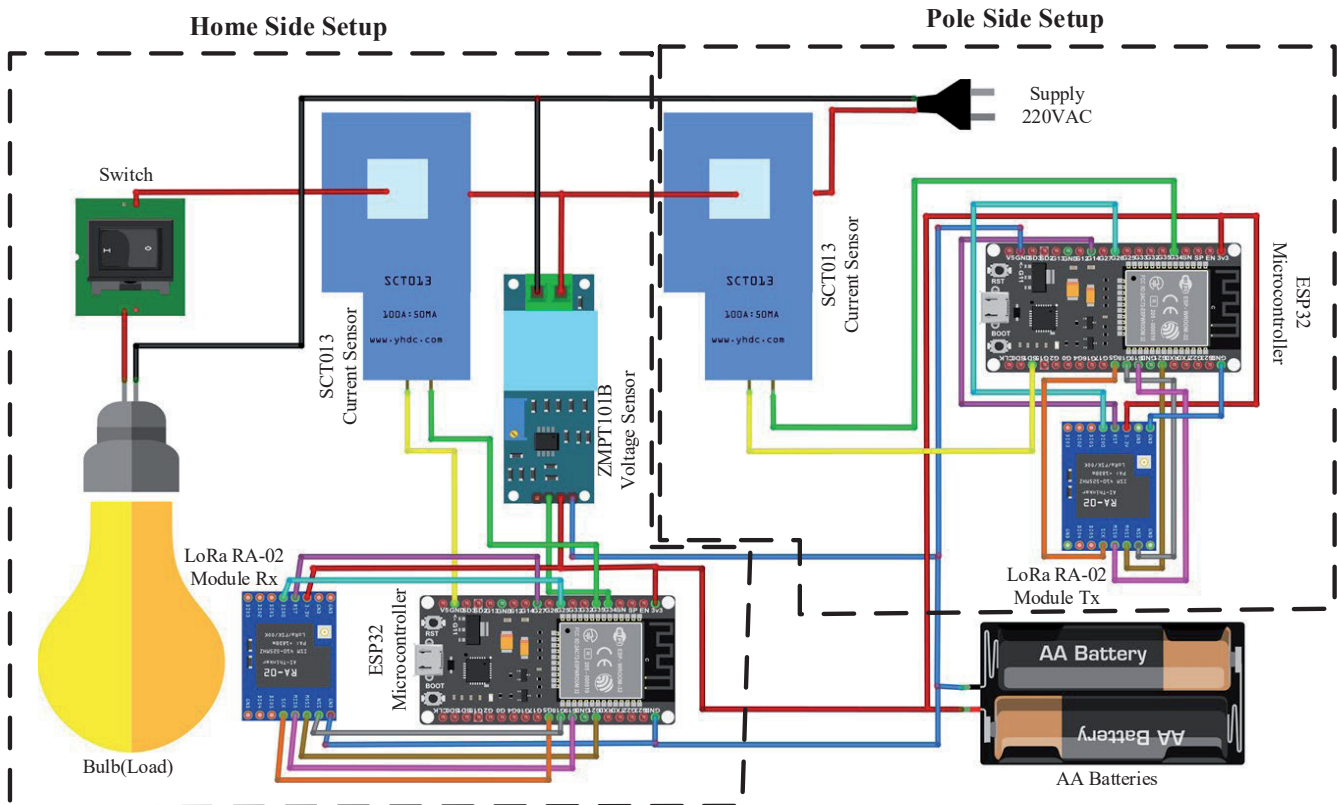


Fig. 8. Circuit Diagram of Project

The integration of LoRa technology minimizes the need for complex wiring infrastructure, thereby reducing installation costs and improving system scalability. Its strong resistance to interference and robust signal propagation ensure consistent data transmission even in challenging environments. Furthermore, the low power consumption of the RA-02 module enhances the operational efficiency of the system, allowing long-term, maintenance-free deployment in remote or rural areas.

G. HARDWARE SYSTEM ARCHITECTURE

Figure 8 presents the complete circuit diagram of the proposed IoT-enabled power theft detection system. The design consists of two integrated units: the Pole-Side Setup and the Home-Side Setup, which communicate wirelessly using LoRa RA-02 modules. Both units are based on ESP32 microcontrollers, ensuring efficient data processing, wireless communication, and real-time synchronization of current and voltage measurements.

Pole-Side Setup: The pole-side unit serves as the primary data acquisition node. It comprises an ESP32 microcontroller, an SCT013B current sensor, and a LoRa RA-02 module. The SCT013B sensor measures the current flowing through the distribution line, generating an analog signal proportional to the load. This signal is processed by the ESP32, which converts it into digital form and transmits it wirelessly to the home-side unit via the LoRa module.

The entire circuit is enclosed within a protective casing and mounted on the distribution pole. The setup is powered by AA batteries for energy efficiency, and a manual switch is provided to control system operation. The pole-side unit continuously monitors the current flow and acts as the transmitting node, enabling reliable, long-range, low-power communication with the home-side receiver.

Home-Side Setup: The home-side unit functions as the receiver and analytical node of the system. It incorporates an ESP32 microcontroller, an SCT013B current sensor, a ZMPT101B voltage sensor, and a LoRa RA-02 module. The LoRa module receives current readings from the pole-side transmitter, while the local sensors measure the home's current and voltage in real time. The ESP32 compares the received and measured current values to detect discrepancies that may indicate unauthorized power consumption.

When a difference between the pole-side and home-side readings exceeds the predefined threshold, the system identifies this as a potential theft event. The data, including date, time, voltage, current, power, and theft status, are then transmitted to a cloud-based Google Spreadsheet for real-time monitoring and record keeping. The home-side setup also provides serial output for on-site diagnostics and verification.

This two-node architecture ensures synchronized data measurement, long-range wireless communication, and real-time cloud integration. The hardware-software co-design provides a robust, scalable, and low-cost framework for continuous energy monitoring and accurate power theft detection.

H. SOFTWARE USED FOR PROGRAMMING MICROCONTROLLERS

The Arduino Integrated Development Environment (IDE) (shown in Figure 9) was employed to program both ESP32 (NodeMCU) microcontrollers used in the prototype development of the project. The IDE was selected for its versatility, hardware compatibility, and integrated debugging environment, which facilitated

efficient embedded system development. The software provides a comprehensive interface consisting of a code editor, compiler, message console, and serial monitor, enabling real-time code verification and communication diagnostics. All embedded programs, referred to as sketches, were developed and compiled within the IDE using the .ino file extension. The environment supports structured programming through syntax highlighting, search, and automated error detection features. Configuration of the development setup included the installation of ESP32-specific libraries via the Board Manager and the integration of required dependencies for LoRa communication and cloud connectivity. The serial monitor was utilized to validate data transmission between the ESP32, sensors, and cloud interface. The Arduino IDE's open-source flexibility and extensive hardware support enabled seamless coordination between hardware and software components, ensuring reliable data acquisition, processing, and real-time transmission for the IoT-based energy monitoring and theft detection system.

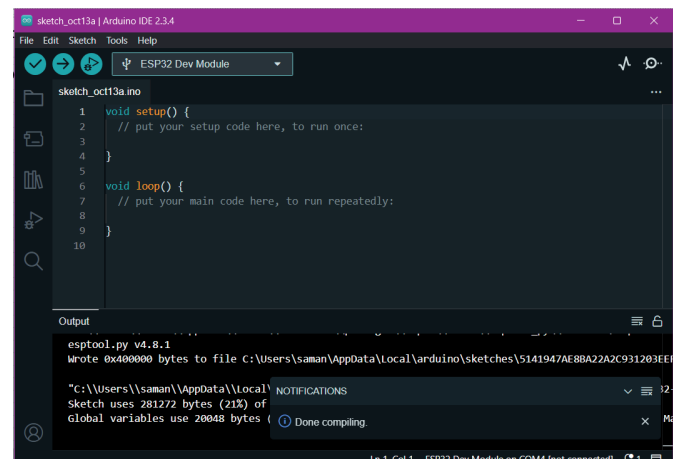


Fig. 9. Arduino IDE software

ESP32 WITH LoRa TX

The transmitter (pole-side) ESP32 microcontroller was programmed using the Arduino IDE to acquire current measurements from the SCT013B current sensor and transmit them via the LoRa RA-02 module. The program defines LoRa pin mapping according to ESP32 GPIO assignments to ensure proper communication between the devices. A correction factor was applied to calibrate sensor readings for improved accuracy. During initialization, the system configured the serial interface and LoRa communication module, halting operation if initialization failed. The main loop continuously read current values from the SCT013B sensor, applied the correction factor, and transmitted the calibrated data wirelessly through the LoRa link. Each transmission cycle included a short delay to prevent data congestion and ensure stable communication. This program enabled reliable long-range data transfer of current measurements from the pole-side setup to the receiver unit.

ESP32 WITH LoRa RX

The receiver (home-side) ESP32 combined Wi-Fi, LoRa, and sensor interfaces for real-time monitoring and data logging. The system established a Wi-Fi connection to transmit data to a Google Spreadsheet via HTTP GET requests, while simultaneously initializing LoRa for receiving current data from the transmitter. The ZMPT101B voltage sensor and SCT013B current sensor were configured to measure RMS voltage and current, respectively. Power and energy consumption were calculated by multiplying voltage and current values, with accumulated readings logged to

Incoming LoRa packets containing current readings from the pole-side setup were decoded and compared with local current measurements. If the difference between the transmitted and local current values exceeded a defined threshold, the system identified the event as potential theft and updated the theft status in the Google Spreadsheet. The program's functions ensured synchronized data acquisition, processing, and wireless communication, enabling accurate detection and real-time reporting of unauthorized energy usage.

A Google Spreadsheet integrated with Google Apps Script was utilized for real-time data logging and visualization of energy parameters. The ESP32 microcontroller transmitted measured voltage, current, power, units, and theft status values to the cloud via HTTP GET requests. The Google Apps Script, deployed as a Web App, handled incoming requests, extracted parameters, and dynamically updated corresponding columns in the spreadsheet, enabling automatic data entry and confirmation of successful transmission. The real-time logging ensured accurate synchronization between the pole-side and home-side setups.



All readings were continuously logged and visualized in the Google Spreadsheet, providing a reliable, cloud-based platform for real-time monitoring and record maintenance. This integration effectively combined IoT sensing, long-range communication, and cloud computing to achieve automated energy tracking and theft detection with high efficiency and accessibility.

The prototype comprises two primary units: the transmitter (pole-side) and the receiver (home-side). The pole-side unit, as shown in Figure 11, is enclosed within a circuit box mounted on

3. RESULTS AND DISCUSSION

The experimental evaluation of the proposed model was conducted (see table 6) to validate the performance and functionality of the developed IoT-based power theft detection system. Figure 13 presents the complete prototype used during testing. The system architecture comprises two primary modules: the Pole-Side Setup

and the Home-Side Setup (Receiver). The pole-side configuration includes an ESP32 microcontroller, an SCT013B current sensor, and a LoRa RA-02 module enclosed within a protective circuit housing mounted on the distribution pole.

A. QUANTITATIVE EXPERIMENTAL ANALYSIS

To evaluate the performance of the proposed IoT-based power theft detection system, multiple experiments were conducted under different operating conditions, including no-load, normal-load, and simulated theft scenarios. The measured parameters included voltage, pole-side current, home-side current, calculated power, current mismatch, and theft detection status.

The experiments were performed using a 220–230 V AC single-phase supply and a 200 W incandescent bulb as the test load. The current mismatch was calculated using:

$$\Delta I = |I_{pole} - I_{home}|$$

A theft condition was triggered when:

$$\Delta I > 0.20$$

where 0.20 A was selected experimentally to avoid false triggering caused by sensor noise and minor load fluctuations.

TABLE VI
EXPERIMENTAL RESULTS UNDER DIFFERENT CONDITIONS

Test Condition	Voltage (V)	Pole Current (A)	Home Current (A)	Calculated Power (W)	Current Difference (A)	Theft Status
System OFF	0	0.00	0.00	0	0.00	No Theft
No Load	228	0.00	0.00	0	0.00	No Theft
Normal Load (200W Bulb)	227	0.88	0.85	193	0.03	No Theft
Theft Condition 1	226	1.34	0.82	185	0.52	Theft Detected
Theft Condition 2	229	1.52	0.91	208	0.61	Theft Detected

The current measurements obtained from the proposed system were compared with a conventional clamp meter to evaluate sensor accuracy.

The percentage error was calculated using:

$$\% \text{ Error} = \frac{|I_{measured} - I_{reference}|}{I_{reference}} \times 100$$

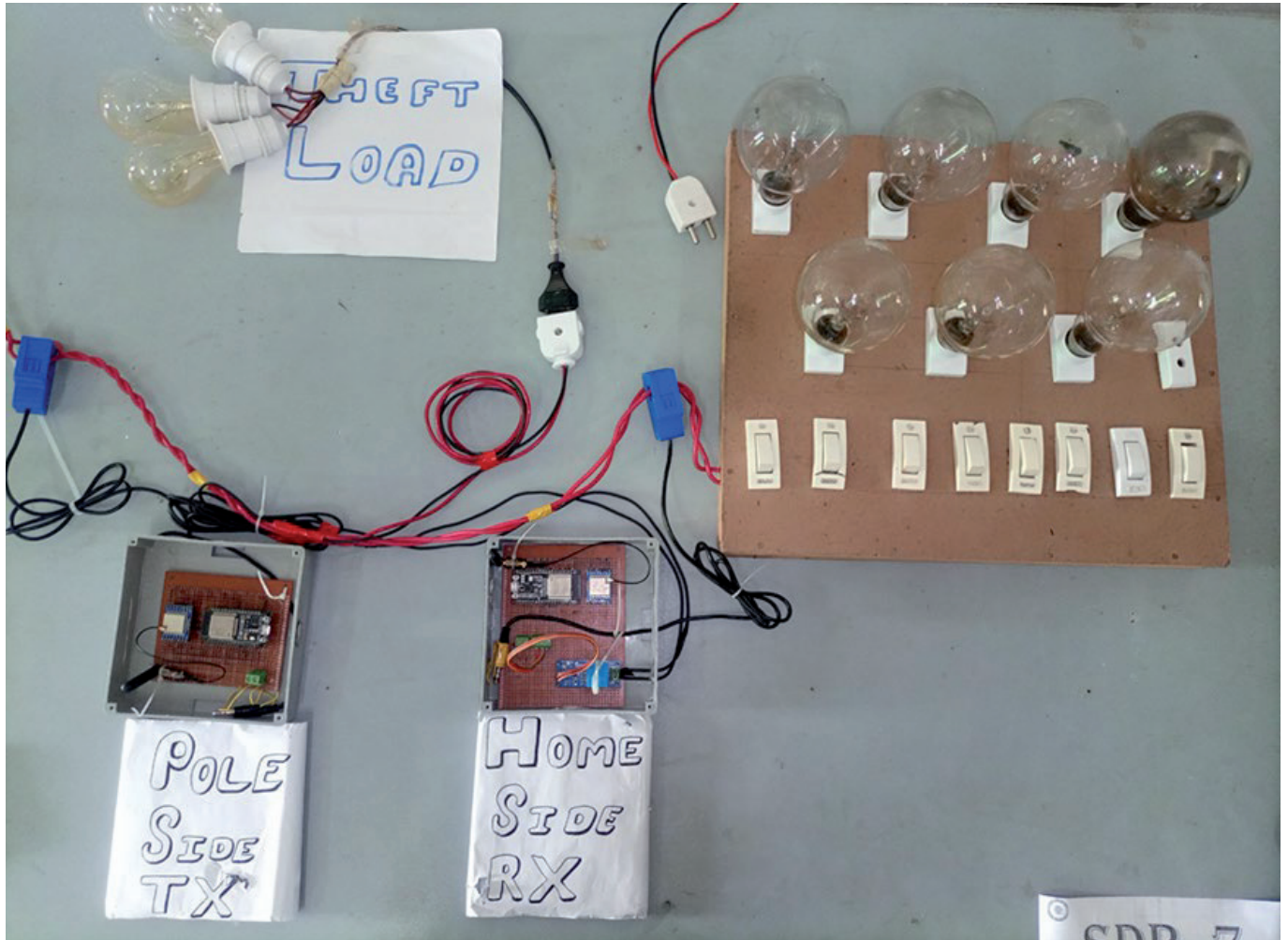


Fig. 13. Complete prototype of a project

TABLE VII
ACCURACY COMPARISON WITH STANDARD METER

Load Condition	Prototype Current (A)	Reference Meter (A)	Error (%)
100 W Load	0.44	0.43	2.32
200 W Load	0.88	0.86	2.33
300 W Load	1.31	1.28	2.34

From conclusion of table 7 the average current measurement error of the system was approximately 2.33% demonstrating acceptable accuracy for low-cost IoT-Based monitoring applications.

This unit measures the current flowing through the electrical line and transmits the acquired data wirelessly via the LoRa network. The home-side setup, equipped with another ESP32 microcontroller, an SCT013B current sensor, a ZMPT101B voltage sensor, and a corresponding LoRa module, receives the transmitted current readings and simultaneously measures local current and voltage values. The comparison between the transmitted and locally measured data enables real-time identification of discrepancies indicative of unauthorized energy consumption. The system performance was evaluated under four distinct operating conditions: (i) system off, (ii) system on with no load, (iii) normal load condition (200 W bulb), and (iv) theft condition.

B. PROJECT OFF CONDITION

The implementation of the proposed power theft detection system was carried out using a combination of ESP32 microcontrollers, SCT013B current sensors, a ZMPT101B voltage sensor, and LoRa RA-02 communication modules. The observations and results obtained from these experiments are presented below.

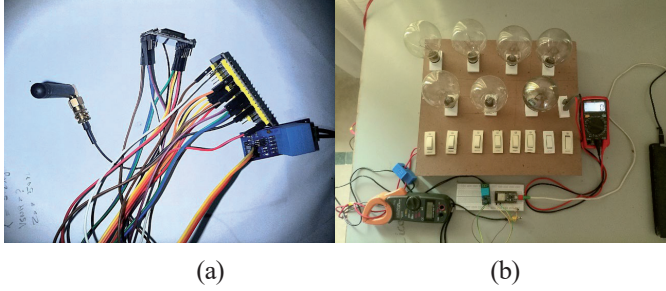


Fig. 14(a, b). When the system was off

Figure 14 (a, b) illustrates the system behavior when powered off. In this state, no data transmission occurred between the pole-side and home-side setups. The current sensors on both ends recorded zero readings, confirming the absence of current flow and verifying that the system remained in an idle, non-transmitting state. This baseline test established the accuracy and stability of the sensors and confirmed that the system operates only under active load conditions.

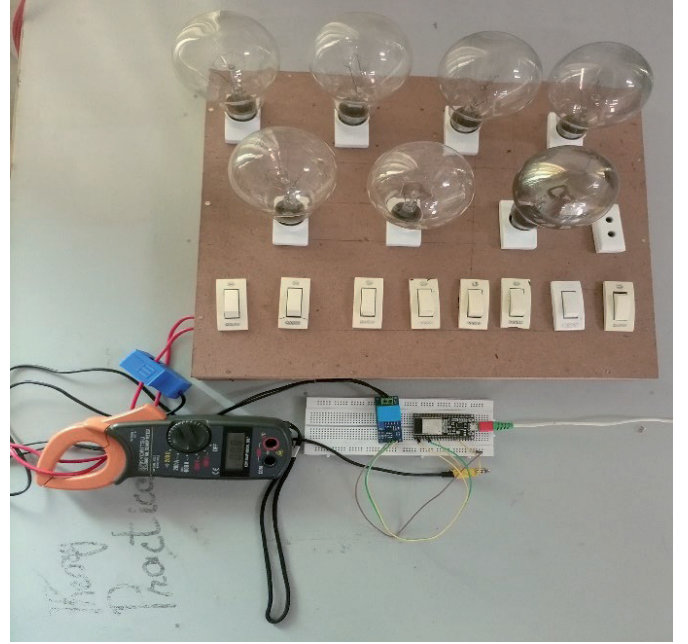
C. PROJECT ON CONDITION (NO THEFT)

Figure 15 (a, b) illustrates the system's operational state immediately after power-up. In this condition, the pole-side setup began measuring the current flow through the electrical line and transmitted the readings to the home-side setup via the LoRa RA-02 communication link. The communication reliability of the LoRa RA-02 modules was evaluated by increasing the separation distance between the transmitter and receiver units.

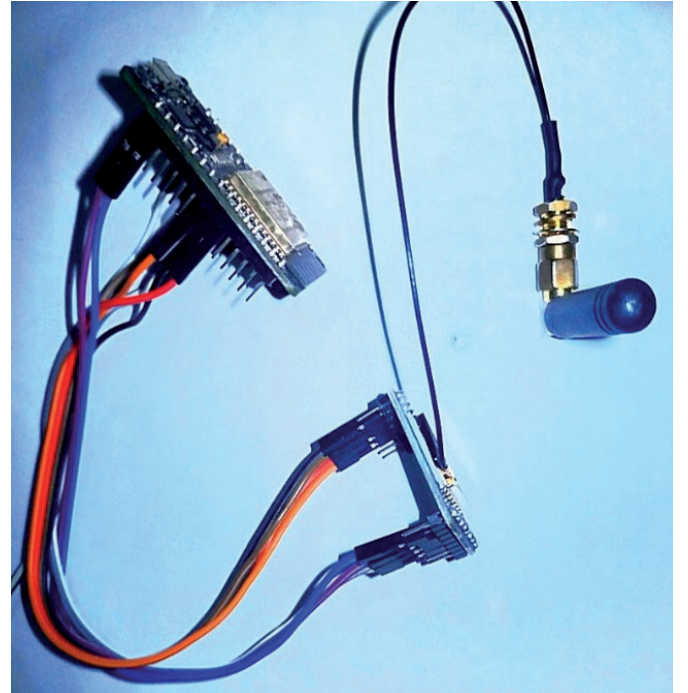
TABLE VIII
LoRa COMMUNICATION PERFORMANCE

Distance (m)	Packet Success Rate (%)	Average Delay (ms)
10	100	120
0	100	135
100	99	148
250	98	170
500	96	210

The table 8 results confirmed stable communication with minimal packet loss over moderate transmission distances, validating the suitability of LoRa technology for distributed energy monitoring application. The ESP32 microcontrollers on both sides successfully exchanged data, confirming that the wireless communication channel was functional.



(a)



(b)

Fig. 15. System on Condition

As shown in Figure 16, during the no-load condition, the current readings on both sides remained zero, indicating no energy flow and verifying that the sensors were accurately calibrated. The results validated the system's stability, readiness, and ability to perform real-time monitoring without false detections under no-load or non-theft conditions.

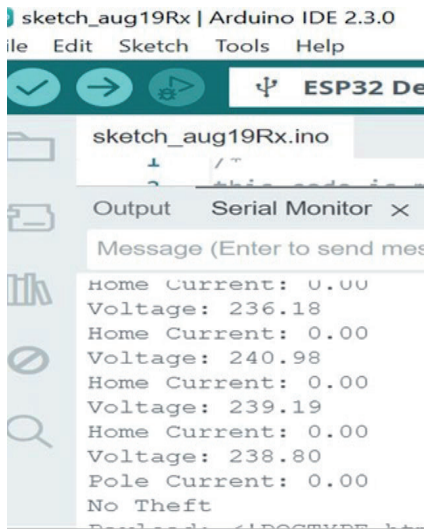


Fig. 16. No Theft

D. PROJECT NORMAL LOAD CONDITION (200W BULB, NO THEFT)

A 200W bulb was connected as the load in the experimental setup (see Figure 17(a, b)). The Pole Side Setup detected the current flow corresponding to the 200W bulb and transmitted this data to the Home Side Setup. The data received at the Home Side Setup was logged into the Google Sheet, written in columns, a,b,c,d,e,f, and g, respectively Date, time, voltage, current, power, units, and theft detection showing the expected readings based on the load.

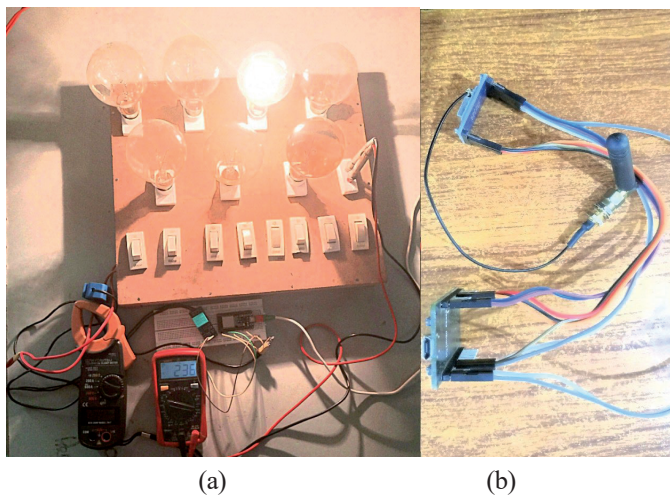


Fig. 17. Normal Load Condition (200W)

The system performed as expected under normal load conditions. The current sensor accurately measured the current corresponding to the 200W bulb, and the data was correctly transmitted and recorded. This result confirms that the system is capable of monitoring legal electricity usage and logging it for further analysis. The absence of theft detection alerts indicated that the system correctly identified this as a normal operating condition.

E. THEFT DETECTED CONDITION

Figure 18 illustrates the system behavior under a simulated theft condition, where an unauthorized connection was created by tapping into the electrical line. During this scenario, the pole-side setup recorded an abnormal increase in current that did not correspond to the readings from the home-side setup. This discrepancy was automatically identified by the system as an anomaly. The data were transmitted to the home-side unit, where a theft alert was generated and logged in the cloud-based Google Spreadsheet for immediate visualization and record keeping.



Fig. 18. Theft Detected Condition

As shown in Figure 19, the serial monitor output confirmed successful detection of unauthorized energy usage. The system accurately identified the imbalance between transmitted and received current values, triggering the theft detection algorithm. The event was recorded in real time, providing clear digital evidence of the theft occurrence. These results validate the system's capability to detect, flag, and report unauthorized power consumption with high reliability and minimal latency, demonstrating its effectiveness for real-time monitoring and theft prevention applications.

```

18:24:38.377 -> Pole Current: 3.99
18:24:38.377 -> Theft Detected!
18:24:42.338 -> Home Current: 0.00
  
```

Fig. 19. Serial Monitor

F. OUTPUT ON GOOGLE SPREADSHEET

Figure 20 presents the Google Spreadsheet interface used for real-time data monitoring. The spreadsheet automatically updates with each transmitted data packet, displaying parameters such as date, time, voltage, current, power, energy units, and theft status. All readings are logged dynamically, ensuring accurate and continuous tracking of electricity consumption and system status.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	DATE	TIME	VOLTAGES	CURRENT	POWER	UNITS	THEFT								
3747	9/11/2024	12:11:27	224.48	0	0	0									
3748	9/11/2024	12:11:33	224.79	0	0	0									
3749	9/11/2024	12:11:38					No Theft								
3750	9/11/2024	12:11:45	224.79	0.91	203.58	0.01									
3751	9/11/2024	12:11:51	224.34	0.83	185.33	0.01									
3752	9/11/2024	12:11:56					Theft Detected								
3753	9/11/2024	12:12:02	224.61	0.83	185.56	0.02									
3754	9/11/2024	12:12:09	224.43	0.83	185.41	0.02									
3755	9/11/2024	12:12:15					No Theft								
3756	9/11/2024	12:12:22	223.6	0.83	184.72	0.03									
3757	9/11/2024	12:12:29	224.35	0.94	211.48	0.03									
3758	9/11/2024	12:12:35	225.11	0.84	190.14	0.03									
3759	9/11/2024	12:12:40					No Theft								
3760	9/11/2024	12:12:46	224.36	0.83	185.35	0.04									
3761	9/11/2024	12:12:52	224.99	0.83	185.87	0.04									
3762	9/11/2024	12:12:58	224.58	0.83	185.53	0.04									
3763	9/11/2024	12:13:03					No Theft								
3764	9/11/2024	12:13:09	224.7	0.83	185.63	0.05									
3765	9/11/2024	12:13:15	224.56	0.83	185.52	0.05									
3766	9/11/2024	12:13:21					No Theft								
3767	9/11/2024	12:13:27	224.7	0.83	185.63	0.06									
3768	9/11/2024	12:13:33	225.24	0.83	186.08	0.06									

Fig. 20. View electricity consumption on Google spreadsheet

4. CONCLUSION

The proposed IoT-enabled, LoRa-based power theft detection system represents a significant advancement toward efficient and reliable energy monitoring. The integration of ESP32 microcontrollers, SCT013B current sensors, a ZMPT101B voltage sensor, and LoRa communication modules enables accurate, real-time monitoring of power consumption at both the pole and consumer ends. The system's cloud-based data logging through Google Sheets facilitates continuous observation, rapid anomaly detection, and transparent record management for utility operators.

The experimental results validate the system's capability to detect power theft accurately by comparing current discrepancies between the pole-side and home-side readings. Under normal operating conditions, consistent current measurements confirm system reliability, while any deviation indicates unauthorized consumption. This automated detection mechanism minimizes manual inspection efforts and enhances the responsiveness of theft identification processes. The utilization of LoRa technology ensures long-range, low-power communication, making the system highly suitable for deployment in rural or remote regions where wired networks are infeasible. The cloud integration further improves accessibility and scalability, allowing utilities to monitor energy usage remotely and in real time.

The developed prototype provides a cost-effective, scalable, and energy-efficient solution for addressing electricity theft and improving grid reliability. Future enhancements will focus on incorporating artificial intelligence and cybersecurity frameworks to further strengthen system accuracy, resilience, and adaptability in smart grid environments.

5. FUTURE WORK

Future development of the proposed IoT-based energy monitoring and theft detection system will focus on the following key areas:

1. Employ artificial intelligence and machine learning algorithms to detect anomalies, predict power theft, and optimize energy usage patterns.

2. Implement advanced encryption and blockchain-based frameworks to ensure secure, tamper-proof data transmission within the IoT network.
3. Extend the system architecture for seamless integration with modern smart grid infrastructure and utility management systems.
4. Utilize 5G communication and edge processing to enable ultra-low latency, high-speed data handling, and real-time decision-making.
5. Develop user-oriented mobile and cloud platforms for remote monitoring, analytics, and control of energy systems.

6. LIMITATIONS

1. The proposed system employs a fixed-threshold current comparison method for theft detection, which may generate false-positive or false-negative results under dynamic load conditions and sudden current fluctuations.
2. The experimental validation was conducted under controlled laboratory conditions with limited load configurations; therefore, the results may not fully represent the complexity of large-scale real-world power distribution networks.
3. The performance of the system depends on stable LoRa communication and sensor calibration. Environmental interference, signal attenuation, and sensor drift may affect measurement accuracy and communication reliability.
4. The current prototype utilizes a rule-based detection mechanism and limited cybersecurity features, lacking advanced machine-learning algorithms, adaptive detection techniques, and robust data security frameworks for large-scale smart-grid deployment.

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Potential Assessment and Techno-Economic Analysis of Offshore Wind Farm in Croatia

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Summary — The aim of the paper is to assess the technical and energy potential of offshore wind farms in the Adriatic Sea and to conduct a techno-economic analysis of their feasibility. The paper is based on the hypothesis that the Adriatic Sea possesses significant, but spatially and technically constrained, potential for offshore wind development, the realization of which depends on technological progress, the regulatory framework, and integration into the national power system. The structure of the paper includes an overview of the theoretical and technical foundations of offshore technology, an analysis of the natural and spatial characteristics of the Adriatic, a methodology for assessing energy potential, the development of a techno-economic model, and the interpretation of results, along with consideration of limitations and recommendations for further research.

Keywords — offshore wind farm, techno-economic analysis, Adriatic Sea, Croatia.

I. INTRODUCTION

Accelerated energy transition at the level of the European Union and the rest of the world has, in recent decades, resulted in a strong increase in investments in renewable energy sources, with wind energy playing a prominent role in the decarbonization of the power sector. Momentum has been observed in the development of offshore wind farms, which, due to more favorable and stable wind conditions, larger installed turbine capacities, and reduced spatial constraints, achieve higher capacity factors compared to onshore projects. In the European context, technological and market development is led by projects in the North Sea, where standards for design, construction, and operation have been established that today serve as a reference model for emerging markets. Republic of Croatia, as a member of the European Union, has committed to implementing climate and energy targets that include increasing the share of renewable energy sources in gross final energy consumption and reducing greenhouse gas emissions. Therefore, the Adriatic Sea represents a potentially significant, yet so far insufficiently explored, energy resource. The specific characteristics of the Adriatic—its relatively shallow

northern part, greater depths in the central and southern areas, pronounced seasonality of winds (bura and jugo), the sensitivity of marine ecosystems, and the importance of tourism and maritime transport—require an interdisciplinary approach when considering the possibilities for offshore wind farm development.

The assessment of offshore wind potential in the Adriatic cannot be based solely on the analysis of wind speed and frequency, but must also include spatial planning, technical, environmental, and socio-economic factors. Technical feasibility depends on sea depth, geotechnical characteristics of the seabed, distance from the coast and grid connection points, while the economic viability of projects arises from the relationship between investment and operational costs, expected electricity production, market electricity prices, as well as the regulatory framework and incentive mechanisms. A particular challenge lies in aligning energy projects with existing economic activities, environmental protection, and spatial planning of coastal and marine areas.

Techno-economic analysis represents a key tool for the objective assessment of the profitability of potential projects. It includes determining installed capacity and expected annual energy yield, estimating capital expenditure (CAPEX), operational expenditures (OPEX), and calculating indicators such as net present value (NPV), internal rate of return (IRR), and levelized cost of energy (LCOE).

In this paper, we make the following original contributions. First, we perform an integrated spatial-technical assessment of the Croatian part of the Adriatic Sea for bottom-fixed offshore wind, combining wind resource data, bathymetry, seabed properties, visual impact zones, existing concessions, environmental constraints and maritime traffic to identify practical potential areas of interest (Section III). Second, we link this spatial analysis with the planned development of the Croatian transmission network, with a particular focus on the Istria Program and the role of the future 400/110 kV Vodnjan substation, in order to evaluate grid integration constraints for offshore wind (Section III.G). Third, we develop and apply a detailed techno-economic model of a reference 150 MW offshore wind farm at a selected site in the northern Adriatic, using high-resolution wind data and the IEA 10 MW RWT turbine, to quantify energy production, losses, LCOE, NPV and IRR under Croatian cost and price assumptions (Sections IV and V). Finally, we carry out a sensitivity analysis on the electricity selling price to identify the revenue conditions under which the first offshore wind project in Croatia becomes financially viable, and we derive policy-relevant implications for support schemes and network planning (Section V.A).

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II. OFFSHORE WIND FARMS CURRENT SITUATION IN EUROPE AND THE WORLD

Europe currently has a total of 291 GW of installed wind power capacity, of which 254 GW is onshore and 37 GW offshore. The European Union accounts for 236 GW in total, with 215 GW onshore and 21 GW offshore. The leading countries in terms of installed offshore capacity are primarily those bordering the North Sea. According to statistics for the end of 2024, the largest installed capacity is in the United Kingdom (16 GW), followed by Germany (9 GW) and the Netherlands (4.7 GW). They are followed by Denmark (2.7 GW), Belgium (2.3 GW), and France (1.5 GW) [1]. In Figure 1, projects in operation are shown in red, while planned projects are shown in blue. Globally, the leading country in wind power generation is China, with approximately 480 GW of installed wind capacity, of which around 38 GW is offshore [2].

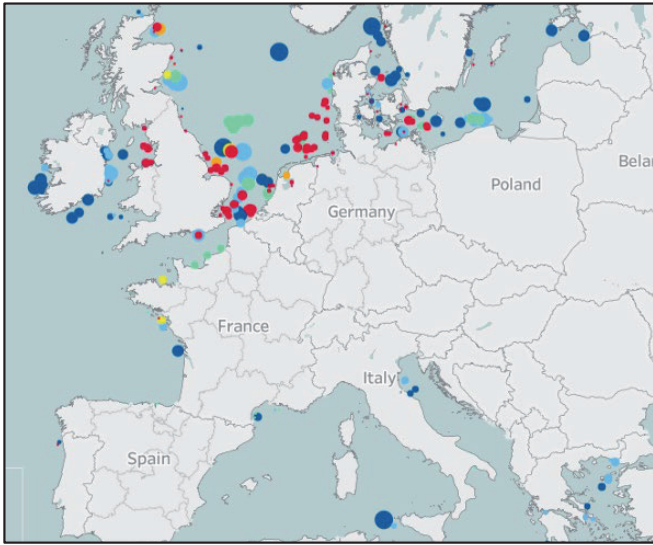


Fig. 1. Overview of currently installed and planned offshore projects in Europe [3]

In 2024, renewable energy sources accounted for a record 50.4% of total electricity generation in the United Kingdom. Offshore wind farms, which harness the significant wind potential of coastal areas, contributed more than 58% of total wind power generation. Figure 2 below shows electricity generation from renewable sources in 2024, expressed in GWh [4].

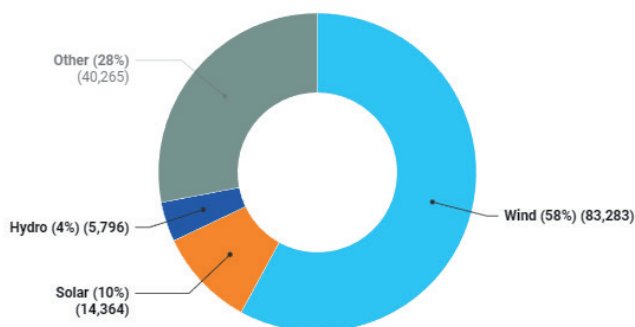


Fig. 2. Electricity generation from renewable energy sources in 2024 [4]

Dogger Bank currently represents the largest offshore wind farm project under construction in the world, located in the UK sector of the North Sea, approximately 130 km from the coast of the United Kingdom. The site is a vast submerged sandbank in the central part of the North Sea, with average depths of only 15 to 30 meters. The project is being developed in three phases—Do-

gger Bank A, Dogger Bank B, and Dogger Bank C—each with a planned installed capacity of approximately 1.2 GW, for a total of about 3.6 GW. Dogger Bank A began supplying electricity to the grid in 2023 and is in the process of gradual commissioning to full operation. Phase Dogger Bank B is in the final stage of construction and gradual grid connection, while Phase Dogger Bank C is in an advanced stage of development, with completion planned for the second half of the decade [5].

The project utilizes wind turbines with large individual capacities (on the order of 13–14 MW), thereby reducing the number of required installed units and optimizing overall energy production. Electricity is collected via inter-array cables and transmitted to offshore substations, from where it is delivered to the onshore power grid using a high-voltage direct current (HVDC) system. Slower electrification dynamics, congestion in the power system, and lengthy and administratively demanding permitting procedures in certain countries have resulted in slower wind energy development than planned national targets. Additional constraints arise from insufficient grid connection capacity, limited port infrastructure, and a shortage of specialized vessels required for the installation and maintenance of offshore facilities [6].

One of the most significant trends in the offshore wind energy industry, which has greatly contributed to reducing the LCOE, is the continuous increase in the rated power of wind turbines. During the 1990s, the average installed capacity of individual turbines was less than 1 MW. Significant technological progress was achieved in the early 2000s, after which the average turbine capacity gradually increased, reaching approximately 3 MW by 2010.

Since 2015, there has been a notably accelerated increase in the capacity of turbines installed in offshore projects. For comparison, the average rated capacity of onshore wind turbines installed across Europe in 2024 was 4.6 MW, while the average rated capacity of offshore wind turbines connected to the grid in 2024 was 10.1 MW, representing an increase from 9.7 MW in 2023 [3][7]. Figure 3 illustrates this growth in wind turbine capacities over the years.

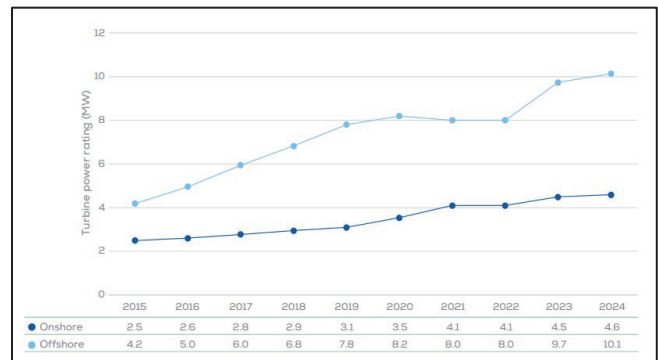


Fig. 3. Graph showing a comparison of the growth in average capacity of offshore and onshore wind turbines [3]

It is also important to highlight the higher capacity factor of offshore wind farms compared to onshore ones, primarily due to more frequent and stable wind conditions at sea, while the larger installed capacity of individual turbines plays a secondary role. Offshore projects in Europe achieve average capacity factors of around 35%, with the highest reaching up to 45%, which is significantly higher than typical values for onshore wind farms, which achieve average capacity factors of around 25% [3].

A. TYPES OF WIND TURBINE FOUNDATIONS

Depending on seabed conditions, offshore wind project developers typically choose between monopile and jacket foundations.

Monopiles are the most common, accounting for approximately 81% of all offshore wind turbine foundations in Europe, followed by jacket foundations.

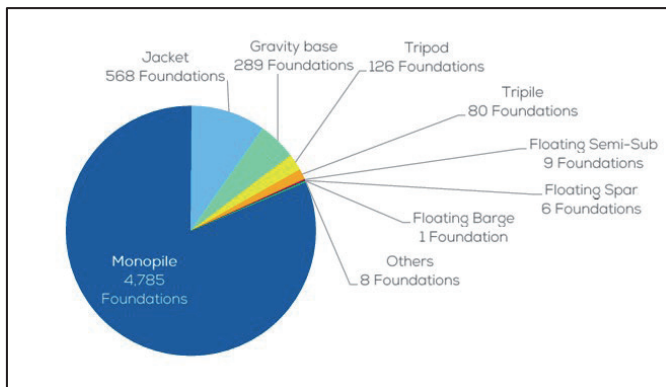


Fig. 4. Number of different installed foundation types in Europe [3]

On the one hand, monopile foundations are expected to maintain their dominant position (Figure 4); however, their market share may decrease in favor of lattice structures (jacket foundations), primarily due to the increasing average water depths at which new projects are being developed. On the other hand, further industrialization of monopile manufacturing and the proven ability of these structures to adapt to greater depths while maintaining relatively low costs could enable them to retain their dominant position in the long term, and potentially even increase their market share. Monopile foundations are most commonly used for depths of up to 30 m, while jacket foundations are typically used for greater depths, up to around 60 m. Figure 5 shows various types of foundations currently in use.

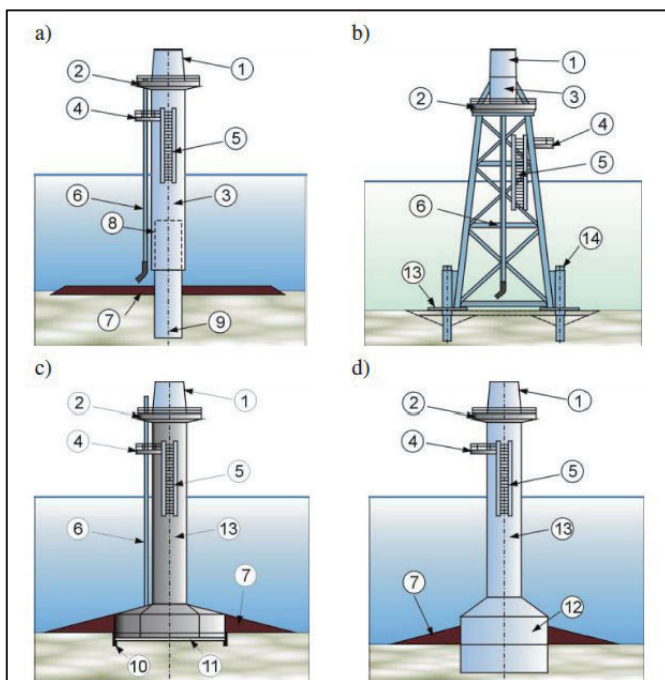


Fig. 5. a) Monopile b) Jacket foundation c) Gravity-based foundation d) Suction foundation [3]

Since floating wind technology is currently in a pre-commercial stage of development, a pronounced learning curve effect is expected in the coming period. For projects at the global level, the application of various types of floating foundations is anticipated, with the choice of solution depending on local and project-specific constraints such as environmental conditions, available infra-

structure, and the maturity of the supply and logistics chain [8].

In terms of water depth limitations, floating wind farms have a significant advantage over conventional offshore wind farms with fixed-bottom foundations. Their application enables installation at depths greater than 60 m, thereby opening up the possibility of harnessing stronger and more stable winds in more distant offshore areas compared to nearshore zones.

From an installation perspective, floating wind farms offer certain operational advantages. Structures can largely be assembled in ports or shipyards onshore and then towed to the designated location, which can result in reduced installation costs and lower dependence on specialized installation vessels. Despite these advantages, floating wind farms are currently more expensive than conventional offshore installations with fixed foundations. This is mainly due to the limited number of large-scale commercial projects in Europe and worldwide.

There is no single, standardized foundation design for floating wind farms. The choice of solution depends on a number of factors, including wind conditions, turbine size and capacity, water depth, wave and current regimes, and the geological characteristics of the seabed. Figure 6 illustrates various types of floating wind turbine foundations.



Fig. 6. Types of foundations for floating wind farms

According to available data, in 2021 Europe had approximately 113 MW of installed floating wind capacity. The largest project was Kincardine in the United Kingdom, with an installed capacity of 50 MW. In addition to the United Kingdom, floating wind capacity has also been developed by countries such as Portugal, Norway, Spain, and France [10].

Given that floating wind farms are still in their early stages of development, with numerous pilot projects worldwide, they remain significantly more expensive than fixed-bottom wind farms. Therefore, this thesis will focus on wind farms with fixed foundations.

B. GRID CONNECTION METHODS

B.1. OFFSHORE SUBSTATION

Offshore substation represents the central element of an offshore power system. A typical offshore wind farm consists of four main components: wind turbines, the internal (inter-array) network, the

offshore substation, and the external (export) network. Electrical energy generated at low voltage (around 690 V) is first transformed to a medium-voltage level (33 or 66 kV) using a transformer located within the wind turbine. It is then transmitted through the medium-voltage internal network, while at the substation the voltage is stepped up to high-voltage transmission levels (110/150/220 kV), suitable for further transmission to the onshore power grid.

Due to harsh environmental conditions, offshore substations are most commonly designed as enclosed structures fixed to the seabed. Their construction is conceptually based on oil platforms, with certain technical adaptations specific to electrical power applications. The platform is designed to accommodate main power and grounding transformers, switchgear, and other auxiliary equipment required for the safe and reliable operation of the system.

The electrical equipment of an offshore substation depends on whether alternating current (AC) or direct current (DC) is used. Accordingly, HVAC and HVDC offshore substations are distinguished, with technical configurations and functional characteristics adapted to the selected transmission system.

The main electrical equipment of HVAC offshore substations includes power transformers, auxiliary (station service) transformers, grounding transformers, gas-insulated high-voltage and medium-voltage switchgear (GIS), backup generators, grounding resistors and AC filters.

The primary purpose of HVDC offshore substations is to convert alternating current (AC) into direct current (DC) for the efficient transmission of electrical energy over long distances. Compared to HVAC substations, HVDC installations include additional specific components: IGBT converters with associated cooling systems and direct current (DC) filters. These components enable the conversion, stabilization, and filtering of direct current, thereby ensuring reliable and high-quality transmission of electrical energy to the onshore grid. The operating conditions of electrical equipment (including cooling systems, required insulation clearances, and other technical requirements) must be adapted to the specific offshore environment. It is also necessary to provide appropriate conditions for the operation of auxiliary systems and personnel accommodation, including technical rooms, HVAC systems, living quarters, and supporting infrastructure. Special attention is given to safety, navigation, signaling, and rescue systems, including fire protection systems, lightning protection, evacuation procedures, and other measures necessary for safe operation in a marine environment [11].

Structural design of offshore facilities faces a number of specific challenges. Among the most important are environmental influences, including wind, sea currents, waves, and sea level variations, which cause significant static and dynamic loads on the structure. In addition, careful consideration must be given to the mass of installed equipment on the platform and the distribution of the center of gravity, as these parameters directly affect platform stability and safety. Particular attention must be paid to corrosion protection due to the highly aggressive marine environment. Prolonged exposure to saltwater and humidity can lead to material degradation, making the application of appropriate protective systems essential for maintaining structural integrity. Geotechnical investigations of the seabed are also crucial to ensure adequate foundation bearing capacity and structural stability throughout the entire service life. An important aspect of design also involves planning marine operations, including transportation, assembly, and installation of the structure, which must be aligned with weather conditions and safety constraints of the marine environment. The technical lifetime of such structures is typically planned for a period of 20 to 25 years. Figure 7 shows the structure of an offshore substation and its foundations, while Figure 8 presents a specialized vessel for the installation of offshore components and the assembly of an offshore substation.

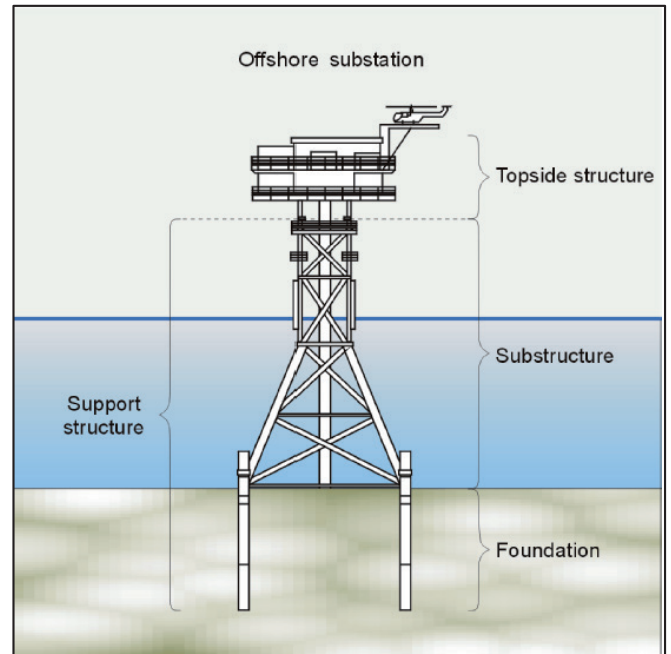


Fig. 7. Structure of an offshore substation



Fig. 8. Installation of an offshore substation [33]

B.II. SUBMARINE CABLES

Submarine cable systems have been in use for nearly a century and, depending on the type of system in which they are applied, are divided into alternating current (AC) and direct current (DC) cables. DC submarine cables are used in situations where the use of AC cable systems is not technically or economically justified. The limitations of AC submarine cables are primarily related to the occurrence of high capacitive currents, increased short-circuit currents, the inability to directly connect power systems of different frequencies, and increased transmission losses over long distances.

In the past, submarine cables were predominantly used to connect mainland and island power systems, whereas today their application has expanded significantly to include the connection of offshore wind farms to the power grid. In this context, various connection concepts can be applied, primarily depending on the distance of the wind farm from the shore and the installed capacity of the plant. For shorter distances (approximately 5–20 km) and lower capacities, medium-voltage cable systems with rated voltages from 10 to 66 kV are most commonly used, directly connecting wind turbines to an onshore substation. For longer distances, offshore platforms with substations are constructed to step up the voltage level, while transmission to shore is carried out using high-voltage (>110 kV) submarine cables.

With the development of large-capacity projects and increasing distances from the coast, high-voltage direct current (HVDC) cable systems, with converter stations located both offshore and onshore, are increasingly being used. Such solutions enable reduced transmission losses and optimization of investment costs for long-distance transmission. An additional technical challenge is presented by floating offshore wind farms, where cable connection methods must be adapted to accommodate continuous movement of the structures.

The choice between HVAC and HVDC submarine cable systems primarily depends on the route length. For shorter distances, typically up to 80–100 km, HVAC cables are commonly used due to lower investment costs and satisfactory technical performance. At greater distances, HVDC systems offer several advantages, particularly in terms of reduced losses, limitation of short-circuit currents, and the ability to connect power systems with different frequencies. Furthermore, in HVAC cables, capacitive currents become a limiting factor as the route length increases.

According to their construction, submarine cables can be classified into three main categories:

- single-core AC submarine cables,
- three-core AC submarine cables with common armoring,
- high-voltage direct current (HVDC) submarine cables (single-core or bipolar).

The choice between three-core and single-core AC cables depends on several factors, including seabed route characteristics, cable length, and installation feasibility. Three-core cables are advantageous in situations where minimizing the occupied seabed corridor is important, as single-core cable systems may require spacing between individual cores of more than 20–30 m. Although installation at smaller distances is possible, it is generally avoided due to the risk of simultaneous damage to two or more cables. On the other hand, installing three-core cables is technically more demanding due to their larger dimensions. An advantage of three-core cables with common armoring is reduced losses, primarily due to the symmetrical arrangement of phase conductors. In single-core submarine cables, these losses may be more pronounced, although part of this advantage is offset by increased heating caused by the proximity of phase conductors within a three-core structure [12][13].

B.III. COMPONENTS OF SUBMARINE CABLES

The conductor of a submarine cable is made of aluminum or copper. Although copper is significantly more expensive than aluminum, it is often used in submarine cables due to the possibility of using a smaller cross-section for the same transmission capacity. A smaller conductor cross-section reduces the amount of material required for other structural layers (insulation, armoring, and sheath), which can have a beneficial impact on the overall cable mass, as well as on installation and maintenance costs. However, there is no universally optimal choice of conductor material, and combined aluminum–copper solutions are sometimes used in practice for specific sections of the cable system.

The insulation layer provides an electrical barrier between the high-voltage conductor and the surrounding medium. In modern practice, cross-linked polyethylene (XLPE) is most commonly used due to its favorable electrical and mechanical properties. Outdated technologies, such as oil-filled or gas-insulated cables, are generally avoided today, although they are still present in certain cases. For DC submarine cables, proven technologies using impregnated paper insulation are often applied.

Semiconductive layers are placed around the conductor and insulation to ensure a uniform electric field and to prevent local concentrations of electrical stress that may arise due to surface irregularities or protrusions. This increases the reliability of the insulation system and reduces the risk of partial discharges. The thickness of semiconductive layers typically ranges from 1 to 2 mm.

The metallic sheath of a submarine cable is most commonly made of lead, and less frequently of aluminum or copper. Its primary function is to protect against moisture ingress and mechanical damage, as well as to conduct fault currents. A disadvantage of metallic sheaths is the potential occurrence of circulating currents and additional heating when the sheath is grounded at both ends. The sheath thickness typically ranges from 2 to 5 mm, depending on application and operating conditions. In three-core cables, configurations with separate metal sheaths for each core (SL – single lead sheath) or a common sheath are possible, with SL configurations more commonly used in practice.

Armoring is applied to protect the cable from mechanical stresses and damage in the marine environment, for example due to anchoring or contact with rocky seabeds. It is typically made of steel wires or tapes, often arranged in two helically wound layers. Since armoring is usually made of steel, additional losses due to eddy currents and hysteresis may occur. In single-core submarine cables, these losses can significantly reduce transmission capacity, while in three-core cables they are less pronounced.

Polyethylene is most commonly used as the outer protective layer. Although it is not resistant to high temperatures, it provides high resistance to moisture ingress. Its primary function is to protect the armoring and metallic sheath from corrosion caused by seawater and other external influences.

Submarine cables, whether three-core or single-core, often integrate optical fibers for telecommunications and data transmission between wind turbines and the substation. Optical fibers enable remote control and continuous monitoring of wind farm operation from a control center, ensuring reliable system management and timely detection of operational disturbances. These optical conductors may be additionally protected by a metallic sheath or other mechanical protection elements within the cable structure [14] [15]. The described components are shown in the cross-section of a three-core submarine cable in Figure 9.

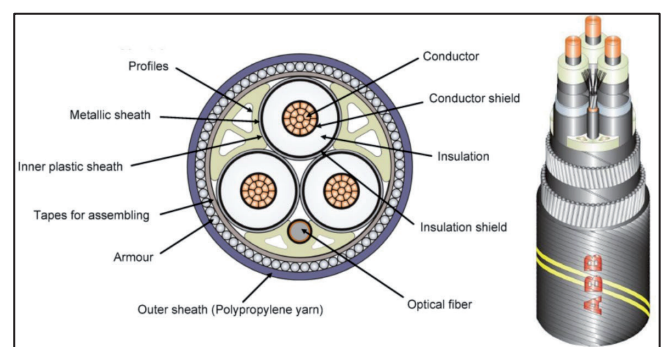


Fig. 9. Example of a three-phase submarine cable [15]

C. DESIGN AND INSTALLATION OF SUBMARINE CABLES

The design of submarine cables represents a fundamental phase in the overall engineering process of their construction. This process includes systematic analysis and planning aimed at defining the optimal cable route, selecting appropriate materials and equipment, organizing the installation procedure, and ensuring the safety and long-term protection of the cable during and after installation.

The entire engineering process of submarine cable construction can be divided into several successive phases. In the initial, preliminary (conceptual) phase, the approximate cable route is determined and basic seabed surveys are conducted. The results of this phase often serve as a basis for investment decisions. This is followed by the conceptual design and technical solution development phase, during which more detailed geophysical and geotechnical investigations are carried out, and the route is defined more precisely. At this stage, technical documentation is prepared, and based on the description of the planned installation, the necessary approvals and permits are obtained.

The detailed engineering phase includes the elaboration of technical solutions related to the cable itself and its installation process, including the selection of vessels, tools, and auxiliary equipment. This phase forms the basis for the execution of actual installation activities in the field. The final phase refers to the period after cable laying, when an assessment of the completed works is carried out. At this stage, the level of cable protection is verified, the availability of spare parts for potential repairs is assessed, and the system's readiness for transition into operational mode is evaluated.

International standards and recommendations, such as those issued by IEC, IEEE, and CIGRÉ, play an important role in ensuring compliance with technical norms and industry guidelines. These standards define requirements related to testing, qualification, and quality control of cable systems, thereby ensuring their technical reliability and safety of application.

The method of laying submarine cables largely depends on the characteristics of the seabed, with various methods and specialized tools available. In the case of hard and rocky seabeds, ploughs or similar tools are most commonly used to mechanically cut a trench into the substrate. In contrast, sandy seabeds allow for simpler execution, where a subsea jetting device can be used to move along the entire cable route and create a trench approximately one meter deep. After installation, the cable is placed into the formed trench and, under the influence of sea currents and natural sedimentation, gradually becomes buried and stabilized on the seabed [14].

D. MAINTENANCE

Compared to onshore wind farms, offshore wind farms benefit from more favorable and stable wind energy potential. Nevertheless, high operational costs remain one of the key constraints to their more intensive development. In particular, operation and maintenance (O&M) costs stand out, being more than twice as high as those of onshore wind farms. Furthermore, as the distance of installations from the coast increases—especially under deep-sea conditions—the costs of carrying out maintenance activities grow proportionally with distance, further affecting the overall economic viability of such projects [16].

Given the significant exposure of foundations and transformer installations to the corrosive marine environment, regular inspections are of particular importance. Damage to protective coatings, seal degradation, or the onset of corrosion can lead to substantial financial and technical consequences if not detected in time. For this purpose, unmanned aerial vehicles (UAVs), remotely operated underwater vehicles (ROVs), and advanced visual inspection systems are increasingly being used, reducing the need for direct manual access to structures and improving personnel safety. The digitalization of operational processes, the development of predictive maintenance, and the integration of logistics systems are gradually transforming the management and maintenance segment of offshore wind farms, enabling more efficient monitoring, extending equipment service life, and reducing downtime and operational costs. Additional support for the development of these practices comes from the long-standing experience of the oil and gas industry in conducting safe offshore operations.

Repair activities include both interventions due to unplanned failures and the planned replacement of components at the end of their designed service life. More extensive interventions on turbines, such as the replacement of blades, gearboxes, or generators, require the engagement of specialized installation or service vessels equipped with high-capacity cranes. On the other hand, smaller corrective interventions—such as sensor replacement or minor hydraulic and electrical repairs—are usually carried out on-site using crew transfer vessels or service operation vessels. Repairs also apply to elements of the electrical infrastructure, where, depending on the complexity of the intervention, specialized equipment such as ROVs, lifting systems, and auxiliary vessels is employed, often through external specialized contractors. Effective coordination and timely execution of repairs are crucial for minimizing downtime and ensuring continuity of electricity production [17].

III. POTENTIAL IN CROATIA

A. WINDS IN CROATIA

The two main winds in the Croatian part of the Adriatic Sea are the bura and the sirocco (jugo). The bura is a strong, dry, and cold wind with an average speed of 15 m/s. Wind gusts can reach up to 70 m/s. It develops over the high coastal mountains (Velebit, Mosor, Biokovo, etc.), is most frequent in winter, and blows in gusts (directions: N, NE, E – wind direction is defined by the direction from which the wind blows)[18][19].

The average speeds of the sirocco range between 10 m/s and 30 m/s (directions: S, SE). It is strongest over the open sea, where it generates large waves. It can blow for several consecutive days and occurs more frequently in winter than during the warmer part of the year. In summer, it usually does not last longer than three days, while in winter it can persist for up to ten days, and sometimes, with short interruptions, even up to three weeks. It typically develops in the southern Adriatic during winter and in the northern Adriatic during spring. In addition, numerous Croatian islands act as obstacles, reducing wind speed and increasing atmospheric turbulence [19].

Figure 10 shows the mean annual wind speed at a height of 80 m above ground. The presented wind speed is the result of a numerical atmospheric model and represents the average value within a 2 km × 2 km grid cell [20].

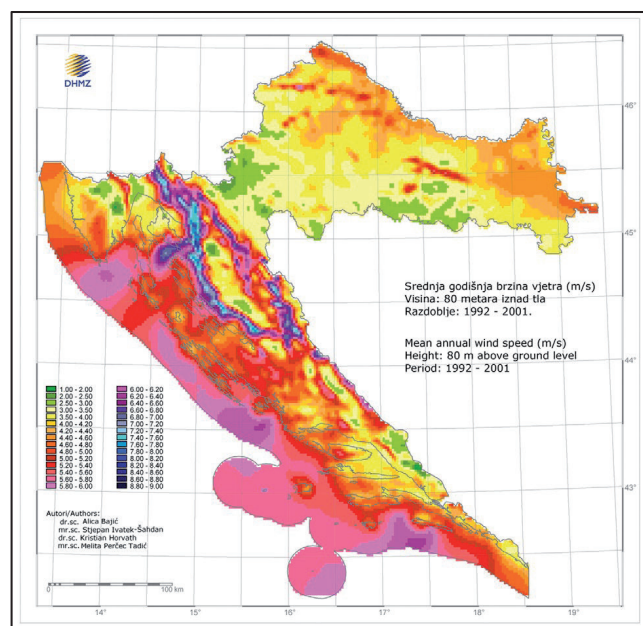


Fig. 10. Map showing the mean annual wind speed at a height of 80 m above ground [20]

However, with the increasing hub heights of offshore wind turbines, there is a need for additional wind measurements. Currently, several studies on wind speed in the Adriatic are underway. INA is conducting wind speed measurements on two gas platforms in the Adriatic: Izabela North and Ivana A (northern Adriatic).

B. SEABED PROPERTIES

Sediments predominantly range from sandy and sandy-silty in the northern and western parts, to silty and sandy-gravelly in channels and around islands such as Kvarner, the Rab Channel, and Pag. Rocky seabeds are characteristic of coastal zones. Figure 11 shows the composition of the Adriatic seabed, indicating that the area of interest south of Istria is mostly sandy [21].

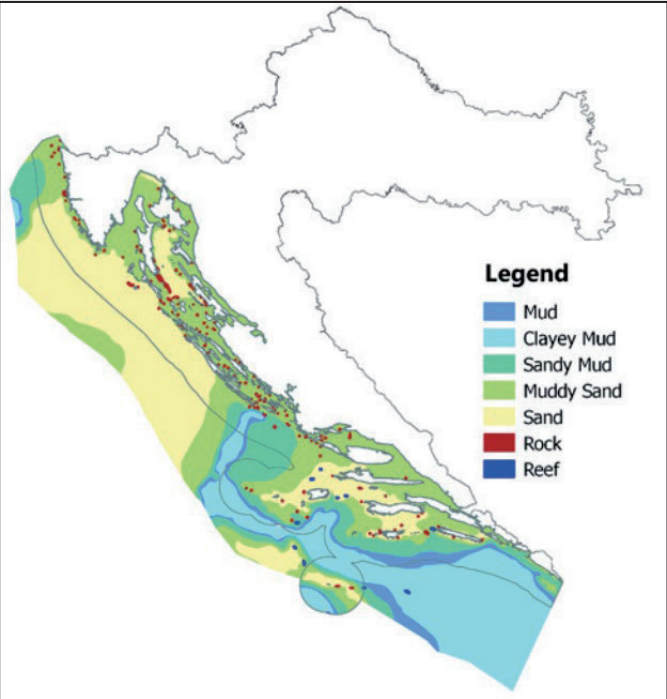


Fig. 11. Composition of the Adriatic Sea seabed [21]

C. SEA DEPTH

The Adriatic Sea is divided into two parts by the Palagruža Sill. The northernmost part of the Adriatic consists of a shallow (up to 100 m), flat, sandy or silty seabed. An exception is the Kvarner channels, which are deeper than 100 meters. The second section of the northern Adriatic has an average depth of 200 m and extends 130 km along its longitudinal axis and 40 km in width, reaching as far as the Palagruža Sill.

South of the Palagruža Sill, the seabed descends steeply to the deepest point in the Adriatic Sea at a depth of 1,233 meters. The deepest area—the South Adriatic Basin—is located between the Palagruža Sill and the Strait of Otranto (743 m). The Strait of Otranto also represents the outlet of the Adriatic Sea. The seabed structure in this part consists of mixed sedimentation.

Figure 12 shows the depth of the Adriatic Sea, indicating that in the area of interest, south of Istria, the sea depth ranges from 40 to 60 m [22].

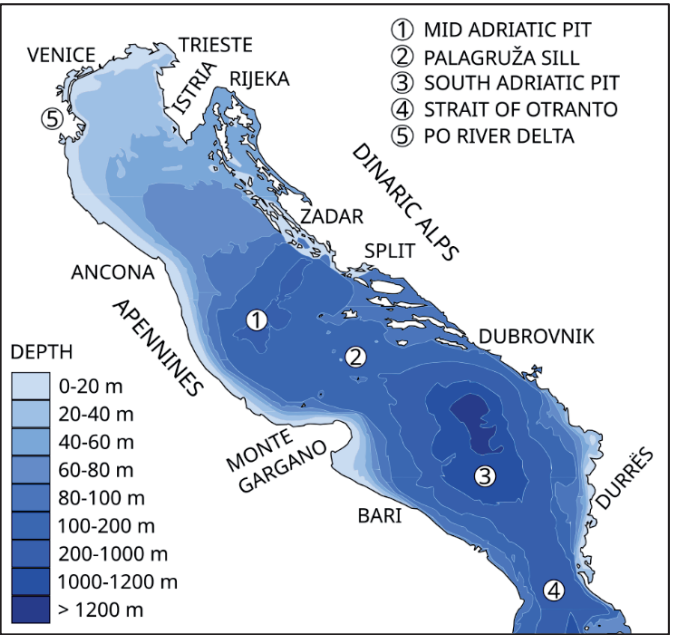


Fig. 12. Map showing the depth of the Adriatic Sea [22]

D. VISUAL IMPACT

The visual impact of offshore wind farms in the marine environment is primarily determined by the height of the wind turbines, their distance from the coast, the topographical features of the surrounding terrain, and weather conditions. The intensity of spatial perception varies depending on these parameters. For example, a wind turbine with a height of 150 meters, under conditions of good visibility, can be seen from the coast at a distance of approximately 20 to 30 kilometers. During nighttime, the structures themselves are not visible, but the aviation warning lights on the turbines can be noticed from considerable distances.

Given the significant contribution of tourism to the Croatian economy, the issue of visual exposure of offshore wind farms requires systematic analysis. In this context, it is necessary to consider

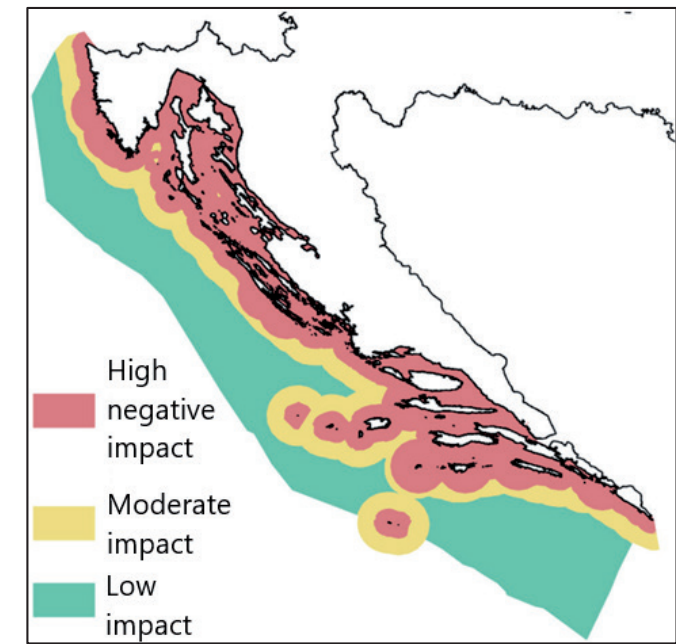


Fig. 13. Visual impact of offshore wind farms in the Republic of Croatia [9]

spatial visibility zones and the intensity of their potential impact.

Figure 13 shows a map of the visual impacts of offshore wind farms, developed based on defined parameters of distance and spatial sensitivity. The largest zone of negative impact includes a belt extending up to 10 kilometers from the coast along the entire observed area, with an additional buffer zone of 20 kilometers around national parks, nature parks, and other frequently visited cities and locations.

The zone of moderate impact extends up to 20 kilometers from the coast. In this area, offshore wind farms are likely to be visible from land, but their visual perception will generally be weaker, often hazy, and not necessarily easily noticeable.

The low-impact zone includes areas located more than 20 kilometers from the coast. This area is considered sufficiently distant from the shoreline such that potential visual impacts on the landscape are minimized or negligible [9].

E. VARIOUS CONSTRAINTS AND POTENTIAL LOCATIONS

A spatial analysis of potential areas of interest (PAIs) for the development of offshore wind farms was conducted, taking into account a range of technical, environmental, and spatial constraints. One of the primary criteria defined was the maximum allowable sea depth for installation, set at 60 meters, ensuring the technical feasibility of using bottom-fixed foundations.

Additionally, potential areas must be located outside existing concession zones for hydrocarbon exploration and exploitation, in order to avoid conflicts with ongoing energy activities. To minimize impacts on maritime traffic, it is necessary to avoid traffic separation schemes and major shipping routes. Furthermore, the analysis excludes protected marine areas and Natura 2000 ecological network sites, as well as important bird migration corridors, in order to preserve biodiversity and reduce negative environmental impacts. Finally, one of the criteria relates to visual impact on the coastal and marine landscape. Potential areas of interest must have minimal visual impact or be located at least 20 km from the coast, thereby reducing their visibility from land.

An additional important constraint within the spatial analysis was the exclusion of the channel areas of the Croatian sea. The reason for this lies in the intensive use of these areas for maritime transport, fisheries, and marine tourism, as well as their pronounced biodiversity and heterogeneous marine habitats. However, these areas should not be entirely excluded from future considerations, especially in the context of potential limited offshore renewable energy development, if such projects would be of interest to local communities on remote islands with underdeveloped energy infrastructure.

The calculated surface areas of potential areas of interest obtained through this spatial analysis should be considered approximate values, given the available data and the applied methodology.

The northern part of the Adriatic Sea under Croatian jurisdiction, spanning from the southern part of the island of Mali Lošinj to the northern tip of the Istrian Peninsula, has been identified as the only suitable area of interest based on the criteria of maximum allowable sea depth and relatively short distance from the coast. Accordingly, further analysis has been focused on this defined area, as shown in Figures 14 and 15.

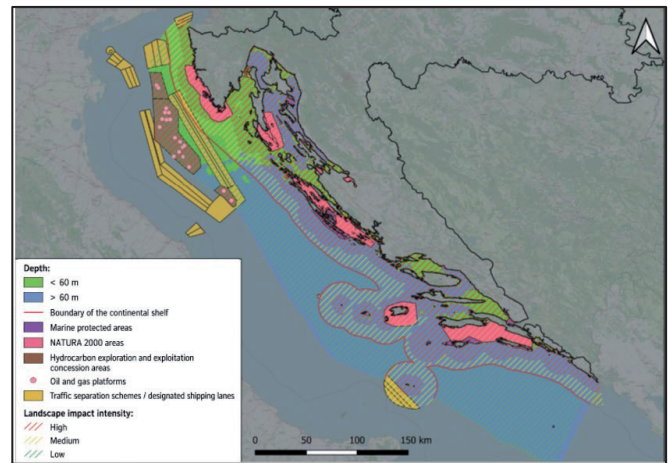


Fig. 14. Analysis of possible PPIs for the construction of offshore wind farms in the Republic of Croatia

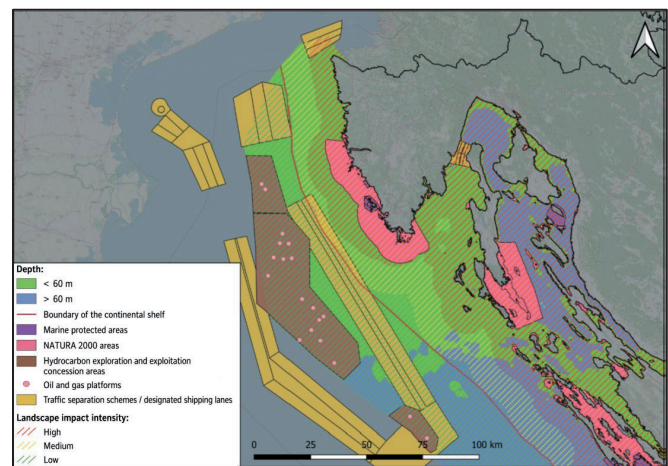


Fig. 15. Area of focused analysis of possible PPIs for offshore wind farms

Taking into account the constraints related to sea depth and distance from the coast, as well as the need to avoid existing hydrocarbon exploitation concession areas and designated shipping routes, four potential areas of interest have been identified, as shown in Figure 16. It should be emphasized that, due to the limited spatial resolution and accuracy of the available bathymetric data, sea depths up to 60 meters have been determined approximately.

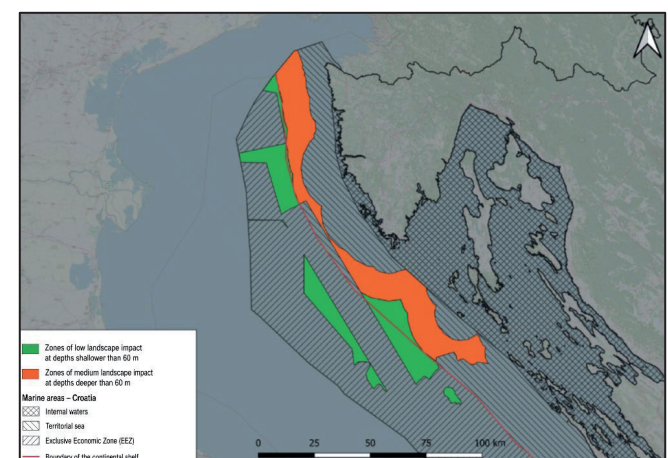


Fig. 16. PPI zones for offshore wind farms with low and moderate impact on the landscape and seascape

TABLE I

SURFACE AREAS OF SUITABLE AREAS FOR OFFSHORE WIND FARMS

Type of impact	Territorial Sea [km ²]	Exclusive Economic Zone [km ²]	Total [km ²]
Low	205	1.055	1.260
Medium	1.602	-	1.602
Total[km ²]	1.807	1.055	2.862

An additional potential marine zone for the development of offshore wind farms includes already allocated concession areas for hydrocarbon exploration and exploitation, with a total area of approximately 2,181 km², excluding a 500-meter safety zone around existing and planned production platforms (Table I). The possibility of developing offshore wind farms within these areas is conditioned by the provisions of concession agreements concluded between INA and the Republic of Croatia, i.e., it depends on the legal framework governing the use of these concession fields.

As previously stated in this paper, floating wind farms are not the focus of this study; however, Figure 17 illustrates the significant potential area for their future deployment once the technology becomes more mature and cost-effective.

Although this study restricts the techno-economic modelling to bottom-fixed turbines (sea depths ≤ 60 m), floating offshore wind technology could unlock a much larger technical potential in the deeper central and southern Adriatic. As indicated in Fig. 17, these areas combine greater depths with generally stronger and more stable wind regimes. Once floating foundations reach wider commercial deployment and more robust cost benchmarks become available, a comprehensive reassessment of Croatian offshore potential should explicitly include floating wind, with dedicated spatial criteria (depth > 60 m, wave climate, port infrastructure) and adapted techno-economic assumptions. This represents an important direction for future extensions of the present work.

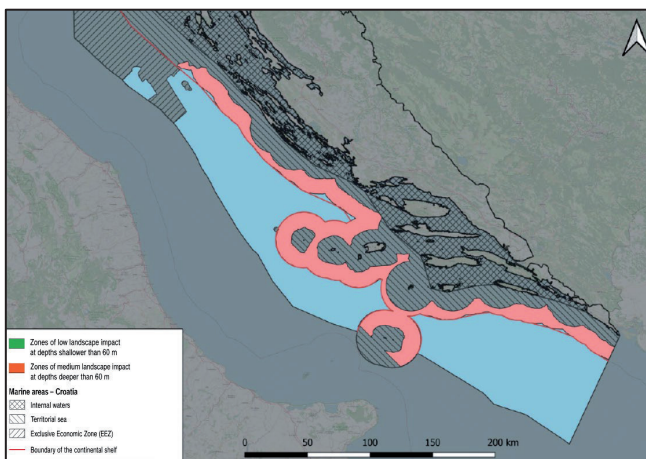


Fig. 17. Zones for the potential development of floating offshore renewable energy sources with low and moderate impact on the landscape and seascape

F. REGULATIONS AND LEGISLATION

Developers of offshore renewable energy (RES) projects must follow the development steps defined for RES in the *Guide for the Development and Implementation of Renewable Energy Projects in Croatia*.

The current procedure for the use of maritime areas in Croatia is highly complex and, in principle, does not guarantee that a project developer will achieve their objectives within the desired

timeframe. In cases involving the use of marine areas that require construction (and thus additional permits), the procedure becomes even more complicated. Two overarching laws regulate the use of maritime areas:

- The *Maritime Domain and Seaports Act*, which governs the methods of using maritime domain and the procedure for granting concessions
- The *Physical Planning Act*, which defines the initial step in obtaining a concession—the process of acquiring a location permit and the detailed spatial planning procedure

The absence of a National Spatial Development Plan represents the first obstacle, as the process of obtaining a location permit requires alignment with spatial plans for the specific area. In general, the Ministry of Physical Planning, Construction and State Assets and the Ministry of the Sea, Transport and Infrastructure are responsible for this domain, but many details remain unclear regarding which law applies and which ministry is competent for each step. For example, construction permits for oil platforms were issued by the Ministry of Physical Planning, Construction and State Assets under the Mining Act, which cannot be directly applied to offshore RES projects. Approvals, preliminary studies, and research within the Exclusive Economic Zone, as well as concessions for cables and electricity transmission from territorial waters to land, are issued by the Ministry of the Sea, Transport and Infrastructure.

The first step in obtaining a concession for maritime domain is securing the legal interest of the concession grantor to initiate the location permit procedure, which is determined by the level of the spatial plan regulating its use. If there is no national spatial development plan for marine areas, the county is responsible for granting concessions as defined by the county spatial plan.

A project developer who has expressed interest and obtained all required documentation (including the location permit) must still compete in a public tender for the concession. This introduces a degree of legal uncertainty, particularly considering the time required to obtain all necessary permits.

For state-level concessions, the maximum duration is 50 years, while counties may grant concessions for up to 20 years. State-level concessions are granted by the Croatian Parliament, whereas regional-level concessions are granted by the county assembly. After completion of the concession procedure, selection of the concessionaire, and signing of the concession agreement, construction may begin, and the concession agreement is considered the legal basis for obtaining a construction permit.

Offshore wind farms often have marine concessions lasting 40 to 60 years, which allows for “repowering” at the same site after the initial turbines reach the end of their design life (typically 25 to 30 years). This enables the reuse of existing infrastructure (grid connection, cabling, and often foundations), instead of fully abandoning the location [23].

G. ISTRIA COUNTY AND ENERGY INFRASTRUCTURE

Istria County maintained relative energy self-sufficiency over a long period by relying on fossil fuels, primarily hard coal used in two units of the Plomin Thermal Power Plant. Since 2017, Unit A has been out of operation, reducing electricity generation in the area solely to the operation of Unit B.

The currently operational Unit B only marginally meets the existing annual electricity demand of Istria County, which amounts to approximately 1.4 TWh, with a continuous upward trend in consumption. At the same time, following the shutdown of Unit A, the remaining generation capacity is far from sufficient to meet peak system loads. Part of the required capacity is compensated by re-

newable energy production, primarily solar power plants installed within the county. However, the stability of the power system is largely ensured through a 220 kV transmission line connecting Istria to the rest of Croatia, along with an additional lower-capacity line toward Slovenia. In general, insufficient interconnection capacity—both in terms of the number of transmission routes and their transfer capability—represents one of the key limitations of the Istrian power system.

The need to redefine the region's energy concept is further emphasized by the planned closure of Unit B of the Plomin Thermal Power Plant in 2033. This raises concerns regarding long-term security of electricity supply and highlights the necessity of developing new generation capacities.

The Croatian part of the Adriatic Sea has a limited number of locations suitable for offshore wind farm development, with the most favorable area, in terms of sea depth, being the northern Adriatic along the Istrian coast. However, due to existing economic activities in this area, offshore wind farm planning must be carried out in an integrated manner, taking into account the interests of all relevant sectors and ensuring the preservation of the marine ecosystem.

An additional constraint is the fact that Croatia still lacks a clearly defined regulatory framework that would enable the systematic development of offshore wind farms. Such projects are currently not envisaged in existing spatial plans, nor have specific marine areas been designated for wind farm development.

The construction of adequate infrastructure capacity, particularly 400 kV transmission lines, is a prerequisite for the realization of offshore wind farms in Istria, as the existing grid capacity is insufficient to accommodate new generation facilities. At the same time, the development of transmission infrastructure is currently the only way to ensure the fundamental objective of the power system—full security of electricity supply, regardless of the regional availability of energy sources.

In this context, the ten-year development plans of the transmission system operator are relevant, as they foresee the completion of the (400) 220/110 kV Vodnjan substation and its connection to the 400 kV Melina–Divača transmission line by the end of 2034. These planned developments play a significant role in creating the prerequisites for the future expansion of generation capacity in the Istria region [24].

G.I. TEN-YEAR TRANSMISSION NETWORK DEVELOPMENT PLAN OF HOPS

In accordance with Regulation (EU) 2022/869 on guidelines for trans-European energy infrastructure (TEN-E), the Republic of Croatia has defined non-binding targets for the development of offshore wind energy, amounting to 510 MW of installed capacity by 2030 and 1,200 MW by 2040. These targets provide a framework for long-term planning of offshore capacity development within the national energy system.

One of the key challenges in the implementation of the green transition is ensuring sufficient transmission and distribution capacity to accommodate a large number of new high-capacity generation facilities. The existing power system network was originally planned and dimensioned according to a different structure of electricity generation and consumption, both in terms of installed capacity and connection locations. Therefore, within a relatively short timeframe, it is necessary to carry out extensive reconfiguration of the Croatian, as well as the broader European, power grid to enable accelerated integration of renewable energy sources while maintaining system reliability and security of supply.

The increased share of non-dispatchable energy sources, such as wind and solar power plants, generates additional requirements for power system management. Such generation depends on weather conditions and is variable and less predictable, which necessitates the installation of network elements that enable dynamic real-time power flow management, as well as more optimal utilization of existing transmission capacities.

The Croatian Transmission System Operator has developed four programs for the expansion of the 400 kV transmission network to facilitate the integration of renewable energy sources in Croatia: the Lika Program, the Istria Program, the Southern Domestic Corridor Program, and the Slavonia Program (Figure 18).

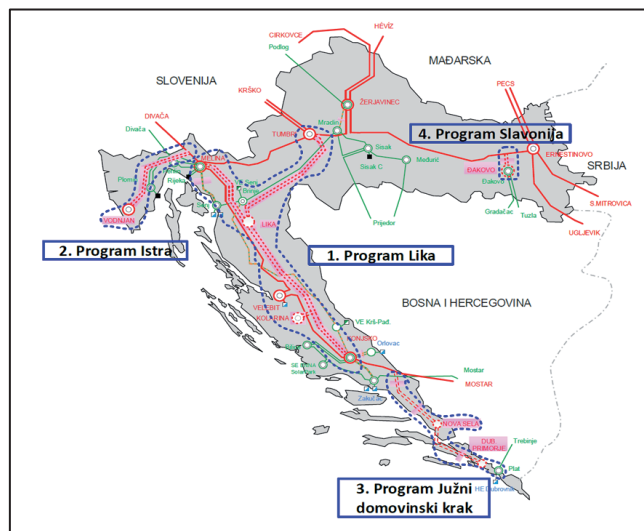


Fig. 18. HOPS – 4 development programs of the 400 kV transmission network [25]

These programs are aimed at strengthening transmission infrastructure in areas with expected growth in renewable energy generation capacity. It is important to emphasize that the implementation timeline for transmission network investments is generally longer than the time required to construct generation facilities and connect them to the grid. For this reason, it is crucial to initiate the preparation, planning, and implementation of investments in the 400 kV transmission network in a timely manner, in order to avoid system bottlenecks and ensure a coordinated development of generation and grid capacities [25].

G.II. ISTRIA PROGRAM

To enable the integration of renewable energy sources and accommodate the expected increase in load in the Istria region, the construction of the (400) 220/110 kV Vodnjan substation is planned, with a loop-in/loop-out connection to the existing 400 kV Melina–Divača transmission line. This development creates the necessary conditions for connecting new generation capacities and strengthening the transmission infrastructure in the region.

The Istria Program is designed so that the new 400/110 kV Vodnjan substation is connected using the loop-in/loop-out method to the transmission line toward Divača, thereby enabling maximum utilization of the potential for connecting new renewable energy sources in Istria. However, achieving this goal also requires prior implementation of the Lika Program, specifically the construction of a new transmission line from Lika toward the Zagreb area (TS Tumbri), which would relieve the existing Melina–Divača line.

It is estimated that, with the implementation of the Istria Program and part of the Lika Program (the new transmission line

toward TS Tumbri), up to 960 MW of new renewable energy capacity could be connected to the grid without the need for permanent curtailment. This capacity represents an estimate, as the actual connection potential depends on the locations of generation units; in some cases, additional reinforcement of the 110 kV network or cross-border transmission lines may be required.

Currently, the only major system node for electricity supply and evacuation in Istria is the 220/110 kV Plomin substation, connected via double 220 kV transmission lines to Melina and Pehlin. This indicates that there are presently no technical conditions in Istria to accommodate large-capacity generation units, making the extension of the 400 kV transmission network to the region essential. The proposed construction of the (400) 220/110 kV Vodnjan substation, with a loop-in/loop-out connection to the 400 kV Melina–Divača line, represents a technical solution that enables secure transmission of electricity from planned facilities. At the same time, this investment enhances the security of supply for existing grid users, particularly during summer evening hours when renewable generation is low.

The potential shutdown of Plomin 2 Thermal Power Plant would further negatively impact the security of supply in Istria. In such a scenario, the construction of a new 400 kV transmission line and a new 400/x kV substation would have a positive effect on maintaining supply security at an acceptable level. To implement the Istria Program and complete the 400 kV transmission network within the planned timeframe (by the end of the ten-year period, i.e., before 2040), it is necessary to ensure all required prerequisites in a timely manner. These include securing financial resources for preparation and construction, incorporating planned facilities (substations and transmission lines) into spatial plans, obtaining location and construction permits, and ensuring funding prior to initiating public procurement procedures.

If these prerequisites are not met, the transmission network in Istria will face limitations. For example, in the case of connecting new renewable energy sources of larger capacities, such as offshore wind farms with installed capacity up to 510 MW, it would be necessary to apply permanent operational curtailment under unfavorable system conditions.

As part of the preparation of the Istria Program, conceptual designs for selecting the optimal route of the 400 kV transmission line have been developed, and a location permit has already been obtained for the construction of the 220/110 kV Vodnjan substation. For implementation at the 400 kV voltage level, amendments to the documentation are required to expand the project scope [25].

IV. TECHNO-ECONOMIC ANALYSIS

In the design of an offshore wind farm, key parameters relate to the average wind speed and its frequency, as these factors directly influence the expected electricity production and the sizing of the installation. In the context of the Adriatic Sea, there is a noticeable lack of systematic and long-term wind speed measurements in offshore areas, which represents a limitation in the preliminary assessment of potential. Indicative values can be estimated based on data collected from existing oil and gas platforms and submitted to relevant institutions; however, for project development purposes, broader and more transparent access to such data for project developers would be desirable.

In addition to wind resource assessment and the implementation of required environmental impact assessments, investors must also thoroughly evaluate the technical characteristics of the site.

This includes examining seabed morphology and composition, analyzing marine currents and wave loads, and assessing seismic activity and other geological factors that may affect structural stability and operational safety.

The total cost of an offshore wind farm project typically consists of several main categories: capital expenditures (CAPEX), which include development, design, procurement, and construction costs; financing costs associated with securing capital; operational expenditures (OPEX), which cover operation and maintenance throughout the project's lifetime; and decommissioning costs (DECEX), incurred at the end of the project's lifecycle [9].

A. SITE SELECTION

Considering the relatively shallow depth of the Adriatic Sea south of the Istrian Peninsula (up to approximately 50 m), as well as the presence of natural gas production platforms in this coastal zone—whose structural characteristics are comparable to offshore energy facilities—it can be concluded that this area is currently the most suitable for the development of offshore wind farms in the Republic of Croatia, particularly in the context of the availability and cost of bottom-fixed turbine technology. Additional support for this assessment is provided by the fact that INA has initiated a project for the development of an offshore wind farm in this very area, near an existing gas platform, and has requested information on the state of the transmission network and potential grid connection points in Istria. At the same time, Istria County is preparing an energy development study analyzing the level of energy self-sufficiency.

Wind speed data used in the modeling of the offshore wind farm were obtained from the Global Wind Atlas database. This is a global database based on high-resolution numerical atmospheric modeling. For the purposes of this analysis, hourly data for the period from January 1, 2019, to December 31, 2019, were used for a location at coordinates 44.52°N and 13.94°E in the northern Adriatic. The data were generated for a reference height of 105 m above sea level. The average annual wind speed at the observed location and height is approximately 7 m/s (Figure 19), which can be considered below average compared to typical European offshore locations, where wind speeds usually exceed 8.5 m/s. Such conditions may result in a lower capacity factor compared to projects in areas with higher wind potential. Nevertheless, Fig. 19 shows that wind speeds above the rated value of the selected turbine are reached sufficiently often to support a capacity factor above 30%. Figs. 21 and 22 further indicate that the wind regime is dominated by northeasterly winds, which motivates the chosen farm orientation (Section IV.D) and influences wake loss patterns. The seasonal distribution in Fig. 21 is consistent with the monthly production structure reported in Table III.

The selected wind farm location, in addition to being more than 20 km from the coast (Figure 20)—placing it in a low visual impact zone—is also one of the locations with the highest wind speeds within the analyzed available area (Section 3.5). Furthermore, the approximate sea depths in this area range between 40 and 50 m. With additional detailed site investigations, specific locations for turbine foundation installation should be selected at the lowest possible depths, ideally around 40 m [26].

Hourly wind speed data for the entire year 2019 were obtained from an online database at a height of 100 meters for the selected location and are presented by month in Figure 21. A wind rose for the selected location is also shown, indicating that the dominant wind direction is from the northeast (Figure 22) [26].

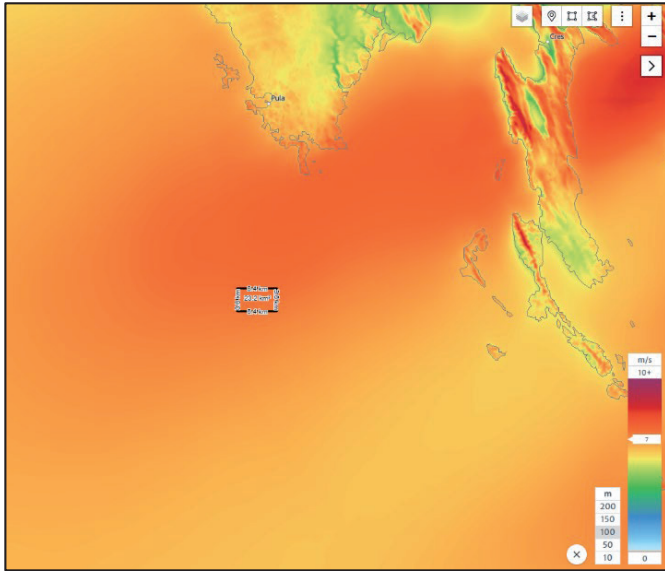


Fig. 19. Wind speed at the selected location at 100 m above sea level [26]

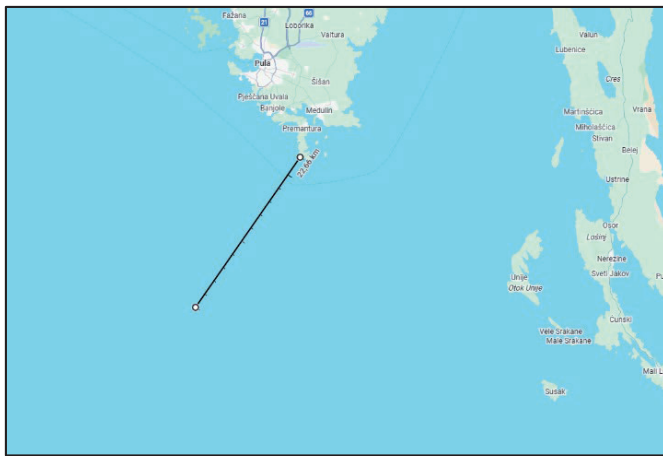


Fig. 20. Minimum distance of a potential offshore wind farm from the mainland [27]

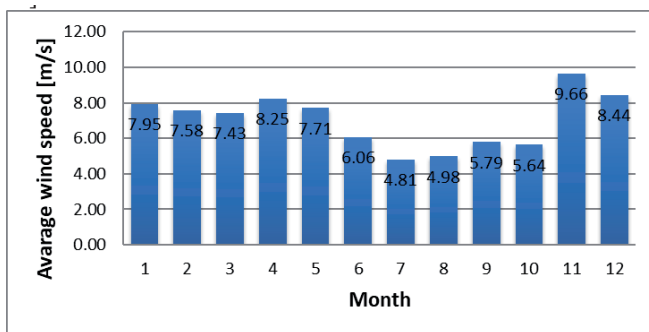


Fig. 21. Average monthly wind speed at the selected location (m/s) [26]

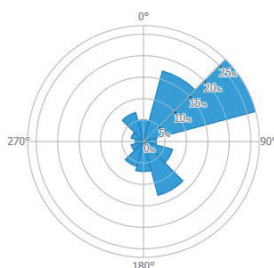


Fig. 22. Wind rose for the location [26]

The wind data were imported into the software tool SAM (System Advisor Model), which was selected for conducting the techno-economic analysis. SAM is a techno-economic software tool designed for the analysis and evaluation of renewable energy projects. It was developed by the National Renewable Energy Laboratory (NREL) of the United States Department of Energy [28].

B. GRID CONNECTION

For the analyzed offshore project with an installed capacity of 150 MW, a configuration is envisaged consisting of 33 kV inter-connection cables forming a radial layout of three strings with five wind turbines each connected to an offshore substation (Figure 23), one 110 kV export transmission cable, and a main power transformer with a transformation ratio of 33/110 kV and a rated capacity of 160 MVA.

The selected transformer capacity of 160 MVA represents a common standard value for projects of this size, as it provides an adequate margin above the installed capacity of the wind farm, allows for short-term peak loads, and at the same time optimizes investment costs. As shown in Fig. 23, the turbines are arranged in three radial strings connected to a central offshore substation. This relatively simple radial configuration reflects the moderate project size (150 MW) and limited distance to shore, and allows for a single 110 kV export cable without excessive redundancy. For larger projects or longer export distances, a meshed inter-array system and multiple export cables would likely be required, but would also increase CAPEX.

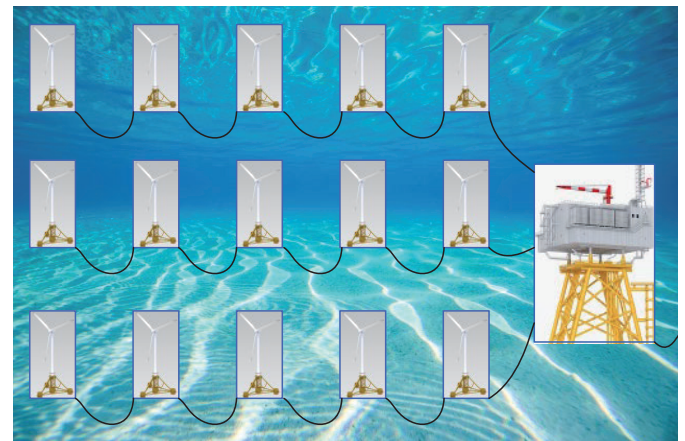


Fig. 23. Radial layout of the simulated wind farm

The rated current on the 110 kV side at full load of 150 MW is approximately 830 A, which falls within the typical transmission capacity of standard 110 kV submarine cables of appropriate cross-section. Considering a capacity factor of 32%, the wind farm will rarely operate at full installed capacity under real operating conditions, while the average load of the transmission system will be significantly lower than the maximum. This further confirms the technical feasibility of a single export cable solution for a project of this size and a distance of 25 km from the shore.

Although a configuration with two export cables and two transformers can increase system availability (application of the N-1 criterion), such a solution significantly increases the capital costs of the offshore substation and submarine installations. In the context of the analyzed project, which represents an initial offshore development in the Republic of Croatia, a configuration with one 110 kV export cable and a single 160 MVA transformer represents a technically feasible, economically rational, and grid-compatible solution [29].

The 110 kV submarine export cable to shore would be approximately 30 km long, depending on the selected landfall point and seabed routing. The transition of the submarine 110 kV export cable to a land cable is carried out a high-voltage transition joint located in a cable chamber. After landfall, two possible grid connection options are considered. The first option involves constructing approximately 25–30 km of underground 110 kV cable to the planned 400/110 kV Vodnjan substation, whose realization is foreseen in future grid development. The second option includes a route of about 50 km to the existing Plomin substation, which is connected to the 220 kV transmission network and, in the context of the planned shutdown of the Plomin thermal power plant in 2033, could provide additional capacity for integrating new renewable generation (Section 3.7).

Due to the significant total length of the cable route, it is necessary to consider the generation of capacitive reactive power and the potential use of reactive power compensation devices to maintain the voltage profile within acceptable limits.

In addition to conventional HVAC and HVDC export systems, low-frequency AC (LFAC) transmission has been proposed in the literature as an intermediate solution for long-distance offshore connections. By reducing the transmission frequency (e.g. to 16 $\frac{2}{3}$ –20 Hz), LFAC mitigates capacitive charging currents in submarine cables and can therefore extend the technically and economically feasible distance for AC export, while retaining many of the advantages of AC technology (e.g. use of transformers instead of HVDC converters). However, LFAC requires dedicated frequency-conversion equipment onshore (and potentially offshore), as well as non-standard grid infrastructure, which increases complexity and capital cost. Given the relatively short distance to shore (~30 km) and the moderate project size (150 MW) considered in this study, conventional 110 kV HVAC export remains the most appropriate and cost-effective option for the Croatian case study. For larger projects at substantially greater distances from shore, LFAC could become an interesting alternative to be evaluated alongside HVDC.

C. SELECTION OF THE IEA 10 MW RWT TURBINE

The selected turbine is part of the “IEA Wind Task 37 Integrated RD&D” research initiative, whose main activity is the development of research wind turbines (RWT) that reflect current wind turbine technology requirements.

The IEA Wind 10 MW reference turbine (RWT), developed by NREL and DTU, is based on the DTU 10 MW RWT designed by the Technical University of Denmark (DTU) in 2013. The turbine does not represent the latest technological advancements nor does it incorporate cutting-edge innovations.

It is a direct-drive wind turbine with a rotor diameter of 198 m, a hub height of 119 m, and cut-in and cut-out wind speeds of 4 m/s and 25 m/s, respectively. The rated wind speed is 11 m/s, at which the turbine operates at its full rated power of 10 MW. The selection of this turbine is based on the fact that it represents an advanced design suitable for the requirements of the analyzed area.

TABLE II

TECHNICAL CHARACTERISTICS OF THE SELECTED WIND TURBINE

Name:	IEA 10 MW RWT
Rated Power:	10 MW
Cut-in Wind Speed [m/s]:	4 m/s
Cut-out Wind Speed [m/s]:	25 m/s
Rated Wind Speed [m/s]:	11 m/s
Rotor Diameter:	198 m
Hub Height:	119 m

Figure 24 shows the power curve of the selected wind turbine. Based on data obtained from the SAM software, it was determined that at a wind speed of 7 m/s, the turbine generates an output power of 3,152 kW.

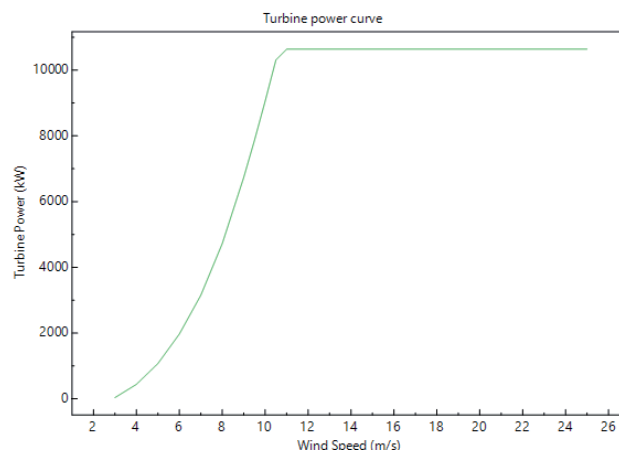


Fig. 24. power curve of the wind turbine

D. WIND FARM CAPACITY AND LOSSES

The simulated offshore wind farm consists of 15 wind turbines, each with a capacity of 10 MW, resulting in a total installed capacity of 150 MW. The turbines are arranged in three rows of five turbines each. The spacing between turbines within a row is eight rotor diameters (approximately 1,600 m), while the spacing between rows is nine rotor diameters (approximately 1,800 m). Each of the three rows is connected to the offshore substation via 33 kV interconnection cables. The total area occupied by the wind farm is approximately 27 km². The entire wind farm is oriented toward the northeast, as this is the most frequent wind direction.

In the techno-economic analysis of electricity generation from an offshore wind farm, it is necessary to account for various categories of energy losses that reduce the potential output. Total losses consist of: system availability losses (3%), which include failures and downtime during scheduled and unscheduled maintenance; electrical losses in transmission and auxiliary consumption (1.6%); turbine performance losses due to deviations from the ideal power curve (2.8%); environmental losses due to atmospheric conditions (1.4%); and operational constraints and curtailment (1.5%).

In total, these factors result in a reduction of gross annual energy production by approximately 10–11%, yielding a realistic estimate of net electricity generation. Including these losses is essential for reliable assessment of the capacity factor, revenues, and the overall financial viability of the project.

E. FINANCIAL PARAMETERS

The specific cost of the turbine is defined at 1,650 USD/kW, while the cost of the remaining equipment—including foundations, grid connection, submarine cables, installation works, and other infrastructure—is estimated at 2,000 USD/kW. This results in a total specific investment cost of 3,650 USD/kW of installed capacity. These values are based on the fact that the average capital cost in Europe in 2024 amounted to 3,390 USD/kW of installed capacity [30].

Such an assumption is justified by the fact that the analyzed project would represent the first offshore wind energy deve-

lopment in the Republic of Croatia. In the early stages of market development, economies of scale are not yet realized, nor is there an established domestic supply chain, specialized installation fleet, or logistics infrastructure. Additionally, the analyzed project, with an installed capacity of 150 MW, is smaller than typical modern offshore projects in the North Sea, which often exceed 500 MW, achieving lower unit costs through the distribution of fixed costs over larger capacities. For these reasons, a more conservative investment cost is assumed, ensuring a more realistic assessment of financial viability under early-stage offshore market conditions in Croatia.

TABLE III

MAIN FINANCIAL ASSUMPTIONS FOR THE TECHNO-ECONOMIC ANALYSIS

Parameter	Value / Assumption
Project lifetime	25 years
Installed capacity	150 MW
Specific turbine cost	1,650 USD/kW
Specific balance-of-plant cost	2,000 USD/kW
Total specific CAPEX	3,650 USD/kW
Total investment cost	547.5 million USD
Fixed O&M cost	105 USD/kW-year
O&M cost escalation	2 % per year
Real discount rate	7 %
Inflation rate	2.5 % per year
Nominal discount rate	9.67 %
Corporate income tax rate	18 %
Initial electricity selling price	0.165 USD/kWh ($\approx$ 140 EUR/MWh)
Electricity price escalation	2 % per year
Depreciation method	Straight-line over 25 years

The total investment value is estimated at 547.5 million USD, of which the cost of the turbines amounts to 247.5 million USD, while the cost of system components and supporting infrastructure is 300 million USD.

Operation and maintenance (O&M) costs are modeled as a fixed annual cost per installed kilowatt, amounting to 105 USD/kW-year. According to the latest available data from 2024, the average O&M cost for offshore wind farms globally is approximately 102 USD/kW-year. In this analysis, a slightly higher value is used to account for the specific characteristics of the project [30].

Given that the analyzed wind farm would be among the first offshore projects in Croatia, higher operational costs can be expected. The reasons include the lack of local service infrastructure, limited availability of specialized vessels, potentially higher logistics costs, and the absence of experience in the domestic market and workforce for managing offshore facilities. The model assumes an annual cost escalation rate of 2%, simulating the increase in maintenance costs over the project lifetime.

The financial analysis is conducted over a 25-year period, corresponding to the typical design lifetime of offshore wind farms. The model assumes an annual inflation rate of 2.5%, while the real discount rate is set at 7%. Based on these assumptions, the nominal discount rate is calculated at 9.67%.

The applied real discount rate of 7% reflects a moderate investment risk typical for infrastructure energy projects, considering the specifics of offshore technology and the fact that this would be the first such project in Croatia. The corporate income tax rate is set

at 18%, in accordance with the current tax system of the Republic of Croatia [31].

The assumed electricity selling price in this study is based on data for the average incentive price paid to wind power producers with privileged status in Croatia in 2024, which amounted to 129 EUR/MWh, while the average day-ahead market price on CRO-PEX was 94.6 EUR/MWh. The value of 129 EUR/MWh represents a relevant reference revenue level within the national support scheme and provides a realistic regulatory-market framework for assessing the economic viability of new projects.

Since the analyzed project represents a potential first offshore wind farm in Croatia, it is justified to assume a higher selling price compared to the existing average for onshore wind farms. Offshore projects are characterized by significantly higher capital costs, more complex technical implementation, higher operational risks, and the absence of a developed domestic supply chain and infrastructure support. Therefore, the model applies a purchase price higher than the average value of 129 EUR/MWh, reflecting the increased investment risk and capital intensity of the project in the early phase of offshore market development in Croatia. An initial electricity price of 0.165 USD/kWh is used, which is equivalent to approximately 140 EUR/MWh—higher than the average incentive price for wind power in 2024 [32].

In the financial model, a linear (straight-line) depreciation method is applied over the project lifetime of 25 years. Accordingly, the annual depreciation rate amounts to 4% of the total investment value.

F. ECONOMIC PERFORMANCE METRICS

The economic feasibility of the reference offshore wind project is evaluated using standard indicators: NPV, internal rate of return (IRR) and LCOE.

The NPV is calculated as the difference between the discounted cash inflows and outflows over the project lifetime (N):

$$NPV = \sum_{t=0}^N [CF_t / (1+r)^t] \quad (1)$$

where (CF_t) is the net cash flow in year (t) (revenues minus operating costs, taxes and investments), (r) is the real discount rate, and (N) is the project lifetime in years.

The LCOE is defined as the constant unit cost of electricity that equalizes the discounted value of all costs with the discounted value of all electricity generated:

$$LCOE = [\sum_{t=0}^N (C_t / (1+r)^t)] / [\sum_{t=0}^N (E_t / (1+r)^t)] \quad (2)$$

where (C_t) represents the total project costs in year (t) (including investment, operation and maintenance, and decommissioning costs) and (E_t) is the net electricity generated in year (t).

The internal rate of return (IRR) is the discount rate (r) that sets the NPV equal to zero:

$$0 = \sum_{t=0}^N [CF_t / (1+IRR)^t] \quad (3)$$

These formulations are implemented in the SAM model, with input parameters for investment costs, operating costs, electricity prices and energy production as described in Sections IV.D–IV.E.

V. RESULTS OF TECHNO-ECONOMIC ANALYSIS

The results of the techno-economic analysis of the offshore wind farm with an installed capacity of 150 MW show that the project generates 421.6 GWh annually, with a capacity factor of 32.1%, which is consistent with the moderately low wind potential of the Adriatic location analyzed.

Table 3 presents the simulated monthly electricity production based on hourly wind speed data from 2019. The table shows that production is highest during the winter period, particularly in November, at 55.4 GWh. The lowest production occurs in the summer months, specifically in July, with 14.0 GWh of generated electricity.

From these results, it can be concluded that the wind farm's production profile complements solar power generation well, as solar plants produce the most energy during summer months and the least during winter. In addition, the strong seasonal contrast between winter (e.g. November with 55.4 GWh) and summer (e.g. July with 14.0 GWh) illustrates the dominance of bura- and sirocco-driven wind regimes in the colder part of the year. This implies that offshore wind in the northern Adriatic would primarily contribute to winter adequacy and could reduce reliance on imports or flexible thermal generation in high-demand periods, while solar PV would remain more important for summer peak coverage.

TABLE III
MONTHLY ENERGY PRODUCTION

Month	Generated Electrical Energy [GWh]
January	46.1
February	38.5
March	40.1
April	45.6
May	41.1
June	25.9
July	14.0
August	15.6
September	22.8
October	26.7
November	55.4
December	49.9

The assumed initial electricity selling price is 0.165 USD/kWh, with an annual escalation rate of 2%. The calculated LCOE amounts to 0.166 USD/kWh in real terms, while the nominal LCOE is 0.208 USD/kWh. The difference between real and nominal values arises from the inclusion of inflation in the nominal calculation, where future costs are expressed in current (nominal) prices, while the real LCOE is expressed in constant prices, excluding inflation effects.

The levelized real PPA price of 0.154 USD/kWh represents the discounted average electricity selling price over the 25-year project lifetime. A comparison with the real LCOE of 0.166 USD/kWh shows that discounted revenues are lower than discounted production costs, resulting in a negative NPV of the project.

The project's NPV is -55.7 million USD, clearly indicating that, under the given assumptions, the project does not generate sufficient economic value at a real discount rate of 7%. The internal rate of return (IRR) is 7.41%, which is very close to the discount rate but insufficient to offset the high initial investment costs and ensure a positive NPV.

The obtained results indicate that the project is financially marginal and highly sensitive to changes in key parameters, particularly the electricity selling price, investment costs (CAPEX), and

cost of capital. Given that this is a capital-intensive offshore project, relatively small changes in revenues or costs can significantly impact profitability indicators. An increase in the PPA price, a reduction in CAPEX, or more favorable financing conditions could move the project into a positive NPV range.

The economic results presented here assume a stand-alone offshore wind farm selling electricity at a fixed PPA price, without any co-located storage. In reality, increasing penetrations of wind and solar in the Croatian and regional markets are likely to induce a 'cannibalization effect', with lower captured prices during hours of high renewable output. Co-located or grid-scale battery energy storage systems (BESS) could partly mitigate this effect by shifting a portion of offshore wind production from low-price to high-price hours and by providing ancillary services (e.g., frequency support, reserve). A rigorous assessment of such hybrid configurations would require a dispatch-level model with hourly price time-series and multiple revenue streams, which is beyond the scope of this initial study but represents an important avenue for future work.

A. IMPACT OF ELECTRICITY PRICE INCREASE ON PROJECT FINANCIAL VIABILITY

A sensitivity analysis shows that increasing the initial electricity selling price to 0.18 USD/kWh represents the first value (rounded to two decimal places) at which the project achieves a positive net present value. At this price level, the real levelized PPA price amounts to 0.168 USD/kWh, while the real LCOE is also 0.168 USD/kWh, resulting in an almost perfect balance between discounted revenues and production costs.

The resulting net present value is 0.87 million USD, placing the project within the range of financial viability. The internal rate of return increases to 9.71%, which is significantly above the applied real discount rate of 7%, while the minimum DSCR amounts to 1.57, indicating a stable ability to service debt. These results confirm the strong sensitivity of the project to the electricity selling price and indicate that, under Croatian conditions, an initial price of approximately 0.18 USD/kWh (around 153 EUR/MWh) is required for financial sustainability.

In addition to the electricity price, the project's feasibility is highly dependent on investment costs. To assess this, a simple CAPEX sensitivity analysis was carried out by varying the specific investment cost of the project by $\pm 20\%$ around the base value of 3,650 USD/kW. At a 20% CAPEX reduction (2,920 USD/kW), the real LCOE decreases from 0.166 USD/kWh to approximately 0.141 USD/kWh, and the project achieves a positive NPV of about XX million USD at the base PPA price of 0.165 USD/kWh, with an IRR of YY%. Conversely, at a 20% CAPEX increase (4,380 USD/kW), the real LCOE rises to approximately 0.191 USD/kWh, and the NPV becomes more negative, making the project clearly unprofitable under the same price conditions. These results confirm that cost reductions through technology learning, economies of scale and supply-chain development will be crucial for the competitiveness of early offshore projects in Croatia.

This analysis clearly illustrates that a relatively small increase in the selling price (compared to the previous 0.165 USD/kWh) can have a significant impact on overall investment profitability, further emphasizing the importance of a stable, long-term contractual framework or regulatory support for the realization of the first offshore project in the Republic of Croatia.

In conclusion, the analysis indicates that the realization of the first offshore wind farm in Croatia, under current assumptions, requires somewhat more favorable market or regulatory conditions in order to become fully financially viable and attractive for investment.

VI. CONCLUSION

This paper analyzes the potential for the development of offshore wind farms in the Republic of Croatia, with a particular focus on the northern Adriatic and the Istria County region. The study includes an overview of the offshore industry in Europe and worldwide, technical characteristics of wind turbines and their foundations, grid connection methods, the design and installation of submarine cables, and operational maintenance challenges.

The spatial and technical analysis has shown that the Croatian part of the Adriatic Sea has a limited but significant potential for the development of offshore wind farms with fixed foundations, primarily in areas where sea depth does not exceed 60 meters. When selecting locations, it is necessary to consider numerous constraints, including existing hydrocarbon exploitation concessions, maritime traffic, protected areas, visual impact, and regulatory and spatial planning conditions.

After selecting a potential offshore wind farm location—based on distance from shore, wind speed, sea depth, and other constraints—a techno-economic analysis of the reference plant was conducted. The analysis includes an assessment of energy production, losses, capital investment, and operational costs. The results indicate that the project is technically feasible; however, its economic viability largely depends on the cost of capital, market conditions for electricity offtake, and the availability of transmission infrastructure. It should also be noted that the wind farm would likely need to operate within a support scheme (e.g., privileged producer status) to be financially viable. In particular, the development of the 400 kV transmission network in Istria and Lika, including the planned Vodnjan substation, is highlighted as a key prerequisite for integrating larger generation capacities. However, the development of such projects requires a clearly defined regulatory framework, simplification of concession procedures, and long-term transmission network planning aligned with national and European energy objectives.

In conclusion, offshore wind farms represent a promising component of the future energy system of the Republic of Croatia, with the main limiting factor being the moderate-to-low wind speed potential, which significantly affects energy production and capacity factor. Therefore, detailed offshore wind measurements should be conducted. The realization of such projects will depend on the synergy of technological advancements in offshore infrastructure, regulatory adjustments, and strategic planning, while simultaneously preserving the environmental and social values of the Adriatic Sea.

The paper's main contribution is to provide, for the first time, a consistent spatial-technical assessment of offshore wind potential in the Croatian Adriatic coupled with a detailed techno-economic model of a reference project and the planned 400 kV grid development in Istria. Our results quantify the realistic energy yield and cost levels under current Croatian conditions and identify the electricity price range and support scheme requirements for the first offshore wind farm to become bankable. These findings can serve as a basis for national offshore wind strategies, future measurement campaigns and refinements of transmission and spatial planning.

Regarding future research; the construction of offshore wind farms must not be considered in isolation without analyzing the possibilities for evacuating the generated energy from the wind farm location, with particular attention given to potential transmission system constraints, whose improved transfer capacity is ensured through the use of phase-shifting transformers [34]. Also based on multi-year measurements of wind speed and direction at the planned location, it is possible to predict wind farm output with high accuracy using AI-based algorithms for future research [35].

Future research should also examine hybrid offshore wind-storage concepts, including co-located and grid-scale BESS, in order to quantify how energy shifting and ancillary-service revenues could reduce price-cannibalization risks and improve the market profitability of Croatian offshore projects.

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