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Intelligent assessment of harmonic distortion compliance in reverse osmosis systems

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ABSTRACT

This study explores the critical challenge of harmonic distortion compliance in reverse osmosis (RO) desalination systems, with a focus on aligning with international standards, specifically IEC 61000, IEEE 519, and EN 50160. High-power equipment, particularly high-pressure pumps (HPP), introduces significant harmonic distortions, threatening power quality and operational reliability. To address this issue, we integrated advanced machine learning (ML) algorithms, namely decision tree (DT), random forest (RF), support vector machine (SVM), and multi-layer perceptron (MLP) to assess harmonic compliance and predict total harmonic distortion (THD) under four operational scenarios. All data used for training and testing were obtained from real-time measurements taken at a large-scale desalination plant using a power quality analyzer (QUALISTAR CA 8336), which guarantees the practical relevance of the analysis. The models were trained on harmonic order and amplitude data and evaluated using accuracy, precision, recall, and F1-score metrics. Among the models, MLP demonstrated superior performance, achieving an accuracy of 99.11% and an F1-score of 98.9%, making it a robust tool for harmonic compliance assessment. SVM and RF also showed commendable results, while DT proved effective for basic analysis. This research underscores the potential of AI-driven approaches in mitigating harmonic-related challenges, optimizing power quality, and enhancing operational efficiency in RO plants. These findings offer a pathway toward more reliable and energy-efficient industrial operations.

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1. INTRODUCTION

The rise of reverse osmosis (RO) desalination plants represents a significant trend in engineering over the last few decades, addressing the increasing demand for freshwater. By 2022, operational seawater desalination plants worldwide exceeded 21,000, nearly double the figure recorded a decade ago [1]. Centrifugal high-pressure pumps (HPP) are critical components in RO systems, and their performance, such as operating pressure, flow rate, feed pressure, and energy efficiency, directly impacts freshwater production and the overall reliability of the desalination process [2]. These pumps, or pump-motor units, are typically powered by electric motors, often three-phase or single-phase induction motors, coupled with static power converters like variable frequency drives (VFD) to regulate speed and pressure [3]. Due to the nonlinear nature of HPP, harmonic phenomena are frequently observed in electrical systems [4]. The severity of these harmonic disturbances in current signals is quantified by the total harmonic distortion of current (THDi). When harmonic currents circulate through a finite system impedance, the vector sum of all individual voltage drops leads to an increase in the total harmonic distortion of voltage (THDu) [5].

The rapid advancement of artificial intelligence (AI) is transforming how we monitor and optimize complex systems. Machine learning (ML), a subset of AI, has demonstrated remarkable success in modeling nonlinear systems across diverse fields, including healthcare, sports, industry, environmental sciences, and water treatment [6]–[15]. AI techniques hold immense potential for tackling complex, nonlinear challenges, particularly in studies related to water treatment processes and beyond.

Over the past few decades, the issue of total harmonic distortion (THD) has become a critical concern in industrial power systems, particularly in RO desalination plants. The increasing reliance on high-power equipment, such as HPP, has led to significant harmonic distortions, adversely affecting power quality and operational efficiency [16]. Ensuring compliance with international standards like IEC 61000, IEEE 519, and EN 50160 is essential to mitigate these challenges and maintain reliable plant operations [17], [18]. Recent studies have emphasized the significant impact of harmonics in industrial systems, where the increasing use of non-linear loads and high-power equipment has led to elevated levels of THD. These distortions can severely affect power quality, causing issues such as equipment overheating, reduced efficiency, and premature failure of electrical components. To address these challenges, researchers have focused on developing advanced mitigation techniques, including active and passive filters, adaptive control strategies, and AI-based solutions. These approaches aim to reduce harmonic distortions and ensure compliance with international standards, such as IEEE 519 and IEC 61000, which set strict limits on THD levels to maintain system reliability and performance [19], [20]. Traditional harmonic mitigation methods, such as passive and active filters, require manual adjustments and struggle to adapt to dynamic operating conditions [21]. Traditional monitoring systems also rely on fixed thresholds, making them ineffective in detecting complex harmonic interactions in real time.

To address the challenges of THD in RO plants, this study leverages AI to automate the classification and prediction of harmonic compliance, ensuring adherence to IEC 61000, IEEE 519, and EN 50160 standards. Using advanced ML techniques such as decision tree (DT), random forest (RF), support vector machine (SVM), and multi-layer perceptron (MLP), we analyze the impact of harmonic distortions on plant performance and propose mitigation strategies. This study introduces a novel AI-based framework specifically tailored to the dynamics of RO desalination systems, which have not been extensively explored in the context of harmonic compliance. This AI-driven framework enhances real-time monitoring, improves predictive accuracy, and enables adaptive control strategies, optimizing power quality and preventing harmonic-related failures in industrial RO plants. Ultimately, this research highlights the potential of AI in maintaining system reliability and advancing efficient energy management in desalination facilities.

2. METHOD

2.1. Electrical system under study

The RO system is powered through a high-voltage/low-voltage (HV/LV) transformer, supported by a backup transformer, each with a capacity of 1,600 kVA. Additionally, a 40 kVAr self-anti-harmonic (SAH) vacuum compensation system is connected to the grid via an 80 A circuit breaker installed on the low-voltage side of each HV/LV transformer. The electrical network supplies four HPP (in a 3+1 configuration), which are the plant's primary energy consumers. Each pump is driven by a 450 kW VFD motor. Figure 1 provides a schematic diagram of the electrical system supplying the HHP in a desalination plant in Morocco. Complementing this, Table 1 presents the technical characteristics of the 1,600 kVA transformers used in the RO system, detailing key parameters such as rated power, voltage, current, losses, and winding configuration.

2.2. International norms

The normative analysis evaluates the compliance of the RO plant’s electrical system with international standards for harmonic distortion. This section examines the limits for voltage and current harmonics as defined by IEEE 519, IEC 61000, and EN 50160, ensuring the system operates within acceptable power quality thresholds. The analysis focuses on harmonic levels at both high-voltage (22 kV) and low-voltage (0.4 kV) sides of the transformer.

2.2.1. IEEE 519

The IEEE 519 standard applies to both high-voltage and low-voltage systems. The limits for voltage harmonics are determined according to Table 2. Since the transformer is supplied with 22 kV, the current harmonics must comply with the limits specified in Table 3 [19].

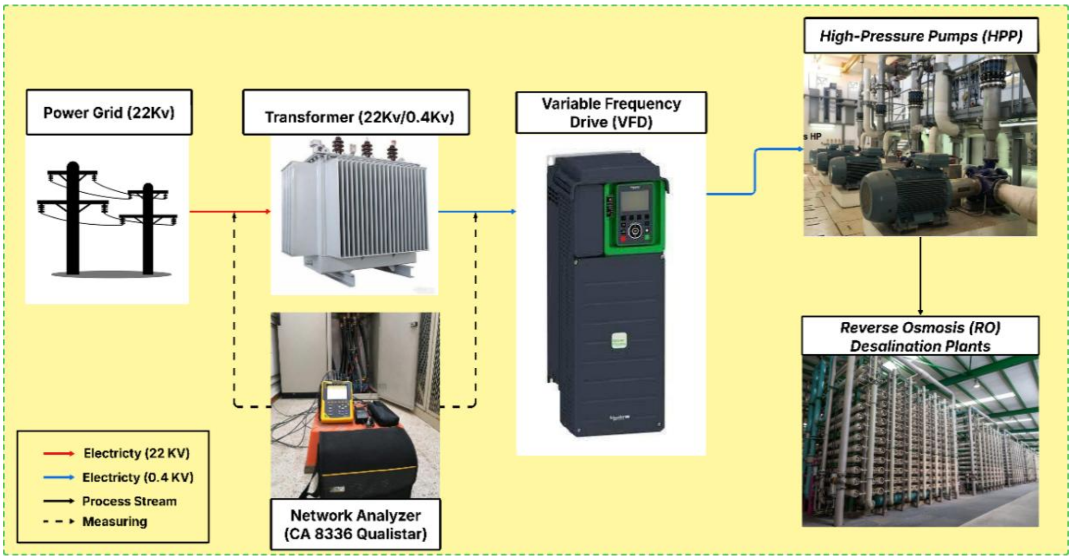


Figure 1. Schematic diagram of the electrical system supplying HPP in the RO plant

Table 1. Technical characteristics of the 1,600 kVA Transformers in the RO system

Parameter	Symbol	Value	Unit
Rated power	S	1,600	kVA
Primary voltage	UHV	22	kV
Secondary voltage	UBT	0.4	kV
Rated primary current	IHV	41.99	A
Rated secondary current	IBT	2309.4	A
Short-circuit voltage*	%Ucc	6±10%	%
Winding connection	---	Dyn11	---
Tap changer	---	±2*2.5	% UHV
Load losses*	Pj	19 (+15%)	kW
No-load losses*	Pv	2.6 (+15%)	kW

Table 2. Voltage harmonic limits (IEEE 519)

Bus voltage V at PCC	Individual harmonic (%)	Total harmonic distortion (%)
V≤1.0 KV	5.0	8.0
1 KV<V≤69 KV	3.0	5.0
69 KV<V≤161 KV	1.5	2.5
161 KV<V	1.0	1.5[a]

Table 3. Current harmonic limits for systems rated 120 V through 69 KV (IEEE 519)

$\frac{I_{SC}}{I_L}$	Maximum harmonic current distortion in percent of I_L Individual harmonic order (odd harmonics)[a, b]					TDD required
	3≤h<11	11≤h<17	17≤h<23	23≤h<35	35≤h<50	
<20[c]	4.0	2.0	1.5	0.6	0.3	5.0
20<50	7.0	3.5	2.5	1.0	.05	8.0
50<100	10.0	4.5	4.0	1.5	0.7	12.0
100<1,000	12.0	5.5	5.0	2.0	1.0	15.0
>1,000	15.0	7.0	6.0	2.5	1.4	20.0

[a]Even harmonics are limited to 25% of the odd harmonic limits above.
[b]Current distortions that result in a dc offset, e.g., half wave converters, are not allowed.
[c]All power generation equipment is limited to these values of current distortion, regardless of actual $\frac{I_{SC}}{I_L}$
Where, I_{SC} maximum short circuit current at P_{CC}, and IL maximum demand load current

2.2.2. IEC 61000

The IEC 61000 standard addresses electromagnetic compatibility (EMC) in low-voltage systems. It recommends harmonic limits applicable to low and medium voltage systems. In most cases, it can also be applied to the input terminals of equipment supplied by low-voltage networks [22]. The voltage harmonic levels for each order are provided in Table 4, with a maximum THD of 8%.

Table 4. Harmonic voltage limits per IEC 61000-2-2 and 61000-2-12 standards

Odd harmonics (Not multiple of 3)		Odd harmonics (Multiple of 3)		Even harmonics	
h	L_h (%)	h	L_h (%)	h	L_h (%)
5	6	3	5	2	2
7	5	9	1.5	4	1
11	3.5	15	0.4	6	0.5
13	3	21	0.3	8	0.5
17<h≤49	$2.27 \cdot \frac{17}{h} - 0.27$	21<h≤45	0.2	10<h≤50	$0.25 \cdot \frac{10}{h} + 0.25$

2.2.3. EN 50160

The EN 50160 standard sets limits for voltage harmonic amplitudes in low-, medium-, and high-voltage networks under normal operating conditions [23]. These limits are designed to ensure the quality and reliability of the power supply, thereby reducing potential disturbances in electrical equipment. The individual harmonic voltage levels specified by this standard are presented in Table 5, which provides detailed values for both odd and even harmonics up to the 25th order.

Table 2. Individual harmonic voltage values at supply terminals (orders up to 25, % of fundamental U1)

Odd harmonics				Even harmonics	
Not multiple of 3		Multiple of 3			
h	L_h (%)	h	L_h (%)	h	L_h (%)
5	6.0	3	5.0	2	2.0
7	5.0	9	1.5	4	1.0
11	3.5	15	0.5	6< h ≤24	0.5
13	3.0	21	0.5		
17	2.0				
19	1.5				
23	1.5				
25	1.5				

2.3. Data collection

2.3.1. Measurement equipment

The data for this study were collected using a high-precision power quality analyzer, the QUALISTAR CA 8336 from Chauvin Arnoux. The main features of this advanced power network analyzer are presented in Table 6. This device was installed to measure the levels of THDi and THDu on the high-voltage (22 kV) and low-voltage (0.4 kV) sides of the transformer feeding the RO system. The measurements were analyzed for the four operating scenarios of the RO system: i) scenario 1: 0 RO trains in operation; ii) scenario 2: 1 RO train in operation; iii) scenario 3: 2 RO trains in operation; and iv) scenario 4: 3 RO trains in operation.

The measurement campaign was conducted over the entire month of May 2024 (31 consecutive days). To minimize disruption to plant operations, data were collected for 1 full day under scenario 1, 1 full day under scenario 2, and 1 day under scenario 3. The remaining 28 days were dedicated to scenario 4, which reflects the plant's typical operating conditions. Measurements were recorded every 5 minutes, resulting in a complete dataset of approximately 8,700 samples. This high-resolution and time-distributed dataset ensures statistical robustness for training and evaluating ML models under realistic operational conditions. For each operating scenario, the spectrum of maximum harmonic amplitudes for both voltage and current is recorded and compared against the relevant normative standards.

Table 3. Key features of the QUALISTAR CA 8336 power quality analyzer

Feature	Specification
Accuracy	±0.5% for voltage, ±1% for current
Frequency range	Measures harmonics up to the 50th order
Data logging	Real-time recording with high resolution
Measurement parameters	Voltage, current, power, energy, harmonics (up to 50th order), THD, power factor
Compliance	Meets IEC 61000-4-30 class A standards for power quality measurements

2.3.2. Measured parameters

To evaluate power quality, several indicators are commonly used to quantify the level of harmonic distortion in both current and voltage signals.

– THDi calculated as the ratio between the sum of harmonic currents to the fundamental current.

$$THDi = \frac{\sqrt{\sum_{h=2}^{H} I_h^2}}{I_1} \times 100\%$$

Where, I_h represents the harmonic current of order h, I_1 is the fundamental current (1st order) and H is the maximum harmonic order measured (e.g., 25).

– THDu calculated as the ratio of the sum of the harmonic voltages to the fundamental voltage.

$$THDu = \frac{\sqrt{\sum_{h=2}^{H} V_h^2}}{V_1} \times 100\%$$

Where, V_h represents the harmonic voltage of order h, I_V is the fundamental voltage (1st order).

– Harmonic amplitudes, the amplitudes of harmonic currents and voltages, represent the magnitude of each harmonic component relative to the fundamental.

$$I_h(\%) = \frac{I_h}{I_1} \times 100\%, \qquad V_h(\%) = \frac{V_h}{V_1} \times 100\%$$

2.4. Harmonic classification

2.4.1. Classification process

This section describes the methodology used for harmonic classification and presents the results for the four operating scenarios of the RO plant. Each harmonic was classified as "compliant" or "non-compliant" based on the following rule:

– If the measured harmonic amplitude≤standard limit → "compliant".
– If the measured harmonic amplitude>standard limit → "non-compliant".

Among the 8,700 collected samples, approximately 51.3% belong to the compliant class and 48.7% to the non-compliant class. This near-even distribution was verified during data preprocessing. Therefore, no resampling techniques such as oversampling (e.g., SMOTE) or undersampling were required.

2.4.2. Machine learning models for harmonic classification

To automate the classification process, a DT, random forest (RF), SVM, and neural network (MLP) were trained on the harmonic data. These models used the harmonic order and measured amplitude as input features to predict the compliance status ("compliant" or "non-compliant"). To ensure model generalizability and avoid overfitting, a 70/15/15 split was applied to divide the dataset into training, validation, and testing sets, respectively. Additionally, a 5-fold cross-validation technique was employed during training to provide a robust estimation of model performance across different subsets of the data. Table 7 provides a clear and concise summary of the AI models used for harmonic classification and evaluation metrics.

Table 4. ML models for harmonic classification

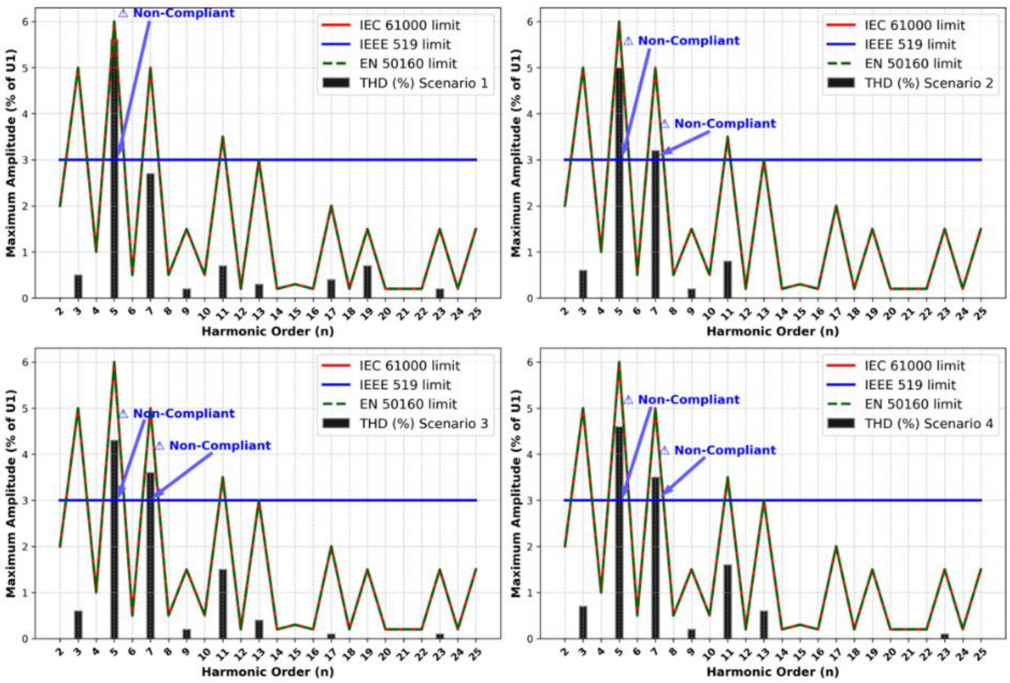
Model	Description	Equation	Reference	Evaluation metrics
DT	A supervised learning algorithm that divides data into branches based on feature values, creating a tree-like model of decisions.	Gini impurity $= 1 - \sum_{i=1}^{n} P_i^2$ where P_i is the probability of class i.	[24]	Accuracy=$\frac{TP + TN}{TP + FP + FN + TN}$ Recall=$\frac{TP}{TP + FN}$ Precision=$\frac{TP}{TP + FP}$ F1score=$\frac{2 \times Recall \times Precision}{Recall + Precision}$
RF	An ensemble of DT that improves accuracy and reduces overfitting by averaging the results of multiple trees.	Prediction $= \mathrm{mode}(T_1(x), T_2(x), \ldots, T_n(x))n$ Here, where $T_i(x)$ represents the prediction of the i-th tree.	[25]	
SVM	A supervised learning model that finds the optimal hyperplane to separate data into classes, maximizing the margin between classes.	$F(x) = \mathrm{sign}(w \cdot x + b)$ Where w is the weight vector, x is the input, and bb is the bias.	[26]	
MLP	A deep learning model that uses layers of interconnected neurons to learn complex patterns in the data.	$y = \sigma \sum_{i=1}^{n} w_i x_i + b$ Where σ is the activation function, w_i are weights, x_i are inputs, and b is the bias.	[27]	

3. RESULTS AND DISCUSSION

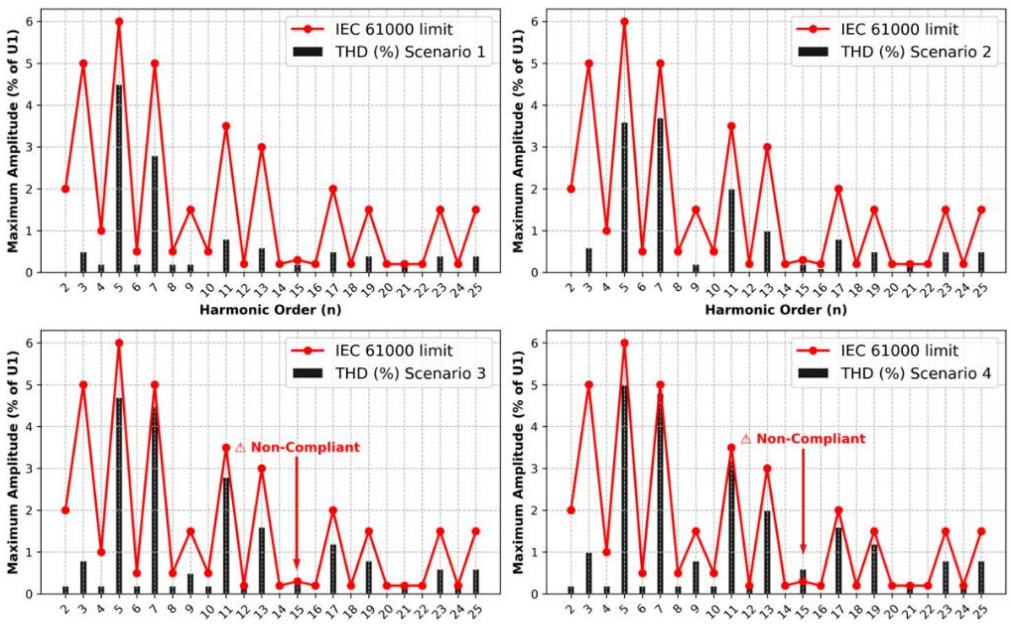
3.1. Analysis of voltage harmonics against applicable standards

This section presents the normative analysis of THDu and THDi at high-voltage (22 kV) and low-voltage (0.4 kV) levels, measured in the RO plant under four operating scenarios. Figure 2 illustrates the variations in the maximum harmonic amplitudes across the four operating scenarios, corresponding to the number of RO trains in service. The limits defined by IEC 61000, IEEE 519, and EN 50160 standards are overlaid on the measurements to assess compliance.

Figure 2(a) displays the THDu under the four scenarios, that figure correspond to a specific operating condition. The harmonic spectrum and standard limits (IEC 61000, IEEE 519, EN 50160) are plotted to assess voltage distortion compliance. While all scenarios are within the IEC 61000 and EN 50160 thresholds at 22 kV, certain harmonic orders, particularly the 5th, 7th, and 11th, exceed IEEE 519 recommendations. At the 0.4 kV level, most values remain below the IEC limit, except for the 15th harmonic in scenarios 2 and 4, indicating non-compliance in these specific cases. Figure 2(b) presents the THDi results under the same four scenarios, that figure show current harmonic amplit.



(a)

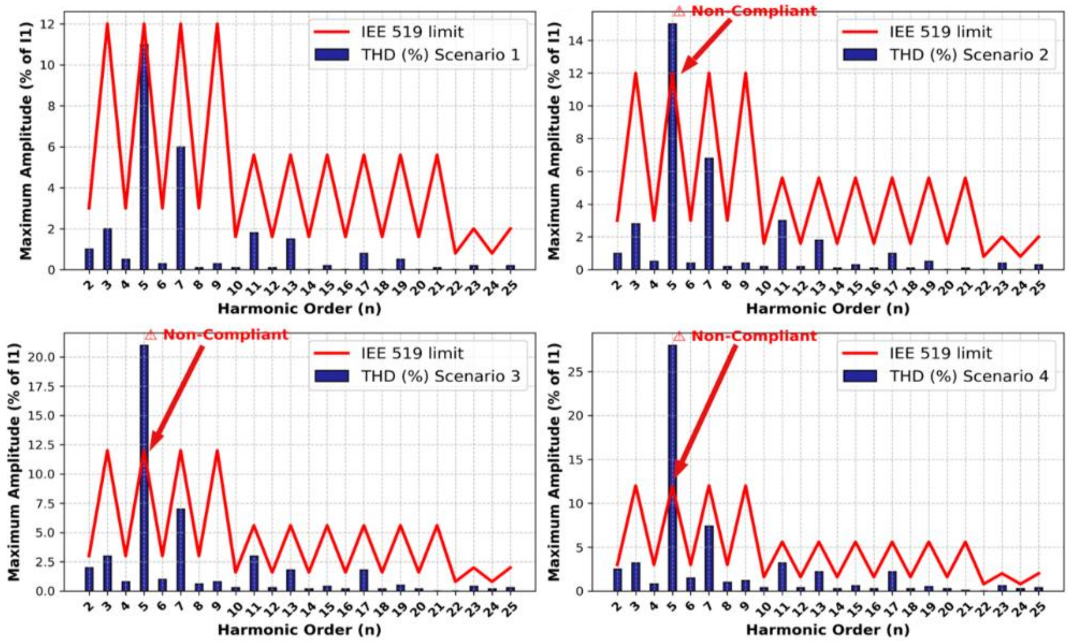


(b)

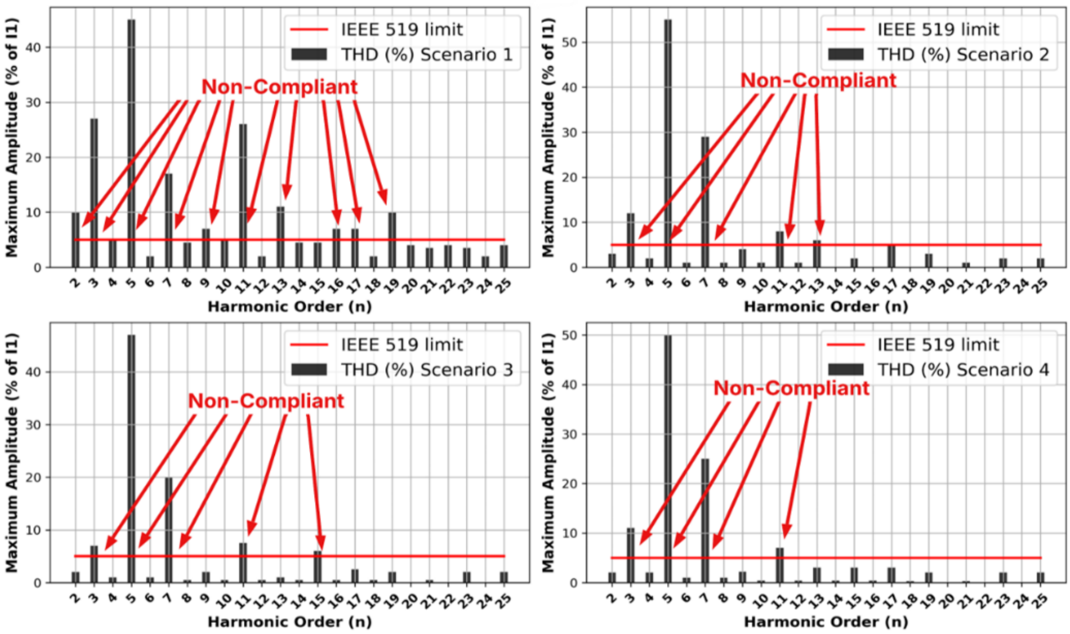
Figure 2. Evolution of maximum harmonic voltage amplitudes across different operating scenarios of the RO Plant at (a) high voltage (22 kV) and (b) low voltage (0.4 kV) levels

3.2. Analysis of current harmonics against applicable standards

Figure 3 illustrates the variations in THDi at high-voltage (22 kV) and low-voltage (0.4 kV) levels under four operating scenarios, compared to IEEE 519 limits. Significant harmonic amplitudes are observed at 22 kV as shown in Figure 3(a), particularly for the 3rd, 5th, 7th, and 11th orders, with exceedances noted in scenarios 2 and 4. The highest THDi values occur at lower fundamental currents, highlighting an inverse relationship. At 0.4 kV, as shown in Figure 3(b), we observe that the 5e harmonic far exceeds the IEEE 519 limit in all scenarios, with maximum amplitudes reaching over 40%. The 3e and 7e harmonics are also significant, but remain below the limit in some cases. The harmonic distribution indicates high harmonic distortion, particularly marked in scenarios 2 and 4. These harmonic distortions can lead to overheating, increased vibration, and premature wear of the HPP, adversely affecting their reliability and overall performance.



(a)



(b)

Figure 3. Evolution of maximum harmonic current amplitudes in different RO plant operating scenarios at (a) high voltage (22 kV) and (b) low voltage (0.4 kV) levels

3.3. Machine learning-based classification of harmonic compliance

The analysis of the figures effectively demonstrates harmonic variations, emphasizing the impact of excessive harmonic distortion on HPP performance in RO plants. Overheating, increased vibrations, and insulation degradation can lead to higher maintenance costs and unexpected failures, affecting operational reliability. To mitigate these issues, this study applies ML models for harmonic classification, automating compliance assessment against IEC 61000 and IEEE 519 standards. Four ML models were trained on harmonic data. Table 8 summarizes the performance of each model. The MLP achieved the highest accuracy (99.11%), proving to be the most effective model for precise classification. Its superior performance is attributed to a deep architecture with two hidden layers (64 and 32 neurons) and rectified linear unit (ReLU) activation, which allowed it to capture complex non-linear relationships between harmonic orders. Dropout regularization was also applied to prevent overfitting, while SVM (96.29%) and RF (96.0%) also demonstrated strong performance. DT, though slightly less accurate (92.5%), remains a viable option for simpler applications. Figure 4 illustrates the precision-recall (PR) curves for all four models. The MLP exhibits a near-perfect PR curve, maintaining high precision across a wide range of recall values. This highlights its robustness in correctly identifying harmonic compliance even in more uncertain prediction zones. SVM and RF models follow closely but show a slight drop in precision as recall increases, indicating a growing number of false positives under broader detection scopes. The DT, while performing adequately, presents a more pronounced decline in precision with increasing recall, confirming its relatively lower ability to generalize across diverse harmonic conditions. These results confirm that AI-driven approaches enhance real-time harmonic compliance monitoring, optimizing power quality and reducing the risk of equipment failures in desalination plants.

Table 8. Performance comparison of ML models for harmonic compliance classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
DT	92.5	91.0	90.5	90.7
RF	96.0	95.5	95.0	95.2
SVM	96.29	96.0	95.8	95.9
MLP	99.11	99.0	98.9	98.9

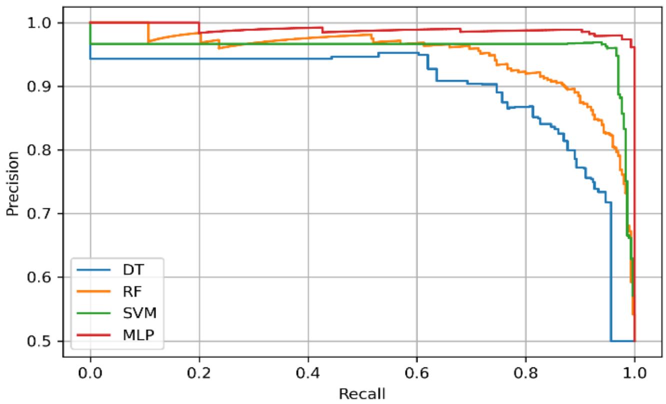


Figure 1. Precision-recall curves of the four ML models for harmonic compliance classification

3.4. Discussion of the results

The results of this study demonstrate the effectiveness of ML models in classifying harmonic compliance and predicting THD levels in RO desalination plants. The superior performance of the MLP model confirms its ability to capture complex, nonlinear relationships between harmonic orders thanks to its multilayer architecture and nonlinear activation functions. This makes it particularly effective in scenarios involving fluctuating loads and diverse harmonic profiles, as found in RO desalination plants. Compared to SVM and RF, which also performed well, MLP's higher accuracy and F1-score underline its robustness for detailed harmonic compliance assessment. Moreover, the computational efficiency of the selected models, especially MLP and RF, enables their integration into industrial systems with moderate hardware, such as edge computing units or industrial PCs, ensuring suitability for real-time deployment [28]. This AI-based approach offers a scalable, proactive solution for monitoring and mitigating harmonic distortions in industrial environments.

4. CONCLUSION AND PERSPECTIVES

This study highlights the effectiveness of ML models, particularly MLP, in analyzing harmonic compliance and predicting THD levels in RO desalination plants. The results demonstrate the potential of AI-driven approaches to ensure power quality and adherence to international standards like IEC 61000, IEEE 519, and EN 50160. Regarding computational efficiency, the MLP model demonstrates superior accuracy but requires higher inference time and computational resources due to its deeper architecture and dense parameter space. This may limit its applicability in highly time-constrained environments. However, the deployment remains feasible on industrial embedded systems with moderate computational power (e.g., industrial PCs supporting TensorFlow Lite or ONNX Runtime). Framework for platform independent ML model execution. In contrast, simpler models such as DT or RF provide much faster inference times, making them more suitable for real-time scenarios where latency is critical. A trade-off between model accuracy and computational cost should be considered based on operational constraints. Moving forward, the installation of active harmonic filters, tailored to the harmonic profiles identified in this study, is a critical next step. Integrating these filters with real-time monitoring systems, powered by AI models, could enable predictive maintenance and adaptive control, enhancing operational efficiency and sustainability. Future work should explore the economic and environmental benefits of such implementations, paving the way for smarter and more sustainable industrial energy systems. Additionally, integrating this AI-powered framework into SCADA systems could enable a fully autonomous power quality management system, enhancing resilience, efficiency, and adaptability in industrial energy networks.

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AUTHOR CONTRIBUTIONS STATEMENT

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Hassan Latrache		✓		✓						✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

As part of the interests associated with this publication, the authors declare that they have no financial conflicts of interest or personal relationships likely to have influenced the work presented in this paper.

DATA AVAILABILITY

The data supporting the results of this study are available on request from the corresponding author.

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