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AI-Driven Stability Prediction of Renewable Electrical Networks with Green Hydrogen Integration

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Abstract. This paper presents a data-driven framework to assess the impact of green hydrogen integration on the voltage stability of a part of the Moroccan electrical transmission network. The main contribution lies in modeling green hydrogen as a long-duration energy storage system capable of absorbing surplus solar and wind generation and reinjecting it into the grid to enhance voltage stability under high renewable penetration. A time-series power flow methodology, implemented in Python using the pandapower library, is developed to generate a large dataset based on voltage criteria. This dataset is then used to train and evaluate four machine learning models (RBF-SVM, Random Forest, QDA and Naive Bayes) through confusion matrices and standard performance metrics. The comparative results indicate that the RBF-SVM model clearly outperforms the other classifiers across all evaluation metrics, including accuracy, precision, recall and F1-score. Beyond model performance, the proposed approach introduces an integrated framework that combines hydrogen-based long-term energy storage modeling with machine learning–based stability prediction.

1. Introduction

The extensive development of renewable resources, especially photovoltaic and wind power, has a substantial impact on modern power systems with the introduction of new challenges for grid stability and ensuring electricity supply [1]. An increasing number of publications emphasize the importance that hydrogen would have in designing and managing modern energy systems. An expanding literature underscores the increasing relevance of hydrogen for the design and operation of modern energy systems. Hydrogen is gaining more importance in the consideration for planning and operating contemporary energy systems. There is an increasing attention to hydrogen in the planning and operation of contemporary energy systems. Publications such as [2] demonstrate how technologies such as electrolyzers, fuel cells or power-to-gas systems provide hydrogen with a strategic role in future energy infrastructures. In a similar vein, [3] indicates that green hydrogen based hybrid systems can contribute to enhance reliability of the grid and storage capacity as well as facilitate the low-carbon energy networks transition. These attributes render hydrogen as an essential energy carrier for sustainable systems. The authors in its reference [4] focuses on the power-to-hydrogen route, emphasizing the technical difficulties that are still in existence but at the same time also pointing out how hydrogen can potentially help shape international transition to cleaner energy. Research on China's hydrogen power-to-X technologies are reported in [5], where technical and policy challenges, as well as status of commercial and demo projects to expedite China's shift into clean energy, were investigated. In addition, these dual usage of batteries and hydrogen storage systems benefit grid stability as well as the optimization of renewable energy penetration and the reduction in overall utilities cost by echoing a wider trend for sustainable energy [6]. In [7], hydrogen energy storage systems (HESS) have

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been a central aspect for power production and scheduling, analyses being challenging due to modeling, optimization and commercialization at study. Chapter [8] gives a detailed review of energy storage options including batteries, fuel cells, solar cells and hydrogen storage pointing at solar and photo-rechargable systems as the optimal solutions to counteract demand for fluctuating electricity. Some reports also highlight that electrolyzers play a crucial role in hydrogen production and provide grid services, which ease the variability of power generation of renewable energy resources, stabilize grid operation and enhance economic efficiency [9]. The work of authors in [10] presents a thorough discussion on hydrogen storage materials with their merits and demerits is highlighted, "it has been pointed out that new unconventional cost-effective method of safe utilization of hydrogen is essential for making it viable as an attractive clean energy carrier". The developments of hydrogen storage technologies are also acknowledged as important in [11] to balance variable renewable energy, and efficiency, storage capacity and sustainability is emphasised, while call for further research on this area to bring performance up and cost down. The ability of the storage system to handle two sources of electricity; photovoltaic and grid, could enable cost effective management of energy at community level using solar produced hydrogen [12]. Reference [13] assesses hydrogen technologies potentials in Europe and its applications for transport, industry and power generation, integration options and long-term roadmaps up to 2050. Last but not least, [14] presents an AI- and IoT-enabled control system for the production of GH in renewable hybrid energy systems. This technique is based on machine learning models (Random Forest, ANN and LSTM) to predict PV generation and load, to balance energy as well as to enhance hydrogen production efficiency when validated in the Rye microgrid. [15] proposes a forecast-free optimization model for the energy management of microgrid with hybrid hydrogen– battery storage and yields substantial savings in operating cost and load loss. An intelligent energy management system based on deep reinforcement learning enhances cost-effectiveness, stability and battery longevity in the context of hybrid hydrogen–battery storage for microgrids [16]. Last but not least, recent papers on machine learning approaches in the hydrogen production and storage pinpoint the existing bottlenecks and the large room for developments that still exist in this emerging area [17].

The paper is organized into the following sections: In the second section, the proposed hybrid framework is described, which integrates renewable generation, hydrogen-based storage and artificial intelligence for grid stability prediction. It details the workflow of renewable–hydrogen–AI interaction, also explains the role of ML models in predicting system stability and presents the dataset description and data source. The third section presents the performance evaluation of several ML models using confusion matrices and performance metrics, followed by a comparative analysis and an interpretation of the results to identify the best-performing model. Finally, the fourth section concludes by confirming the reliability of the proposed hybrid physics–data framework for grid stability prediction and highlighting the effectiveness of hydrogen integration and AI-based prediction based on the best-performing model across multiple metrics.

2. Methodology

2.1 Comprehensive Process of Renewable–Hydrogen–AI Integration

The proposed approach consists of a series of interrelated tasks including renewable energy modeling, hydrogen-based power-to-power storage design, and artificial intelligence for stability assessment as illustrated in Fig. 1. The modelling of renewable energy generation the electricity generated from solar and wind sources is injected into the electrical grid constitutes one of the starting points. As soon as, renewable power generation exceeds system load, the surplus electricity is supplied into an electrolyzer for green hydrogen production. The generated hydrogen is then stored, and can be returned to the grid at a later stage, providing extra power when little or no renewable power generation takes place, mitigating intermittency.

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To assess grid stability under varying operating conditions, several well-established ML classifiers are employed, namely Radial Basis Function Support Vector Machine (RBF-SVM) [18], Random Forest (RF) [19], Quadratic Discriminant Analysis (QDA) [20] and Naive Bayes (NB) [21]. These models are used to classify the grid operating state as stable or unstable based on voltage-related and operational features obtained from power flow simulations.

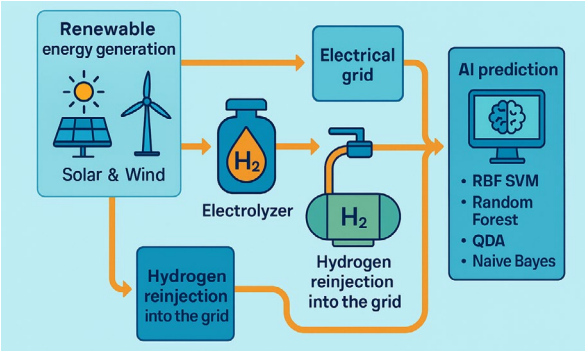


Fig. 1 : Global scheme of the proposed methodology integrating renewable energy, hydrogen storage and ML models for stability prediction.

Fig. 2 illustrates the integrated energy and hydrogen supply chains from renewable energy generation to final distribution and end-use applications. Electricity generated from solar and wind sources is supplied to the grid through renewable energy systems, while surplus power is converted into green hydrogen via electrolysis. The produced hydrogen can be stored or reconverted into electricity using fuel cells, and it is distributed for various applications, including transportation and industrial uses.

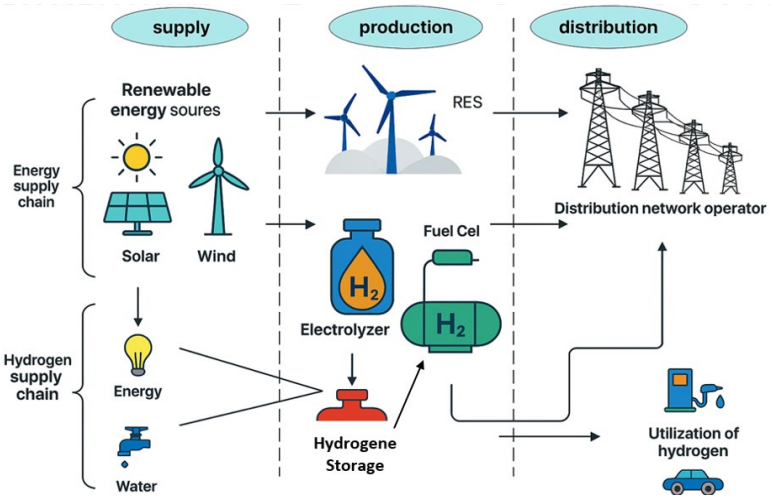


Fig. 2 : Energy and Hydrogen Supply Chains from Generation to End-Use Applications.

In this work, the impact of hydrogen integration is defined as the contribution of green hydrogen systems to enhancing grid stability and operational flexibility by providing long-duration energy storage. Surplus renewable energy is converted into hydrogen and later reconverted into electricity, helping to reduce intermittency and support grid stability. Compared with batteries and pumped hydro storage, hydrogen offers greater scalability and longer storage duration, making it well suited for power systems with high renewable penetration.

2.2 Role of ML in Predicting Grid Stability with Green Hydrogen Integration

Machine learning (ML) techniques are employed to predict grid stability in the presence of green hydrogen integration, by capturing interactions between variable renewable generation and

hydrogen production, storage and reinjection. ML models, based on learning from operational data, classify grid states into stable and unstable and enable the early warning of potentially dangerous operating situations. Grid stability is assessed using voltage criteria which are the result of power flow simulations and grid stability is maintained when minimum bus voltage level is over 0.98 p.u., along with the consideration of voltage spread and power losses. The ML models also estimate the probability of system stability based on voltage and operational characteristics.

2.3 Dataset Description and Data Source

The dataset used in this study was created on the basis of time-series power flow simulations performed by developing a python code, using a 5-bus model (representing an extraction phase in Moroccan electrical network) with actual data from the national office of electricity and drinking water (ONEE), as well as based on datasets previously presented and validated in [1]. The pandapower framework was used for deterministic steady-state AC simulation over wide range of operating regime. The final database includes renewable generation from the Tinghir (solar station) and the Midelt (wind park) power plant, fixed load demands in Errachidia, Midelt and Mibladen buses as well as system variables like active power losses and minimum/maximum buses voltages. Every operating point is determined stable or unstable by the voltage stability criteria based on power-flow. The dataset is simulated and consequently machine learning models are trained and evaluated using the generated dataset, where model performance is estimated with confusion matrices as well as standard classification metrics including accuracy, precision, recall, and F1-score.

3. Simulation results and Discussion

This section presents the simulation results obtained from the generated dataset and evaluates performance of the trained machine learning models for grid stability prediction. Then, the four classifiers are analyzed through confusion matrices and performance metrics. Finally, the comparison study between those models is offered to illustrate their precision, robustness and generalization in predicting power system stability with renewable energy and green hydrogen integration.

3.1 Performance Evaluation and Error Analysis of ML Models used in grid stability prediction

a) RBF SVM

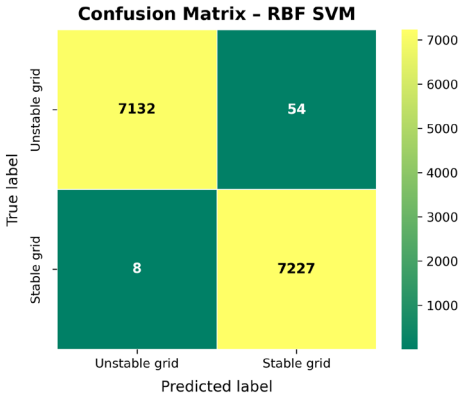


Fig. 3 : Confusion Matrix of the RBF SVM Model for Grid Stability Prediction.

The confusion matrix shown in Fig. 3 indicates that the RBF SVM model achieves strong performance in predicting grid stability. It correctly classifies 7,132 unstable states and 7,227 stable states, reflecting high sensitivity and specificity. Misclassifications are minimal, with only 54 unstable states incorrectly predicted as stable and 8 stable states incorrectly classified as

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unstable. This indicates a low rate of false positives and false negatives. The findings show that the RBF SVM is a useful tool for predicting grid stability in the context of hydrogen integration and renewable generation since it reliably distinguishes between stable and unstable operating scenarios.

b) Random Forest

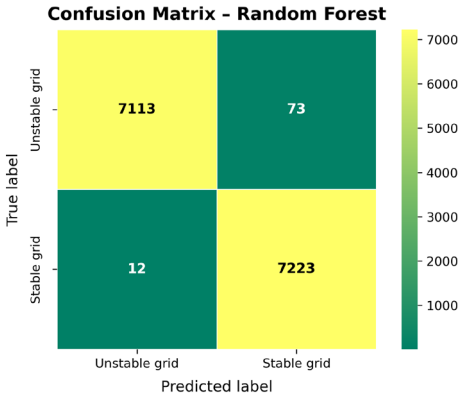


Fig. 4 : Confusion Matrix of the Random Forest Model for Grid Stability Prediction.

As shown in Fig. 4, the Random Forest model effectively differentiates between stable and unstable grid states, achieving high accuracy for both classes. It correctly identifies 7,113 unstable operating conditions and 7,223 stable ones. Only a small number of misclassifications are observed, with 73 unstable states predicted as stable and 12 stable states classified as unstable, resulting in very low false-negative and false-positive rates. These results indicate that the Random Forest model provides reliable grid stability assessment in scenarios involving renewable energy and hydrogen integration.

c) QDA

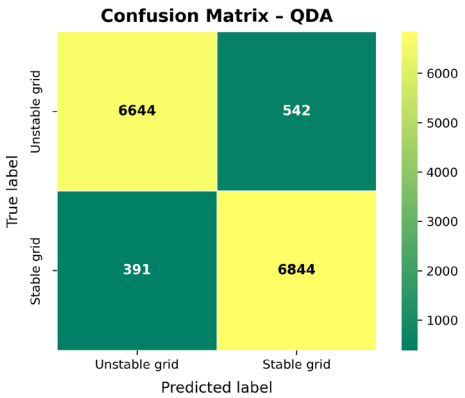


Fig. 5 : Confusion Matrix of the QDA Model for Grid Stability Prediction.

As illustrated in Fig. 5, the QDA model shows moderate performance in predicting grid stability. Compared with the RBF SVM and Random Forest models, it correctly identifies 6,644 unstable states and 6,844 stable states, but with a noticeably higher number of misclassifications. In particular, 391 stable states are incorrectly classified as unstable, while 542 unstable states are predicted as stable. These higher false-positive and false-negative rates indicate that QDA is less reliable for grid stability assessment under the studied conditions.

d) Naive Bayes

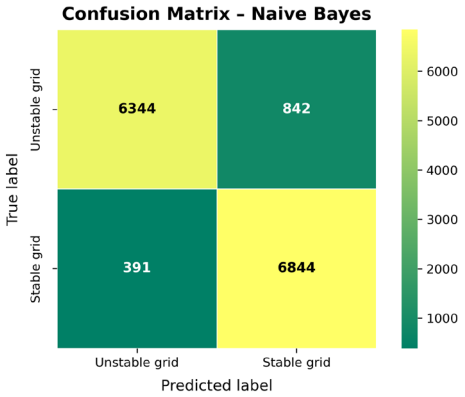


Fig. 6 : Confusion Matrix of the Naive Bayes Model for Grid Stability Prediction.

Among the evaluated classifiers, Fig. 6. shows that the Naive Bayes model performs the poorest among the classifiers. While it correctly identifies 6,844 stable and 6,344 unstable states, it misclassifies 842 unstable states as stable and 391 stable states as unstable. These errors highlight the model's limited ability to capture the complex interactions governing grid stability, making it less suitable for reliable stability prediction.

3.2 Comparison between ML models metrics

Table 1 provides performance numbers that strongly distinguish ML models from simpler statistical classifiers. The best performing model is the RBF SVM (99.57% accuracy) with very good precision, recall and F1-score being able to discern well between stable and unstable grid statuses. The Random Forest also does well on this problem, achieving 99.42% accuracy and very high scores across all metrics. On the other hand, QDA performs moderately well (accuracy of 93.53%), reflecting the fact that it has difficulty learning non-linear patterns in this data. The output clearly shows that Naive Bayes has the weakest performance as the accuracy is only 91.45% and precision is lower, indicating a greater false positive potential in prediction. In general, RBF SVM and Random Forest outperform QDA and Naive Bayes obviously, which verifies that they are more suitable for evaluating grid stability.

Table 1: Evaluation metrics (Accuracy, Precision, Recall, and F1-score) of different ML models applied to grid stability prediction.

Model	Accuracy [%]	Precision [%]	Recall [%]	F1-score [%]
RBF SVM	99.57	99.26	99.89	99.57
Random Forest	99.42	99.01	99.85	99.43
QDA	93.53	92.66	94.6	93.62
Naive Bayes	91.45	89.05	94.6	91.74

3.3 Interpretation of the results

Results in Fig. 7 reveal a clear performance ranking among the evaluated models. RBF SVM and Random Forest achieve the best performance, with accuracies above 99% and very low misclassification rates, which confirms their ability to capture the nonlinear behavior of the grid under renewable and hydrogen integration. In addition, QDA and Naive Bayes achieve lower accuracy rates of approximately 93.5% and 91.5%, also produce more false positives and false negatives. Overall, RBF SVM is the most effective model for grid stability prediction, closely followed by Random Forest.

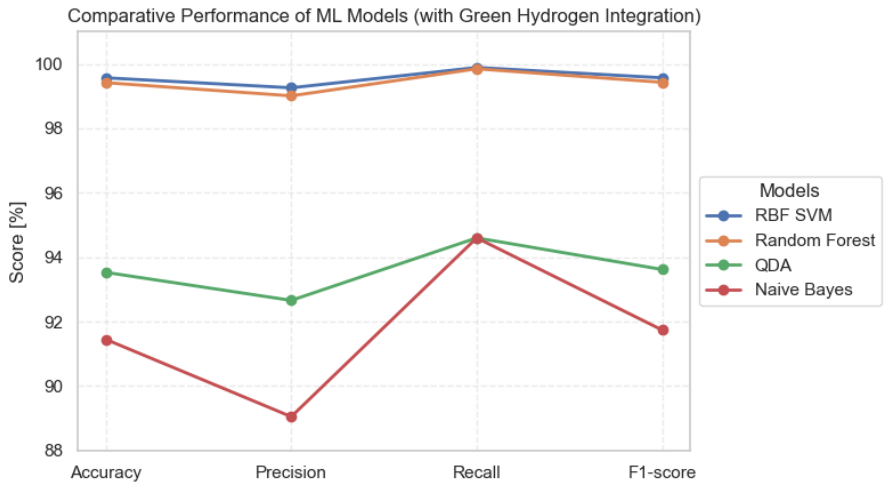


Fig. 7: Comparative Performance Analysis of ML Models for Electrical Grid Stability Prediction Under Green Hydrogen Integration.

Conclusion

This work combines time-series power-flow simulations in pandapower with machine learning to assess voltage stability in a Moroccan transmission network segment with green hydrogen storage. To do this, a large dataset was generated from many operating scenarios, then used to be trained by machine learning models, namely RBF-SVM, Random Forest, QDA and Naive Bayes. The performance of the different machine learning models was evaluated using confusion matrices and performance indicators such as accuracy, precision, recall and F1-score. The results show that RBF-SVM achieves the best overall performance, closely followed by Random Forest, while QDA and Naive Bayes deliver lower accuracy with more false positives and false negatives. Overall, the model choice should balance predictive performance with ease of implementation and the need for rapid real-time tracking of network stability. Future work may focus on extending this approach to larger-scale networks and on its deployment in real-time applications.

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