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RESEARCH ARTICLE

Tuar–Transitory–Instabilità (T^2i): An ML-Based Framework to Predict Transient Instability in a 7-Power Plant Network

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ABSTRACT With the expansion in recent power systems, the boost in renewable energy resources with multiple interconnections, overloading of existing power networks, increased load growth, and equipment failures, power system transient instability issues have exponentially increased. Transient stability in power systems is of particular importance even while performing the steady state analysis of a power system. Power system transient stability assessment is mandatory regularly for power system operation and has a major impact on power system planning. Potential risks of blackouts and failures in power systems can be avoided or minimized with the prompt prediction of transient instability. This research work presents a predictive approach for power system transient instability. The case study is a 735kV, 29-bus, 7-powerplant network involving precise modeling of generators. In particular, the proposed method is represented by different machine learning models through extraction and regression, in which the variables of the power-generating units are used as primary sources/features. Data cleaning and sorting out techniques are being used for refining data. Feature extraction has also been implemented for further cleansing of the data. The result is in the form of concrete and robust classifier models that can overcome power systems' instability concerns through prompt prediction.

INDEX TERMS Renewable energy sources, large-scale integration, power system transients, transient analysis, power system stability, machine learning.

I. INTRODUCTION

Power systems are expected to provide steady and reliable power to its consumers. The behavior of power systems is adversely affected due to external and internal perturbations, both natural and man-made.

For instance, a major disturbance is (i) the addition of large-scale photovoltaic (PV) systems in existing infrastructure to accommodate high load demand. These PV generation sources present higher intermittent characteristics and lower inertial response [1], [2].

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Additionally, (ii) overloading of existing transmission lines, (iii) increased load growth, (iv) equipment failures, and (iv) interconnecting power networks arising from diverging sources are collectively responsible for disturbing a power system [3], [4], [5].

Moreover, modern power systems have evolved to accommodate novel topologies within renewable energy. One of which is the '*distributed generati*' (DG) topology. Within the confine of renewable energy, DG(s) encompasses both converters and inverters, which operate non-linearly. Furthermore, DG(s) lack backup within the system. Together, these (v) non-linear operations and (vi) lack of backup severely impact the stability of an existing system both in the form of line and generator outages leading to blackouts [6], [7], [8].

As the above set of disturbances is unavoidable, for a power system to provide steady and reliable power to its consumers, it must stabilize the system in the least amount of time.

Therefore, in the default case, a power system exists in a healthy state (S_0). After the onset of a multitude of disturbances, a power system enters an unstable state (called 'transient instability $\equiv S_1$), which is transient in nature as the system is designed to withstand and address these perturbations, to finally achieve equilibrium ($S_2 \equiv$ 'steady state').

While in a 'transient instability' state, a power system exhibits a significant power imbalance between generating stations and load dispatch centers causing oscillations. These oscillations if left unchecked can lead to brownouts to blackouts.

Hence, '*power system transient stability analysis*' (PSTSA) is essential in evaluating whether a system can withstand these disturbances and achieve an equilibrium state after such incidences within a reasonable time [9], [10], [11].

As transitioning from 'transient instability' (S_1) to equilibrium is essential for a healthy power system, a fast detection method that recognizes 'transient instability' may help to mitigate disturbances in the power system [12], [13], [14].

The literature offers several methods for assessing transient instability measures [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27]. One such approach employs the Taylor series, incorporating (a) angular changes during S1, (b) associated clearance time, and (c) dynamic resistance to maintain system synchronization with stability enhancement. As this technique does not require a specific network, stated alternatively, applies to all networks, it acts as a suitable benchmark for stability studies [15].

The following two equations summarize this scheme:

$$T = \left(\frac{\pi}{8}\right) \cdot P^2 \cdot \phi_a \cdot \mathrm{F}_r \cdot \sin(\delta) \tag{1}$$

$$M\frac{d^2\delta}{dt^2} + \frac{d\delta}{dt} = P_{I,M} - P_{O,E} \tag{2}$$

Here above, equation (1) measures mechanical shaft torque (T) of the generator concerning the number of poles (P), air gap flux (ϕ_a), rotor field magnetomotive force (F_r), and power angle $\{\sin(\delta)\}$.

Whereas equation (2) above, relates the inertia constant $\left(M\frac{d^2\delta}{dt^2}\right)$ and damping constant $\left(\frac{d\delta}{dt}\right)$ of the generator to the difference of the input mechanical ($P_{I,M}$) and output electrical power ($P_{O,E}$) [15].

Similarly, Zhang et al. proposed a model of PSTSA using principal component analysis [16]. While [17] recommended using a hybrid approach incorporating both higher-order Taylor series and block-bordered diagonal algorithm for PSTSA. Similarly, [18] suggests an intermediate model between transient stability and electromagnetic transients for the same.

Non-linear model decoupling (NMD) is another approach that measures transient instability by transforming a multi-oscillator system into a series of decoupled oscillators. Since each oscillator represents a single item of interest, its dynamics can be analyzed separately, making NMD suitable for large utility grids [19], [20].

Additionally, Ashraf and Chakrabarti recommend using Kalman Filters to track rotor angles in real time for measuring transient stability [21].

Similarly, Gupta and Gurrala propose a Convolution Neural Network (CNN) to present an online monitoring solution for predicting instability within a power system [22].

Furthermore, Shi et al. employ CNN to analyze both periodic and aperiodic stability. The model transforms voltages into a grid-like topology, analogs to images, and then feeds them into a CNN, thereby mapping it to three classes, each quantified by their likelihoods, as shown in Figure 1 [23].

Extending CNN(s), deep learning too has made its way to PSTSA [24], [25], [26], [27], [28], [29], [30], [31]. Some research methodologies are extending the task for economic dispatch to ease real-time energy management [32], [33].

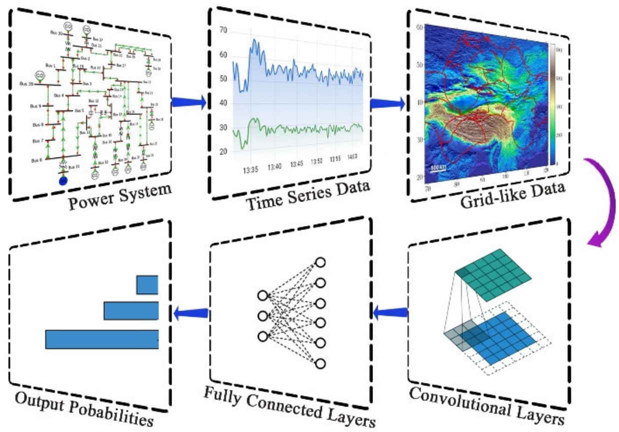


FIGURE 1. The model transforms voltages into a grid-like topology and then feeds them into a CNN. Thereafter, the model presents three normalized probability measures, each catering to a class of interest.

The above-mentioned techniques present the following gaps.

1) CNNs and deep-learning frameworks are computationally expensive to operate and require comparatively greater time to predict the unstable state of the power system.
2) They are designed to address a limited number of disturbances leading to transient instability, as shown in Table 1.
3) They refer to a reduced set of parameters to draw their conclusions, as shown in Table 2.
4) They do not present safe – operating ranges for different parameters that are required to smoothly run the power system.

TABLE 1. Number of faults addressed in the literature survey.

# of Faults	Description
1	LLL faults [23], [27]-[30].
1	LLLG faults [22]-[25].
2	LG and LLLG faults [24].
4	LG, LL, LLG, LLL [31].

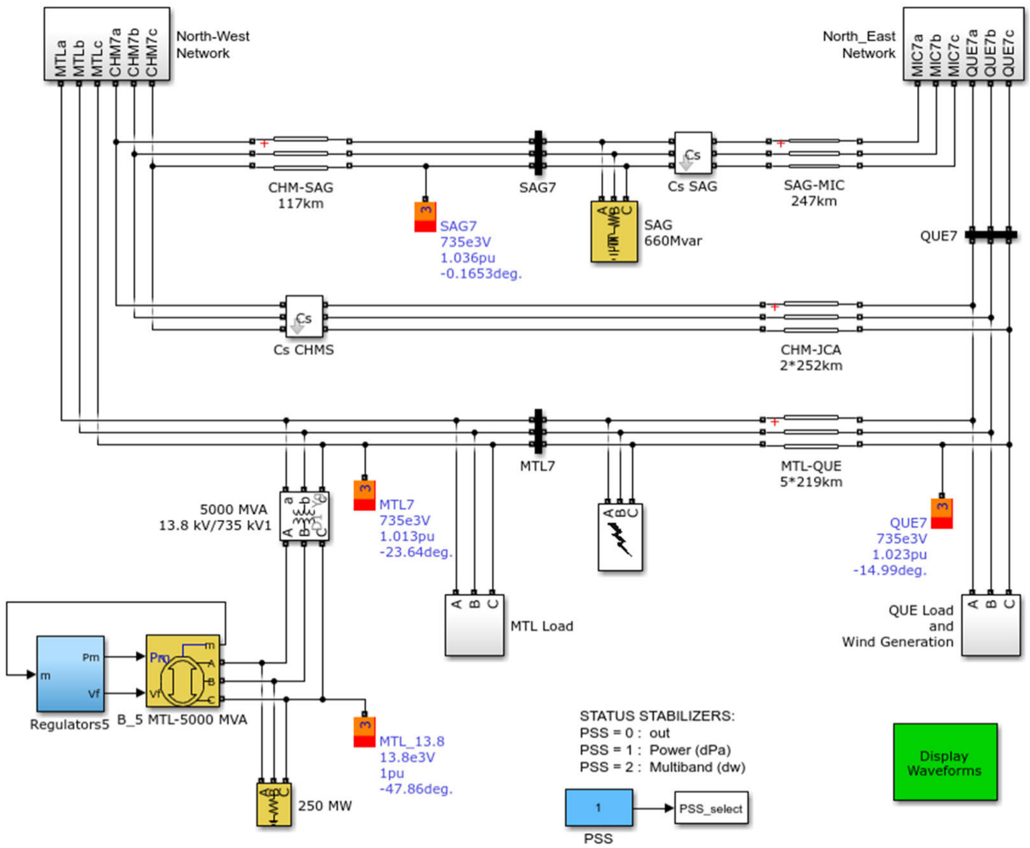


FIGURE 2. Diagram of MathWorks 29-bus power plant network with a transmission system of 735kV. The transmission system is compensated with series and shunt compensation too so that every cause of instability should be there on board. Moreover, detailed modeling of turbines, voltage regulators, stabilizers, and excitation system is there in the network.

TABLE 2. Number of parameters considered in the literature survey.

# of Parameters	Description
1	Voltage [31].
1	Rotor Angle [25]-[27].
2	Voltage magnitude and phase angles [23].
3	Speed, active and reactive powers [28].
3	Voltage magnitude with phase angle and frequency [22].
4	Voltage magnitude with angles, active and reactive powers [29].
4	Power angle, angular velocity, unbalanced power, and reactive power [30].
5	Voltage, frequency, load angle, active and reactive powers [24].

TABLE 3. States of the power system.

State No.	Description
0	Normal/stable state
1	Transient instability state
2	Steady state

TABLE 4. Faults categories.

Fault tags	Description
F1	LG - Single line-ground fault for 0.2 seconds
F2	LLG - Double line-ground fault for 0.2 seconds
F3	LLLG - Triple line-ground fault for 0.2 seconds
F4	LLL - Triple line fault for 0.2 seconds
F5	LL - Double line fault for 0.2 seconds
F6	LLLG – Triple line-ground fault for 1.2 seconds

II. METHODS

The following summarizes the methodology:

A. STATES AND FAULTS

To investigate the transient instability of the power system, we are considering a total of three states (stable, transiently unstable, and steady states) as given in Table 3. Several faults are being simulated to generate the data against each state and generator of the given power system. Different fault categories are mentioned along with the tags, in Table 4.

B. SYSTEM UNDER CONSIDERATION

We employ MathWorks 29-bus power plant network, comprising a 735kV transmission system, and 7-generating units with power generation of 26,200 MVA, as shown in Figure 2. Total simulation time is 0 – 9.975 seconds and fault duration are 3.8–4.0 seconds. Step size is approximated to get 44689 samples against twelve (12) features as per the Nyquist criteria which is the minimum data requirement for a signal. Samples generated against 6 faults, 7 generating units, and

TABLE 5. Proposed features of the power system.

#	Features	Description
1	Is-a (pu)	Stator current of phase A in per unit
2	Is-b (pu)	Stator current of phase B in per unit
3	Is-c (pu)	Stator current of phase C in per unit
4	Wm (pu)	Rotor speed in per unit
5	dW (pu)	Deviation in rotor speed in per unit
6	$\boldsymbol{\theta}$ (deg)	Rotor mechanical angle in degrees
7	$\boldsymbol{\theta_D}$ (rad)	Deviation in rotor angle in radians
8	$\boldsymbol{\delta}$ (deg)	Load angle in degrees
9	P (pu)	Output active power in per unit
10	Q (pu)	Output reactive power in per unit
11	T (pu)	Electromagnetic torque in per unit
12	V (pu)	Terminal voltages in per unit

3 states are being concentrated, to sum up the data in a single file. A list of these proposed features is shown in Table 5.

Please note in Table 5 above, the feature $\boldsymbol{\theta}$: rotor angle represents the angular displacement of the rotor in mechanical degrees with respect to the stationary axis whereas, the component $\boldsymbol{\delta}$: load angle denotes the angular displacement of the rotor with respect to the synchronously rotating reference axis.

C. STATE BOUNDARIES APPROXIMATION

To determine the boundaries of different states, we looked at the amplitude of each signal independently along both the x and y-axis, as shown in Figures 3 and 4, and Table 6.

A typical case has also been considered in which the fault duration is increased from 0.2 seconds to 1.2 seconds. This is comparatively a long-lasting fault that pushes the system to permanent instability as shown in Figure 5.

D. NORMALIZING THE DATA

We normalized the data using 'MinMaxScaler,' (MMS) such that the least value is reduced to 0 while the largest is scaled to 1. MMS has the added advantage, that any new value less than the smallest value of a feature is reduced to 0, while any value larger than the highest value is scaled to 1. Below, Table 7 enumerates the minimum and maximum values of each of the twelve features.

E. SPLITTING THE DATA

Total samples of the data generated are being divided into train samples, test samples, and validation samples. Train samples are used to train the machine learning models and they require a bigger data set as compared to test and validation samples, to master the prediction model. Test samples and validation samples require comparatively small data sets as they are only required for validating the accuracy of any prediction models. 60% of the total data samples are classified as train samples for the training of the model, 20% as test samples, and 20% as validation samples. The stratified details of the data samples against different states of the power system are also presented in Table 8. Table 8 gives a fair estimate that the data is approximately balanced and there is no need for any further process on the normalized data. One major advantage of pre-data processing and balancing is that

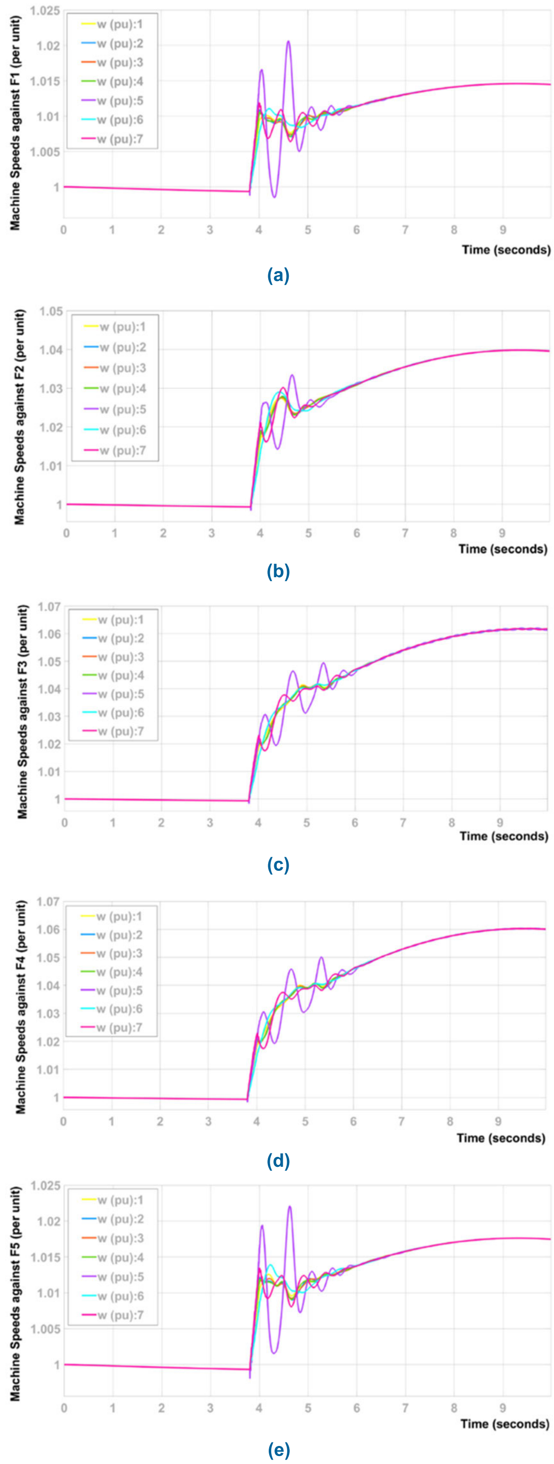
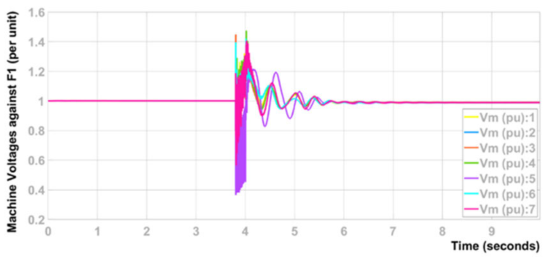


FIGURE 3. Waveforms of generating units' rotor speed against (a) Line-ground fault, (b) Double line-ground fault, (c) Triple line-ground fault, (d) Triple line fault, and (e) Double line fault.

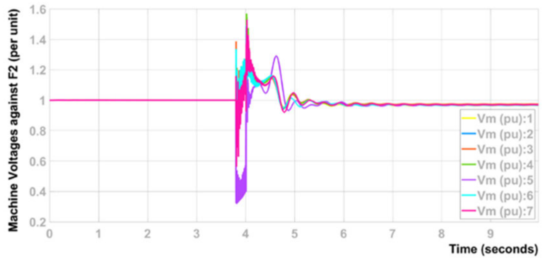
classifiers will yield comparatively better accuracies of tests and validation against the data samples.

F. FEATURE SELECTION

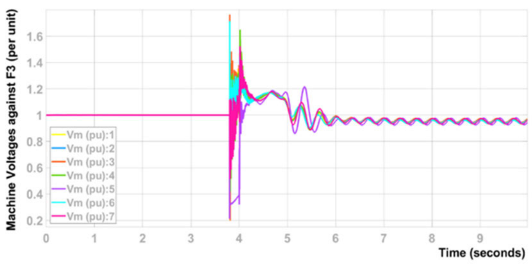
If all the available data samples are presented to machine learning models, then it will take a comparatively longer



(a)



(b)



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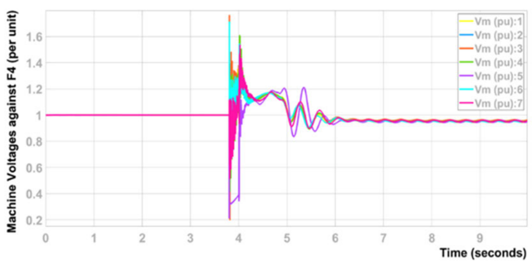

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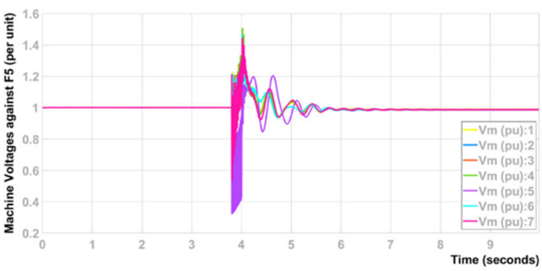
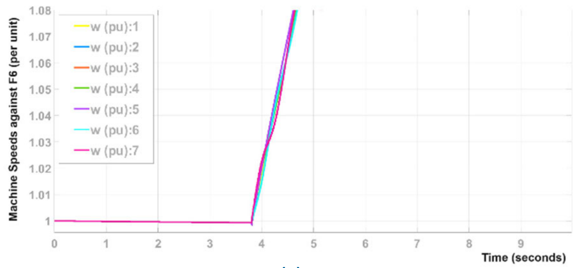
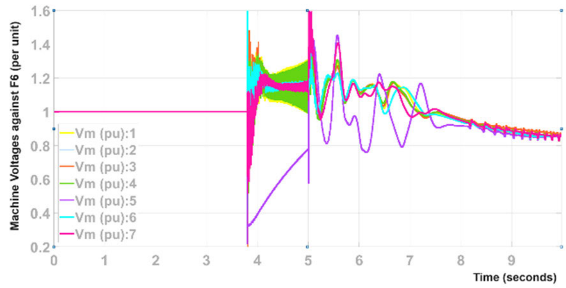


(e)

FIGURE 4. **Waveforms of generating units' terminal voltage against (a) Line-ground fault, (b) Double line-ground fault, (c) Triple line-ground fault, (d) Triple line fault, and (e) Double line fault.**



(a)



(b)

FIGURE 5. **Waveforms of generating units' (a) Rotor speed, and (b) Terminal voltage against the long-lasting triple line-ground fault of 1.2 seconds.**

TABLE 6. **State boundaries against each category of fault.**

State estimation	S1	S2	S3
F1 (sec)	0 – 3.8	3.8 – 7.0	7.0 – 9.98
F2 (sec)	0 – 3.8	3.8 – 7.0	7.0 – 9.98
F3 (sec)	0 – 3.8	3.8 – 7.0	7.0 – 9.98
F4 (sec)	0 – 3.8	3.8 – 7.0	7.0 – 9.98
F5 (sec)	0 – 3.8	3.8 – 6.5	6.5 – 9.98
F6 (sec)	0 – 3.8	3.8 – 9.98	Nonexistent

TABLE 7. **Minimum and maximum values of input features.**

#	Features	Min. value	Max. value
1	Is-a (pu)	-5.3993	5.4401
2	Is-b (pu)	-5.6364	5.6991
3	Is-c (pu)	-5.7278	5.6871
4	Wm(pu)	0.9985	1.3377
5	dW (pu)	-0.0015	0.3377
6	θ (deg)	-2.0389	359.9986
7	θ_D (rad)	-2.4931	475.7835
8	δ (deg)	-25.7896	50.3981
9	P (pu)	-1.8163	5.2446
10	Q (pu)	-1.6615	5.0408
11	T (pu)	-2.3955	4.7424
12	V (pu)	0.3188	1.6553

TABLE 8. **The samples are generated for the representation of all three states.**

Type of state	Percentage
0 – No fault state	38.07 %
1 – Transient instability state	36.19 %
2 – Steady state	25.73 %

time for prediction of the required state with compromised accuracy but if only the specific data that does matter, is presented to models then it will be a big favor to prediction accuracy and time required [34]. Box plots may give an approximate idea of important features in which there are large deviations in data. To mature this process of fetching out the optimal features, a comprehensive feature selection is required. Feature selection facilitates making a subgroup of

TABLE 9. Results of exhaustive feature selection.

Features	Sets	Acc. (%)	Is-a	Is-b	Is-c	W	dW	θ	dθ	δ	P	Q	T	V
1	12	95.57				×								
2	66	99.79				×			×					
3	220	99.83				×			×					×
<u>4</u>	495	<u>99.84</u>				×	×		×					×
5	792	99.82				×	×		×	×			×	
6	924	99.81				×			×	×	×	×	×	
7	792	99.81				×	×		×	×	×	×	×	
8	495	99.76				×	×		×	×	×	×	×	×
9	220	99.16	×			×	×		×	×	×	×	×	×
10	66	98.83	×	×	×	×	×		×		×	×	×	×
11	12	98.64	×	×	×	×	×		×	×	×	×	×	×
12	1	95.76	×	×	×	×	×	×	×	×	×	×	×	×
Selected Features						×	×		×					×

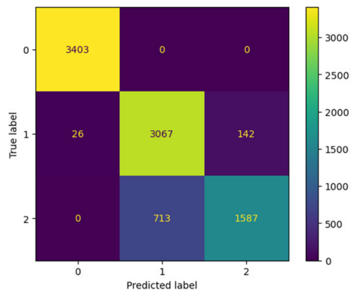


FIGURE 6. Confusion matrix against linear support vector machine classifier.

TABLE 10. Confusion matrix results against linear support vector machine classifier.

State	Correct classified	Wrong classified	Accuracy (%)	Combined accuracy (%)
0	3403	0	100%	
1	3067	168	94.80%	90.14%
2	1587	713	69%	

features that play a vital role in making a prediction model for transient instability. This technique also reduces the amount and dimensionality of the data which is further required to get a handsome prediction accuracy. Many features in the data are just a waste of time and computational resources [35].

In the proposed scheme, exhaustive feature selection is employed for feature selection and extraction. Exhaustive feature selector uses K Neighbor classifier algorithms that is a non-parametric classifier. With 12 features, the total number of feature sets is 4095, as per the following formula in equation (3).

$$C(n,k) = \frac{n!}{k!\,(n-k)\,!} \tag{3}$$

where n represents the total number of features and k represents the selected features in equation (3). The results of exhaustive selection against a selected number of features are given in Table 9. Here, Table 9 indicates that the top four features are (i) rotor speed (W), (ii) rotor speed deviation (dW), (ii) rotor angle deviation ($d\theta$), (iv) terminal voltage (V). However, literature suggests that (v) load angle (δ) which is also an important measure [36]. As Table 9 indicates that almost all top feature sets display an accuracy above 98%, the authors decided on five features $\{W, dW, d\theta, V, \delta\}$.

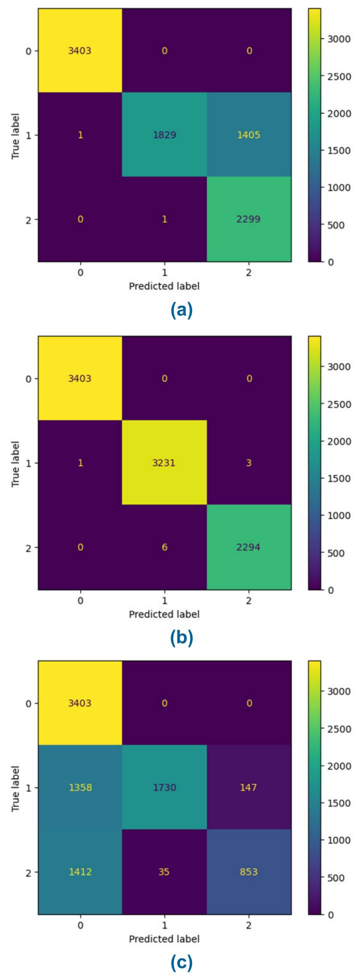


FIGURE 7. Confusion matrices for (a) Gaussian Naïve Byes classifier, (b) Random Forest classifier, and (c) Linear Discriminant Analysis classifier.

III. RESULTS AND DISCUSSION

In this section, the performance of all the classifiers has been presented in the form of confusion matrices and tables.

TABLE 11. Confusion matrix results against gaussian Naïve byes classifier.

State	Correct classified	Wrong classified	Accuracy (%)	Combined accuracy (%)
0	3403	0	100%	
1	1829	1406	56.54%	84.26%
2	2299	1	99.96%	

TABLE 12. Confusion matrix results against random forest classifier.

State	Correct classified	Wrong classified	Accuracy (%)	Combined accuracy (%)
0	3403	0	100%	
1	3231	4	99.88%	99.89%
2	2294	6	99.74%	

TABLE 13. Confusion matrix results against linear discriminant analysis classifier.

State	Correct classified	Wrong classified	Accuracy (%)	Combined accuracy (%)
0	3403	0	100%	
1	1730	1505	53.48%	66.97%
2	853	1447	37.09%	

TABLE 14. Results of the classifiers on the test and validation set.

#	Type of classifier	Test accuracy (%)	Validation accuracy (%)
1	Gaussian Naïve Classifier	84.26	83.59
2	Decision Tree Classifier	99.82	99.82
3	KNN – 3 Classifier	99.86	99.83
4	KNN – 5 Classifier	99.86	99.83
5	Logistic Reg. Classifier	89.53	89.43
6	Random Forest Classifier	99.92	99.91
7	Linear Disc. Analysis	66.97	66.66
8	Quadratic Disc. Analysis	52.33	51.48

Results for the Linear Support Vector Machine (SVM) classifier are given in Figure 6 and Table 10 with the test set accuracy of 90.14%.

Confusion matrices against some other classifiers like the Gaussian Naïve Byes classifier, Random Forest classifier, and Linear Discriminant Analysis classifier are given in Figure 7 with detailed classification details in Table 11-13 with the individual state accuracies and the combined test set accuracies.

We tested eight (8) classifiers for the predictive approach, as shown in Table 14.

As can be seen from Table 14, the Decision Tree (DT) Classifier, KNN – 3, KNN – 5, and Random Forest Classifier (RFC) have performed very well, even though the sampling rate, as highlighted in Section II-B, was kept close to the Nyquist criteria. These high accuracies may be attributed to a softer noise model within the underlying MathWorks 29-bus power system, which may not do justice to the real system with similar characteristics. Among these four models, we choose RFC as the model of choice for T^2i because (i) it presents the highest accuracy, and (ii) is more robust than DT and KNN rules [37].

Please note, among the limitations of T^2i is its overarching reliance on one 29-bus power system for training, making it overfit the existing framework. As maxima and minima values of selected features will differ widely depending upon the impedances and transient response of different power systems, revising state boundary approximations, hence, T^2i needs to be both trained and evaluated on multiple systems.

IV. CONCLUSION

As mentioned in Section I, there were four (4) research gaps and this research work have covered three (3) of them, which are as follows,

1) This research work has predicted transient instability within one second using an Intel Core i7, 2 GHz processor.
2) This framework has addressed, comparatively a greater number of disturbances (six), as mentioned in Table 4.
3) A considerable set of parameters were considered and the top five features delivered very promising results.

Overall, this research work provides proof of concept for Tuar – transitory – instabilità, (T^2i), a transient instability prediction model showing very promising results and covering most of the research gaps presented in the literature survey. Moreover, T^2i potentially facilitates power plant operators to identify the transient instability state within a second, allowing them to take remedial measures for stabilizing the system by controlling generator parameters, thus avoiding permanent instability and blackouts.

Future work will focus on addressing existing limitations by extending and evaluating T^2i to real-world power networks with different operating characteristics, containing fault occurrence at distinct locations, and increased durations, which will also help improve T^2i's robustness.

Lastly, the authors chose the phrase "Tuar – transitory – instabilità" for the proposed framework as it is a combination of three words 'predict,' 'transient,' and 'instability.' The word for predict in Irish is 'Tuar', while transient is translated as 'transitory' in Catalan. Finally, instability is translated as 'instabilità' in Italian. As the paper introduces a novel framework for detecting transient instability in a medium-scale power plant network, the phrase 'Tuar – transitory – instabilità' (T^2i) is appropriate.

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