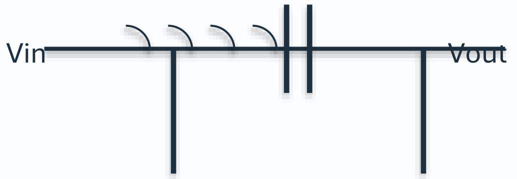
14th International Scientific Conference • COMPUTER SCIENCE 2026 September 13–15, 2026 • Sozopol, Bulgaria

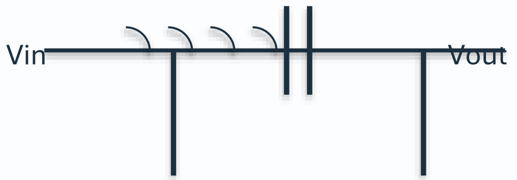
From Power Electronics to Data Intelligence:

Comparative Study of SEPIC and ĆUK Converters with Weka Analysis

SEPIC



ĆUK



Mirjana Kocaleva Vitanova[1] • Elena Karamazova Gelova[1] • Zoran Zlatev[1] • Nikolay Hinov[2,3] • Biljana Zlatanovska[1]

[1] Goce Delcev University, North Macedonia [2] National Center of Mechatronics and Clean Technologies [3] Technical University of Sofia

2. Motivation and Background

- DC–DC converters are essential in renewable energy, electric vehicles, storage systems and industrial electronics.
- Converter faults can reduce efficiency, cause instability, or lead to complete system shutdown.
- Traditional diagnostic methods may be limited under nonlinearities, parameter variations and changing operating conditions.
- Machine learning offers a data-driven approach for automatic fault detection and classification.

ML

Research goal

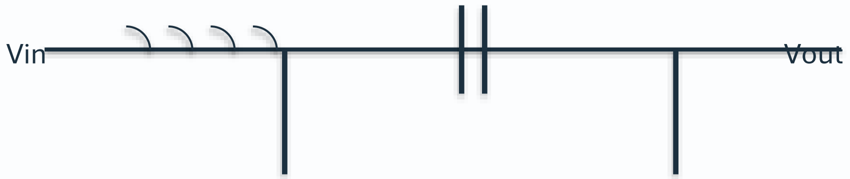
Evaluate fault classification for SEPIC and Ćuk converters under both fixed and variable input voltage.

Topology × Vin × Classifier

3. DC–DC Converter Topologies

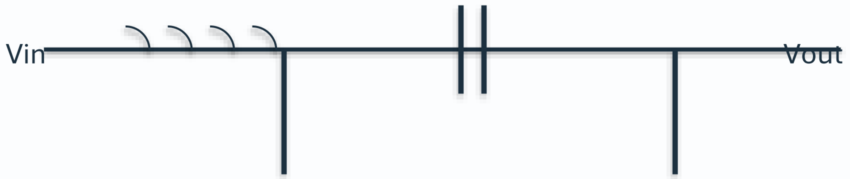
Two converter structures evaluated under the same diagnostic framework

SEPIC Converter



- Non-inverted output voltage
- Wide operating range
- Suitable for PV, battery and EV systems
- Additional passive components create multiple possible fault modes

Ćuk Converter



- Continuous input and output current
- Reduced current ripple
- Strong dynamic interaction between components
- Fault patterns may respond differently to Vin variation

4. Dataset Description

Four complementary datasets enable controlled and realistic comparisons

Converters	SEPIC and Ćuk
Input conditions	Fixed Vin and Variable Vin
Datasets	**A.1 SEPIC Fixed • B.1 SEPIC Variable** **A.2 Ćuk Fixed • B.2 Ćuk Variable**
Instances	200 per dataset
Classes	**NoFault • CapacitorFault • InductorFault • SwitchFault**
Features	Vin • Vout • Iin • Iout • Temperature

5. Methodology

From converter data to validated machine-learning models

1. **Data generation**

   Normal and faulty states under fixed and variable Vin.

2. **Feature extraction**

   Vin, Vout, Iin, Iout and temperature.

3. **Weka classification**

   Eight supervised algorithms from different learning families.

4. **Validation**

   Identical 10-fold cross-validation and multiple performance metrics.

Accuracy
Correct classes

F1
Precision + Recall

Kappa
Chance-corrected

ROC
Class separation

10-fold cross-validation

9 folds train → 1 fold test → repeat ×10

6. Machine Learning Algorithms

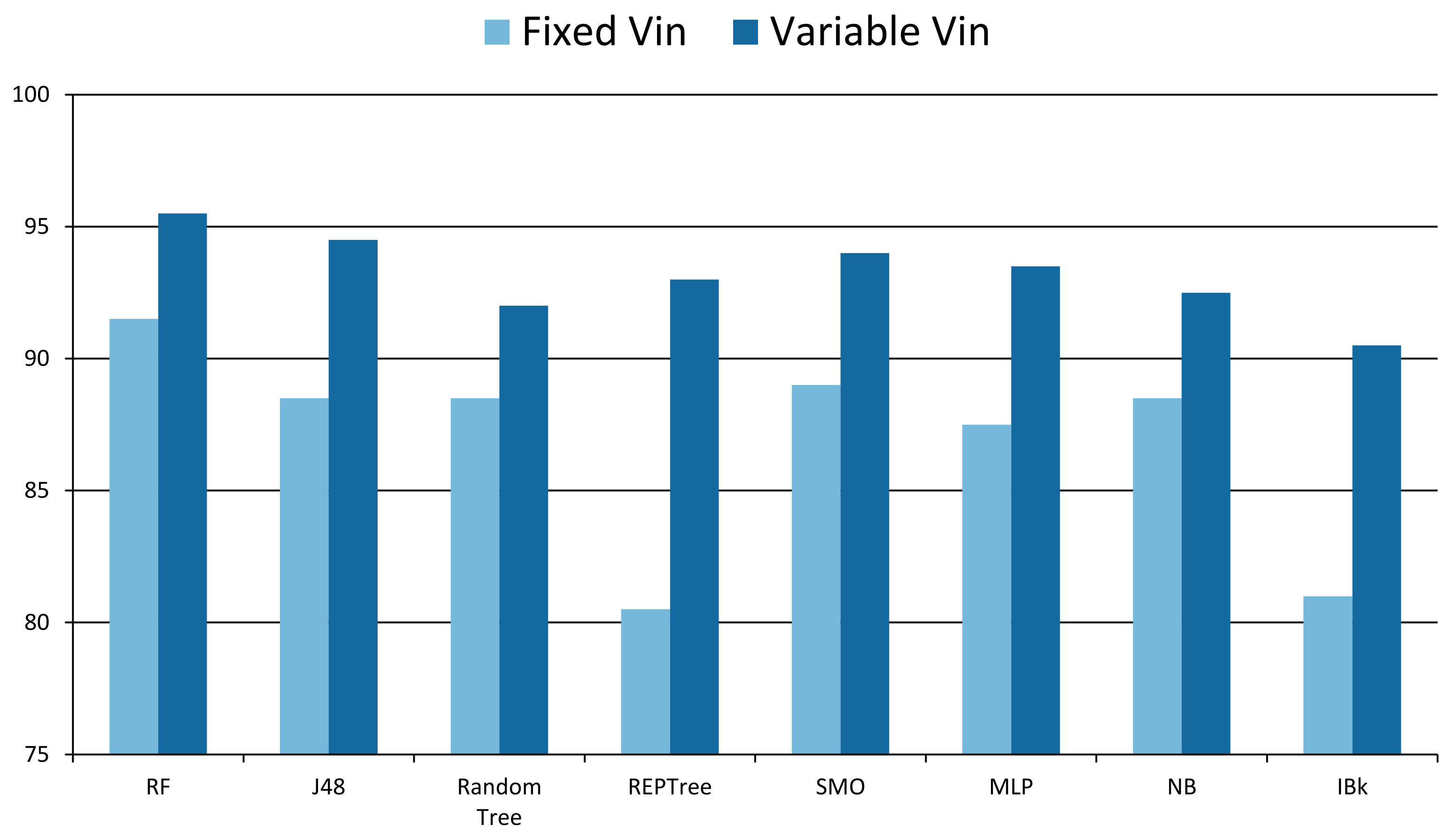
A diverse set of classifiers was evaluated in Weka

1. **Random Forest** — Ensemble trees
2. **J48** — Decision tree
3. **Random Tree** — Randomized tree
4. **REPTree** — Pruned fast tree
5. **SMO** — Support Vector Machine
6. **MLP** — Neural network
7. **Naïve Bayes** — Probabilistic
8. **IBk** — k-Nearest Neighbors

Same validation protocol → fair classifier comparison

7. Results – SEPIC Converter

Variable input voltage improves classification performance



95.5%

Best accuracy • Random Forest

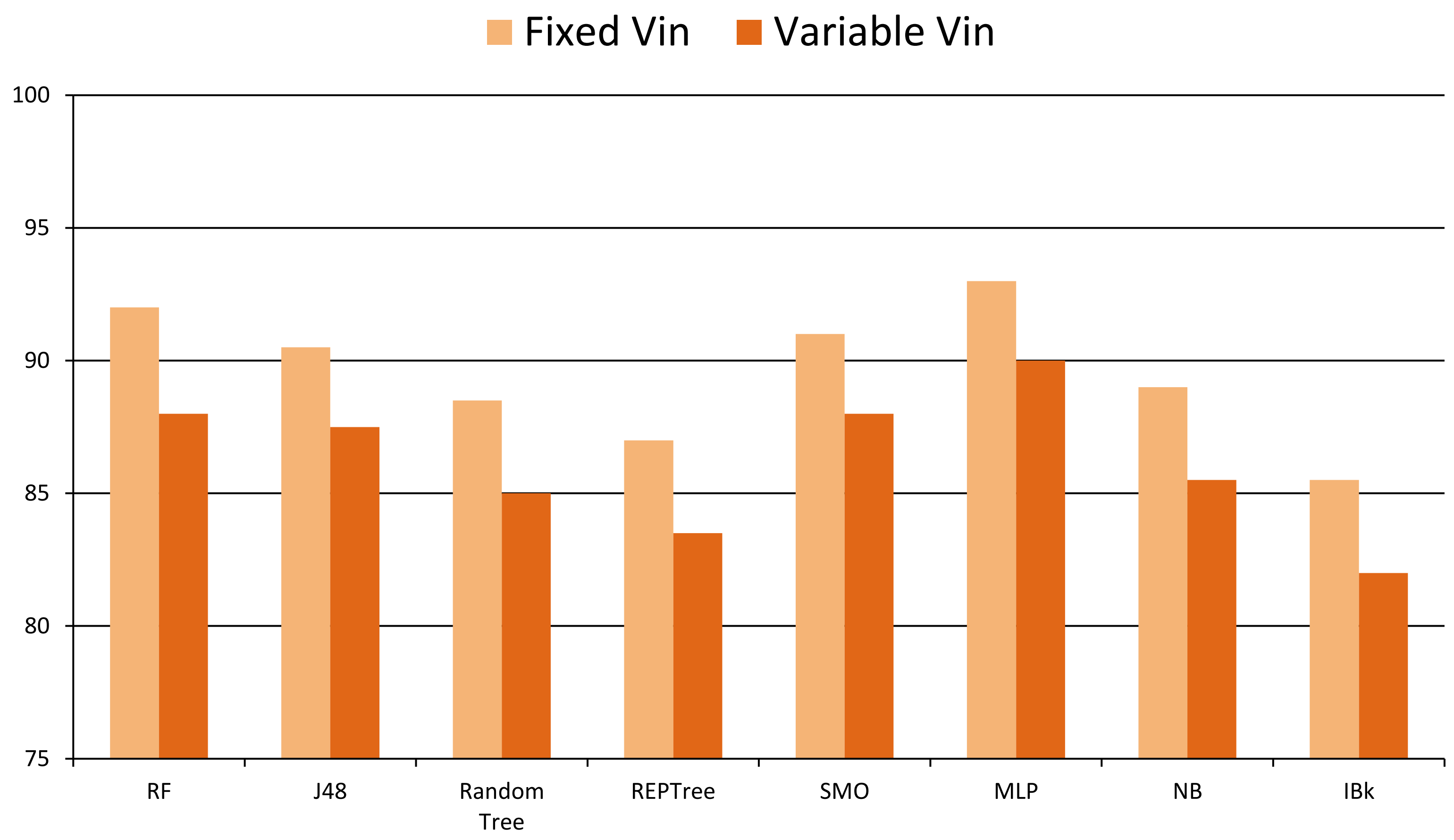
+5.19 pp

Average: 87.94% → 93.13%

Key result: all eight classifiers improve with variable Vin.

8. Results – Ćuk Converter

Variable Vin produces the opposite trend



93.0%

Best fixed-Vin result • MLP

−2.12 pp

Average: 89.56% → 87.44%

Ćuk is more sensitive to input-voltage variation.

9. Key Comparison

Topology determines whether variable Vin helps or hurts classification

Converter	Condition	Average accuracy	Trend	Interpretation
SEPIC	Fixed Vin	**87.94%**	**Baseline**	Controlled
SEPIC	Variable Vin	**93.13%**	**↑ +5.19 pp**	Improves
Ćuk	Fixed Vin	**89.56%**	**Baseline**	Controlled
Ćuk	Variable Vin	**87.44%**	**↓ −2.12 pp**	Decreases

SEPIC benefits from variable Vin, while Ćuk shows reduced classification performance.

10 Robustness Beyond Accuracy

- F1-score and Cohen's Kappa support the same conclusion

SEPIC • Variable Vin

Random Forest

F1 = 0.955

Kappa = 0.940

SEPIC • Variable Vin

J48

F1 = 0.955

Kappa = 0.940

Ćuk • Fixed Vin

MLP

F1 = 0.930

Kappa = 0.9067

Ćuk • Variable Vin

MLP

F1 = 0.900

Kappa = 0.8667

The additional metrics confirm reliable multi-class discrimination and the same topology-dependent trend.

11 Discussion and Practical Interpretation

•

1	**Operating variability**	Variable Vin can reveal useful fault patterns instead of simply adding noise.
2	**Topology dependence**	The same Vin variation improves SEPIC classification but reduces Ćuk performance.
3	**Model robustness**	Random Forest is among the best algorithms in all four scenarios.
4	**Dataset design**	Realistic operating variability should be represented when developing diagnostic systems.

Practical message: validate the diagnostic model on the actual converter topology and operating range.

12 Conclusions and Future Work

•

Conclusions

- Machine learning effectively distinguishes normal and faulty converter states.
- Random Forest shows the highest overall robustness; peak accuracy is 95.5%.
- SEPIC benefits from variable Vin, while Ćuk is more sensitive to voltage variation.

Future work

1. Extend datasets with more fault severities and operating points.
2. Validate the approach with measurements from physical converter prototypes.
3. Explore advanced ML and deep-learning models for real-time diagnostics.

Thank you for your attention!