Intelligent Fault Diagnosis of SEPIC and Ćuk Converters Using Machine Learning Techniques

Mirjana Kocaleva Vitanova*, Zoran Zlatev*, Elena Karamazova Gelova*, Biljana Zlatanovska* and Nikolay Hinov**

* Faculty of computer science, “Goce Delcev” University, Stip, Republic of North Macedonia

** Faculty of Electronic Engineering and Technologies, Technical University of Sofia, Bulgaria

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Motivation

- **Why intelligent fault diagnosis?**
- DC–DC converters are widely used in modern energy and electronic systems.
- Reliability and fault tolerance are critical requirements.
- Traditional diagnosis methods rely mainly on:
  - analytical models
  - predefined thresholds
  - expert rules
- Complex nonlinear behavior makes traditional approaches less effective.
- Machine Learning enables:
  - automatic pattern recognition
  - early fault detection
  - predictive maintenance
  - analysis of complex electrical signals.

SEPIC and Ćuk Converters

- Two DC–DC converter topologies

Characteristic	SEPIC	Ćuk
Voltage conversion	Step-up / Step-down	Step-up / Step-down
Output polarity	Positive	Negative
Input current	Continuous	Continuous
Output current	Pulsating	Continuous
Ripple	Higher	Lower
Efficiency	Moderate	Slightly higher
Complexity	Lower	Higher

Fault Types

- **Main fault types considered**

1. **Capacitor Fault**
    1. reduced capacitance
    2. increased ESR
    3. increased ripple
    4. unstable output voltage
2. **Inductor Fault**
    1. magnetic saturation
    2. winding damage
    3. increased losses

3. Switch Fault

1. MOSFET short circuit
2. MOSFET open circuit
3. disruption of switching process
4.

4. Diode Fault

1. short circuit
2. open circuit
3. irregular current flow
4. increased losses.

RESEARCH GAP

- **Why SEPIC and Ćuk?**
- Most existing studies focus on buck and boost converters.
- SEPIC and Ćuk converters are less explored.
- Faults produce different electrical signatures depending on topology.
- Comparative studies using the **same ML framework** are limited.
- There is a lack of standardized datasets for fault classification.
- **Main motivation:**
  Develop a unified framework for comparing intelligent fault diagnosis in SEPIC and Ćuk converters.

PROPOSED APPROACH

- **Machine Learning-Based Fault Diagnosis**
- **Converter simulation → Dataset generation → Data preprocessing → WEKA → Classification → Performance evaluation**
- The investigated algorithms are:
- Random Forest
- J48 Decision Tree
- Support Vector Machine (SMO)
- Naïve Bayes
- k-Nearest Neighbors (IBk).

DATASET

- **Unified SEPIC + Ćuk Dataset**
- **200 instances**
- Features:
- **Vin** – input voltage
- **Vout** – output voltage
- **IL1, IL2** – inductor currents
- **Ripple** – current ripple
- **Temp** – temperature
- **Efficiency** – efficiency
- **FaultClass** – fault category

Fault classes:

•Normal

•Capacitor Fault

•Inductor Fault

•Switch Fault

•Diode Fault

Vin = 12 V

Approximately equal number of samples per class and converter.

Data Preparation and WEKA

WEKA implementation

- Unified dataset for both converter topologies
- ConverterType used as a categorical feature
- 10% noise introduced using AddNoise
- Data normalization performed
- IBk:
    - k = 5
    - Euclidean distance
- 10-fold cross-validation
- 70% training / 30% testing where applicable.

EVALUATION METRICS

- **Performance evaluation**
- The classifiers were evaluated using:
- **Accuracy**
- **Precision**
- **Recall**
- **F1-score**
- **ROC Area / AUC**
- **Confusion Matrix**
- These metrics provide information about both overall accuracy and the ability to distinguish individual fault classes.

Experimental Results

Classifier	Accuracy	Precision	Recall	F1-score	ROC Area
Random Forest	83%	0.829	0.830	0.829	0.909
J48	**84%**	**0.840**	**0.840**	**0.839**	**0.914**
SMO	62%	0.645	0.620	0.616	0.839
Naïve Bayes	77%	0.806	0.770	0.765	0.899
IBk	**90%**	**0.900**	**0.900**	**0.899**	**0.924**

Best classifier: IBk (k-NN)
Accuracy = 90%

WHY IBK?

- **IBk achieved the best overall performance**
- Highest accuracy: **90%**
- Precision: **0.900**
- Recall: **0.900**
- F1-score: **0.899**
- Highest ROC Area: **0.924**
- Precision, Recall and F1-score are very close.
- This indicates stable and consistent classification performance.
- **J48 was the second-best classifier.**
- **SMO achieved the weakest results.**

CONFUSION MATRIX

IBk Confusion Matrix

Actual / Predicted	Normal	Capacitor	Inductor	Switch	Diode
Normal	36	2	0	0	0
Capacitor	0	36	2	2	4
Inductor	0	2	36	2	0
Switch	0	0	0	36	0
Diode	4	0	2	0	36

180 / 200 instances correctly classified
Error rate ≈ 10%
The largest classification difficulties occur mainly between **Capacitor, Inductor and Diode faults**.

Main Contributions

- **The main contributions of the research are:**
- **Unified fault dataset** for SEPIC and Ćuk converters
- Inclusion of:
  - normal operation
  - capacitor fault
  - inductor fault
  - switch fault
  - diode fault
- Extraction of relevant electrical features
- Comparative evaluation of **five ML algorithms**
- Implementation in **WEKA**
- Detailed performance evaluation using multiple metrics
- Analysis of the influence of converter topology on fault classification.

Conclusion & Future Work

- **Conclusions**
- Machine Learning is effective for intelligent fault diagnosis of DC–DC converters.
- **IBk achieved the best performance with 90% accuracy.**
- Ćuk converters are suitable for intelligent diagnostic applications.
- The unified framework enables direct comparison between SEPIC and Ćuk topologies.
- AI-based diagnosis can contribute to more reliable and autonomous energy systems.

- **Future direction**
- More experimental/real-world measurements
- Larger datasets
- More complex operating conditions
- Investigation of additional ML and Deep Learning models
- Real-time fault diagnosis.

Thank you for your attention !!!