Adaptive Application for Enhancing Feedback in Teaching

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WORK IN PROGRESS

An AI-Assisted Rubric-Based Feedback Framework to Enhance Instructor Effectiveness in Undergraduate Circuits Course

Abstract

Advancements in artificial intelligence (AI) are transforming engineering education by enabling adaptive and data-driven assessment methods. This paper presents an AI-assisted rubric-based feedback framework designed to enhance learning and evaluation across core Electrical Engineering subjects, including Circuits, Electrical Machines, and Power Systems. The proposed system utilizes natural language processing (NLP) and machine learning techniques to interpret student submissions such as lab reports, design explanations, or numerical problem-solving steps and automatically evaluate them against predefined rubrics. The AI module provides instant, criterion-specific feedback aligned with learning objectives, helping students identify conceptual misunderstandings and improve performance iteratively. Each interaction is logged to build an error database, allowing instructors to analyze trends and target recurring learning gaps. Case studies, including Thevenin's theorem in Circuits and single-phase transformer tests in Machines, demonstrate measurable improvements in student self-correction, conceptual understanding, and laboratory efficiency. The integration of AI-based rubrics and analytics offers a scalable approach to personalized learning, reduces instructor intervention time, and supports continuous improvement in engineering pedagogy.

I. Introduction

Assessment and feedback play a central role in engineering education, particularly in analytically intensive courses such as circuit analysis. In courses like Circuits II, instructors routinely evaluate multi-step handwritten solutions involving phasor representations, power calculations, and symbolic manipulation. While these tasks are essential for learning, grading them is time-consuming and often repetitive, limiting the instructor's ability to focus on conceptual intervention, mentoring, and reflective teaching practice.

Recent advances in artificial intelligence (AI) have enabled new approaches to educational feedback, especially through natural language processing and machine learning. However, concerns persist regarding over-automation, lack of transparency, and the potential erosion of the instructor's role. These concerns are particularly relevant in engineering education, where reasoning processes matter as much as final numerical answers.

This paper addresses these concerns by presenting an AI-assisted rubric-based feedback framework that explicitly supports, rather than replaces, instructors. The framework automates first-pass, criterion-level feedback aligned with instructor-authored rubrics and provides analytics that help instructors identify recurring misconceptions and design targeted instructional interventions. The system is validated using authentic student homework submissions from a Circuits II course, grounding the work in real instructional practice.

II. Course Context and Assignments Selection

The framework was explored in the context of a junior-level Circuits II course covering Thevenin's Theorem, AC steady-state analysis, phasor-domain methods, and power calculations. Students submitted handwritten homework solutions that were scanned and uploaded as PDF files through the learning management system i.e. CANVAS, reflecting common instructional practice in electrical engineering programs. These assignments were intentionally selected to span conceptual reasoning, structural mathematical formulation, and quantitative interpretation, which are central to electrical engineering problem solving.

Assignment 1: Thevenin's Theorem (Conceptual + Procedural)

This assignment focused on circuit reduction and conceptual interpretation of equivalent networks. Students were required to identify appropriate output terminals, remove the load element, and determine the open-circuit voltage and Thevenin resistance of linear circuits containing both independent and dependent sources. The assignment emphasized correct source deactivation procedures, use of test sources when dependent sources were present, and construction of the Thevenin equivalent circuit. Students were also expected to validate their results by reasoning about load behavior and comparing responses between the original and equivalent circuits.

Assignment 2: Phasor-Domain Equation Formulation (Structural)

This assignment focused on symbolic reasoning, requiring students to write nodal or mesh equations in the phasor domain, correctly eliminate dependent variables, and express the resulting system in matrix form.

Assignment 3: AC Power Analysis (Conceptual + Quantitative)

This assignment required students to compute instantaneous, average, and apparent power; distinguish between RMS and peak quantities; interpret leading and lagging power factors; and relate real, reactive, and apparent power through power triangles.

These assignments generated a wide range of solution strategies and common misconceptions, making them suitable for AI-assisted analysis.

III. Framework Overview

The proposed framework is grounded in a human-in-the-loop, instructor-centered design philosophy. All evaluative authority originates from instructor-authored rubrics, which encode disciplinary expectations, acceptable reasoning pathways, and known misconceptions. AI components operate strictly within the boundaries defined by these rubrics and do not introduce independent grading criteria.

The framework consists of three conceptual layers:

1. **Rubric Definition:** Instructors decompose complex problem-solving tasks into rubric criteria that represent conceptual checkpoints rather than final answers.
2. **AI-Based Interpretation:** AI techniques interpret student submissions relative to these criteria.
3. **Feedback and Analytics:** Criterion-specific feedback and aggregated analytics are delivered to support student revision and instructor reflection.

This modular structure ensures transparency, traceability, and adaptability across courses, aligning the framework with faculty development goals. This human-in-the-loop design aligns with prior work emphasizing complementary roles for instructors and AI systems in educational settings [1].

IV. Rubric Design for AI-Assisted Feedback

A. Rubric Design Philosophy for Machine Interpretation

Rubrics were designed to be **hierarchical and multi-granular**, enabling both human interpretability and machine-based mapping. Each rubric criterion (C1, C2, …) was decomposed into **sub-criteria (C1.1, C1.2, …)** corresponding to distinct, observable reasoning steps. This structure enables machine learning models to map extracted features to specific conceptual checkpoints rather than broad correctness labels.
This design serves three purposes:

1. Supports precise formative feedback
2. Improves robustness of ML classification
3. Enables fine-grained learning analytics

Assignment 1: Thevenin’s Theorem
Learning Focus: Circuit reduction, source handling, conceptual validation

Table 1. Assignment 1 Rubric: Thevenin’s Theorem

Criterion	Sub-Criterion	Description	Detectable Feature (for ML)
C1: Terminal Identification	C1.1	Correct identification of output terminals	Terminal labels, load removal
	C1.2	Correct removal of load element	Absence of load impedance
	C1.3	Consistent polarity/reference	Polarity symbols
C2: Open-Circuit Voltage (Vth)	C2.1	Correct open-circuit condition	No current through load
	C2.2	Correct handling of dependent sources	Presence of dependent source

Criterion	Sub-Criterion	Description	Detectable Feature (for ML)
	C2.3	Correct nodal/mesh setup	Equation structure
	C2.4	Algebraic correctness	Symbol consistency
C3: Thevenin Resistance (Rth)	C3.1	Independent sources deactivated correctly	Voltage/current source removal
	C3.2	Dependent sources retained	Source symbols present
	C3.3	Test source applied (if needed)	Test source insertion
	C3.4	Equivalent resistance computed correctly	Resistance combination
C4: Equivalent Circuit	C4.1	Correct placement of Vth	Circuit topology
	C4.2	Correct placement of Rth	Series resistance
	C4.3	Correct labeling	Labels and units
C5: Interpretation	C5.1	Logical comparison with original circuit	Reasoning text
	C5.2	Correct load behavior prediction	Qualitative explanation

Assignment 2: Phasor-Domain Analysis
Learning Focus: Symbolic structure, dependent sources, matrix formulation

Table 2. Assignment 2 Rubric: Phasor-Domain Equation Formulation

Criterion	Sub-Criterion	Description	Detectable Feature
C1: Phasor Conversion	C1.1	Correct impedance representation	$Z = R + j\omega L$
	C1.2	Correct frequency dependence	ω terms
C2: Dependent Variable Handling	C2.1	Control variable identified	Variable reference
	C2.2	Correct substitution	Equation replacement
	C2.3	Elimination before matrix form	Absence of control variable
C3: Matrix Construction	C3.1	All equations included	Matrix rows
	C3.2	Correct coefficient placement	Coefficient positions
	C3.3	Variable ordering consistency	Column consistency

Criterion	Sub-Criterion	Description	Detectable Feature
C4: Reference Consistency	C4.1	Current direction consistency	Sign patterns
	C4.2	Voltage polarity consistency	Polarity notation

Assignment 3: AC Power Analysis
Learning Focus: Conceptual interpretation of AC quantities

Table 3. Assignment 3 Rubric: AC Power Analysis

Criterion	Sub-Criterion	Description	Detectable Feature
C1: RMS vs Peak	C1.1	RMS-based formula identified	RMS keywords
	C1.2	Peak-to-RMS conversion	$\sqrt{2}$ factors
	C1.3	Consistent usage	No mixed quantities
C2: Power Factor	C2.1	Correct phase sign	θ sign
	C2.2	Leading/lagging classification	Keyword usage
	C2.3	Physical interpretation	Explanatory text
C3: Instantaneous Power	C3.1	Phase angle included	$\cos(\omega t+\theta)$
	C3.2	Correct trigonometric form	Equation structure
C4: Power Components	C4.1	Correct P, Q, S computation	Symbol usage
	C4.2	Correct power triangle	Geometric relation

V. Artificial Intelligence Components and Automated Workflow

The proposed framework integrates three complementary artificial intelligence components natural language processing, supervised machine learning, and generative AI within a unified, automated workflow. Each component serves a clearly defined role aligned with instructor-authored rubrics and operates sequentially to support formative feedback generation. The system is intentionally designed so that AI assists with interpretation and feedback delivery while all evaluative authority remains embedded in the rubric structure defined by the instructor.

A. Natural Language Processing for Interpreting Student Reasoning

Natural language processing (NLP) is used as the first stage of analysis to interpret what students have written and how they have structured their solutions. Because student submissions are handwritten and scanned as PDF files, NLP techniques operate on text extracted through optical character recognition. The primary goal at this stage is not to judge correctness, but to reconstruct the student's reasoning process in a machine-interpretable form.

Specifically, NLP methods are used to extract equations, symbols, and variable names, and to identify keywords commonly associated with circuit analysis, such as *Vrms*, *Vpeak*, *power* *factor*, *leading*, and *lagging*. In addition, structural patterns in the solution such as the progression from given quantities to governing equations, substitutions, and final results are identified to capture the logical flow of the student's work.

For example, in Assignment 3 (AC Power Analysis), NLP detects whether a student substitutes peak voltage values directly into apparent power equations. This distinction is critical for identifying RMS-versus-peak misconceptions and serves as an input to subsequent rubric-based classification.

B. Supervised Machine Learning for Rubric-Based Classification

Following feature extraction, supervised machine learning models are used to evaluate student work relative to instructor-defined rubric criteria. The role of machine learning in this framework is not to assign grades or infer correctness independently, but to map extracted features to specific rubric sub-criteria in a consistent and scalable manner.

The classification model evaluates features such as equation structure, variable usage, unit consistency, and numerical relationships. Each rubric criterion or sub-criterion is then classified into one of three states: **correct**, **partially correct**, or **incorrect**. This tri-level classification reflects common instructional practice and allows the system to distinguish between minor procedural errors and more substantive conceptual misunderstandings.

Because rubrics are hierarchical, classification occurs at the sub-criterion level, enabling fine-grained diagnostic feedback.

For example, in the Thevenin's Theorem assignment, the system can distinguish between incorrect deactivation of independent sources and improper handling of dependent sources, even though both errors relate to Thevenin resistance calculation.

Supervised classification is well suited to this task because rubric criteria define labeled outcomes derived from instructor judgment rather than inferred correctness [2]

C. Generative AI for Criterion-Specific Formative Feedback

Once rubric classification is complete, a constrained generative AI component is used to produce formative feedback aligned with the identified criteria. Importantly, generative AI is not used to make evaluative decisions or generate grades. Instead, it operates within instructor-approved feedback templates to ensure consistency, transparency, and pedagogical alignment.

Feedback generation occurs only after rubric classification and is limited to articulating guidance associated with specific criteria. Templates follow a structured format, such as:
"Your solution shows an issue with [criterion]. Review [concept] and reconsider [specific step]."
This approach ensures that feedback remains focused on learning objectives and mirrors the language an instructor would typically use when annotating student work. This feedback

approach is consistent with established principles of formative assessment that emphasize timely, criterion-referenced guidance to support student self-regulation and revision [3]

Example of Prototype Execution Homework 1 (Thevenin's Theorem)

In Assignment 1, a student correctly identified output terminals but incorrectly deactivated a dependent source while computing Thevenin's Resistance Rth. NLP detected source deactivation patterns, and the solution was flagged under **C3.2**. Feedback generated by the system prompted the student to retain dependent sources and apply a test-source method.

This example demonstrates how **sub-criteria enable precise diagnostic feedback**, which would be difficult to achieve using coarse rubric categories.

D. Step-by-Step Automated Workflow

These AI components are integrated into a batch-mode automated workflow executed using a single Python-based script on the instructor's computer. After students submit scanned PDF files through the learning management system, the instructor places the submissions into a designated directory and initiates the workflow. Optical character recognition converts handwritten content into machine-readable text, after which NLP extracts relevant variables, equations, and reasoning patterns.

Extracted features are then evaluated against instructor-defined rubrics using supervised machine learning, resulting in criterion-level classifications. Based on these classifications, the generative AI module produces targeted formative feedback for each submission. Finally, rubric-level outcomes are logged to create aggregated analytics that summarize error frequencies across the class.

Throughout this process, no manual intervention is required for individual submissions, and students are not required to install or interact with any AI software. The workflow is designed to reduce repetitive grading effort while preserving instructor oversight and pedagogical intent.

VI. Instructor Dashboard and Analytics — Expanded Description

Aggregated rubric-level analytics provide instructors with a quantitative view of recurring misconceptions across the class. Rather than reviewing dozens of individual submissions to identify patterns, instructors can quickly determine which concepts require targeted review or instructional redesign. By organizing results at the rubric and sub-criterion level, the framework transforms assessment data into actionable pedagogical insight while preserving student anonymity as shown in Table 4.

How instructors can use this table: This dashboard allows instructors to identify high-frequency misconceptions at a glance and prioritize instructional responses accordingly. For example, a high incidence of errors related to RMS versus peak quantities in Assignment 3 suggests the need for additional conceptual reinforcement before introducing power calculations in subsequent modules. Similarly, persistent issues with dependent source handling in

Assignment 1 indicate a need for clearer procedural scaffolding when introducing equivalent circuit techniques. Aggregating rubric-level outcomes in this manner aligns with established learning analytics practices that emphasize actionable insight for instructors rather than automated decision-making [4].

Table 4. Example Instructor Dashboard Summary Across Assignments

Assignment	**Rubric Criterion**	**Sub-Criterion**	**Description of Issue**	**% of Submissions Flagged**	**Instructional Implication**
Assignment 1: Thevenin's Theorem	C3	C3.2	Dependent sources incorrectly deactivated while computing Rth	38%	Reinforce rules for source deactivation; add in-class example using test source
	C2	C2.1	Incorrect open-circuit condition applied	22%	Review definition of open-circuit voltage
Assignment 2: Phasor-Domain Formulation	C2	C2.3	Dependent variable retained in matrix equation	41%	Emphasize elimination of control variables before matrix formulation
	C4	C4.1	Sign convention inconsistencies	19%	Provide structured sign-convention checklist
Assignment 3: AC Power Analysis	C1	C1.2	Peak values used in RMS-based power equations	47%	Revisit RMS–peak relationships with numerical examples
	C2	C2.2	Incorrect leading/lagging classification	26%	Add conceptual explanation of phase angle interpretation

VII. Limitations and Ethical Considerations

While the proposed AI assisted rubric-based feedback framework demonstrates promising feasibility, several limitations must be acknowledged. First, the effectiveness of the system is inherently dependent on the quality and granularity of instructor authored rubrics. Poorly defined or overly coarse rubrics limit the ability of both human instructors and machine learning models to generate precise diagnostic feedback. This reinforces the importance of thoughtful rubric design as a foundational component of the framework. Second, the current implementation relies on optical character recognition to process handwritten student submissions. Although OCR enables automation of existing instructional workflows, variability in handwriting quality, scanning resolution, and notation styles can introduce extraction errors. Such errors may propagate into subsequent stages of NLP and classification, underscoring the need for instructor oversight and iterative refinement of feature extraction methods.

From an ethical perspective, AI usage within the framework is intentionally constrained. The system does not assign grades, make summative evaluations, or perform plagiarism detection. All evaluative authority remains embedded within instructor defined rubrics, and AI is used solely to support formative feedback and instructional analytics. Student submissions used during prototype testing were anonymized, and no personally identifiable information was retained beyond the scope of analysis.

Transparency and instructor agency were prioritized throughout the design. AI outputs are traceable to specific rubric criteria and sub-criteria, allowing instructors to audit feedback and override system outputs when necessary. This human-in-the-loop design mitigates risks associated with opaque decision-making and helps maintain student trust in the assessment process.

Finally, as a Work-in-Progress, this study does not claim causal improvements in learning outcomes. Instead, it establishes feasibility and identifies design considerations that must be addressed in future large-scale evaluations. The design choices reflect broader ethical guidelines for responsible and transparent use of AI in educational contexts [5].

VIII Conclusion and Future Directions

This Work-in-Progress presents an AI-assisted rubric-based feedback framework grounded in authentic Circuits II assignments. By decomposing complex analytical tasks into hierarchical rubric criteria and leveraging AI for interpretation and feedback delivery, the framework demonstrates a practical approach to reducing repetitive grading effort while preserving instructional authority.

The inclusion of three distinct assignments Thevenin’s Theorem, phasor-domain equation formulation, and AC power analysis illustrates the framework’s ability to operate across conceptual, structural, and quantitative dimensions of engineering problem solving. Hierarchical rubrics with sub-criteria enable fine-grained diagnostic feedback that mirrors instructor reasoning and supports meaningful student self-correction.

Beyond student feedback, the framework offers significant value for faculty development. Aggregated rubric-level analytics transform assessment data into actionable instructional insight, enabling instructors to identify recurring misconceptions and adjust teaching strategies accordingly. The rubric design process itself encourages reflective teaching by externalizing tacit grading knowledge into explicit, shareable criteria.

Future work will focus on expanding deployment across additional courses and institutions, improving robustness of OCR and feature extraction for diverse handwriting styles, and systematically evaluating impacts on instructor workload and student revision behavior. With continued refinement, the framework has the potential to support ethical, transparent, and pedagogically aligned adoption of AI in engineering education.

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