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Undergraduate Submission

Washington, D.C.

Industrial Integration of AI Predictive Thermal Testing Technology

Applying machine learning for rapid prototype testing for innovative and competitive solutions

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1. Abstract

As a demonstration to advanced research and dedication to innovation, this study applies the inner workings of ML Solutions Advisory (a.k.a. ML Solutions), a consulting firm integrating solutions within thermal testing neural network applications. ML Solutions Advisory's focus, as a high-tech global design and manufacturing enterprise in the year 2040, is to apply machine learning to domestic and global industries during model thermal analysis. Further investigation through interviews and on-site visits were assessed alongside a literature review to evaluate educational systems and Human-AI interaction for machine learning applications. To address the challenge of closing the gap in thermal testing solutions, this study provides a discussion of Human-AI trust, Explainability, Bias, and Dependency. The study concludes with recommendations of how ML Solutions Advisory plans to implement the expansion of machine learning solutions, Artificial Neural Networks and Non-Dominated Sorting Genetic Algorithm II, to further build the optimization of thermal analysis testing alongside manual testing.

2. Introduction

Thermal analysis is one of the most significant contributors to efficiency of avionics, engines, heat exchangers, fluid dynamics, etc. In the past, thermal analysis has received less attention to electric machines and applications [1]. Finite element analysis, FEA, and Computational Fluid Dynamics, CFD, analysis is commonly used to measure temperature, efficiency and heat transfer, but require man-made designs. Heat exchangers, mentioned earlier, use a design made by a student, worker, or designer following CFD and FEA to measure temperatures and pressure drops [2]. Manually designing, identified from on-site interviews at avionic industries and with consideration of stakeholders, is a labor and time extensive process in which design, testing, and optimizing is done by human experts. ANN, Artificial Neural Networks, analysis also still relies heavily on human experts who have sufficient knowledge to solve problems [3]. ML Solutions Advisory, seeks to optimize thermal testing, but also seeks to form a solid foundation in the inner workings of ANN and Non-Dominated Sorting Genetic Algorithm II, NSGA-II. In the process, ANN models, when provided with a specific data set, answer any question based on the thermal data provided, such that possible outcomes of parameters are estimated. NSGA-II uses optimization techniques to process thermal data generated by ANN models to provide minimum, average, and maximum non-dominated optimal solutions [4, 5].

ML Solutions seeks to propose the ANN and NSGA-II as a combination for industrial design such that thermal optimal solutions can be met with a decrease in manual testing. The proposition will experience challenges within the current industry, such as human-AI trust, code of ethics to avoid bias and protect users and company data, dependence on AI, and lack of AI explainability. Today, ML Solutions plans to overcome these challenges by providing a plan for implementation including a testing pack for industries to have a secure demonstration of the technology, a security package application and contract, and providing documentation and training to notify industries to include manual testing alongside or independently of the use of ANN and NSGA-II configuration, as seen in Figure 1.

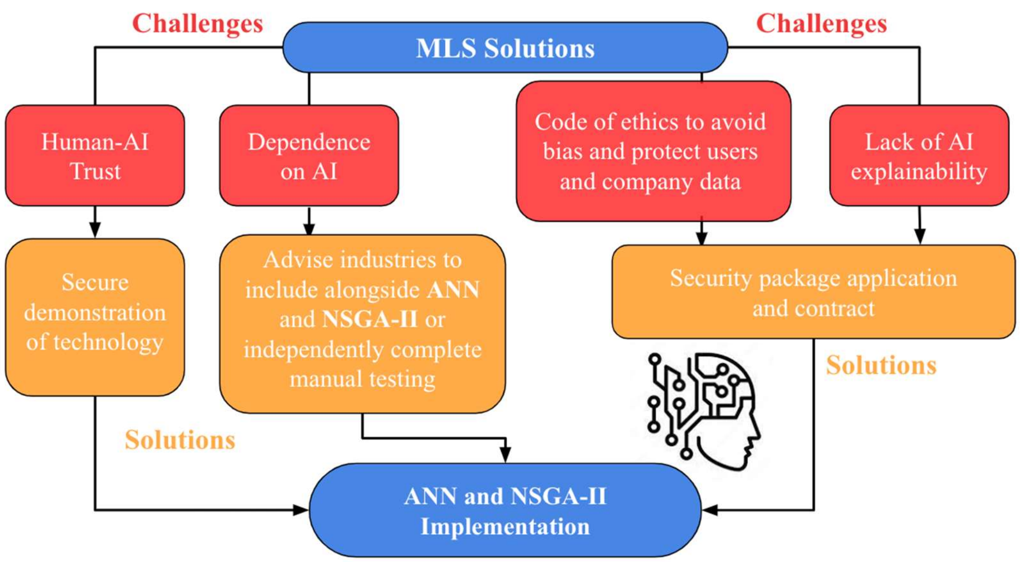


Figure 1 - *ML Solutions AI Implementation*

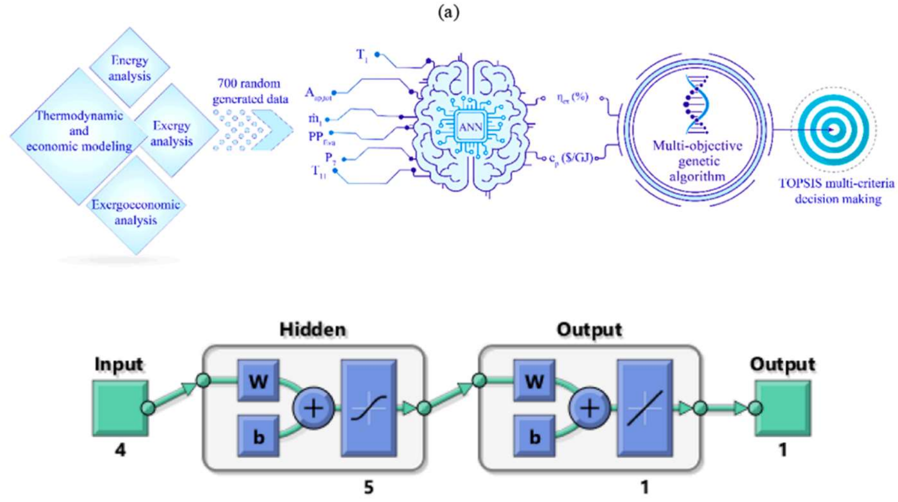
3. Background

Technical papers published to date highlight a number of thermal design issues that are difficult to analyze throughout design and manufacturing [6]. Machines, engines, and electronic components must undergo thermal analysis for overall performance. More importantly, thermal analysis centers around man-made designs that continue through testing and optimization based on the human experts' perception, but industry is migrating toward integrated use of AI applications.

Vishnukumar (2017) study depicts the importance of testing and validation toward AI dependency in autonomous vehicles. Though the study does not portray thermal analysis, the study does consider transition to AI applications through a sequence of steps. First, AI-core is fed with available test scenarios, boundary conditions for the test cases and scenarios, such as virtual tests on simulation environments [7]. The tests are meant to cover multiple hypothetical scenarios and lead to more critical and important tests to be repeated in the real-world environment [7]. Current studies of ANN algorithms are considered across different industries of thermal analysis, such as the findings of Rehman (2024) on the non-magnetic Nusselt number as an increasing function of the Prandtl number, Mohanraj's (2015) innovation of thermal analysis of heat exchangers, and Kurt (2009) predicting the thermal conductivity of ethylene glycol [8,9,10]. ML Solutions will use an AI combination, ANN and NSGA-II application, and will consider these applications in order to complete full validation before full integration in manufacturing thermal analysis.

Thermal analysis testing currently uses Computational Fluid Dynamics, CFD, Analysis, and ANN to find possible solutions based on parameters that the industry sets, but includes limitations between computational intelligence [11].

(a)



(b)

Figure 2 - *(a) Flowchart of the optimization methodology. (b) Architecture of the neural networks. [12]*

ANN creates computational models based on the biological theory that contain a significant number of computing elements (linear or nonlinear) called neurons [12]. The computational model is further described as a model that learns from previous data, in which the initial neurons send data to one another and configures an elimination process [12]. By the end of the configuration, ANN models answer any question based on the provided data and number of samples provided for testing. Assareh (2023) is a recent study that proposes this framework in thermal analysis to investigate a poly-generation system using ANN and NSGA-II, as seen in Figure 2, to maximize energy efficiency and reduce the cost rate. The findings in this study suggest that an optimal value can be found based on their design and hydraulic fluid chosen for the study. Concluding that with the addition of NSGA-II, the outcomes from the ANN computational models can be processed for the most optimal solution based on multiple parameters [12]. ML Solutions proposes that a novel AI combination of ANN and NSGA-II can be used across multiple analyses for industries that require thermal testing applications. For which, the industries will provide their input parameters to produce the most optimal output results stemming from the desired criteria.

4. Challenges and Implementation

A. Navigating the *Human-AI Trust* Challenge: Understanding, Mitigation, and Building Confidence

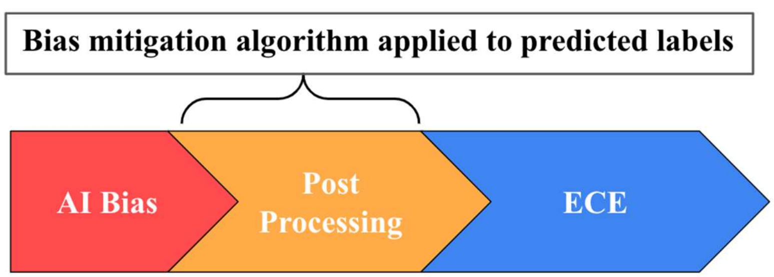
Human-AI Trust has grown to be one of the most integral challenges in the current part of the twenty first century. As more AI technology is developed, Human-AI trust must be considered as trust holds a considerable influence on whether an operator will use the new technology. Industries today rely on current and traditional methods of design and manufacturing. Therefore, these industries will be the most difficult to impact as they are more likely to negate the use and future application. In sight of fostering trust between humans and AI across education systems and diverse industries, ML Solutions offers a test system where the individual and/or group interested in the use of the technology can attend training sessions and use AI algorithms with a mock-data set. Datasets can be pre-generated or generated by the individuals attending the training session. Training sessions are also not confined to scheduled sessions in a prospective area, but ML Solutions offers an application to complete training in-house.

B. Enhancing Clarity: Confronting the *Issue of AI explainability*

Part of Human-AI trust is the issue of AI explainability. The coherent increase in AI and machine learning also proposes that industries are required to explain their outputs to their stakeholders. Stakeholders include, but are not limited to affected citizens, government regulators, domain experts, and system developers [13]. To describe outputs for a thermal analysis system, ML Solutions provides an AI Explainability 360 extension tool to provide stakeholders with needed information. AI Explainability 360 is an extensible open-source toolkit that helps individuals comprehend how machine learning models predict labels by various means throughout the AI application lifecycle [13]. Furthermore, the application continues to build confidence in domestic and global companies when using ANN and NSGA-II.

C. Unveiling the Challenge of AI *Bias*: Addressing Subjective Bias in Machine Learning Systems

In the past few years, AI applications have grown in popularity and use resulting in the importance of bias. Bias, in terms of AI usage, means “unfair”, “unwanted” or “undesirable” data [14]. Existing bias in data can be amplified in algorithms due to specific design choices by the user [15]. For example, web search engines will provide the most interacted links at the top of the list where users are less likely to interact with the further down results [16]. In the same way, bias can occur with interaction between the user and data generated by the AI algorithm causing an inaccurate estimation for occupant needs and leading to suboptimal controls [17]. ML Solutions targets bias in the algorithm through post-processing, as seen in Figure 3. Post processing treats the learned model as a black box without any ability to modify the training data or learning algorithm [15]. Following the training, labels are assigned by the black box model and are initially reassigned based on the function during the post-processing phase [15]. ML Solutions uses Expected Calibration Error, ECE, to measure the probabilities to match to true (observed) probabilities and accurately predict outputs of the thermal analysis testing.



$$ECE = \sum_{m=1}^{M} \frac{|B_m|}{n} |acc(B_m) - conf(B_m)|$$

Figure 3 - ML Solutions Plan To Target Bias

D. The Dilemma of *Dependency*

Lastly, when new technology is in use, it is common for users to become dependent on the technology resulting in a loss in traditional methods in case the technology is inaccessible and/or is unable to function due to some external circumstance. Included in the ML Solution training, the consultant recommends, and the information is included in the training packet to integrate manual testing in conjunction with AI applications across diverse industries. ML Solutions is not responsible for dependency on the technology but encourages users to use it as a resource for improving optimization and reducing time expenditure on thermal testing.

5. Conclusion

In conclusion, ML Solutions Advisory plans to implement the expansion of machine learning solutions, using ANN and NSGA-II, to position itself to be a high-tech global design and manufacturing enterprise in the year 2040. ML Solutions, as a thermal analysis consulting firm, provides on and off-site training to foster trust between Human-AI, applies AI Explainability 360 for user understanding of AI algorithms, addresses subjective bias through post processing and ECE calculations for accurate thermal testing results based on industry needs and requirements, and encourages users to apply manual analysis alongside the use of AI to negate complete dependency.

The use of ANN and NSGA-II is a novel researched topic as of the past few years allowing ML Solutions to advance thermal analysis testing across all industries, to grow the knowledge of AI capabilities and develop a novel method for thermal testing.

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Appendix

I used ChatGPT to structure my essay in a more formal and research format. ChatGPT, however, is specific on the exact methodology and what is wanted for an output. The queries provided were as follows:

- structure the essay below in a formal way for research purposes
- correction, restructure the essay
- keep the content provided from first time but only restructure the format
- Given the essay below, keep the content and research materials, but rearrange or expound on the information provided
- keep all points
- Keep citations
- Keep all seventeen citations

After multiple outputs of the algorithm giving me short summaries of my essay, I realized that it was difficult to explain the research and citation portion of the essay. Though close in content to the original essay, some important research was lost due to what ChatGPT may have deemed as "unnecessary" content. This was the final raw output given the queries above:

Abstract

This study explores the integration of machine learning (ML) solutions within thermal testing neural network applications, with a specific focus on ML Solutions Advisory (ML Solutions), a consulting firm committed to innovation and advanced research. ML Solutions aims to revolutionize thermal analysis by applying machine learning techniques to domestic and global industries, positioning itself as a premier high-tech global design and manufacturing enterprise by the year 2040. Through a combination of interviews, on-site visits, and literature review, the research evaluates educational systems and Human-AI interaction for machine learning applications. Furthermore, the study addresses critical challenges such as Human-AI trust, Explainability, Bias, and Dependency. It concludes with recommendations on how ML Solutions Advisory plans to expand machine learning solutions, specifically Artificial Neural Networks (ANN) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II), to optimize thermal analysis testing alongside manual methods.

Introduction

Thermal analysis plays a pivotal role in ensuring the efficiency of various systems, including avionics, engines, heat exchangers, and fluid dynamics. Despite its importance, thermal analysis has historically received less attention in electric machines and applications [1]. While Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD) are prevalent methods for measuring temperature, efficiency, and heat transfer, they rely heavily on manual designs [2]. ML Solutions Advisory seeks to enhance thermal testing by harnessing the power of machine learning, particularly through the utilization of ANN and NSGA-II. This section provides an overview of thermal analysis techniques and the transition towards AI-driven solutions.

Background

Numerous technical papers have underscored the challenges inherent in thermal design throughout the design and manufacturing processes [6]. While traditional methods heavily rely on manual expertise, there is a growing trend towards integrating AI applications into thermal analysis. Recent studies on ANN algorithms in thermal analysis demonstrate their potential to improve efficiency and optimization [8-10]. ML Solutions aims to leverage these advancements by validating and integrating ANN and NSGA-II for thermal analysis in manufacturing, drawing insights from various studies in the field.

Challenges and Implementation

This section addresses the key challenges in implementing ML solutions for thermal analysis, including Human-AI trust, AI explainability, bias, and dependency. Strategies for fostering trust, enhancing clarity, mitigating bias, and managing dependency are discussed. ML Solutions proposes comprehensive training programs and post-processing techniques to address these challenges and ensure the effective integration of ML solutions into thermal analysis processes.

A. Navigating the Human-AI Trust Challenge: Understanding, Mitigation, and Building Confidence

Human-AI trust is a critical factor in the adoption of new technology. ML Solutions offers training sessions and mock-data sets to foster trust between humans and AI across various industries and educational systems. Training sessions are flexible and can be completed in-house, providing users with hands-on experience with AI algorithms.

B. Enhancing Clarity: Confronting the Issue of AI Explainability

AI explainability is essential for stakeholders to understand AI outputs. ML Solutions provides an AI Explainability 360 extension tool to help stakeholders comprehend how machine learning models predict labels. This tool enhances confidence in AI applications, particularly in ANN and NSGA-II.

C. Unveiling the Challenge of AI Bias: Addressing Subjective Bias in Machine Learning Systems

AI bias poses a significant challenge in machine learning systems. ML Solutions targets bias in algorithms through post-processing techniques, such as Expected Calibration Error (ECE) calculations, to ensure accurate thermal analysis testing results.

D. The Dilemma of Dependency

Dependency on technology is a common challenge when implementing new solutions. ML Solutions encourages users to integrate manual testing alongside AI applications to mitigate complete dependency on technology, improving optimization and reducing time expenditure on thermal testing.

Conclusion

In conclusion, ML Solutions Advisory aims to implement the expansion of machine learning solutions, particularly ANN and NSGA-II, positioning itself as a leading global design and manufacturing enterprise by 2040. The company plans to foster trust between Human-AI, enhance clarity through AI Explainability 360, address bias through post-processing and Expected Calibration Error (ECE) calculations, and encourage the integration of manual analysis alongside AI applications. The use of ANN and NSGA-II represents a novel approach to thermal analysis testing, offering opportunities for advancement across industries.

References

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[2] Reference citation for FEA and CFD methods in thermal analysis.
[6] Reference citation for technical papers highlighting thermal design challenges.
[8-10] Reference citations for ANN algorithms in thermal analysis and specific study findings related to thermal analysis.