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DESIGN AND DEVELOPMENT OF TOPOLOGICALLY OPTIMIZED EARLY FIRE DETECTION MOBILE ROBOT

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Abstract: In this study, the comprehensive design, development, topology optimization, and power analysis of a mobile early fire detection robot were conducted. All subcomponents and the full assembly model were created using computer-aided design (CAD) tools. Electronic hardware-including RGB and thermal cameras, Raspberry Pi, and motor drivers-was selected, and corresponding mounting parts were designed to integrate the components into the structure. Finite element analyses (FEA) were performed to evaluate structural strength and stability. Topology optimization was applied to reduce the overall weight and energy consumption of the system. A specialized power analysis tool was developed to compare the energy usage of the non-optimized and optimized designs. The FEA and power analysis results confirmed that the optimized structure achieved a 25% weight reduction and an 11% decrease in energy consumption, demonstrating improved efficiency in the mobile fire detection robot.

Keywords: CAD-based fire detection robot, Computer-aided engineering, Energy-efficient mobile robot, Finite element analysis, Power analysis, Topology optimization

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1. Introduction

Fire represents a category of disaster that causes harm in a variety of settings, including residential areas, industrial zones, and forest lands. Despite the inherently dangerous nature of firefighting, which encompasses tasks such as fire extinguishment and victim rescue, the work is still conducted by human operators, thereby placing firefighters at risk. Once a fire has spread, it is impossible to control, and the process of recovery in a damaged area is inherently challenging. Consequently, the optimal approach to firefighting is to identify and locate the fire before it reaches a point of no return (Sucuoglu, 2015; Sucuoglu, et al., 2018; Sucuoglu et al., 2019; Saeed et al., 2020; Sucuoglu, 2020). A multitude of devices and systems have been designed and developed with the objective of facilitating early fire detection. Optical flame and smoke detectors, camera systems equipped with fire detection algorithms and capabilities represent the various types of early fire detection devices. These systems have certain disadvantages, including high cost, the necessity of fixing, and inflexibility. This situation gives rise to the utilization of effective technologies such as artificial intelligence, image processing methods and mobile systems for the purpose of early fire detection (He et al., 2022; Khan et al., 2022).

A significant approach in the field of early fire detection is the development and utilization of video-based systems. Those types of the systems utilize spatial-temporal flame modelling and dynamic texture analysis. Dimitropoulos et al. (2014) developed a method using the video-based system. They achieved a high frame rate for early fire detection. One of the most important parameters of the video-based fire detection systems is the development of a precise filtering system. This filtering is required to decrease the level of environmental noise and thus false alarm rates.

Madsen et al. (2018) proposed a method including the usage of chemical markers for early fire detection. They used laevulose as an indicator for early detection of fires burning in cellulose-based material as an improvement of the video-based detection systems. Although their method is seen as promising, it is limited to detect certain types of fires.

Zamal et al. (2017) developed a multi-sensor early fire detection. They equipped the system with GSM technology. They proposed real time monitoring and analysis of indicators such as smoke level and temperature changes. While the structure is effective for detection of flaming and non-flaming fire types, it has disadvantages such as high sensor costs, calibration and maintenance requirements.

One of the important problems and challenges of the usage of sensor-based detection systems is the effects of the environmental factors. Those factors cause noises and fail detections. For instance, smoke and heat detectors might be confused via increasing level of ambient noise and complexity.

Zhang and Du (2010) emphasized that smoke detectors frequently fail to detect and cause false alarms in the operations of early fire detection. As a solution they proposed more sophisticated detection algorithms and developed a hybrid model to consider many different parameters.

Biase and Laneve (2018) investigated the SFIDE algorithm. This algorithm uses remote sensing satellite imagery technology for early fire detection, especially in forest fires. Their system includes ground-based sensors and image processing techniques to monitor forest fires in real time to decrease the rates of the false alarms. Their system achieved highly effective detection. However, it has some disadvantages such as high investments costs.

Wei et al. (2014) developed a fire detection system based on wireless sensor network and artificial intelligence (AI) based structure to enhance accuracy as a significant contribution. Their system is adaptable to dynamic environmental conditions. By this way it decreases the false and failed alarms.

Frizzi et al. (2016) proposed an AI based system using CNN (convolutional neural networks) for early fire detection. They combined convolution and maximum pooling methods to create a model to enhance the data training efficiency and to decrease the risk of false alarms.

Zhong et al. (2018) developed a fire detection system based on CNN using video sequences. Their structure passes a fire image based on the RGB model through three convolution layers with kernel sizes of 11x11, 5x5, and 3x3, respectively. Then adapts a maximum pooling window of size 3x3 to reduce the cost of the computational function. Their structure aims to reduce the computational load during the detection processes.

Zhao and Ban (2022) studied and demonstrated the significant accuracy improvement effects of the deep learning models for forest fire detection. They have used the analyses of the time series data from the geostationary satellites.

Abdusalomov et al. (2021) studied the application of convolutional neural networks for fire detection. They developed a model to improve the classification and identification of fire events.

Li and Zhao (2020) proposed an image fire detection algorithm based on the advanced object detection CNN models of Faster-RCNN, R-FCN, SSD, and YOLO v3. They proved that developed algorithms could achieve 28 FPS and 83.7% accuracy in real-time fire detection applications.

Yang et al. (2024) developed an image fire algorithm based on YOLOv3 to detect smoke and flame simultaneously. They then enhanced the early fire detection capability of the algorithm by making various improvements. Tests and benchmarks demonstrated that the developed structure can be used for real-time detection.

Ahn et al. (2023) developed a computer vision-based early fire detection model. They used closed-circuit television (CCTV) surveillance. Their model facilitates rapid fire detection through the acquisition of data from authentic fire tests.

Biswas et al. (2023) modified the third version of the Inception Convolutional Neural Network (Inception-V3). They integrated images including smoke into the dataset and optimized the functions to reduce the computational load.

Rahayu et al. (2023) emphasized the significance of IOT for the development of synchronized automatic early fire detection systems. Proposed structure could perform early fire detection operations with the help of continuous monitoring, data collection, and the analysis of the collected data.

Currently, topology optimization is an important tool in product design processes. It is used in a wide range of industries such as automotive and aerospace. Additive manufacturing technologies also have expanded their applications. There is a strong and useful relation between topology optimization and additive manufacturing to increase the prototyping efficiency to decrease the production time.

Topology optimization is technique that can be explained as general as optimizing material distribution within a designated design space, considering specific loads, boundary conditions, and constraints. The objective is to reduce the weight of the structure while keeping or improving its strength and natural frequencies. One of the main aims of optimization is to determine the appropriate material usage within the specified design area to achieve the desired structural performance. In the process, the designed volume is divided into smaller elements, a FEA model is created, and boundary conditions are applied to perform the FEA. During the analysis, the elements exhibit intermediate density values. These values approach 1 or 0 by employing penalization techniques such as the power law to penalize higher-density elements. This process ensures convergence towards

solid and void regions to build the final structure.

The optimization process uses an iterative updating of the material density by the optimization algorithm to converge to a solution. By this way it tries to achieve the optimal performance and design volume. The final structure is determined by ensuring a smooth transition between solid and void regions.

Two commonly preferred methods for determining the distribution of elements in topology optimization are Solid Isotropic Material Penalization (SIMP) and the Evolutionary Structural Optimization Technique (ESO) (Yurdem et al., 2019). The mathematical equations 1 and 2 of the SIMP method can be written as (Zhu et al., 2016):

$$E(\rho_e) = \rho_e^{\rho} E_0 \quad (1)$$

$$C_{ijkl} = \rho C_{ijkl}^{0}, 0 \leq \rho(x) \leq 1, Vol = \int_{\Omega}^{1} \rho(x) d\Omega \quad (2)$$

The SIMP interpolation and generalized schemes are shown in Figures 1 and 2.

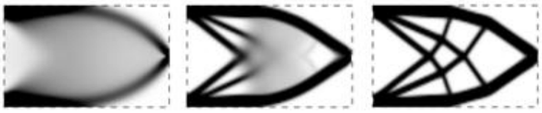


Figure 1. Interpolation scheme used in the SIMP method for topology optimization, illustrating the relationship between material density and stiffness.

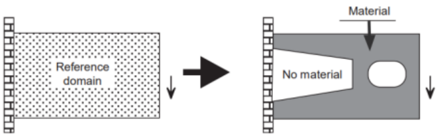


Figure 2. Generalized SIMP scheme demonstrating the penalization approach for differentiating solid and void regions during optimization.

Barbieri and Muzzupappa (2022) conducted a comparative study to compare the mechanical performance results of topology-optimized and generatively designed rocker arms and brake pedals for the Formula Student race car. Their results demonstrated that both optimized and generatively designed structures yielded effective outcomes.

Meng et al. (2020) studied a comprehensive account of the entire process of a bracket for the aviation industry, from topology optimization to additive manufacturing. The authors created and published a valuable guide for researchers engaged in topology optimization.

Cavazzuti et al. (2020) conducted studies involving optimization techniques for automotive chassis design. Their target of the optimization process was to reduce the weight of the chassis while ensuring structural performance constraints, as defined by Ferrari standards, were met. Their objective was to create the optimum chassis configuration by combining topology, size optimization and FEA. They used the structural performance of the Ferrari F458 as a reference point. They achieved a significant reduction in weight along with the creation of an optimized chassis structure.

Today, computer-based tools are essential for the design and analysis of structures. Solid modelling using CAD (Computer Aided Design) methods allows designers to define parts and assemblies and utilize geometry for simulations, analysis and prototyping. CAE methods enable virtual prototype simulations and static, kinematic and dynamic analysis (Sucuoglu et al., 2020; Demir et al., 2021a; Demir et al., 2021b).

In this study, a mobile early fire detection robotic structure was designed and developed. All sub parts and assembly model were created using Computer Aided Design tools. The electronic hardware (Rgb - thermal camera, raspberry pi, motor drivers and etc.) were selected, the mounting parts were designed and that hardware integrated into the structure. Required (FEA) finite element analyses were applied to check the structural strength and stability of the system. Then, topology optimization was conducted to decrease the weight and energy consumption of the mobile robot. A proper power analyses tool was developed to calculate and to compare the energy consumption of the non-optimized and optimized structures.

2. Materials and Methods

2.1. Design of the Robotic Structure

n this phase of the project, the robotic structure was designed using Fusion 360 CAD software. All subcomponents, including the top and bottom frames, motor connectors, and hardware mounts—were modeled and assembled accordingly. The mounting parts for electronic hardware were custom-designed and integrated into the chassis. Aluminum 6061 was selected as the structural material due to its favorable strength-to-weight ratio and machinability. The chassis was designed with pre-defined placement holes to ensure modularity and ease of assembly. The fully assembled robotic system is illustrated in Figure 3.

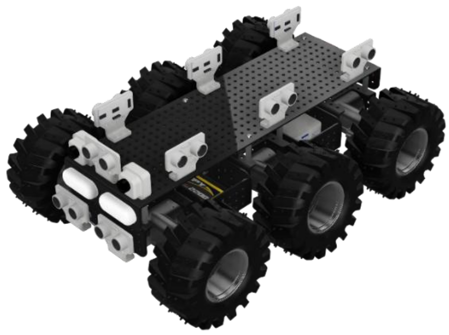
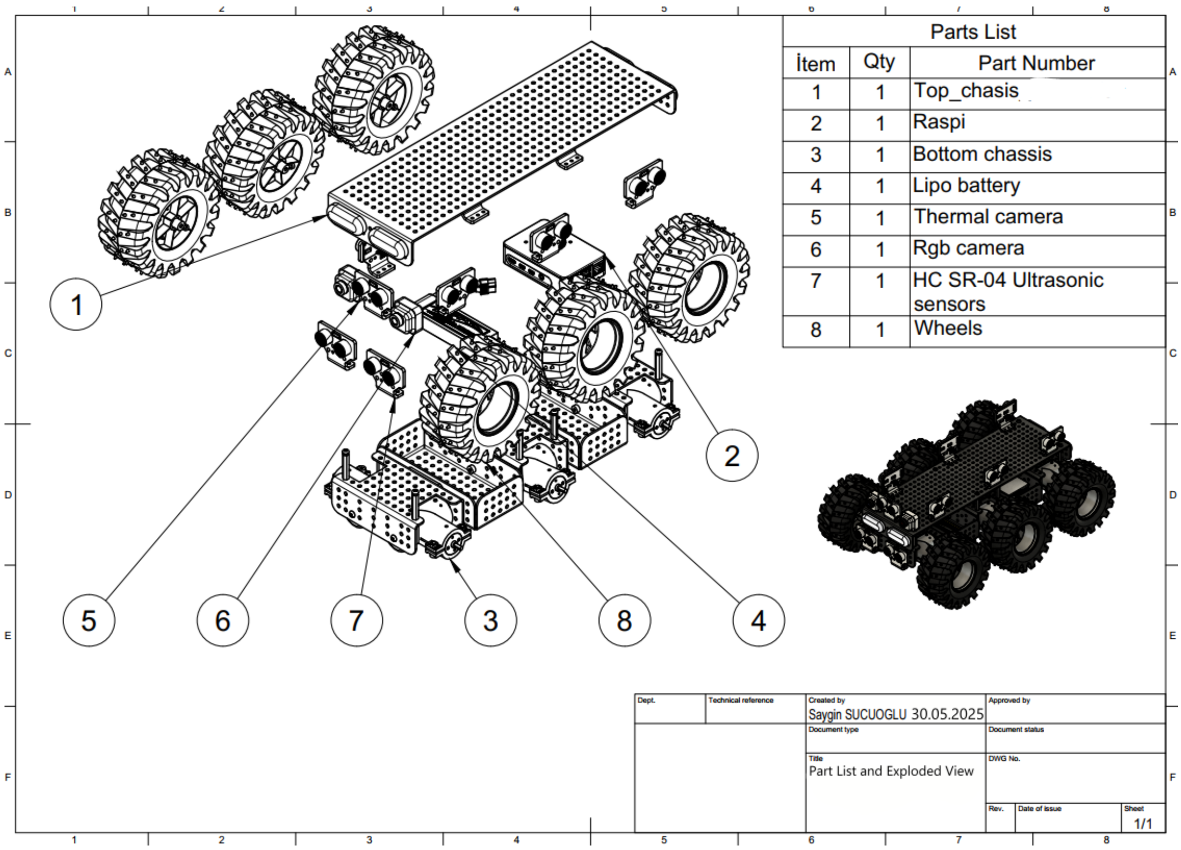
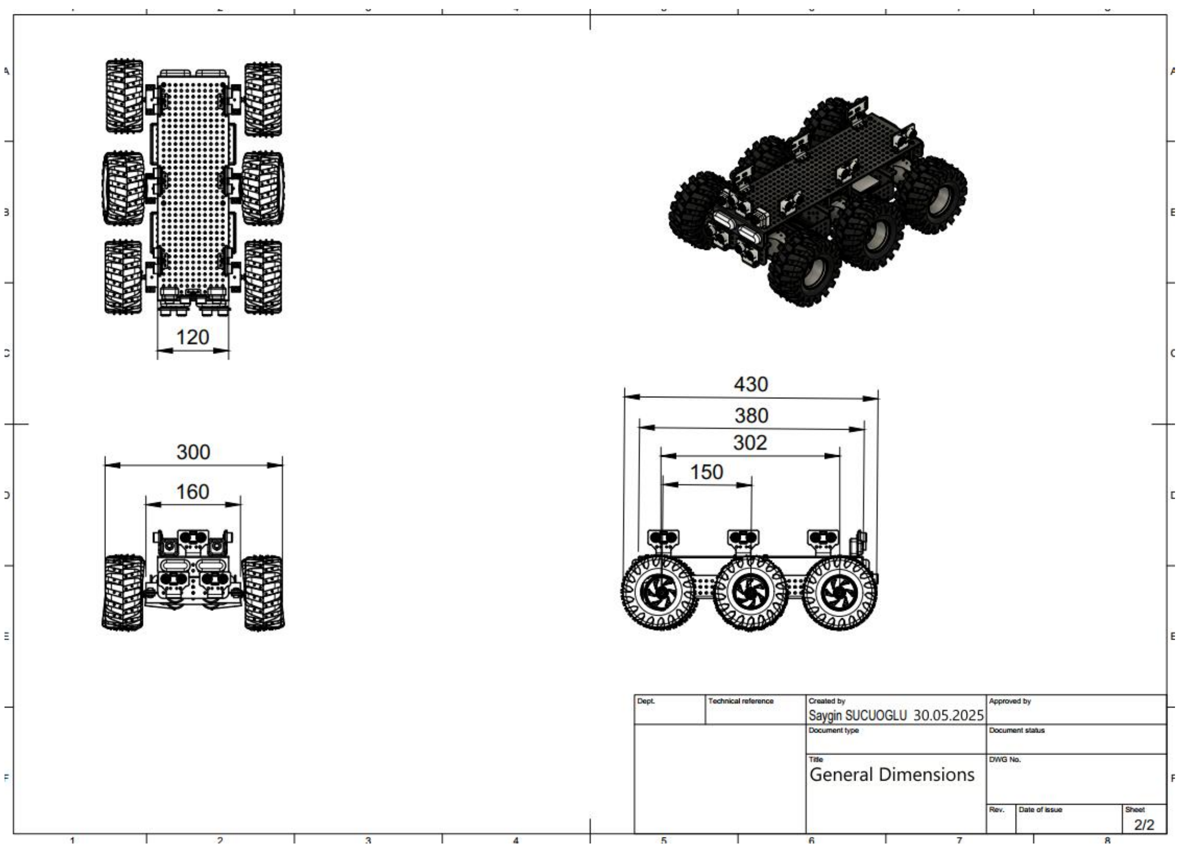


Figure 3. Assembled structure of the robotic system.

Following the 3D design process, a comprehensive part list, exploded view, and detailed engineering drawings—including general dimensions—were generated. These documents facilitated component selection and procurement. The robotic system was equipped with six DC motors and corresponding wheels, along with appropriate mounting elements. To enable path planning and obstacle avoidance, nine HC-SR04 ultrasonic sensors were integrated. For early fire detection, both RGB and thermal cameras were incorporated. Key hardware components, including a Li-Po battery, Raspberry Pi 5 (as the main controller), and motor drivers, were selected and embedded into the structure. The part list, exploded view, and engineering drawings are presented in Figure 4.



(a) Part list and exploded view



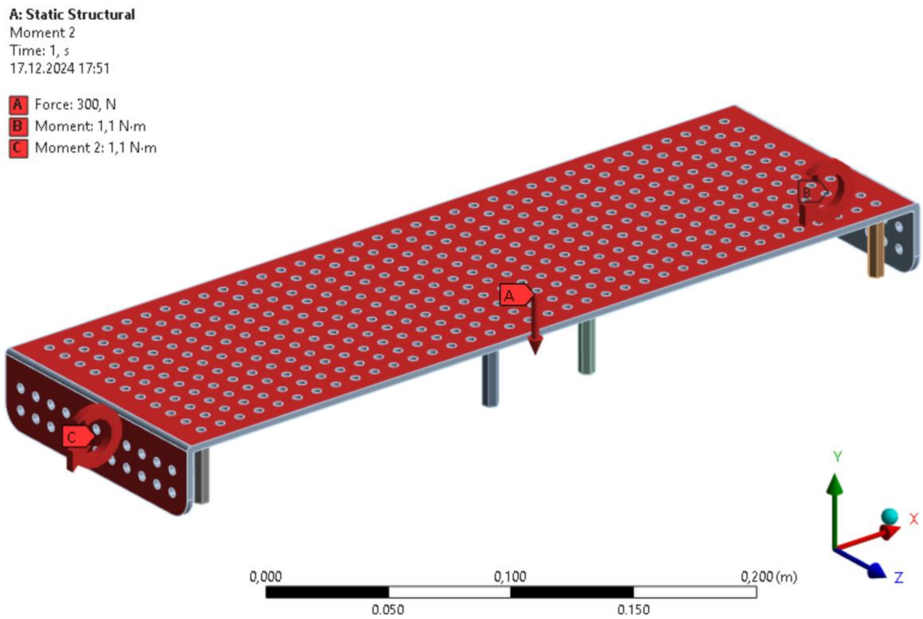
(b) Part list and exploded view (Engineering drawings)

Figure 4. Part list and exploded view and engineering drawings of the mobile robotic system, showing the dimensions, subcomponents, hardware integration and assembly layout.

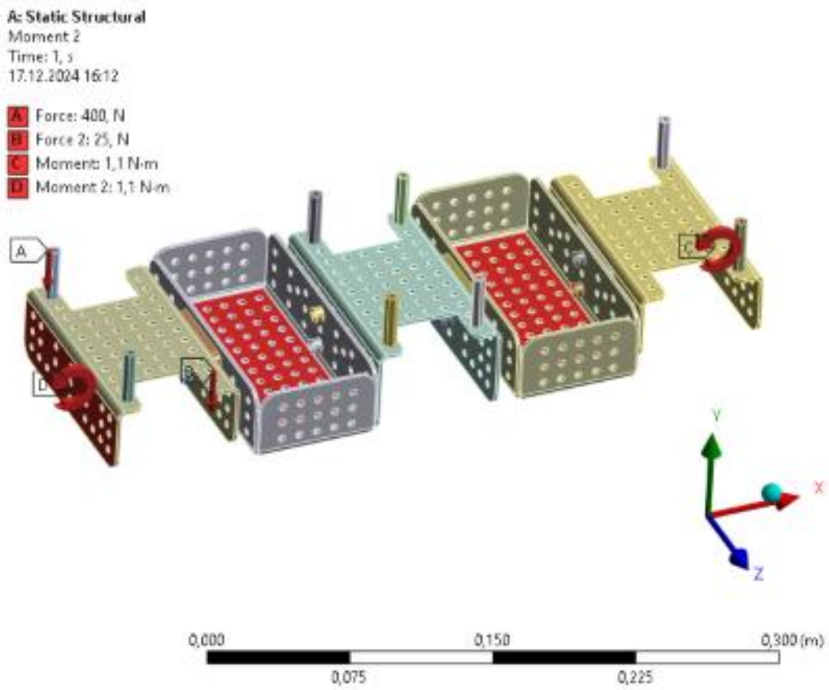
2.2 Engineering Analyses of Non-Optimized Structure

Engineering analyses using finite element analysis (FEA) were performed to assess the structural strength and stability of mechanical design. A key objective was also to evaluate the suitability of the structure for topology optimization. For these analyses, the chassis material was defined as Aluminum 6061, and relevant loads were applied to determine the resulting stress values and factor of safety.

The simulations were conducted in the Static Structural environment of ANSYS Workbench 2024. Separate analyses were performed for the top and bottom frames. The applied loads for each component are illustrated in Figure 5. Forces of 300 N and 400 N were applied to the top and bottom frames, respectively. Additionally, torques of 1.1 Nm and 2.1 Nm—generated by the driver motors—were applied to the front and rear surfaces of the frames.



(a) Top frame

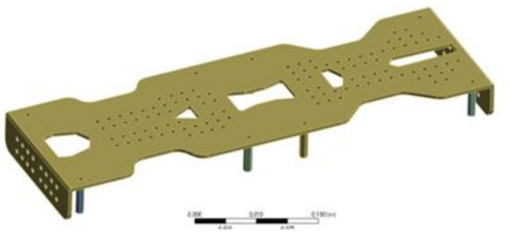


(b) Bottom frame

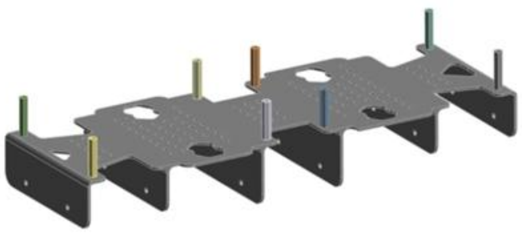
Figure 5. Topology-optimized configurations of the top and bottom frames generated through density-based analysis, showing reduced weight while preserving structural integrity.

2.3 Topology Optimization Process

Topology optimization was carried out using the ANSYS Structural Optimization tool. The same loading conditions applied in the previous engineering analyses were used for consistency. The optimization type was set to topology density, with a threshold value of 50%. Connection regions of the frames were designated as preserved areas to ensure structural integrity and were excluded from the optimization process. After multiple iterations, optimized structural configurations were generated. Based on the resulting data and exported design files, new top and bottom frames were created. These optimized structures are illustrated in Figure 6.



(a) Top frame



(b) Bottom frame

Figure 6. Optimized structures.

The weights of the top and bottom frames were reduced to 0.3 kg and 0.35 kg, respectively. These reductions are considered promising in terms of lowering the overall energy consumption of the system. To verify the structural integrity of the optimized frames, finite element analyses were performed using the same load conditions as those applied to the non-optimized structures. The results confirmed that the optimized designs maintained sufficient strength and stability.

2.4 Power Analysis Tool

A custom software tool was developed to enable energy consumption and weight analysis for robotic systems, employing Python's tkinter library to construct a user-friendly graphical user interface (GUI). This application was utilized to perform comparative power analysis between two robotic designs by processing part lists that include components such as motors, batteries, sensors, and chassis materials (Figure 7).

The interface allows users to input detailed specifications for each component, including voltage, current, quantity, and weight—directly reflecting the part list data. These entries are systematically aggregated, enabling iterative analysis and comprehensive evaluation. The tool performs real-time calculations of total power consumption and overall system weight, thereby supporting informed design optimization decisions.

An additional feature of the tool is its integrated image visualization function, which permits users to upload and display images of individual components within the GUI. This functionality enhances component identification and facilitates a more intuitive correlation between visual data and quantitative metrics, contributing to a more holistic approach to system design and evaluation.

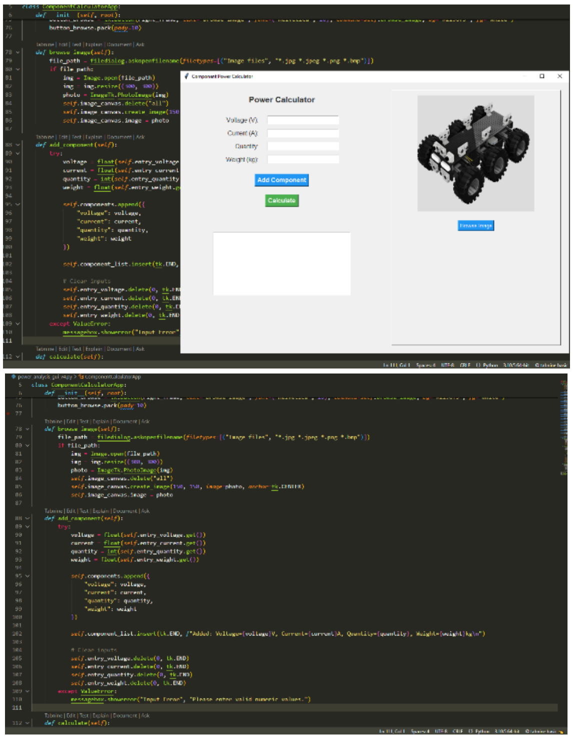


Figure 7. Power analysis tool.

In the comparative analysis of the two robotic designs, the developed tool facilitated the calculation of total energy requirements and weight distribution based on the detailed part lists. This capability enabled the identification of design efficiencies, including reduced power consumption and optimized chassis configurations with lower weight. By integrating component visualization with critical computational functions, the tool supports a streamlined and iterative design workflow while enhancing the clarity and completeness of engineering documentation.

This tool proves particularly valuable during early-stage design, prototyping, and comparative evaluation of mechanical and electronic systems, where rapid and accurate assessment of power and weight parameters is crucial for informed decision-making and overall performance optimization (Figure 8).

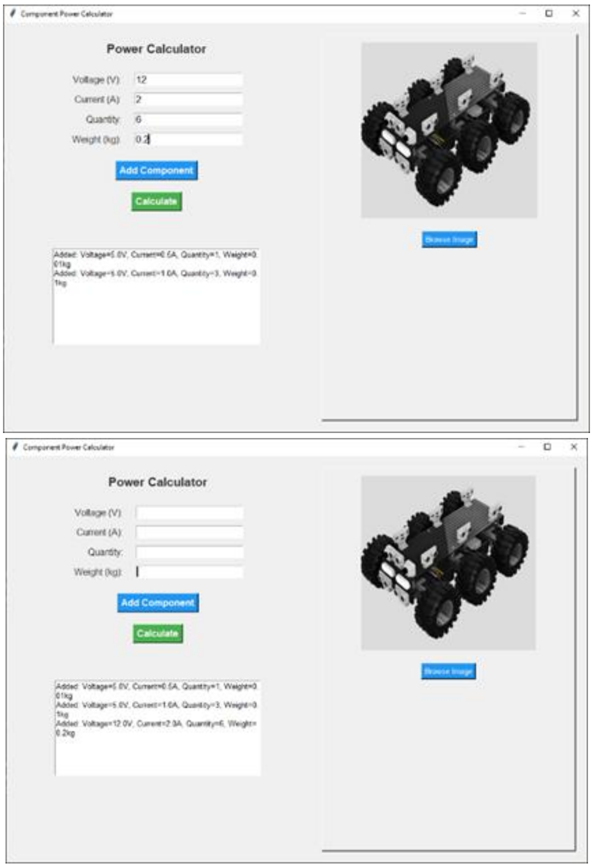


Figure 8. Calculations with power analysis tool.

2.5 New Optimized Assembly Model

In this phase of the study, a new assembly model was developed using the topology-optimized frames (Figure 9). Since the connection regions were preserved during the optimization process, they remained compatible for integration. The battery, controllers, and DC motors were successfully mounted onto the bottom frame, while all cameras and sensors were positioned on the top frame. The optimized structure was thus fully assembled and prepared for subsequent power analysis.

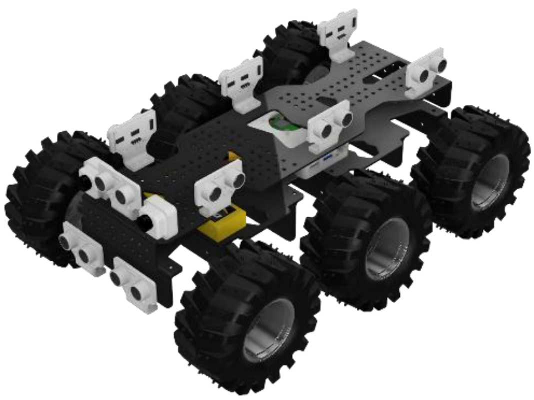


Figure 9. Assembly model of optimized structure.

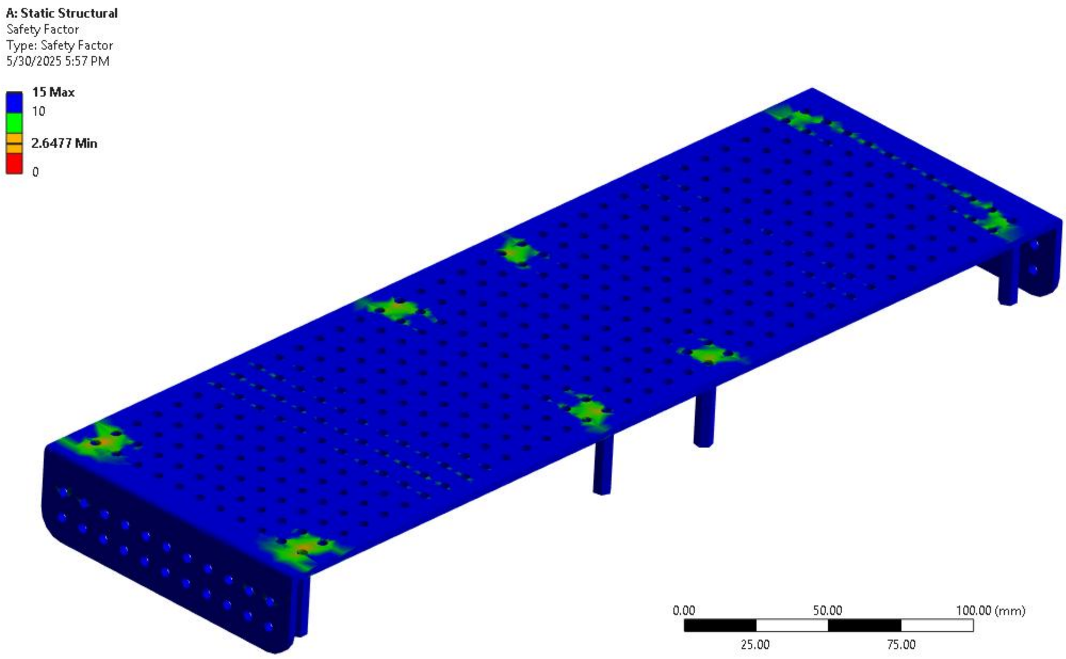
3. Results and Discussion

3.1. Engineering Analyses Results of Non-Optimized and Optimized Structures

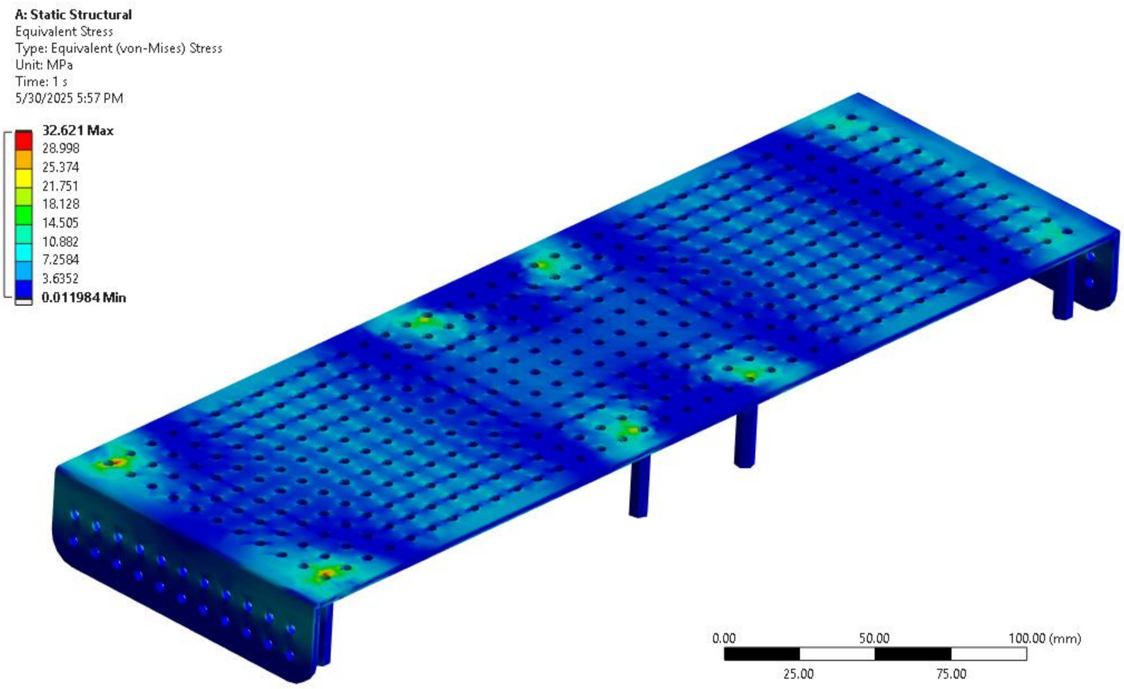
The analysis results strongly supported the implementation of topology optimization as a necessary design enhancement. In the initial non-optimized configuration, the top and bottom frames had approximate weights of 0.4 kg and 0.5 kg, respectively, with each part modeled using a uniform plate thickness of 3 mm. Under the applied loading conditions, the calculated factor of safety (FoS) was approximately 2.7, indicating a structurally conservative design with excess material usage. The corresponding von Mises stresses were recorded in the range of 40–45 MPa, well below the yield strength of the Aluminum 6061 material. These findings suggested that the structure possessed significant potential for mass reduction without compromising mechanical integrity, thereby validating the feasibility of topology optimization to improve overall energy efficiency.

Following the optimization process, the structural frames were redesigned based on the density distribution maps generated by the topology solver. Critical connection regions were preserved to ensure assembly compatibility and mechanical continuity. Finite element analyses of the optimized frames showed that the weight of the top and bottom frames was reduced to 0.3 kg and 0.35 kg, respectively representing a total reduction of approximately 25%. Despite the reduction in mass, the structural performance remained within acceptable limits. The factor of safety decreased to approximately 1.8, while the von Mises stress values remained consistent, around 45 MPa. Importantly, there were no significant increases in localized stress concentrations or indications of mechanical failure. All the data obtained from engineering analyses are shown in Figures 10 and 11, respectively.

These results confirm that the optimized frames retain adequate strength and stability while achieving meaningful reductions in material usage and energy consumption. By lowering the total system weight, the robotic platform benefits from improved energy efficiency, extended battery life, and enhanced mobility. Thus, the application of topology optimization not only satisfies mechanical performance requirements but also contributes to the development of a more sustainable and operationally efficient robotic system.

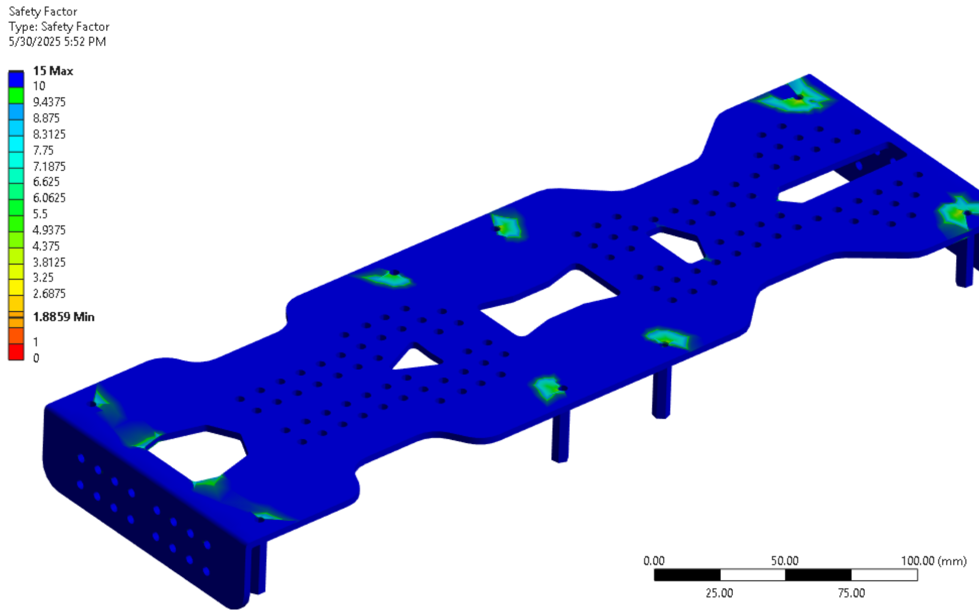


(a) FOS of non-optimized top frame

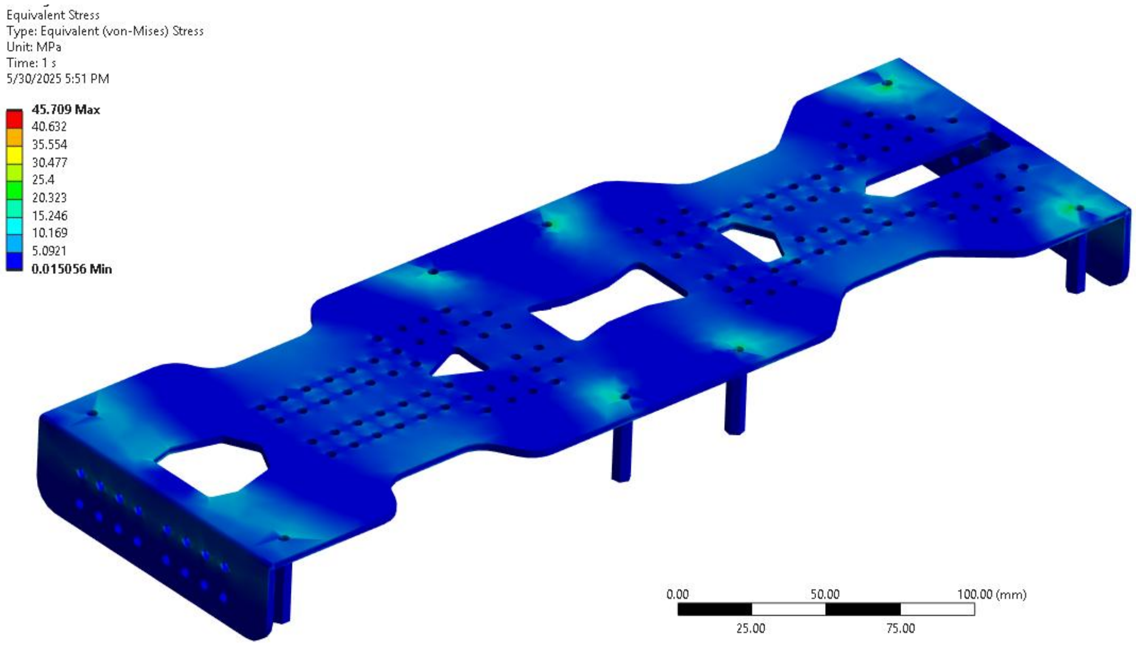


(b) Occurred stresses of non-optimized top frame

Figure 10. Finite element analysis results of the top frame before topology optimization, showing factor of safety and stress distribution.



(a) FOS of optimized top frame



(b) Occurred stresses of optimized top frame

Figure 11. Finite element analysis results of the top frame after topology optimization, showing factor of safety and stress distribution.

3.2. Power Analysis Results

A comprehensive power analysis was conducted to evaluate the energy efficiency and operational performance of the optimized mobile early fire detection robot in comparison to its non-optimized counterpart. The primary objective was to quantify the benefits achieved through topology optimization, particularly in terms of reduced structural weight, power consumption, and overall energy requirements.

The analysis was based on conventional electrical and energy calculation principles, including the following formulas:

- Power (P) = Voltage (V) × Current (I)
- Total Energy (E) = Power (P) × Time (t)
- Total Power Consumption = Σ (Power usage of individual components)
- Weight Comparison = Σ (Weight of all components in each design)

Key assumptions incorporated into the analysis included:

- A standard Li-Po battery voltage of 11.1V (3S configuration)
- DC motors operating at 12V with a nominal current of 2A per motor
- Ultrasonic sensors drawing 30mA at 5V
- RGB and thermal cameras consuming 500mA at 5V

- Raspberry Pi and motor controllers requiring 1A at 5V

The comparative analysis between the non-optimized and optimized robotic platforms indicated notable gains in energy efficiency, with measurable reductions in both power consumption and system weight. These findings confirm the effectiveness of topology optimization in enhancing the energy performance of mobile robotic systems. The detailed data is presented in Table 1.

Table 1. Data summarization of power analysis

Component	Non-optimized	Optimized	Remarks
Chassis weight (gr)	900	650	Optimized design is lighter.
Total power requirement (W)	90	80	Optimized design consumes less power.
Energy consumption per Hour (Wh)	90	80	Lower energy demand for same duration.

Calculations assume six DC motors (12V, 2A), one Li-Po battery (11.1V), RGB + thermal cameras (5V, 500mA), ultrasonic sensors (5V, 30mA), Raspberry Pi + motor controllers (5V, 1A), with an operating duration of one hour.

The results demonstrate that the optimized design achieved a 25% reduction in chassis weight, contributing directly to decreased energy consumption and enhanced operational efficiency. The total power consumption of the optimized robot was 10 W lower than that of the non-optimized structure, confirming improved energy management.

The weight reduction, achieved through topology optimization, led to a decreased load on the drive motors, which in turn reduced the power requirements. This improvement enhances the robot's operational duration, making it more suitable for extended fire detection tasks in remote or hazardous environments.

Furthermore, the lower energy consumption of the optimized design enables the use of smaller or fewer battery modules without compromising operational endurance. This contributes to a lighter and more cost-effective system, emphasizing the importance of structural optimization in the development of energy-efficient robotic platforms.

The optimized structure significantly improved both structural and energy efficiency, highlighting the benefits of topology optimization in mobile robotics.

Overall, the power analysis results validate the effectiveness of topology optimization in improving the energy performance and functionality of mobile fire detection robots. The optimized system not only achieved 25% weight reduction but also demonstrated an 11% decrease in energy consumption, underscoring its potential for real-world applications in fire detection scenarios.

4. Conclusion

In this study, a comprehensive workflow encompassing design, development, topology optimization, and power analysis of a mobile early fire detection robotic system was successfully implemented. All subcomponents and complete assemblies were meticulously developed using advanced Computer-Aided Design (CAD) tools. Engineering analyses, including finite element analysis (FEA), were conducted to evaluate the structural strength of both the non-optimized and optimized configurations. These analyses validated the structural integrity and confirmed the necessity of applying topology optimization to enhance performance without compromising mechanical reliability.

Furthermore, a custom-built power analysis tool was developed to accurately assess and compare the energy consumption profiles of the non-optimized and optimized designs. The results demonstrated that the topology-optimized structure achieved a 25% reduction in chassis weight while maintaining acceptable safety margins and stress levels. This structural lightweighting process directly contributed to an 11% reduction in energy consumption, confirming the effectiveness of the optimization approach for mobile robotic applications operating in energy-sensitive scenarios such as early fire detection in remote environments.

The findings underscore the potential of topology optimization not only as a tool for mass reduction but also as a key enabler of energy-efficient design in robotic systems. The integration of structural optimization and tailored power assessment offers a holistic framework for designing high-performance, lightweight, and power-aware robotic platforms.

Future work will focus on several key areas:

- Experimental validation: A physical prototype will be developed to correlate simulation results with real-world operational behavior.
- Adaptive control algorithms: The current system will be expanded to incorporate adaptive control algorithms that dynamically adjust power distribution based on mission demands.
- Enhanced fire detection capability: The fire detection system will be improved through the integration of additional sensors and machine learning–based decision systems.
- Modular deployment: The system architecture will be adapted for modular deployment in larger coordinated robotic fleets to support scalable and cooperative fire monitoring applications in hazardous environments.

Author Contributions

The percentages of the author' contributions are presented below. The author reviewed and approved the final version of the manuscript.

	H.S.S
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because there was no study on animals or humans.

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