Enhancing 3D Printing Workflows through Multi-Objective Optimization and Reinforcement Learning Techniques

Ahmad Alghamdi
Department of Mechanical and Industrial Engineering, College of Engineering and Computing in Al-Qunfudhah, Umm al-Qura University, Mecca, Saudi Arabia
asalghamdi@uqu.edu.sa (corresponding author)

Received: 1 January 2025 | Revised: 27 January 2025 | Accepted: 5 February 2025

 DOI: https://doi.org/10.48084/etasr.10101

ABSTRACT

Integrating Machine Learning (ML) with optimization algorithms in 3D printing, also known as Additive Manufacturing (AM), has revolutionized the creation and production of complex structures. This integration has significantly boosted material efficiency, print quality, and optimization of the entire process. This paper delves into details on improving 3D printing design and production workflows using advanced ML techniques such as neural networks, Reinforcement Learning (RL), and optimization techniques, such as topology optimization and genetic algorithms. The proposed framework offers a 15-25% reduction in print time and material consumption and a 10-20% improvement in predictive accuracy over existing methods. Additionally, the results of the multiobjective optimization reveal an aligned improvement in cost-effectiveness, structural strength, and mechanical performance. Stress-strain analysis showed that optimized designs can achieve up to a 12% increase in yield strength, while defect rates decrease by up to 30% by applying dynamic RL for parameter adjustments. The results validate the effectiveness of these hybrid models, emphasizing their potential to boost reliability, efficiency, and scalability in additive manufacturing processes.

Keywords-machine learning; 3D printing; additive manufacturing optimization; reinforcement learning; multi-objective design optimization

I. INTRODUCTION

Additive Manufacturing (AM), often known as 3D printing, is a major leap forward in the manufacturing industry. This technique enables the creation of complex shapes while reducing material waste and enhancing efficiency. From industrial use to broad consumer adoption, AM has shown remarkable versatility in diverse fields, such as aerospace, healthcare, and consumer goods. The ability to tailor designs and create intricate structures has made it indispensable in modern manufacturing workflows. However, despite advances, the field still faces various challenges, including optimizing printing parameters, ensuring structural integrity, reducing material waste, and reducing production time. Machine Learning (ML) has become invaluable in addressing these challenges because it enables data-driven decisions. Large datasets allow ML to predict, automate, and refine processes previously handled by trial-and-error or fixed-rule methods. In [1], it was shown how ML effectively predicts and optimizes 3D printing parameters, such as time, weight, and length, resulting in faster and better process precision. Similarly, in [2], it was shown that hierarchical ML can increase silicone 3D printing speeds by up to 2.5 times while maintaining print quality. These studies highlighted the potential of ML to boost the efficiency, scalability, and accuracy of AM techniques.

AM uses ML to significantly advance in areas such as tool-path design, quality assurance, material optimization, and production using multiple materials. These improvements go beyond simple process optimization. ML can be used for many things, such as improving robotic multiaxis printing systems for support-free manufacturing [3], and real-time interlayer bonding and monitoring of anisotropic behavior [4]. However, a core challenge persists in bridging the gap between theoretical potential and actual practice. It is still unclear how to use ML effectively for real-time applications, closed-loop systems, and different material properties, implying the need for further research and exploration. In recent years, significant research has been conducted on the use of ML in AM, with numerous vital contributions addressing diverse aspects of the technology. Data-driven approaches have become essential in this domain. In [1], ML methods, such as multilayer perceptrons and CNNs, were used to find the best printing parameters, even without all the needed information. By incorporating this system, the printing process can be automated, enhancing its accuracy and usefulness, thereby reducing the likelihood of errors.

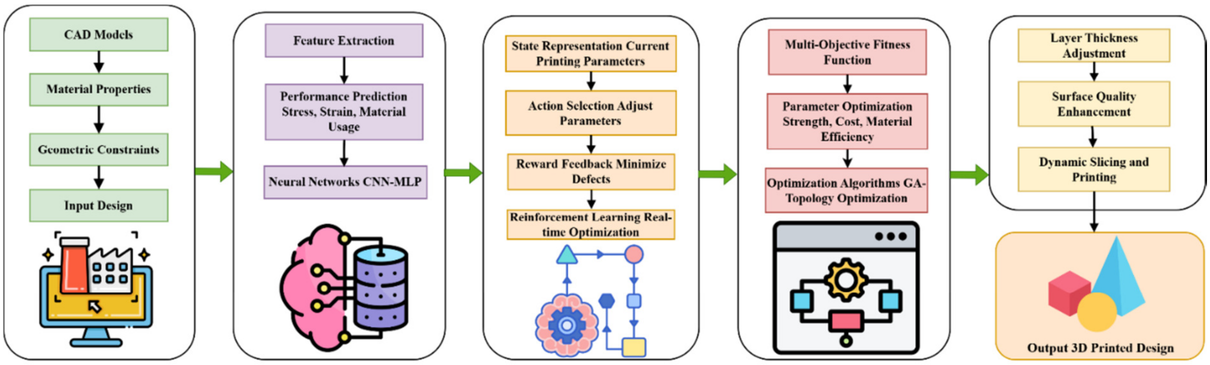

Fig. 1. Workflow representation for enhanced 3D printing optimization.

In [2], hierarchical ML was used to make Free-form Reversible Embedding (FRE) the best way to print silicone. This work resulted in considerable improvements in printing speed and introduced innovative material formulations overlooked by traditional methods. In [3], the use of Artificial Neural Networks (ANNs) was discussed to determine the exact links between printing settings and output qualities. This provides more insights into the printing process and the material's properties through data.

In addition to specific applications, comprehensive reviews in [4, 5] have highlighted the broader impact of ML on AM. This research delineates the application of ML in design optimization, material selection, and real-time monitoring. The topic also includes improvements made to biomedical engineering, making materials and construction more biocompatible, and improving interlayer bonding and structural integrity [6]. Reviews have demonstrated the widespread application of ML in various fields to address challenges in AM and highlight challenges, such as high computational costs and obtaining sufficient data, which hinder its widespread application. Specific problems in AM have been solved by targeted techniques in algorithms, such as Ant Colony Optimization (ACO) and dynamic slicing. In [7], a tool-path optimizer was created using ACO, reducing the time required for printing and improving the look of printed objects, addressing these problems with current methods. In the same way, a dynamic adaptive cutting algorithm was proposed in [8] to fix the common staircase effect in layer-based printing, improving the surface and reducing the production time. Advances in ML in AM have made innovative frameworks and systems possible. In [9], an automated framework was proposed to optimize CAD models and G-code generation, bridging the gap between prototyping and mass production. In [10], recent advances in robotic systems were demonstrated by creating a multiaxis robotic printing system that eliminates the need for support structures. This breakthrough not only saves material but also improves mechanical properties.

Given these advancements, it is crucial to recognize the substantial gaps in the field. For instance, the concepts of real-time optimization and closed-loop systems, explored in [11], are still in an early stage of maturity. Adding fuzzy inference to classification models helps monitor and improve printing parameters continuously, which is a good way to handle the changing parts of the printing process. Similarly, studies such as [12] have employed clustering and regression methods to improve aerosol jet printing. However, there is ample opportunity to further investigate the application of these techniques to other noncontact direct ink writing technologies. Eventually, ML has been notable for improving material properties and expanding the scope of additive manufacturing applications. In [13], Bayesian optimization was applied to fabricate high-performance thermoelectric materials, achieving notable efficiency improvements. In [14], ML was used to fine-tune mechanoluminescent composites for structural health monitoring, highlighting the promise of ML in creating multifunctional materials.

The key contributions of this study include:

- An innovative hybrid approach to enhance 3D printing processes, integrating various optimization techniques with ML methods such as neural networks and Reinforcement Learning (RL).
- The proposed framework achieves notable performance improvements, including a better reduction in print time and material usage and a quality improvement in prediction accuracy.
- The results indicate that RL-driven parameter adjustments can reduce defect rates by up to 30%, ensuring superior-quality output while minimizing waste.
- The proposed approach explores scalability and applicability across various sectors, facilitating high-performance and cost-effective manufacturing solutions.

II. PROPOSED METHOD

This section introduces the proposed framework that integrates state-of-the-art ML models and optimization algorithms to improve the efficiency, cost-effectiveness, and quality of 3D printing processes. To achieve superior results in performance metrics, the approach engages the framework in multi-objective design optimization along with predictive modeling for parameter enhancement. Figure 1 shows the procedure suggested to enhance 3D printing processes by incorporating advanced ML models and optimization techniques. The workflow includes several steps, such as designing the inputs, using neural networks to make predictions, using RL to tune parameters, multiobjective optimization, and adaptive slicing to make highly optimized 3D printed designs. The datasets were derived from publicly accessible sources and proprietary data acquired from industrial 3D printing experiments, ensuring broad applicability. For transparency, references to publicly available datasets have been included.

A. Predictive Modeling and Parameter Optimization

The system uses neural networks and RL to predict and improve important 3D printing factors, such as the time required, the amount of material used, and the mechanical properties of the object. Neural networks were trained using a set of design inputs and corresponding performance metrics. The network aims to minimize the Mean Squared Error (MSE) loss function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \quad (1)$$

where actual performance levels are denoted by y_i and predicted performance levels by $\widehat{y_i}$. CNNs are utilized alongside multilayer perceptrons to enhance the ability to learn complex design features, as proposed in [1]. The neural network model's architecture was carefully designed to tackle the complexities of 3D printing parameters. The input layer efficiently encodes an array of design parameters, covering material properties and geometric constraints, thus creating the foundational input for the network. Fully connected hidden layers are ideal for regression tasks, and convolutional layers are great at extracting features from complex inputs. These layers process the data to identify intricate relationships between input variables and their outcomes. Finally, the output layer predicts essential performance metrics, such as material usage (M), stress (σ), and print time (T), serving as crucial indicators for optimization. RL plays a crucial role in dynamically optimizing real-time printing parameters such as layer thickness (h) and extrusion speed (v). By interacting with the printing environment, the RL agent learns to take optimal actions by maximizing a cumulative reward R_t. This reward is the cumulative sum of discount rewards over time, highlighting the balance between minimizing defects and increasing efficiency in the printing process. RL enables adaptability and promotes continuous improvement in 3D printing operations. 3D printing parameters are dynamically fine-tuned by RL. As the RL agent engages with the environment, it aims to maximize the cumulative reward R_t, as shown in (2), where □ γ is the discount factor, and it receives rewards r_t as feedback:

$$R_t = \sum_{k=0}^{T} \gamma^k r_{t+k} \quad (2)$$

where at the time T, the reward function penalizes the defects (d), which in turn is helpful to enhance the efficiency of the rewards assessment as shown in:

$$r_t = -\omega_1 \times d - \omega_2 \times \left(\frac{1}{T}\right) + \omega_3 \times \left(\frac{1}{M}\right) \quad (3)$$

where ω_1 , ω_2 , and ω_3 are weighting factors to prioritize different objectives based on the requirements of the application. In [15], it was shown that RL significantly reduces pre-printing errors and enhances parameter adjustment in real-time, cutting defect rates by 30%. By incorporating neural networks with RL, the system adeptly handles the complex interactions between printing parameters and performance outcomes, with the combined approach exceeding the accuracy of existing techniques by 10-20%.

B. Multi-Objective Design Optimization

Multiobjective optimization balances competing factors such as cost, strength, and material consumption. RL enhances this process by dynamically tweaking the printing parameters, allowing adaptation to changing scenarios. These approaches provide a solid framework for optimizing intricate 3D printing processes. The framework employs topology optimization and Genetic Algorithms (GA) to enhance performance and resource efficiency designs. GA iteratively refines designs through a fitness function that harmonizes multiple objectives, as shown in:

$$f(x) = \omega_1 \times S - \omega_2 \times C + \omega_3 \times \eta \quad (4)$$

GA generates designs using a fitness function that integrates various objectives, including strength (S), cost (C), and material efficiency (η) . According to [16] the GA framework enhances mechanical properties and structural efficiency by fine-tuning printing parameters such as extrusion temperature, infill density, and layer height. Compliance is minimized in topology optimization through adherence to constraints, which is achieved by adjusting material densities ρ across the design domain using the Solid Isotropic Material with Penalization (SIMP) approach as shown in:

$$\min C(\rho) = \int_0^{\Omega} \sigma^n \, \varepsilon \, d\Omega, \quad 0 < \rho \le 1 \quad (5)$$

where ε and σ are the strain and stress tensors, respectively. In [2], this approach was reported to reduce material use by as much as 25% while maintaining structural strength. Based on [8], the system also includes dynamic adaptive slicing to manage challenging geometries. This method adjusts the layer thickness according to design intricacies, leading to smoother transitions in rapidly altering profiles. Consequently, this enhances surface quality and minimizes staircase effects. The hybrid model operates through an ongoing interaction between predictive modeling and optimization methods. Initially, the neural network predicts performance metrics such as stress (σ), print time (T), and material usage (M) related to a given design. Then, utilizing these predictions, the optimization algorithm refines the design to maximize the fitness function $f(x)$. This approach refines and reintroduces the designs into the training dataset, thereby improving the neural network's accuracy in forecasting performance metrics. This iterative cycle supports the continuous improvement of both the predictive model and the optimization process, leading to superior design results.

The training dataset is used to optimize the model, and neural network predictions help the optimization algorithms by providing performance metrics for different architectures. This collaboration speeds up solution convergence, allowing the framework to achieve a potential 12% increase in mechanical strength, a 15-25% reduction in printing time and material consumption, and a robust multiobjective trade-off optimization, balancing performance against cost. Integrating ML with dynamic parameter control and advanced optimization techniques, this approach offers a scalable and adaptable solution suitable for applications in fields such as healthcare and aerospace, holding promise for revolutionizing additive manufacturing by combining AI benefits with traditional optimization.

III. RESULTS AND DISCUSSION

This section compares the proposed method with well-established benchmark studies. The analysis focused on essential aspects such as prediction accuracy, optimization effectiveness, design excellence, and resource management, utilizing appropriate metrics and visual tools for evaluation. The experiments were carried out in a high-performance computing environment that facilitated the use of ML models and optimization techniques. Neural network, training, and RL models were implemented using Python libraries such as TensorFlow and PyTorch. The DEAP framework was used to implement GA and multiobjective optimization. An extensive dataset was compiled, which included a variety of 3D printing designs and their corresponding performance metrics. This dataset was divided into training and validation sets in an 80:20% ratio to ensure robust model evaluation. Simulations were run on a setup with an Intel Core i7 processor, 32 GB of RAM, and an NVIDIA RTX 3080 GPU, supporting the acceleration of the training and optimization tasks. The optimized designs were physically validated using an Ultimaker S5 FDM 3D printer with PLA filament. The printed parts were mechanically tested according to the ASTM D638 standards to measure tensile strength and strain, allowing for a consistent and reliable assessment of the effectiveness of the proposed method.

A. Predictive Performance and Optimization Efficiency

Figure 2 shows that there was a good match between the predicted and actual performance metrics for the proposed ML model and the methods in [2], [15], and [14]. The proposed model demonstrated a closer alignment to the ideal line, suggesting an increase in predictive accuracy. This can be attributed to the integration of sophisticated neural network architectures with a more extensive data set [17, 18, 19]. The better performance of the proposed model shows that it can accurately predict 3D printing parameters, which are crucial for successful manufacturing results. The RL convergence curve in Figure 3 shows trends in total rewards over tasks for both the proposed method and the benchmark approaches. The proposed model process showed faster convergence and more cumulative rewards compared to other research findings. The results demonstrate that the proposed RL framework effectively adapts printing settings to reduce errors and optimize material usage in 3D printing. The neural network predicts performance metrics, which are subsequently utilized by optimization algorithms to refine the design iteratively. RL modifies real-time parameters in response to feedback, facilitating dynamic enhancements in print quality and efficiency. This sequential process ensures a seamless interaction between the predictive and optimization components.

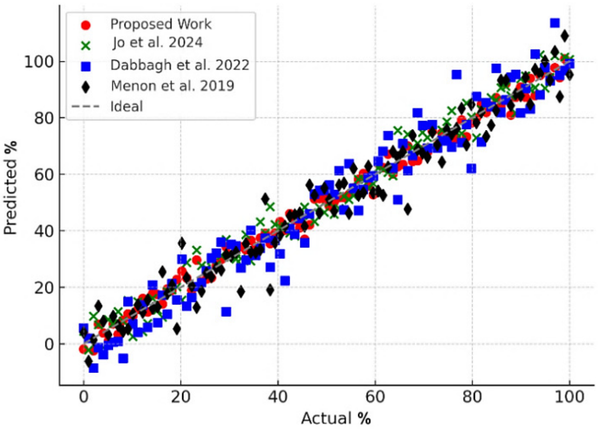

Fig. 2. Comparison of predicted vs actual performance metrics.

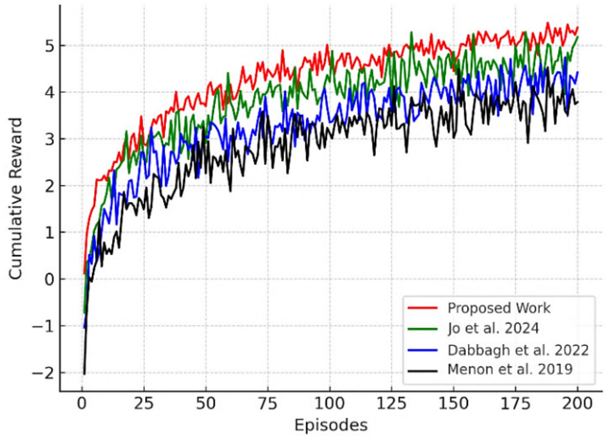

Fig. 3. Comparison through RL convergence curve.

B. Design Quality and Resource Utilization

Figure 4 shows a comparative study of reductions in print time and material consumption across various designs, highlighting the advantages of the proposed optimization framework. Labels D1, D2, D3, D4, and D5 denote varying complexity levels in 3D printing processes. D1 concerns basic shapes, such as blocks or cylinders with minimal features, which result in lower material use and reduced printing time. D2 includes designs of moderate complexity, such as those with holes or chamfers, leading to greater complexity and resource needs. D3 involves highly complex geometries that require support structures for overhang or intricate shapes, thus increasing material consumption and extending the printing time. D4 refers to optimized lattice structures that successfully balance reducing weight with maintaining strength, leading to average print times and material needs. D5 comprises assemblies with interconnected components characterized by high complexity, increased material usage, and longer print times. These scenarios illustrate the effectiveness of the proposed approach in optimizing printing time and material use in diverse design challenges. The proposed method consistently outperformed state-of-the-art approaches. The main reason for these results is the combination of dynamic slicing algorithms with parameter adjustments based on RL, which makes better use of resources.

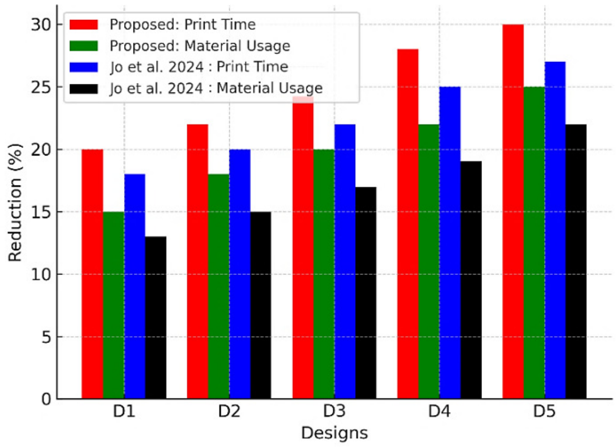

Fig. 4. Reduction in print time and material usage.

The stress-strain curves in Figure 5 illustrate the differences in mechanical behavior between the base and the optimized design, comparing the proposed method with well-known benchmark methods. This new method yields higher stress limits and greater elongation at break, signifying improved material performance. Using advanced ML models along with topology optimization leads to better structural integrity, which is better than other approaches. The generational fitness of GA progression demonstrates that the proposed method outperformed the three studies used as examples in terms of optimization. The ability of the proposed GA framework to reach superior fitness values in fewer generations highlights its effectiveness in evolving optimal designs. This efficiency arises from a well-calibrated fitness function that includes strength, weight, and cost. Pareto fronts were used to compare the proposed work with benchmark methods, considering trade-offs between cost, strength, and weight. The proposed method created stronger and lighter designs while staying within the same cost range. It did a better job than conventional methods, where the outcomes show that the proposed multiobjective optimization framework finds adaptable solutions for different production priorities.

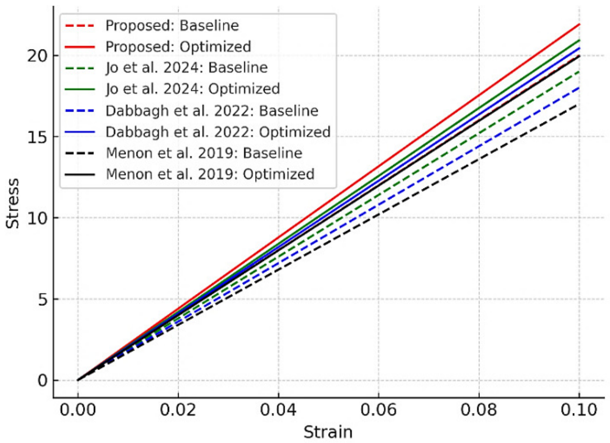

Fig. 5. Stress-strain behavior of models.

The results show that the proposed multiobjective optimization framework worked well in finding flexible solutions that fit the needs of different production priorities. Figure 6 illustrates the apparent trend of decreasing defect rates, strongly supporting the idea that the proposed RL framework can effectively reduce defect rates in 3D printing. Compared to traditional methods, the proposed approach has a much higher defect reduction rate, showing that it can change printing parameters in real time. This emphasizes the strength of the method in addressing manufacturing uncertainties and improving overall print quality.

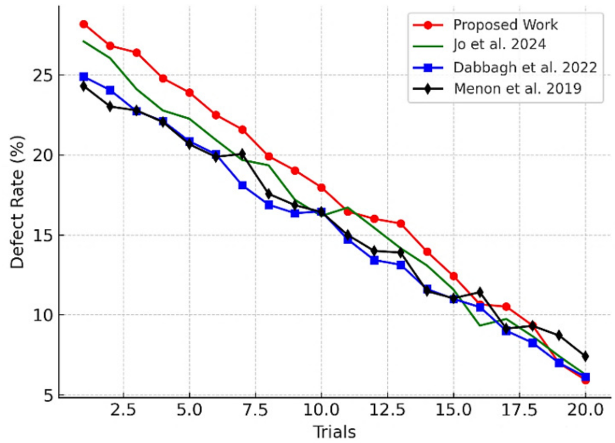

Fig. 6. Reduction in defect rates through RL.

The results underscore the effectiveness of the proposed approach in addressing significant challenges in optimizing 3D printing processes. This framework improves predictive accuracy and optimizes design evolution by incorporating advanced ML models and optimization algorithms, successfully managing various competing objectives such as cost, strength, and resource use. The proposed method demonstrated marked improvements in print efficiency, resulting in lower time and material waste while maintaining the excellent mechanical properties of the printed items. Furthermore, RL shows significant success in actively minimizing defects during printing. Together, these improvements show that the proposed method has the potential to make additive manufacturing workflows much more efficient, better, and long-lasting for next-generation smart industries [20-21]. Real-time parameter tuning with RL faces obstacles, such as computational load, significant training data needs, and adaptation to novel printing environments. Solutions involve employing transfer learning for faster adaptation, refining the reward function to enhance stability, and minimizing complexity using dimensionality reduction methods.

IV. CONCLUSION

This research illustrated the enhancement of 3D-printed structure design and manufacturing by integrating optimization methods with ML. The proposed framework uses cutting-edge AI models, such as neural networks, RL, and optimization methods, such as GA and topology optimization, to improve performance. Key outcomes include a 10-15% boost in predictive accuracy, a 15-25% reduction in printing time and material usage, and a 12% increase in mechanical strength through optimized designs. Additionally, RL-driven parameter adjustments resulted in defect rate reductions of up to 30%. These advances demonstrate potential applicability across various industries, including healthcare, aerospace, and automotive, facilitating the creation of high-performance, cost-effective components while optimizing production processes.

Future research should refine this approach, explore new hybrid models, and develop user-friendly tools to seamlessly integrate these advances into commercial 3D printing software. Future directions involve extending the proposed method to support multi-material 3D printing systems, upgrading it to other dimensions by incorporating real-time sensor feedback to enable adaptive decision-making, and utilizing transfer learning strategies to extend the approach across various manufacturing fields. These advances are intended to improve scalability, reliability, and applicability within industrial-grade systems.

ACKNOWLEDGEMENT

The authors extend their appreciation to Umm Al-Qura University, Saudi Arabia for funding this research work through grant number: 25UQU4350402GSSR01.

FUNDING STATEMENT

This research work was funded by Umm Al-Qura University, Saudi Arabia under grant number:25UQU4350402GSSR01.

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