Cost and Density Evaluation Function Application, for Optimal Biodiesel Mixtures by Genetic Algorithm Implementation

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Abstract: - The current document presents a fresh method for addressing the optimization challenges concerning fuel mixtures in the production of Biodiesel. Given the rising concerns over diesel emissions and the associated expenses, there's a growing interest in exploring alternative fuel options. Traditional desulphurization methods are time-consuming and require substantial financial investments. Conversely, Biodiesel offers a promising solution as it's derived from renewable resources and is environmentally sustainable. This study introduces an enhanced genetic algorithm that assesses the proportions of components within a fuel mixture blend, aiming to create optimal combinations for Biodiesel production. Apart from cost considerations, the density of the fuel, a key physicochemical characteristic, is pivotal in determining its suitability for widespread use and commercialization. Rigorous experimentation has resulted in highly precise Biodiesel blends, suggesting an optimal fuel solution for each specific set. For instance, in Set 1, Biodiesel was composed of 75.031% diesel and 24.969% biodiesel, with a mixture cost of 1.6975 €/l and a density of 0.8355 g/ml. In Set 2, the fuel mixture consisted of 75.016% diesel and 24.984% biodiesel, with a cost of 1.6977 €/l and a density of 0.8366 g/ml. Notably, the new Biodiesel fuels are significantly cheaper, costing 15.13% less (Set 1) and 15.12% less (Set 2) than diesel (priced at 2.0000 €/l) and are proposed between $1.5 * 10^9$ evaluated biodiesel mixtures.

Key-Words: - Ideal combinations of biodiesel blends, challenges in finding the best solutions, algorithms based on genetic principles, computational methods inspired by evolutionary processes, optimization problems, environmentally friendly biodiesel, experimentation through simulations.

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1 Introduction

Over recent decades, as society has progressed, there has been a steady rise in energy demands. The dwindling availability of diesel reserves, coupled with the environmental repercussions of diesel consumption such as harmful emissions, alongside global crises, have prompted extensive exploration into alternative fuel sources by numerous researchers, [1], [2]. Biodiesel emerges as a renewable energy option, offering several environmental benefits: it is non-toxic, biodegradable, and clean, devoid of aromatic compounds. Furthermore, it reduces noticeably emissions such as sulfur dioxide, carbon monoxide, and hydrocarbons that remain unburnt and suspended of fine particles originating from diesel engine combustion, as various testifies reports, [3], [4], [5], [6], [7]. On the contrary, the use of diesel entails the presence of sulfur, which mainly contributes to harmful oxide emissions. Although her process of Diesel removal is time-consuming and requires significant investment, the most effective approach to reducing emissions is to boost fuel by blending diesel with biodiesel. This approach ensures that the fuel maintains its quality as long as it significantly reduces sulfur content. Another critical aspect regarding fuel characteristics is density, which has a decisive role in determining fuel performance in compression engines (CI), [7], [8], [9]. The experimental reduction process of these mixes in the labs is time-consuming and accurate, as the researchers reported at-length analyses to achieve the optimal balance between fuel quality and cost, [10].

Advanced methodologies such as sophisticated methods, approaches inspired by natural processes, algorithms for learning by machines, and computational strategies influenced by evolution offer sophisticated solutions to complex optimization challenges, yielding near-optimal outcomes of high quality. Consequently, operational research (OR) endeavors heavily rely on the utilization and advancement of these techniques, [11], [12], [13], [14], [15].

Although many studies are concerned with improving the biodiesel production process, none emphasize finding the best combination of raw materials for its production. The current study deals with the optimal combination of the basic raw materials (Diesel and biodiesel are comprised of an equal combination of animal-derived fats and plant-derived oils, with each contributing 50% to the overall composition).

The effectiveness of this approach is contingent upon two main factors: a) innovative modeling techniques, particularly in terms of function evaluation modeling enhancements, and b) the precise definition and fine-tuning of the genetic algorithm. The current approach has yielded significant results through experimental simulations, including 1) minimizing experimental costs, 2) reducing experiment durations, 3) enhancing both cost and density through minimization of the evaluation function, and 4) promoting the development of ecologically sustainable fuels.

Now, laboratory researchers have access to this innovative tool for decision-making, facilitating the advancement of optimal fuel formulations. Employing a genetic algorithm, it rapidly generates optimal fuel mixtures for laboratory experimentation, sifting through a vast array of approximately 750 million different combinations tested in each experimental set. The benefits of this method or strategy are evident in streamlining the mixture production process, particularly when the newly developed biodiesel proves to be more appealing than competing fuels.

The rest of the document follows this structure: In Section 2, the mathematical groundwork is laid out for addressing the fuel blending challenge., detailing the constraints imposed by ingredient availability. Section 3 covers the key methodological aspects of the suggested approach and aims to provide a deeper insight into the operational principles of the algorithm employed. Lastly, the concluding segment offers a summary of key findings and noteworthy observations.

2 Fuel Mixture Problem

The issue or challenge concerning fuel blends is a subject of extensive investigation within the research community due to its complex and dynamic nature. Given the practical challenges associated with this practical or tangible issue, it's impractical to physically generate every conceivable combination via laboratory experimentation experiments due to their sheer volume, which would incur significant costs and lengthy execution times. The current approach offers a solution by allowing for flexible management of mixture production through simulation processes, thereby mitigating the challenges posed by experimentation.

With the implementation of the current Evolutionary Algorithm (GA), each formulation undergoes a full analysis of its performance, ensuring the identification of specific and high-quality fuel mixtures. This approach to work effectively suggests an excellent solution within a concise experimental time frame. In the minimization of the fuel problem fitness function, the values are achieved through a mathematical function that addresses multiple targets of fuel production simultaneously.

2.1 Reducing the Overall Function Value of the Mixture to Its Lowest Possible Level (min TMFV)

The value of the function for the entire set mixture of raw materials represented as "i", is calculated by combining two weighted compositions. The first sum (w_(1)) involves multiplying the normalized cost per liter of each ingredient by its respective percentage in the mixture, while the second sum (w_(2)) is the result of multiplying the normalized density per liter of each ingredient by its percentage in the mixture.

$$TMFV = w_1 * \sum_{i \in \{1,..,n\}} (\frac{c_i}{c_{max}}) * p_i - w_2 * \sum_{i \in \{1,..,n\}} (\frac{d_i}{d_{max}})^4 * p_i \quad (1)$$

The optimization problem regarding raw materials aims to reduce the function value to its minimum of the new biodiesel mixture, denoted as

TMFV (Total Mixture Function Value), represented by the equation: min TMFV (2).
The constraints for the problem are as follows:

The percentage of each ingredient must fall within the minimum and maximum allowable values.

The cost of each ingredient, is represented by c1 for diesel and c2 for biodiesel.

The density of each ingredient, is indicated by d1 for diesel and d2 for biodiesel.

The weights assigned to the ingredients, ensure that their sum equals 100%.

3 Algorithmic Framework

Various industries have adopted nature-inspired methodologies, yielding superior outcomes. Genetic algorithms, a prominent example, draw from evolutionary computation principles, initially introduced by [16]. In this study, a Genetic Algorithm (GA) evolutionary approach is applied to tackle the biodiesel mixture problem (Figure 1). These algorithms employ choice, crossover, and mutation operations to gradually develop the genetic material of individuals within a group over successive generations through iteration.

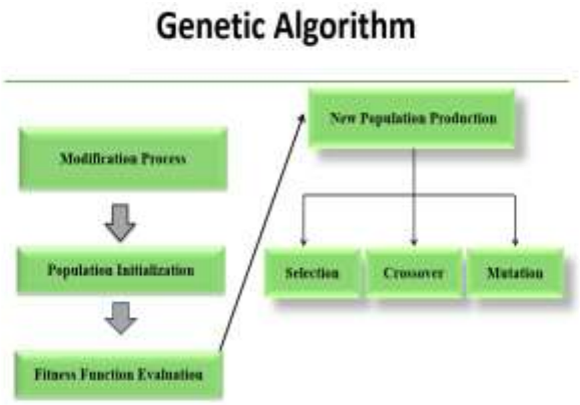

Fig. 1: Genetic Algorithm Approach

3.1 Reducing the Overall Sum of the Function's Values Across the Mixture (min TMFV)

Consider an illustration of a chromosome representing a mixture composed of two ingredients. In such examples, the total percentage of ingredients always sums up to 100%. For instance, Diesel might constitute 76.22% of the mixture, while Biodiesel makes up the remaining 23.78%.

3.2 Reducing the Overall Sum of the Function's Values Across the Mixture (min TMFV)

The generation process is split into two phases. Firstly, the initial generation is formed by randomly creating feasible mixtures. Secondly, for subsequent generations in the second phase, chromosome production comprises three separate steps.

a) Part 1: The top 10% of chromosomes from the present iteration of the population, deemed as the best mixtures (TOP Mixtures), are directly transferred toward the succeeding iteration.

b) Part 2: The following 70% of solutions are comprised of chromosomes generated through the crossover operator, which combines genetic information from two parent chromosomes.

c) Part 3: The remaining 20% of chromosomes are generated through mutation, introducing small random changes to the genetic makeup of chromosomes, akin to how the initial population was formed.

The process involves creating fuel mixtures by assigning percentages of diesel and biodiesel to each chromosome. Subsequently, a fitness function is applied to assess each mixture (chromosome) based on criteria such as cost and density, allowing for the ranking of all mixtures. Solutions generated through crossover and mutation operators adhere to specific ingredient percentage ranges (minimum % to maximum %), ensuring that the total percentage of ingredients always equals 100%. Importantly, the proposed approach only yields feasible solutions, ensuring that every potential solution is considered in the evaluation process.

Following the creation of the initial population, a framework known as ± IPLS, derived the proportions derived from the top-performing chromosome have been included. This framework, introduced by [14], enhances the optimization process by centering it around the best chromosome from the previous generation. A specific range of values for IPLS (e.g., 5% - 10%) a value called IPLS is established, and for every generation, a fresh IPLS value is chosen at random (for instance, Generation 1, IPLS: 6%; Generation 2, IPLS: 9%; ... Generation 100, IPLS: 10%). Through extensive experimentation, involving over 100,000 simulations, all Genetic Algorithm (GA) parameters have been meticulously selected by [12]. These parameters have proven to be highly effective and remain competitive today, consistently yielding superior results.

3.3 Benchmark Experiments

Assessing the effectiveness of the proposed Genetic Algorithm (GA) method was conducted through two distinct sets of experiments, categorized based on the temperature of the mixtures: 5°C, 10°C, 15°C, 20°C, and 25°C (referred to as sets hereafter):

(a) Set 1 - Priority on Cost: The importance assigned to the weight value (w_(1)) assigned to the cost aspect in the Evaluation Function TMFV was set to 50% or higher.

(b) Set 2 - Priority on Density: The significance attributed to the weight value (w_(2)) attributed to the density aspect in the Evaluation Function TMFV was also set to 50% or higher.

(c) For both Sets: The population was consistently 150 individuals, evolving over 200 generations. The ingredient costs were predetermined: diesel priced at 2.0000 €/liter and biodiesel at 0.7901 €/liter. Furthermore, the ingredient densities were established at diesel 0.8191 g/ml and biodiesel 0.8855 g/ml at 5°C. The ingredient densities varied depending on temperatures ranging from 5°C to 25°C.

(d) In each subsequent generation, the top 10% of chromosomes from the previous generation, based on their performance, were directly carried over.

(e) The crossover operator produced 70% of the population, with the IPLS value selected randomly for each generation, fluctuating within a range of ±5% to 10%.

(f) The mutation operation was implemented on the remaining 20% of the chromosome set.

(g) Every experiment involved conducting 1000 separate simulations for each Set and temperature variation (for instance, Set 1 - 5°C - 1000 iterations, Set 1 - 10°C - 1000 iterations, ..., Set 2 - 25°C - 1000 iterations).

Biodiesel, functioning as the secondary component, is sourced equally from two primary origins: The mixture contains an equal amount of fat from animal and plant origins. The expenses associated with plant sources, specifically rapeseed oil and sunflower oil, can be accessed globally through the [17], as well as locally in Greece via the [18].

Within Greece, 15 companies are tasked with collecting animal fat and processed olive oil. The prices of these components are shaped by refinery demands, consequently impacting the ultimate price of biodiesel.

The groups of experiments are categorized according to temperature ranging from 5°C to 25°C. Set 1 emphasizes cost (w1 ≥ 50%), while Set 2 emphasizes density (w2 ≥ 50%). For instance, when w1 equals 70% and w2 equals 30%, the focus is on cost, indicating that cost is considered more significant than density.

- Set 1: Half and half (50% / 50%), Sixty-forty (60% / 40%), Seventy-thirty (70% / 30%), Eighty-twenty (80% / 20%), Ninety-ten (90% / 10%)
- Set 2: Equal split (50% / 50%), Forty-sixty (40% / 60%), Thirty-seventy (30% / 70%), Twenty-eighty (20% / 80%), Ten-ninety (10% / 90%)

Additional experimental details are provided: Diesel is priced at 2.000 €/l, while biodiesel costs 0.7901 €/l. Additionally, the density ranges from 0.8191 g/ml to 0.8855 g/ml, varying with temperature. Moreover, the percentages of ingredients in mixtures are specified, with diesel ranging from 1% to 99% and biodiesel from 1% to 30%. These values reflect the availability and actual prices during the laboratory experimentation period.

3.4 Experiments Results

Initially, the performance of the suggested Genetic Algorithm (GA) was assessed in Set 1. This involved conducting 25,000 independent simulations for each combination of temperatures (ranging from 5°C to 25°C) and weights (w1 and w2). The total duration of these simulations amounted to 3,536.29 seconds (equivalent to approximately 59.41 minutes or roughly 1 hour).

Figure 2 contains information about the biodiesel evaluation criteria of Set 1 and Set 2 experiments at a temperature of 5°C. For all w1 and w2 combinations of priority on cost (w1 ≥ 50%) and for all w1 and w2 combinations of priority on density (w2 ≥ 50%) are presented the cost and the density of the evaluated fuel mixtures. For example, in group w1 = 90% and w2 =10%, the blue column refers to the cost criterion = 1.6981€/l, which is part of Set 1 (priority on cost). On the other hand, the yellow column (w1 = 10% and w2 =90%) concerns the cost criterion = 1.7787 €/l, as part of Set 2 (priority on density).

The ideal fuel blend in Set 1, at a temperature of 5°C with weights distributed evenly between w1 and w2, consists of 75.031% diesel and 24.969% biodiesel. The Total Mixture Function Value (TMFV) is recorded at -0.0727, with the mixture costing 1.6975 €/l and having a density of 0.8355 g/ml (Figure 2).

Set 2 provides details regarding the optimal mixture derived from 1000 independent simulations, resulting in a total of 25 optimal mixtures. The evaluation is centered on minimizing the Total Mixture Function Value (TMFV). With an increase in the value of w2, the TMFV also increases, indicating an emphasis on the density criterion over the cost criterion. Although the ingredients' percentages, optimal mixture costs, and densities vary slightly, they remain within proximity as indicated earlier.

Figure 3 contains information about the biodiesel evaluation criteria of Set 1 and Set 2 experiments at a temperature of 20°C. For all w1 and w2 combinations of priority on cost (w1 ≥ 50%) and for all w1 and w2 combinations of priority on density (w2 ≥ 50%) are presented the cost and the density of the evaluated fuel mixtures. For example, in group w1 = 80% and w2 =20%, the blue column refers to the cost criterion = 1.6979€/l, which is part of Set 1 (priority on cost). On the other hand, the yellow column (w1 = 20% and w2 =80%) concerns the cost criterion = 1.7037 €/l, as part of Set 2 (priority on density).

The best fuel blend identified in Set 2, at a temperature of 20°C with a distribution of 10% for w1 and 90% for w2, comprises 75.016% diesel and 24.984% biodiesel. The Total Mixture Function Value (TMFV) is recorded at -0.8146, with the mixture costing 1.6977 €/l and having a density of 0.8366 g/ml (Figure 3).

4 Conclusion

This paper introduces a genetic algorithm approach aimed at offering the best possible resolutions for the fuel-related matter blending issue. The key novelty lies in determining viable proportions for diesel and biodiesel, sourced equally from 50% animal fat and 50% vegetable sources, are determined, resulting in enhanced fuel formulations. The efficiency of the IPLS mechanism enables decision-makers to explore the vicinity of optimal ingredient percentages effectively.

Moreover, the Total Mixture Function Value (TMFV) is utilized to evaluate the new biodiesel mixtures to signify the creation of competitive fuel, taking into account the accessibility of ingredients. This evaluation process emphasizes two crucial fuel parameters: cost and density. The priorities assigned to "Emphasis on Cost" and "Emphasis on Density" during the evaluation of experimental fuel are determined by the weights w1 and w2, respectively.

The investigation of the new ideal biodiesel blend involved extensive experimentation, covering 150 million mixtures. Two sets were identified, each spanning temperatures ranging from 5°C to 25°C: Set 1, focused on cost optimization, and Set 2, prioritizing density optimization.

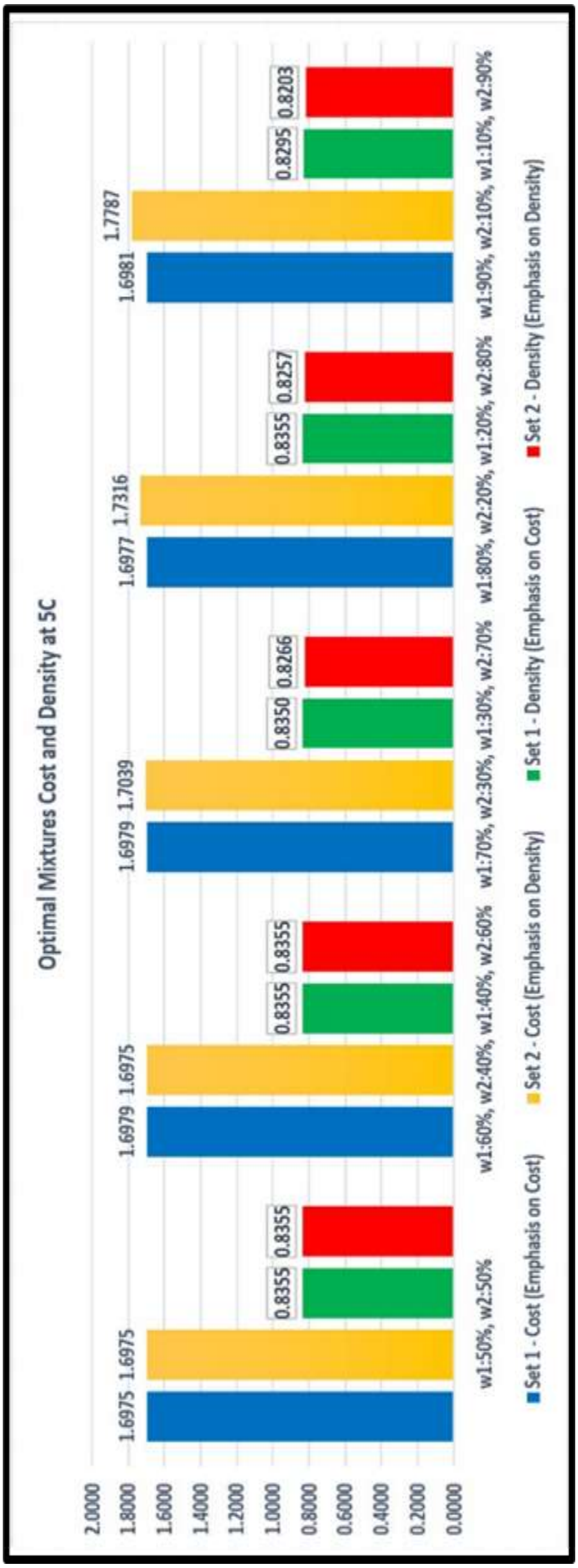

Fig. 2: The cost and density of the optimal mixtures at a temperature of 5°C

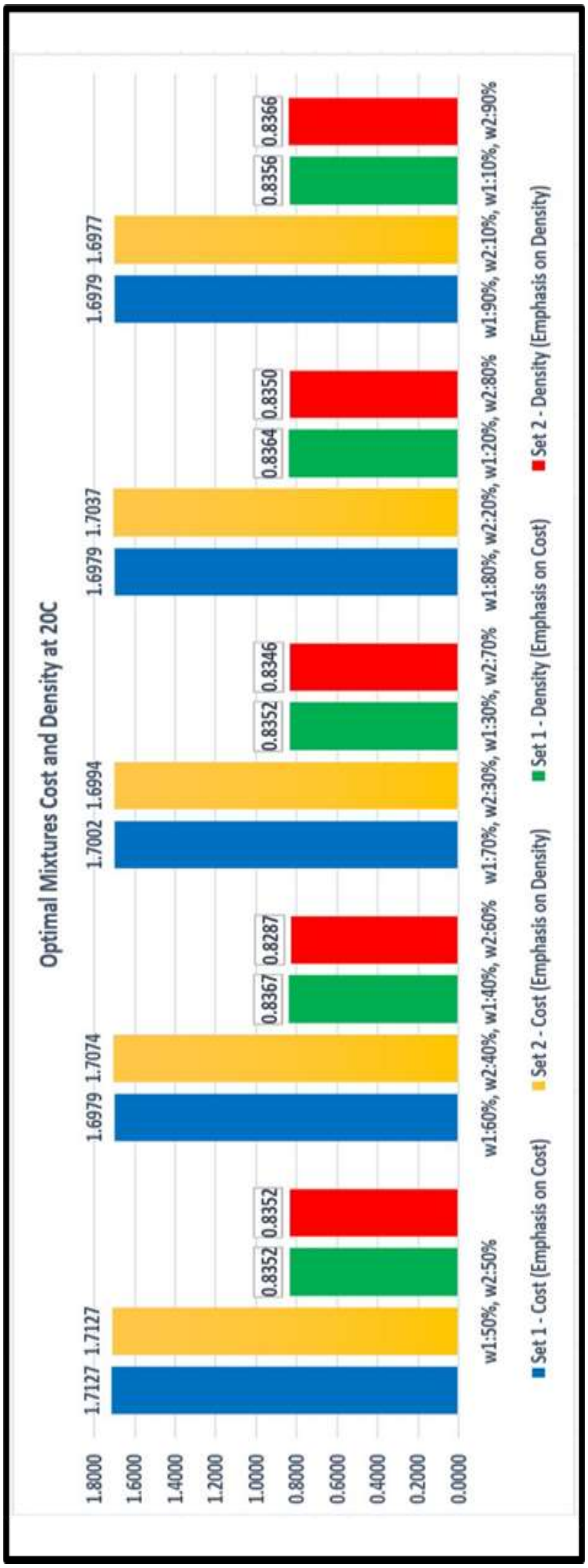

Fig. 3: The cost and density of the optimal mixtures at a temperature of 20°C

In Set 1, at a temperature of 5°C with equal emphasis on cost and density (w1 = 50%, w2 = 50%), the optimal mixture comprised 75.031% diesel and 24.969% biodiesel, with a TMFV of -0.0727, a cost of 1.6975 €/l, and a density of 0.8355 g/ml. In Set 2, at a temperature of 20°C with an emphasis on density (w1 = 10%, w2 = 90%), the optimal mixture consisted of 75.016% diesel and 24.984% biodiesel, yielding a TMFV of -0.8146, a cost of 1.6977 €/l, and a density of 0.8366 g/ml. Compared to diesel priced at 2.0000 €/l, the new biodiesel fuels are approximately 15.13% (Set 1) and 15.12% (Set 2) cheaper, offering competitive pricing, lower sulfur content, and reduced pollutant emissions upon consumption.

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Conflict of Interest

The authors have no conflicts of interest to declare.