A Robust Approach for Cooperation and Coopetition of Bio-Refineries Under Government Interventions by Considering Sustainability Factors

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Abstract: The most significant international issue affecting society and the economy today is energy. Also, addressing sustainability issues, including environmental, economic, and social issues are the main goals of governments in developing and developed countries. Therefore, it has been in the interest of governments to consider strategies that could move the energy industry, especially fuel, towards clean fuel production. In this paper, the effect of government financial interventions under the coalition of bio-refineries to achieve sustainability goals has been studied. The proposed nonlinear model aims to obtain the optimum amount of biofuel production under the conditions of the cooperation of bio-refineries and government financial interventions. On the other hand, government sustainability goals are considered as functions related to economic, social, and environmental issues. Mulvey’s robust approach is employed for controlling model uncertainties. For finding the best tariff policy, the MULTIMOORA approach is used by considering sustainability considerations, and the Best-Worst Approach is followed in obtaining the weights of the criteria. Furthermore, for the best tariff policy in a general coalition, sharing the profits among the bio-refineries as players in a cooperative game, fair profit distribution methods were applied. Finally, managerial results were presented by a sensitivity analysis of the tariff parameter.

Index Terms: Biofuel production, government interventions, sustainability, cooperative game theory, robust optimization.

I. INTRODUCTION

Nowadays, energy is the most sensitive issue in the world, which is encompassing environmental, economic, and social aspects of sustainability [1]. Environmental pollution, especially air pollution, is one of the apparent threats to environmental health in all nations, leading to diseases such as asthma which can lead to premature death in some instances [2], [3]. It is assumed that global warming and air pollution are caused by the rise in greenhouse gas (GHG) emissions due to the exponential growth in industrial activity. Many international climate agreements and treaties have been signed, and many countries have placed environmental protection measures in place to compel companies to reduce their CO2 emissions [4], [5]. For example, the Kyoto Protocol was one of the first international treaties in which the countries involved agreed to minimize their GHG emissions. At a regional level, different environmental policies have been implemented by the European Union (EU) to reduce the effects of global warming. The EU’s most significant effort to combat climate change was the development of the Emissions Trading Scheme of the EU. The Paris Climate Agreement has become the most significant environmental agreement after the expiry of the Kyoto Protocol [6].

Using forest and wood residues to produce energy and fuel could create extra income streams for forest industries, decrease their impact on the environment, and create fresh possibilities for forest-dependent communities to develop [7]. Biofuels are renewable energy sources obtained from biological materials that distinguish them from other sources
of non-fossil fuel energy such as wind and wave energy. Biofuels can be solid, liquid or gaseous, and all three energy forms are sustainable and renewable because they are generated from plants and animals and can be replaced in a short time [8], [9].

There have been developed four generations of technologies for producing biofuels. The most prevalent and commercially available technology is the processing of first-generation biofuels. First-generation biofuels feedstocks are the edible crop portion such as corn, sugarcane, rapeseed, etc [10], [11]. The main drawback of the first-generation biofuel is the resulting food versus fuel competition caused by production using edible parts of the crop as the feedstock for biomass, which can lead to a global increase in food prices and significantly affect human well-being [12]. Biofuel production technology of the second generation has been developed to tackle the rivalry of food versus fuel induced by biofuel of first-generation. Second-generation biofuel feedstock is the cellulosic biomass forestry residues, such as corn stovers, switchgrass, and wood chips. It does not entail additional planting and harvesting of wildlands and is considered capable of reducing pollution and costs as opposed to biofuel technology of the first generation [10], [11]. Biofuels of the third generation are made from energy crops specially engineered, such as algae. Fourth-generation biofuel is a moderately innovative concept aimed at trapping and disposing of carbon dioxide (CO₂) back to earth at any point in biofuel production [11].

By comparison, the production of fossil fuels took 10 to 100 million years, and what we are burning is ancient solar energy. Also, the energy obtained from plant material should be fundamentally carbon neutral, as the carbon collected in crops is released when the material is burned by fixing carbon dioxide in photosynthesis. Currently, it is evident that the fossil fuel supply is limited and can be foreseen when fossil fuel supplies become scarce or even run out. Carbon dioxide accumulation in the atmosphere seems to be the main cause of global warming [13]. The consensus indicates that with dramatic modifications in climate and sea levels, the long-term impacts of global warming will be dangerous.

Some studies have been carried out to measure, analyze, monitor, and reduce production-related GHG emissions to overcome such a hurdle by concentrating on different biofuel manufacturing processes. Melillo et al. [14] examined GHG emissions by changing land use and applying nitrogen-based fertilizers to growing biofuels crops. In the production of first and second-generation biofuels, Naik et al. [15] investigated the manufacturing processes and their environmental impacts. Li et al introduced an enhanced preprocessing scheme for biofuel to reduce energy consumption and GHG emissions without compromising output throughput. Zhang et al. [16]–[18] carried out the pelleting process research, which can reduce the size of biomass to expose the mechanism of energy consumption and reduce the pelleting process’s energy intensity. Designing an optimal biofuel supply chain is considered another significant way to overcoming the current hurdle. An environmentally sustainable supply chain of biofuels (BSC) would unlock the full potential of that renewable source of energy.

Working on the design and optimization of BSC at both strategic and operational levels can be classified into the following three categories [19]. The first group focuses on applying the Life-Cycle Analysis (LCA) approach to the study of total BSC emissions. The LCA of biofuel production includes establishing a system boundary for the BSC and using data from the process analysis to estimate the carbon impacts within the system boundary of the selected supply chain [20]. The second group focuses on designing BSCs to improve the competitive cost of feedstock and ongoing supply of feedstock to alleviate the impacts due to the uncertainties and risks of demand and price of final biofuel products, production and yield, and transport [21]. The third group makes use of mathematical programming to develop and automate various BSC behaviors [19].

The significant concerns in BSC research are summed up in three different aspects [21]–[23]. The first concern is to monitor the resulting GHG emissions due to transportation, preprocessing, and bioconversion operations [21]. The second challenge is to find the most profitable BSC network to draw further investment to make this developing industry commercially viable as the biofuel market eventually has to compete with petroleum-based fuels [23]. The third issue is the socioeconomic implications of BSCs (e.g., the potential for poverty reduction, indirect impacts on land and crops, effects on social capital, and substitution of conventional fossil fuels) [22].

Social issues have become more and more prominent over time, such as environmental pollution, labor conflicts, food safety, etc. Governments at different levels must enact a sequence of policies, legislation, and regulations to motivate industries to take on sustainability characteristics. So, considering the refining industry as the most significant part of a country in achieving sustainability in the energy sector is a priority [24]. Energy sector strategies are one of the most effective policies in a country’s growth. Climate change and energy security are significant factors in energy policies, laws, and energy investment models [25]. It is essential to decrease GHG emissions to regulate climate change [5]. Therefore, many nations have set road maps, objectives, and compulsory objectives for reducing GHG emissions to create renewable energy [26], [27].

Some measures are taken by the government to direct industrial activities towards specific socially desirable results. In recent years, one strategy that has gained significant assistance is to provide tariffs as a subsidy or tax for refineries. In this article, we consider the coalition of bio-refineries under the government tariff policy. First of all, the bio-refineries model has been formulated in the shape of forming a coalition and independent activity of bio-refineries. Second, due to uncertainties in the parameters, the robust counterpart model is offered by using Mulvey’s robust approach. The government objectives consider
sustainability factors such as economic, environmental, and social factors. For achieving the best tariff policy, the MULTIMOORA method, by considering the government objectives and profit of bio-refineries, is employed and Best-Worst Method (BWM) is used for obtaining the weights of the criteria. Next, we applied some payoff distribution methods to share the profits of each player in the cooperative game (CGT) model. The main contribution of this research is investigating the effect of interventions by governments and policymakers on the price of biofuel and output quantities of bio-refineries under the coopetition of bio-refineries to achieve sustainability aspects like economic, environmental, and social welfare.

In particular, the objective of this paper is in answering the following questions:

1) How can the government reach its sustainability objectives? And what is the best tariff policy to help achieve government objectives?
2) What are the advantages of establishing collaboration among bio-refineries?
3) What is the best mechanism for allocating saving costs among coalition makers in models with government tariff strategy?

The rest of the study is organized as follows; a brief literature review of the cooperative game theory (CGT) applications, government policies, and robust optimization (RO) have been presented in Section II. The problem definition, model assumptions, and robust formulations are presented in Section III. Solution approach and computational results of solution approach for a set of numerical examples are discussed in Section IV. Also, the managerial insights are given in this section. The conclusions and some possible ideas for further researches are presented in Section V.

II. LITERATURE REVIEW

The coalition of bio-refineries under government financial interventions is considered in this paper. The amount of production under government interventions is a significant issue in the production planning of bio-refineries. The government attempts to achieve its sustainability factors from imposing the appropriate value of tariff, which affects the profit of bio-refineries and the sustainability factors. The related literature is reviewed in this section.

A. THE COMPETITION AND COOPERATION IN THE BIOFUEL SUPPLY CHAIN (SC)

The main concerns of designing bio-refineries are the low return and the highly variable investment costs. Therefore, forming a coalition among bio-refineries can be useful and may reduce the costs. In SCs being aware of the profit of each participant may help players to attempt to gain a significant role in the chain. Some of the papers that used GT in the biofuel SC are as follows:

Skovsgaard and Jensen [28] developed a mixed integer programming model to find the optimum value chain for biogas. To understand the observations of the real world compared to the results of their study, they used the CGT approach. To allocate benefit among heterogeneous owners in the value chain, they implemented three profit allocation mechanisms. Massol and Tchung-Ming’s [29] research looks at developing cooperative strategies between Liquefied Natural Gas (LNG) exporting countries and Gas Exporting Countries Forum members. Their economic study focuses specifically on a frequently raised scenario: the emergence of a cooperative approach designed solely for logistical rationalization that would not affect LNG prices. Bai et al. [30] proposed game-theoretical models that integrate farmer’s land use and market choice decisions into the SC issue of bio-fuel manufacturers. To address possible business relationship scenarios between feedstock suppliers and biofuel manufacturers, a non-cooperative bi-level Stackelberg leader-follower game model, and a CGT model was created by them.

In Chalmardi and José-Fernando [31] proposed model, an official Environmental Protection Agency has the leading role and serves as the decision-maker at the upper level. The objective function of the leader included environmental aspects, while the objective function of the follower was composed of economic aspects. In their model, the government is trying to affect circumstances by offering financial incentives (subsidies) and encouraging the SC manager in applying cleaner technologies. Parsaeifar et al. [32] studied a SC involving one manufacturer and multiple suppliers and retailers, where the two latter compete horizontally, but all three compete vertically by maintaining the Stackelberg balance on the assumption that the manufacturer is stronger in the market. Andiappan et al. [33] showed that involving stakeholders in participating in green technology projects is a challenge. Therefore, they presented a C approach to determine the allocation of increased mental benefits to green technology systems such as a palm-based bio-refinery in an eco-industrial park. Gaoa et al. [34] considered a SC in which a manufacturer, in its direct channel, produces and sells two types of green products under government interventions aimed at improving social welfare. Between the two stakeholders, there is a Stackelberg game. Their work stems from closed-form approaches for the optimum commodity tax, green degree, and price and obtains strategies for the government and the producer under various environmental policies. Table 1 illustrates the characteristics of the published papers on the game theory approaches in biofuels.

B. GOVERNMENT INTERVENTION AND REGULATIONS

Consumer awareness about environmental protection requirements is becoming increasingly important in relation to the government’s concerns, and people will consider environmental factors such as energy savings and reductions in emissions when buying products [35]. The government attempts to encourage consumers and manufacturers to consume and produce products, especially fuels with fewer pollutants by considering financial interventions.
To examine how carbon taxes and subsidies for energy-saving products affect the operational decisions of companies, Yuyin and Jinxi [36] considered a manufacturer-retailer channel in which the manufacturer has the choice to design a product which release less carbon during production and uses less energy when customers use the product. Cucchiella et al. [37] represented an economic analysis of biogas and biomethane plants using various animal residue typologies. Indexes are used for Net Present Value and Discounted Payback Time. Biogas plant production of electricity helps to reduce emission levels, but its upgrade can lead to increased environmental performance. Their search reveals the significant role of subsidies attempting to provide government and planners policy guidance.

Bajgiran et al. [38] presented a model in a biofuel SC as a single follower multi-leader game to obtain the farmer’s land-use decisions as well as the farmer’s proposed prices for refineries. They considered subsidizing on the farmer and the refinery using the energy crop to test whether a subsidy program will increase the production of advanced biofuels and meet the Environmental Protection Agency’s mandate. Wu and Langpap [39] developed a game model to evaluate the effect of biofuel mandates and subsidies on prices and welfare. Results illustrated that mandates for biofuels are a primary cause of some of the major crop-based biofuel production concerns, including higher food prices and lower consumer welfare.

Huang et al. [9] investigated the economic and GHG consequences of stacking a low carbon fuel standard on the Renewable Fuel Standard with and without a carbon price policy. They compared the results of different food and fuel price policy combinations, fuel mix, and fuel consumption. Sivaraman et al. [40] discussed the effect on the economic performance of grid-connected photovoltaic (PV) systems of investment incentives, GHG rates, and renewable energy credit prices in their research. To evaluate new PV installations in California and Texas, their model combined PV efficiency, capacity-based dispatch, and cost-benefit financial components. Monasterolo and Raberto [41] expanded the Stock-Flow Consistent behavioral model to research the effect on sustainable development of gradual phasing out of subsidies for fossil fuels, the proceeds of which could be used by the government to subsidize energy investments in renewable infrastructure through financial policies.

Chen and Hu [42] developed an evolutionary GT model based on the static carbon tax and subsidy interaction between governments and manufacturers. The evolutionary GT is used to analyze the manufacturer’s behavioral strategies in response to various combinations of carbon taxes and subsidies. Halat and Hafezalkotob [43] proposed a Stackelberg game between the government and a multi-stage green supply chain (GSC), where the government aims to increase social welfare, and the goal of the GSC is to reduce its costs. [44], [45], and [46] are other researches that consider government policies.

Table 2 is related to characteristics of the published studies on the government intervention.

### C. THE ROBUST OPTIMIZATION IN RELATED MATHEMATICAL MODELS IN TO BIOFUELS

In real-world problems, changing one of the data may violate several constraints, making the answer impractical or even impossible. Therefore, RO generates an answer that is resistant to data uncertainty. We review some of the studies that are related to uncertainty in the biofuel SC as follows:

Sharma et al. [47] presented an integrated approach for assessing the optimum SC of biofuels, taking into account the uncertainty of biomass yield. A two-stage stochastic linear mixed-integer programming was used to minimize predicted system cost while integrating yield uncertainty in strategic level decisions related to the production of biomass and investment in the biorefinery. Caldeira et al. [48] developed a stochastic blending model by considering feedstock price uncertainty. The stochastic blending model embeds a chance-constrained algorithm to compensate for variation in composition and uses time-series approaches to resolve...
TABLE 2. Characteristics of the published papers on government intervention.

| Reference                        | Energy | Fuel | Carbon policy | Social welfare | Economic | Environmental | Case study | Statistical | Game Theory |
|----------------------------------|--------|------|---------------|----------------|----------|---------------|------------|-------------|-------------|
| Sivaraman et al. [40]            | *      |      |               |                |          |               |            |             |             |
| Huang et al. [9]                 | *      | *    |               |                |          |               |            |             |             |
| Wu and Langpap [39]              | *      | *    |               |                |          |               |            |             |             |
| Yuin and Jinx [36]               | *      |      |               |                |          |               |            |             |             |
| Chen and Hu [42]                 |        |      |               |                |          |               |            |             |             |
| Cucchiella et al. [37]           | *      |      |               |                |          |               |            |             |             |
| Bagjiran et al. [38]             | *      | *    |               |                | *        |               | *          |             | *           |
| Monasterolo and Raberto [41]     | *      |      |               |                |          |               |            |             |             |
| Halat and Hafezalkotob, [43]     | *      | *    |               |                | *        |               | *          |             | *           |
| In our research                  | *      | *    |               |                | *        |               | *          | *           | *           |

volatility in feedstock prices. The model was developed to support decision-making in production planning to minimize the cost and cost variations in biodiesel production. In order to build a second-generation biodiesel SC network under epistemic input data ambiguity, Babazadeh et al. [49] suggested a potential programming model. The developed model minimized the total SC costs from supply centers to market centers for biodiesel and glycerin. Waste cooking oil and Jatropha plants are considered in the production of biodiesel as non-edible feedstocks. In order to cope with the epistemic ambiguity of the parameters, a credibility-based approach to potential programming is used to transform the original programming possibility model into a crisp equivalent. To deal with the uncertainty of the parameters, a new version of the possible programming model is proposed based on the theoretical mean and the absolute variance of the fuzzy numbers [50].

Bairamzadeh et al. [51] proposed a model for determining lignocellulosic bioethanol SC strategic and tactical decision-making at different sources and various types of uncertainty. A hybrid RO model is proposed to control various forms of uncertainty, including randomness, epistemic, and deep uncertainty. Jouzdani et al. [52] studied a robust supply chain (RSC) model. They considered transport costs, demand, and supply as uncertainty values.

Sy et al. [53] described a new Multi-Objective RO framework for integrated biorefinery development. Their strategy simultaneously maximized income and minimized the environmental footprint, while considering uncertainty about demand. Mohseni and Pishvaee’s [54] research adopts data-driven RO that generates uncertainty sets from unknown parameter data by promoting vector clustering, whereas traditional uncertainty sets are based on integrating data resulting in high robustness costs. Under epistemic uncertainty, Ghaderi et al. [55] developed a reliable multi-objective programming model for a sustainable switchgrass-based bioethanol SC network. Their proposed model should optimize the mean value of the efficiency of the SC, robustness of optimality, and robustness of feasibility. Table 3 is relevant to the characteristics of the RO in related mathematical models to biofuels.

The literature review represents that there are a few studies that considered the competition and coopetition of bio-refineries under government finance interventions such as tax or a subsidy. The main contributions of this study are as follows:

(i) Defining the best tariff policy by the government and policymakers influence the price of biofuels and the profit of bio-refineries.
(ii) The sustainability aspects of the government such as economic, environmental, and social are investigated in our models.
(iii) Considering the cooperation of bio-refineries in order to achieve sustainability aspects such as economic, environmental, and social welfare under government tariff policy.
(iv) Using robust optimization to avoid risk uncertainty.

III. PROBLEM DEFINITION AND MATHEMATICAL NOTATIONS

This section presented a nonlinear mathematical programming model intended to maximize refinery profits by considering cooperation between bio-refineries and competing with oil refineries. Several bio-refineries defined as game players to allow each of them to manage one or more refineries. Bio-refineries seek to maximize profits by forming coalitions under various government strategies. The nonlinear single-level model is presented to maximize the profits of refineries in operating independently and forming a coalition between bio-refineries that compete with fossil refineries. The purpose of competition between refineries is to achieve
TABLE 3. Characteristics of the robust optimization in related mathematical models to biofuels.

| Reference               | Mathematical programming | Source of uncertainty                        | Uncertainty modelling approach            |
|-------------------------|--------------------------|----------------------------------------------|-------------------------------------------|
| Bairamzadeh et al [51]  | *                        | Biomass supply, biofuel demand, and technology | Hybrid robust optimization approach       |
| Sharma et al. [47]      | *                        | Feedstock yield uncertainty                  | A two-stage stochastic programming        |
| Ghaderi et al. [55]     | *                        | Costs                                        | Robust possibilistic programming          |
| Caldeira et al. [48]    | *                        | Feedstock price uncertainty                  | A stochastic blending model               |
| Babazadeh et al. [49]   | *                        | Demand, costs, Amount of JCL yields, Selling price | A credibility-based possibilistic programming |
| Babazadeh [50]          | *                        | Demand, costs, Amount of JCL yields, Selling price | Possibilistic Mean-Absolute Deviation model |
| Mohseni and Pishvane [54]| *                        | Costs, Price of biofuel, Amount of oil fuel production | Robust convex Programming (Bertsimas & Sim’s approach) |
| In our research         | *                        |                                              | Robust convex Programming (Mulvey’s approach) |

The optimal amount of Nash equilibrium production for each of the refineries under government tariff strategies. A tariff is defined as a government subsidy or tax policy intended to achieve sustainability goals. It means that the government seeks to generate income, reduce pollution, and increase social welfare through its policy-making. Figure 1 illustrates the schematic diagram for the problem definition.

A. ASSUMPTIONS

- The total production of bio and oil refineries is equal to the demand of the whole society.
- Bio-refineries produce a similar product with the same quality in which the emissions from the fuel consumption of each is the same.
- The set of bio-refiners that have formed a coalition together with the sum of oil refineries and non-coalition bio-refineries participate in a non-cooperative competitive game.
- Government policy to achieve sustainability goals, includes the definition of tariffs as subsidies or taxes.
- Following Bárcena-Ruiz and Espinosa [56], Goering [57], Xia et al. [58] the inverse demand function is used for biofuel i in scenario s where $a_{bi}$ is the highest price of biofuel i in scenario s and $p_{bi}$ is the biofuel price sensitivity coefficient against its production for bio-refinery i in scenario s. Also, $\gamma_{bi}$ describes the cross-complementary effect of oil fuel production in scenario s on biofuel production i ($0 \leq \rho_{bi}, \gamma_{bi} < 1$). We assume that the price function is linear and related to the production of refineries according to the Cournot model. The price function of biofuels is as follows:

$$p_{bi}(Q_b, q_{f}) = a_{bi} - \rho_{bi}q_{bi} + \gamma_{bi}q_{f} \quad \forall i \in I, s \in S$$  \hspace{1cm} (1)

$$Q_b = \sum_i q_{bi} = (q_{b1} + q_{b2} + \cdots + q_{bn})$$  \hspace{1cm} (2)

B. MODEL FORMULATION

Mathematical models of bio-refineries under government tariff policy in competition and coalition form are formulated in this section. Then, the government functions to achieve sustainability factors such as economic, environmental, and social functions are represented. To deal with uncertainties in the parameters of the model, a RO model is considered. Finally, the nonlinear robust model for the competition and cooperation between refineries is represented. A list of mathematical notations such as input parameters and decision variables when bio-refineries operate independently and form a coalition are presented in Tables 4 and 5.

The formulation of a mathematical model in forming a coalition between bio-refineries is mentioned below. In modeling problems, the set of $I_c$ is related to the set of bio-refineries which are considered for forming a $c_n$ coalition.

C. THE STOCHASTIC PROGRAMMING MODEL OF BIO-REFINERIES IN THE COMPETITIVE AND COOPERATIVE FORM UNDER GOVERNMENT TARIFF POLICY

It is assumed that all bio-refineries work together in a zero-sum game. In this game, each participant’s gain or loss of utility is exactly balanced by the losses or gains of the utility of the other participants and the players are aware of each other’s situation. So the profit function of all the bio-refineries is integrated, and they all have a profit function. The principal profit function is equal to the sum of the profits of all the biofuel refineries participating in the coalition. The profit function of bio-refineries is calculated from the difference between the revenue and the costs of refineries. Costs are the production cost per unit of biofuel, the fixed set up cost of bio-refineries, and the variable cost of production. To offer a production level, bio-refineries incur a variable cost $\sum i \eta_{bi}q_{bi}^2 [59]$, and [60], where $\eta_{bi}$ is referred to as the bio-refinery’s variable
cost factor, reflecting the efficiency of production. The higher the variable cost factor, the lower the production and the profit of the bio-refinery. That is, bio-refineries need to spend more to achieve a desired level of production. This cost structure describes the economic phenomenon that marginal cost of production increases with the level of production, which ensures that the bio-refineries do not produce excessive biofuels, and thus the level of production equilibrium exists. Also, it satisfied the concavity of the profit function.

On the other hand, the government’s tariff policy, as a parameter, applies in the profits of the refineries. The amount of negative tariffs in the refineries model determines tax and positive tariff will decrease government interest. The constraints in models indicate that the operational costs of production should be less than the maximum available budget of refineries. Also, the minimum expected profit of refineries to be fulfilled. Therefore, the stochastic model of bio-refineries in two modes of independent activity and forming a coalition between them is as follows:

**Mathematical model of bio-refineries in their independent activity ∀i∉I_{[ca]}**

\[
\begin{align*}
\text{Max } & \pi_{bi} = \sum_{s \in S} \text{prob}_i q_{bi} (p_{bi} - c_{bi}) - q_{bi} t_{bi} \\
\text{Subjected to:} & \\
& c_{bi} q_{bi} + \frac{1}{2} \eta_{bi} q_{bi}^2 + t_{bi} q_{bi} \leq \text{Budget}_{bi} \\
& \forall i \notin I_{[ca]}, s \in S \quad (3)
\end{align*}
\]

**D. PROPOSED ROBUST OPTIMIZATION MODEL**

Considering that there are parameters in the model that are scenario-based and probabilistic uncertainties, RO can be used to avoid risk uncertainty. Depending on the problem conditions, a RO is used with the approach of Mulvey et al. [61].

Mulvey’s approach is the first approach in applying the concept of optimization. In this model, the results have little sensitivity to the value of the scenarios, and the obtained results are close to the optimal values by changing the data. There are two types of variables, including control variables and design variables in this model. In design variables, it is not possible to change after the parameters are specified, but in control variables, it is possible. Also, constraints are
TABLE 4. A list of mathematical notations when bio-refineries operate independently.

| Notations: | Description |
|------------|-------------|
| \( b \) | Bio-refinery |
| \( f \) | Oil refinery |
| \( i \) | Set of bio-refineries, \( i \in I \) |
| \( s \) | Set of scenarios, \( s \in S \) |
| \( n \) | Coalition index |

PARAMETERS:

| Parameters: | Description |
|-------------|-------------|
| \( F_{hi} \) | Fixed set-up cost of bio-refinery \( i \) |
| \( c_{bi} \) | Production cost per unit of biofuel at bio-refinery \( i \) |
| \( a_{bi} \) | The maximum base price of biofuel for bio-refinery \( i \) |
| \( \beta_{bi} \) | Biofuel price sensitivity coefficient against its production for bio-refinery \( i \) |
| \( \gamma_{bi} \) | Minimum expected profit of a bio-refinery \( i \) |
| \( d_s \) | Total market demand for fuel in scenario \( s \) |
| \( \eta_{bi} \) | The variable cost coefficient of production of bio-refinery \( i \) |
| \( \theta_i \) | The rate of pollution caused by each unit of oil fuel consumption |
| \( \theta_s \) | The rate of pollution caused by each unit of biofuel consumption |
| \( \text{Budget}_{hi} \) | Maximum budget of bio-refinery \( i \) for production operating costs |
| \( \Psi_i \) | The social welfare due to the production of each oil fuel unit |
| \( \Psi_s \) | The social welfare due to the production of each biofuel unit |
| \( q_i \) | The amount of oil fuel production in scenario \( s \) |
| \( \text{prob}_s \) | Probability of occurrence of scenario \( s \) |
| \( t_i \) | Government tariff rate per unit of production in bio-refineries |
| \( t_s \) | Government tariff rate per unit of production in oil refinery |

Decision Variables:

| Decision Variables: | Description |
|---------------------|-------------|
| \( q_{hi} \) | The amount of production for bio-refinery \( i \) |
| \( p_{hi} \) | The price of biofuel \( i \) in scenario \( s \) |

TABLE 5. A list of mathematical notations when bio-refineries form a coalition.

| Parameters: | Description |
|-------------|-------------|
| \( F'_{hi} \) | Fixed set-up cost of bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) |
| \( c_{hbi} \) | Production cost per unit of biofuel at bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) |
| \( a'_{hi} \) | The maximum base price of biofuel for bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) |
| \( \beta'_{hi} \) | Biofuel price sensitivity coefficient against its production for bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) |
| \( \gamma_{bi} \) | Biofuel price sensitivity coefficient of bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) relative to oil fuel production in scenario \( s \) |
| \( \eta_{hi} \) | Minimum expected profit of a bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) |
| \( d_s \) | Total market demand for fuel in scenario \( s \) |
| \( \eta_{hi} \) | The variable cost coefficient of production of bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) |
| \( \theta_i \) | The rate of pollution caused by each unit of oil fuel consumption |
| \( \theta_s \) | The rate of pollution caused by each unit of biofuel consumption |
| \( \text{Budget}_{hi} \) | Maximum budget of bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) for production operating costs |
| \( \Psi_i \) | The social welfare due to the production of each oil fuel unit |
| \( \Psi_s \) | The social welfare due to the production of each biofuel unit |
| \( q_i \) | The amount of oil fuel production in scenario \( s \) |
| \( \text{prob}_s \) | Probability of occurrence of scenario \( s \) |
| \( t_i \) | Government tariff rate per unit of production in bio-refineries |
| \( t_s \) | Government tariff rate per unit of production in oil refinery |

Decision Variables:

| Decision Variables: | Description |
|---------------------|-------------|
| \( q_{hi} \) | The amount of production for bio-refinery \( i \) in coalition \( c_n \) and \( i \in I \) |
| \( p_{hi} \) | The price of biofuel \( i \) in coalition \( c_n \) and \( i \in I \) in scenario \( s \) |

The constraint (12) is a structural constraint and is free from data variability, and the constraint (13) is control constraint. By defining \( \Omega = \{1, 2, 3, \ldots, s \} \) and \( \{d_s, B_i, C_i, e_s \} \), respectively, as the set of scenarios and uncertain parameters divided into structural and control classes, where control constraints are affected by changing data, while structural constraints are similar to linear programming constraints.

\[ x \in \mathbb{R}^n \] is the vector of decision variables, which is called design variables and \( y \in \mathbb{R}^n \) vector is defined as the control decision variables that are assigned to match the uncertain parameters. The optimal amount of these variables depends on both the uncertain parameters and the optimal value of the design variables. Therefore, the general form of the model is as follows:

\[
\begin{align*}
\text{Min} & \quad c^T x + d^T y \\
\text{Subjected to:} & \quad Ax = b \\
& \quad Bx + Cy = e \\
& \quad x, y \geq 0
\end{align*}
\]

(11)

(12)

(13)

(14)

The first expression in the objective function indicates the stability of the solution, and the second expression designates the establishment of the model. With multiple scenarios, the objective function \( \xi = c^T x + d^T y \) is a random variable that takes the value of \( \xi_s = c^T x + d^T y \) with probability \( p_s \).
For achieving an optimal approach close to robust, the expression of the objective function can be converted to the expected value and variance of the objective function. In other words, the expected value of the objective function can be optimized in one scenario. Also, by minimizing the variance of the objective function in different situations, it reduces the risk level of the model. In this case, the related formulation will be as follows:

\[
\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s (\xi_s - \sum_{i \in S} p_i \xi_i)^2
\]

In equation (19), \( \lambda \) is related to the risk level of the model. As shown in equation (19), there is a quadratic statement in the objective function. Instead of the quadratic statement, Yu and Li [62] applied the absolute value as follows:

\[
\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s \in S} p_s |\xi_s| + \lambda \sum_{s \in S} p_s \left| \xi_s - \sum_{i \in S} p_i \xi_i \right|
\]

The objective function is still nonlinear. Therefore, Yu and Li [62] converted this function to a linear one by introducing a constraint and a non-negative variable for each scenario. The related linear model will be as equations (21)-(23).

\[
\begin{align*}
\text{Min } Z &= \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left( |\xi_s - \sum_{i \in S} p_i \xi_i| + 2\theta_s \right) \\
&\text{Subjected to:} \\
&\theta_s \geq 0 \quad \forall s \in \Omega \\
&\xi_s - \sum_{s \in S} p_s \xi_s + \theta_s \geq 0 \quad \forall s \in \Omega
\end{align*}
\]

If \( \xi_s - \sum_{s \in S} p_s \xi_s \geq 0 \), then in minimization function \( \theta_s = 0 \) and the objective function will be as \( \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left( |\xi_s - \sum_{i \in S} p_i \xi_i| \right) \). Also, if \( \theta_s = \sum_{s \in S} p_s \xi_s - \xi_s \), then the objective function will be as \( \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left( |\xi_s - \sum_{i \in S} p_i \xi_i| - \theta_s \right) \).

By using this approach, the final linear model will be as equations (24)-(28).

\[
\begin{align*}
\text{Min } Z &= \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left( |\xi_s - \sum_{i \in S} p_i \xi_i| + 2\theta_s \right) \\
&\text{Subjected to:} \\
&Ax = b \\
&\xi_s - \sum_{s \in S} p_s \xi_s + \theta_s \geq 0 \quad \forall s \in \Omega \\
x \geq 0, \xi_s \geq 0 \quad \forall s \in \Omega \\
&\theta_s \geq 0 \quad \forall s \in \Omega
\end{align*}
\]

The parameters and control variables in the RO approach for our problem are:

- **Parameters added to the bio-refinery model in their independent operation (\( \forall i \notin I_{[ca]} \))**
  - \( \text{prob}_s \) Probability of occurrence of scenario \( s \)
  - \( \varphi' \) Fixed value

- **control variables**
  - \( \nu_{s} \) Linearization coefficient under scenario \( s \) for \( \forall i \notin I_{[ca]} \)
  - \( \varphi \) Fixed value

Since the cost parameters in the objective function of the bio-refineries have scenario-oriented uncertainty, according to Mulvey’s RO model, the objective functions are transformed as follows by penalties on the amount of profit per \( i \notin I_{[ca]} \), and \( i \in I_{[ca]} \). By considering the consistency of the response in two modes of independent activity and the formation of a coalition between bio-refineries, the robust counterpart model will be as follows:

**Robust counterpart model (\( \forall i \notin I_{[ca]} \))**:

\[
\begin{align*}
Z' &= q_{bi} (p_{bi} - c_{bi}) - q_{bi}b - \frac{1}{2} \eta_{bi}p_{bi}^2 - F_{bi} \\
&\forall i \notin I_{[ca]}, s \in S \\
\text{Max } Z_i' &= \sum_s \text{prob}_s \nu_{s} \varphi_s - \varphi' \sum_s \text{prob}_s \left( \varphi_s \nu_{s} + 2\nu_s \right) \\
&\forall i \notin I_{[ca]} \\
\text{Subjected to:} \\
&c_{bi}, b_{bi} + \frac{1}{2} \eta_{bi}p_{bi}^2 + 2\nu_{bi}b_{bi} \leq \text{Budget}_{bi} \\
&\forall i \notin I_{[ca]}, s \in S \\
&\pi_{bi} \geq \pi_{bi} \\
&\forall i \notin I_{[ca]} \\
&z_{s} - \sum_{s' \in S} \text{prob}_{s'} z_{s'} + \nu_{s} \geq 0 \quad \forall s \in S \\
&\forall i \notin I_{[ca]}, s \in S \\
&\nu_{s} \geq 0 \quad \forall s \in S
\end{align*}
\]

**Robust counterpart model (\( \forall i \in I_{[ca]} \))**:

\[
\begin{align*}
Z_i &= \sum_{i \in I_{[ca]}} q_{bi} (p_{bi} - c_{bi}) - q_{bi}b_{bi} - \frac{1}{2} \eta_{bi}p_{bi}^2 + F_{bi} \\
&\forall i \in I_{[ca]}, s \in S \\
\text{Max } Z_{i} &= \sum_s \text{prob}_s \nu_{s} \varphi_s - \varphi' \sum_s \text{prob}_s \left( \varphi_s \nu_{s} + 2\nu_s \right) \\
&\forall i \in I_{[ca]} \\
\text{Subjected to:} \\
&c_{bi}, b_{bi} + \frac{1}{2} \eta_{bi}p_{bi}^2 + 2\nu_{bi}b_{bi} \leq \text{Budget}_{bi} \\
&\forall i \in I_{[ca]}, s \in S \\
&\pi_{bi} \geq \pi_{bi} \\
&\forall i \in I_{[ca]} \\
&z_{s} - \sum_{s' \in S} \text{prob}_{s'} z_{s'} + \nu_{s} \geq 0 \quad \forall s \in S \\
&\forall i \in I_{[ca]}, s \in S \\
&\nu_{s} \geq 0 \quad \forall s \in S
\end{align*}
\]
E. Government Functions to Achieve Sustainability Goals

In the government model, we seek to achieve sustainability goals, including economic, social, and environmental goals, which are presented in three distinct functions. The economic function (54), which relates to the government’s net revenue, is the sum of the tariffs received or paid to the bio-refineries. The government attempts to decrease the amount of pollution caused by fuel burning, so the environmental function (55) is determined by considering the production rates of each refinery and the amount of pollution produced by the consumption of each fuel. Another concern of the government is to create employment and increase social welfare through fuel consumption. To this end, the social welfare function (56) is also formulated to maximize social welfare from fuel production and consumption.


table 6. The value of parameters.

| Parameters | Value of parameters |
|------------|---------------------|
| $F_{bi}$  | $F_{b1} = 1.10E + 6$, $F_{b2} = 1.00E + 6$, $F_{b3} = 1.40E + 6$ |
| $c_{bi}$  | $c_{b1} = 0.72$, $c_{b2} = 0.7$, $c_{b3} = 0.64$, $c_{b4} = 0.62$, $c_{b5} = 0.84$, $c_{b6} = 0.82$ |
| $\alpha_{bi}$ | $\alpha_{b1} = 2.3$, $\alpha_{b2} = 2.1$, $\alpha_{b3} = 4.15$, $\alpha_{b4} = 4.6$, $\alpha_{b5} = 7$, $\alpha_{b6} = 7.2$ |
| $\beta_{bi}$ | $\beta_{b1} = 1.80E - 8, \beta_{b2} = 1.60E - 8, \beta_{b3} = 2.50E - 8, \beta_{b4} = 2.30E - 8, \beta_{b5} = 3.30E - 8, \beta_{b6} = 3E - 8$ |
| $\gamma_{bi}$ | $\gamma_{b1} = 6E - 9, \gamma_{b2} = 5E - 9, \gamma_{b3} = 4E - 9, \gamma_{b4} = 4E - 9, \gamma_{b5} = 3E - 9$ |
| $\eta_{bi}$ | $\eta_{b1} = 1.35E - 7, \eta_{b2} = 9.5E - 8, \eta_{b3} = 5.5E - 8$ |
| $d_{i}$ | $d_{1} = 5.5E + 7, d_{2} = 5.4E + 7$ |
| $\pi_{bi}$ | $\pi_{b1} = 215000, \pi_{b2} = 220000, \pi_{b3} = 218000$ |
| $\theta_{b, \theta_{I}}$ | $\theta_{b} = 0.0075, \theta_{I} = 0.0182$ |
| $\Psi_{b, \Psi_{I}}$ | $\Psi_{b} = 0.60, \Psi_{I} = 0.65$ |
| $q_{i}$ | $q_{i1} = 1.75E + 7, q_{i2} = 1.70E + 7$ |
| $\text{prob}_p$ | $\text{prob}_p = 0.4, \text{prob}_2 = 0.6$ |
| $\varphi$ | $\varphi = 0.4$ |

IV. Solution Approach and Case Study

The government seeks to determine the optimal amount of tariffs to achieve its sustainability goals by defining different tariff strategies. For this purpose, numerical examples are defined, and different government strategies on tariff rates are evaluated in terms of the cooperation and independent operation of the bio-refineries. By obtaining the Nash equilibrium of bio-refineries, the benefits of independent activity and cooperation between them are evaluated. Then, the values related to government functions are calculated. For defining the numerical example, we consider three bio-refineries that produce the same type of biofuel for forming a coalition. The fuel demand was calculated according to the usage of the transportation part per day. The fixed refinery set-up costs
TABLE 7. The value of variables in the independent activity and coalition of bio-refineries under different tariff policies (values $E + 0.6$).

| $t_h$ | $t_f$ | Coalitions | $q_h$ | $q_s$ | $q_o$ | $n_{H_h}$ | GNR | EI | SW | U |
|-------|-------|------------|------|------|------|----------|-----|----|----|---|
| $S_1$ | +0.3  | 1.3  | 10.7 | 13.3 | 13.5 | 2.78     | 16.4| 0.594| 33.7| 84 |
|       |       | 2.0  | 10.7 | 13.3 | 13.5 | 33.8     | 16.4| 0.594| 33.7| 84 |
|       |       | 3.0  | 10.7 | 13.3 | 13.5 | 69.6     | 16.4| 0.594| 33.7| 84 |
| $S_2$ | +0.3  | 1.3  | 5.48 | 20.9 | 13.5 | 45.7     | 17.1| 0.612| 35.1| 99.1|
|       |       | 1.3  | 0.175| 13.3 | 25.6 | 114      | 16.9| 0.606| 34.7| 117|
|       |       | 2.0  | 10.7 | 33.8 | 23.4 | 118      | 16.4| 0.594| 33.7| 95.8|
|       |       | 2.3  | 0.756| 10.9 | 28.2 | 152      | 17.1| 0.611| 35   | 120|
|       | -0.3  | 1.3  | 11.1 | 13.3 | 13.5 | 9.22     | -6.21| 0.597| 33.9| 102|
|       |       | 2.0  | 11.1 | 13.3 | 13.5 | 41.8     | -6.21| 0.597| 33.9| 102|
|       |       | 3.0  | 11.1 | 13.3 | 13.5 | 77.7     | -6.21| 0.597| 33.9| 102|
|       |       | 1.2  | 4.75 | 21.6 | 13.5 | 61.7     | -6.81| 0.612| 35.1| 110|
|       |       | 1.3  | 1.25E-06| 13.3 | 26.6 | 133     | -6.81| 0.612| 35.1| 138|
|       |       | 2.3  | 11.1 | 2.54 | 24.3 | 135      | -6.21| 0.597| 33.9| 114|
|       |       | 2.3  | 4.49 | 15.4 | 34.2 | 209      | -11.1| 0.719| 45.7| 166|
|       | -0.3  | 1.3  | 4.75 | 21.6 | 13.5 | 61.7     | -17.1| 0.612| 35.1| 110|
|       |       | 1.3  | 5.04E+00| 13.3 | 26.6 | 133     | -17.1| 0.612| 35.1| 138|
|       |       | 2.3  | 11.1 | 2.54 | 24.3 | 135      | -16.5| 0.597| 33.9| 114|
|       |       | 2.3  | 4.49 | 15.4 | 34.2 | 209      | -21.4| 0.719| 43.7| 166|
| $S_4$ | -0.3  | 1.3  | 10.7 | 13.3 | 13.5 | 5.99     | 0    | 0.594| 33.7| 92.9|
|       |       | 2.0  | 10.7 | 13.3 | 13.5 | 37.8     | 0    | 0.594| 33.7| 92.9|
|       |       | 3.0  | 10.7 | 13.3 | 13.5 | 73.6     | 0    | 0.594| 33.7| 92.9|
|       |       | 1.2  | 4.75 | 21.6 | 13.5 | 53.8     | 0    | 0.612| 35.1| 101|
|       |       | 1.3  | 0    | 13.3 | 26.6 | 125      | 0    | 0.612| 35.1| 129|
|       |       | 2.3  | 10.7 | 2.54 | 24.3 | 126      | 0    | 0.594| 33.7| 105|
|       |       | 2.3  | 4.49 | 15.4 | 34.2 | 209      | -21.4| 0.719| 43.7| 166|
|       | 0     | 1.3  | 4.75 | 21.6 | 13.5 | 48.5     | 11.4| 0.612| 35.1| 94.3|
|       |       | 2.3  | 10.7 | 2.54 | 24.3 | 121      | 10.9| 0.594| 33.7| 98.9|
|       |       | 2.3  | 1.33 | 11.5 | 29    | 160      | 11.8| 0.627| 36.3| 126|
| $S_6$ | +0.2  | 1.2  | 4.75 | 21.6 | 13.5 | 48.5     | 11.4| 0.612| 35.1| 94.3|
|       |       | 1.3  | 0    | 13.3 | 26.6 | 120      | 11.4| 0.612| 35.1| 122|
|       |       | 2.3  | 10.7 | 2.54 | 24.3 | 121      | 10.9| 0.594| 33.7| 98.9|
|       |       | 2.3  | 1.33 | 11.5 | 29    | 160      | 11.8| 0.627| 36.3| 126|
|       | +0.2  | 1.2  | 4.75 | 21.6 | 13.5 | 48.5     | 11.4| 0.612| 35.1| 94.3|
|       |       | 1.3  | 0    | 13.3 | 26.6 | 120      | 11.4| 0.612| 35.1| 122|
|       |       | 2.3  | 10.7 | 2.54 | 24.3 | 121      | 10.9| 0.594| 33.7| 98.9|

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are based on the daily equivalent of the annual operating costs and initial investment and, the cost of biofuel production is considered per liter in bio-refineries. Also, the refinery’s capacity is dependent on the daily rate of production. The government aims to reach the best tariff policy so that the tariff values are defined based on one liter of fuel production.

In this research, two kinds of scenarios with different intensities are considered. The amount of fuel demand and the amount of oil fuel production are two fundamental parameters that are uncertain. The first scenario is related to low demand and low oil production with less intense, and the second scenario is related to high demand and high oil production with more intense. The probability of occurrence of each scenario is 0.6 and 0.4, respectively. The values of the relevant parameters in Table 6 are given for each of the scenarios.

According to literature reviews, the highest price for biofuel is assigned to the \( \alpha \) parameters in Table 6 are given for each of the scenarios. The linear model of the above function is also presented below. In this paper, the weights of the criteria are determined by decision-makers. Pairwise comparisons are made between each of the two criteria (the best and the worst) and the others. Then a max-min problem is formulated and solved to determine the weight of different criteria. It also provides a formula for calculating the inconsistency rate to evaluate the validity of the comparisons. The prominent features of this method compared to other multi-criteria decision-making methods are: Requiring less comparative data and reaching more reliable answers.

### BWM method steps:

1. Determining the set of decision criteria
2. Identifying the best and the worst decision criteria
3. Determining the preference of the best index over other indexes with numbers from 1 to 9: The preference vector of the best index over other indexes is expressed as \( A_B = (a_{b1}, a_{b2}, \ldots, a_{bn}) \). In this vector \( a_{bj} \) indicates the preference of best index (B) over index j.
4. Prioritizing all the indicators in comparison to the worst indicators with numbers 1 to 9: The preference vector of the other indexes over the worst one is expressed as \( A_W = (a_{w1}, a_{w2}, \ldots, a_{nw}) \). For finding the optimal values of weights, the pairs of \( W_B = a_{Bj} \) and \( W_W = a_{Wj} \) are formed. Then to satisfy these conditions in all j’s, a solution must be found to maximize the expressions of \( W_B - a_{Bj} \) and \( W_W - a_{Wj} \) for all j’s which are minimized. According to the non-negativity of the weights and the sum of the weights, the model can be formulated as equations (57)-(59).

\[
\begin{align*}
\text{minmax}_j \left\{ \frac{W_B}{W_j} - a_{Bj}, \frac{W_W}{W_j} - a_{Wj} \right\} & \quad (57) \\
\text{Subjected to:} & \quad \sum_j W_j = 1 \\
& \quad W_j \geq 0, \quad \text{for all } j \quad (58) \\
& \quad W_j \geq 0, \quad \text{for all } j \quad (59)
\end{align*}
\]

We can also convert the above model to the following:

\[
\begin{align*}
\min \xi & \quad (60) \\
\text{Subjected to:} & \quad \frac{W_B}{W_j} - a_{Bj} \leq \xi, \quad \text{for all } j \\
& \quad \frac{W_W}{W_j} - a_{Wj} \leq \xi, \quad \text{for all } j \\
& \quad \sum_j W_j = 1 \\
& \quad W_j \geq 0, \quad \text{for all } j \\
& \quad W_j \geq 0, \quad \text{for all } j
\end{align*}
\]

The linear model of the above function is also presented below. In this paper, the weights of the criteria

| Scenario | GNR | EI | SW | \( \pi_{b[c_j]} \) |
|----------|-----|---|----|-----------------|
| S₁       | 1.71E+07 | 6.11E+05 | 3.50E+07 | 1.52E+08 |
| S₂       | 6.77E+06 | 6.11E+05 | 3.50E+07 | 1.52E+08 |
| S₃       | -1.11E+07 | 7.19E+05 | 4.37E+07 | 2.09E+08 |
| S₄       | -2.14E+07 | 7.19E+05 | 4.37E+07 | 2.09E+08 |
| S₅       | 0     | 6.60E+05 | 3.90E+07 | 1.78E+08 |
| S₆       | 1.18E+07 | 6.27E+05 | 3.63E+07 | 1.60E+08 |
| S₇       | 4.92E+06 | 6.27E+05 | 3.63E+07 | 1.60E+08 |
| S₈       | -6.84E+06 | 6.98E+05 | 4.20E+07 | 1.98E+08 |
| S₉       | -1.37E+07 | 6.98E+05 | 4.20E+07 | 1.98E+08 |
TABLE 9. The weights of the criteria.

| criteria  | \( W_j \) |
|-----------|-----------|
| GNR       | 0.079     |
| EI        | 0.491     |
| SW        | 0.301     |
| \( \pi_{t[c]} \) | 0.129 |

\( \xi = 0.412 \)

\( (W_1^*, W_2^*, \ldots, W_n^*)\) \( (W_1^*, W_2^*, \ldots, W_n^*) \) and \( \xi \) are obtained by using the following linear model.

\[
\min \xi \quad (65)
\]

Subjected to:

\[
\begin{align*}
|W_B - a_B W_j| & \leq \xi, \quad \text{for all } j \\
|W_j - a_j W_0| & \leq \xi, \quad \text{for all } j \\
\sum_j W_j & = 1 \\
W_j & \geq 0, \quad \text{for all } j
\end{align*}
\]

MULTIMOORA method. Also, final rankings illustrate the validation of computations. Fig 2 demonstrates that \( S_1 \) and \( S_4 \) are ranked as the best and worst scenario for optimal tariff selection among all the alternatives. According to the results which are obtained from the MULTIMOORA technique and radar graph the best alternative is \( S_1_S_6 = +0.3 \), \( t_f = +0.3 \). Now for the next section, the examination of the fair distribution of profits among players by using different profit-sharing techniques for the selected scenario will be done.

First of all, we will solve the cooperative robust production planning problem for each bio-refinery independently as a non-cooperation situation. Second, we will solve the model of all coalitions of two bio-refineries. Then the model will be solved for all coalitions of three bio-refineries, and so on until the grand coalition is reached. According to the property of super-additive in TU games, the optimal profit for any coalition of bio-refineries should be higher than the sum of the individual maximum profits of the coalition’s members, i.e. \( v(c_m) \geq \sum_{p \subseteq C_m} v(p)\forall c_m \in p \). Extra utility \( EU(c_m) \) [66] for coalition \( c_m \) is generated by calculating the difference between the profit of the coalition \( c_m \) and the sum of the individual maximum profits of the coalition’s members, i.e. \( EU(c_m) = v(c_m) - \sum_{p \subseteq C_m} v(p)\forall c_m \in p \). The extra utility of the coalition partners should be measured. The following specification is a more reliable measure for a coalition’s synergy:

\[
\text{Synergy} (c_m) = \frac{EU (c_m)}{v (c_m)} \quad (70)
\]

As a numerical example which is mentioned before, \( \text{Synergy} (c_m) \) and \( EU (c_m) \) will be as follows (Table 11):

The results from Table 11 indicate that, when the owners function independently, the extra benefits and synergies are null. In a coalition form, their members are not equal in the collaborative effects. Furthermore, TU game between partners is supr-additive. It means that, as the size of the coalition expands, the extra utility and synergies increase.
TABLE 10. The final ranking of alternative tariff scenario using MULTIMOORA technique.

|       | MOORA       | MULTIMOORA  |
|-------|-------------|-------------|
|       | Ratio system | Reference point approach | Dominance theory |
|       | $y_i'$ | Rank | $\max \{r_i - x_{0i}'\}$ | Rank | $U_i'$ | Rank |
| $S_1$ | 0.0121 | $S_1$ | 0.022169 | $S_6$ | 0.000796771 | $S_1$ |
| $S_2$ | -0.0104 | $S_6$ | 0.022484 | $S_1$ | 0.000315447 | $S_6$ |
| $S_3$ | -0.0402 | $S_2$ | 0.06138 | $S_2$ | -0.000754552 | $S_2$ |
| $S_4$ | -0.0626 | $S_7$ | 0.083799 | $S_7$ | -0.001454721 | $S_7$ |
| $S_5$ | -0.0208 | $S_5$ | 0.03722 | $S_5$ | 0 | $S_5$ |
| $S_6$ | 0.0018 | $S_3$ | 0.018856 | $S_8$ | 0.000584936 | $S_8$ |
| $S_7$ | -0.0132 | $S_3$ | 0.026511 | $S_3$ | 0.000243889 | $S_3$ |
| $S_8$ | -0.0327 | $S_9$ | 0.052108 | $S_9$ | -0.000436096 | $S_9$ |
| $S_9$ | -0.0476 | $S_4$ | 0.067039 | $S_4$ | -0.000873468 | $S_4$ |

TABLE 11. Optimal profit of coalitions and synergy of the possible coalitions.

| $c_m$ | $v(c_m)$ | $EU(c_m)$ | $Synergy(c_m)$ |
|-------|---------|----------|---------------|
| $C_1$ | (1) | 2.78E+06 | 0 | 0 |
| $C_2$ | (2) | 3.38E+07 | 0 | 0 |
| $C_3$ | (3) | 6.96E+07 | 0 | 0 |
| $C_4$ | (1, 2) | 4.57E+07 | 9097000 | 0.25 |
| $C_5$ | (1, 3) | 1.14E+08 | 41911000 | 0.58 |
| $C_6$ | (2, 3) | 1.18E+08 | 14925000 | 0.14 |
| $C_7$ | (1, 2, 3) | 1.52E+08 | 45541000 | 0.43 |

C. COLLABORATIVE FRAMEWORKS FOR THE BIO-REFINERIES COOPERATIVE ROBUST PROBLEM

When the benefit of the coalition is obtained for cooperating bio-refineries, the utility should be distributed among the members. The significant problem is sharing the benefits of the coalition among different participants. CGT strategies have developed suitable approaches for equal utility distribution [67, 68, and 69]. Here, some of these strategies are briefly reviewed, then they will be developed for the bio-refineries cooperative robust problem. Finally, the well-known techniques, such as the Shapley value, Equal Utility Method (EUM), $\tau \rightarrow value$, Core center, and Least core are applied to distribute the utility from coalitions.

The set of players shown as $P= 1, 2, 3, \ldots, N$ and $v(P)$ is related to the available utility when all players participate in a coalition. Assume that $y_i$ for each player $i= 1, 2, 3, \ldots, N$ be the real numbers with $\sum_{i=1}^{n} y_i \leq v(P)$. The vector $\vec{y} = (y_1, y_2, y_3, \ldots, y_n)$ is an imputation if it follows the criteria for individual and group rationality i.e. $y_i \geq v(P)$, and $\sum_{i=1}^{n} y_i = v(P)$. Each $y_i$ represents each player’s share of the value of $v(P)$. Consequently, the imputation set for a game will be $Y = \{\vec{y} = (y_1, y_2, y_3, \ldots, y_n) | y_i \geq v(P), \sum_{i=1}^{n} y_i = v(P)\}$. The main objective of the CGT is to determine the type of imputation $Y$ that gives the total benefit a reasonable allocation. Many assignment approaches have been developed based on different definitions of equal allocation, and some of them are discussed here. For more information refer to [70], and [71].

The core is a set of allocations so that each coalition receives the minimum amount of rewards for the alliance. It is defined by:

$$\text{core}(0) = \{\vec{y} \in Y | e(C, \vec{y}) \leq 0, \forall C \subset P\}$$

In equation (71) the excess of coalition is related to $C, \vec{y} = v(C) - \sum_{i \in C} y_i$. The game is referred to as stable if the core is not empty. For real number $\varepsilon, \varepsilon - \text{core}$ is defined as:

$$\text{core}(\varepsilon) = \{\vec{y} \in Y | e(C, \vec{y}) \leq \varepsilon, \forall C \subset P, C \neq \emptyset\}$$

The first value for $\varepsilon$ for which core$(\varepsilon) \neq \emptyset$ is called Least core. The value of the least core can also be calculated from solving the following mathematical model:

$$\text{Min} \ \varepsilon$$

Subject to:

$$e(C, \vec{y}) = v(C) - \sum_{i \in C} y_i \leq \varepsilon, \text{ for all } C \subset P, C \neq \emptyset$$

Shapley [72] developed a method of assignment based on four efficiencies, symmetry, additive, and dummy axioms. $\vec{y} = (y_1, y_2, y_3, \ldots, y_n)$ is related to Shapley value if:

$$y_i = \sum_{e \in N_i, p \in e} (|C| - 1)! - (|N_i | - |C|)! \times [v(C) - v(C - \{P\})] \quad i = 1, 2, \ldots, n$$

Equal Utility Method (EUM) is another allocation method which provides equal relative profit to the individual utility [73]. It minimizes the maximum differences in the owners
TABLE 12. Profit allocation using different allocation methods.

| Bio-refinery | Shapley | τ – value | Core center | Least core | EUM |
|--------------|---------|-----------|-------------|------------|-----|
| (1)          | 2.16E+07| 2.18E+07| 2.19E+07   | 3.4E+07   | 7.7E+06 |
| (2)          | 3.92E+07| 3.61E+07| 3.60E+07   | 3.8E+07   | 3.8E+07 |
| (3)          | 9.12E+07| 9.41E+07| 9.42E+07   | 8.0E+07   | 1.1E+08 |

stable YES  YES  YES  YES

of the bio-refineries relative to usefulness in pairs. EUM is calculated from solving the mathematical model:

\[ \text{Min } z \] (76)

Subject to:

\[ z \geq \frac{y_i}{v(i)} - \frac{y_j}{v(j)} \quad \forall (i, j) \in p \] (77)

\[ \sum_{i \in c} y_i \geq v(C), \quad \text{for all } C \subseteq P, C \neq P \] (78)

\[ \sum_{i \in p} y_i \geq v(P) \] (79)

The constraint (77) indicates the difference between the relative profits of the two players. Z also represents the biggest difference that should be minimized in the objective function.

Lingo 11 software is used to perform calculations related to the least core and EUM. The rest of the results are calculated using the TUGlab tool in MATLAB software. The results are shown in the following Table 12.

The core space under the grand coalition of bio-refineries in the imputation space is shown below as Fig 3. The core is the shaded zone. Since the core is not connected to all three edges of the imputation set, therefore, the game will not be convex.

To measure the satisfaction of forming a coalition, \( F_\delta (C, \bar{y}) \) will be defined as follow:

\[ F_\delta (C, \bar{y}) = \sum_{P \subseteq s} y_P - v(c) \quad \forall s \neq \emptyset, s \subseteq N \] (80)

\( F_\delta (C, \bar{y}) \), calculates the difference between the revenue generated by the formation of the S coalition from the total revenue of each player in the S coalition if they operate alone. The higher the criterion, the greater the satisfaction of the players with the income allocated to them. The satisfaction level of each coalition is calculated based on the corresponding formula and is shown in Table 13.

The minimum satisfaction level of any coalition is the value that determines the minimum distance from the core space. In other words, this value is used to determine the centrality of responses for each coalition in the core space. These values can also provide simple calculations to determine the consistency of each answer. Table 13 represents that the highest value for the least satisfaction is related to the core center method with the utility of 2.04E + 06. There is only dissatisfaction with the Shapley method with the amount of profit allocated to the coalition \( C_5 = \{1, 3\} \).

The Mean Absolute Deviation (MAD) index is used to evaluate the similarity of the revenue allocation methods among players. If the MAD value between the two different methods of revenue allocation was lower, they would have had similar performance in allocating revenue to players. This criterion can be defined as equation (81):

\[ \text{MAD} (\bar{y}, \bar{y}') = \frac{N}{v(c)} \sum_P |y - y'| \] (81)

FIGURE 3. Schematic diagram of the core and imputation.

TABLE 13. Coalition satisfactions for different methods of CGT.

| \( c_m \) | Shapley | Coalition surplus | Coalition satisfactions | \( \tau – value \) | Coalition surplus | Coalition satisfactions | Core center | Coalition surplus | Coalition satisfactions | Least core | Coalition surplus | Coalition satisfactions | EUM | Coalition surplus | Coalition satisfactions |
|----------|---------|------------------|------------------------|----------------|------------------|------------------------|-------------|------------------|------------------------|-----------|------------------|------------------------|-----|------------------|------------------------|
| \( C_1 = \{1\} \) | 1.89E+07 | 6.79 | 1.90E+07 | 6.85 | 1.91E+07 | 6.87 | 3.1E+07 | 11.23 | 4.9E+06 | 1.77 |
| \( C_2 = \{2\} \) | 5.35E+06 | 0.16 | 2.26E+06 | 0.07 | 2.16E+06 | 0.06 | 4.2E+06 | 0.12 | 4.2E+06 | 0.12 |
| \( C_3 = \{3\} \) | 2.16E+07 | 0.31 | 2.45E+07 | 0.35 | 2.46E+07 | 0.35 | 1.0E+07 | 0.15 | 3.7E+07 | 0.53 |
| \( C_4 = \{1, 2\} \) | 1.51E+07 | 0.33 | 1.22E+07 | 0.27 | 1.21E+07 | 0.27 | 2.63E+07 | 0.58 | 0 | 0.00 |
| \( C_5 = \{1, 3\} \) | -1.15E+06 | -0.01 | 1.94E+06 | 0.02 | 2.04E+06 | 0.02 | 0 | 0.00 | 0 | 0.00 |
| \( C_6 = \{2, 3\} \) | 1.24E+07 | 0.10 | 1.22E+07 | 0.10 | 1.22E+07 | 0.10 | 2.63E+07 | 0.22 | 2.63E+07 | 0.22 |
| min | -1.15E+06 | -0.01 | 1.94E+06 | 0.02 | 2.04E+06 | 0.02 | 0 | 0.00 | 0 | 0.00 |
| max | 2.16E+07 | 6.79 | 2.45E+07 | 6.85 | 2.46E+07 | 6.87 | 3.12E+07 | 11.23 | 3.67E+07 | 1.77 |
| sum | 7.21E+07 | 7.68 | 7.21E+07 | 7.66 | 7.22E+07 | 7.67 | 9.84E+07 | 12.30 | 7.21E+07 | 2.64 |


TABLE 14. Mean absolute deviation.

|          | MAD     | Shapley | $\tau - $value | Core center | Least core | EUM    |
|----------|---------|---------|----------------|-------------|-----------|--------|
| Shapley  | -       | 0.41    | 0.42           | 1.64        | 2.00      |        |
| $\tau - $value | -       | -       | 0.01           | 1.87        | 1.87      |        |
| Core center | -       | -       | -              | 1.88        | 1.88      |        |
| Least core | -       | -       | -              | -           | 3.48      |        |
| EUM      | -       | -       | -              | -           | -         | -      |

Fig 4 illustrates the effect of $b_0$ sensitivity in bio-refineries robust cooperative model on the Shapley values gained from a grand coalition.

From the figure we can illustrate that, with the increase in $b_0$ value, the Shapley value of players decrease. A decrease in $b_0$ has a significant role in the profit of bio-refineries. Therefore, this will affect the utility of the participants and their share in the Shapley value method.

D. MANAGERIAL INSIGHTS

From the numerical example, the following observations and management insights are derived:

(i) The definition of the tariff can motivate bio-refineries to balance their production to achieve the optimal profit.

(ii) Defining tariff policy from governments has a significant role in the sustainability factors such as economic, environmental, and social factors.

(iii) An alliance between bio-refineries may result in special cost-saving and increase their profit.

(iv) The cooperative game theory can be used as a justifiable theoretical basis in the design of a policy of equal benefit allocation for the distribution of profit.

V. CONCLUSION AND FURTHER RESEARCH

This research is investigated the effect of interventions by governments and policymakers on the price of biofuel and output quantities of bio-refineries under the cooperation of bio-refineries to achieve sustainability aspects like economic, environmental, and social welfare.

For future researches, first, the model can be formulated as a bi-level nonlinear model by considering the government as a leader. Second, providing pricing models to determine the price of biofuels in competition with other fuels can be considered as another innovation.

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