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Determining energy and climate market policy using multiobjective programs with equilibrium constraints

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ABSTRACT

Energy and climate market policy is inherently multiobjective and multilevel, in that desired choices often conflict and are made at a higher level than influenced actors. Analyzing tradeoff between reducing emissions and keeping fuel prices low, while seeking compromise among producers, traders, and consumers is the crux of the policy problem. This paper aims to address this issue by combining multiobjective optimization problems, which allow the study of tradeoff between choices, with equilibrium problems that model the networks and players over which these policies are chosen, to produce a formulation called a Multiobjective Program with Equilibrium Constraints. We apply this formulation to the United States renewable fuel market to help understand why it has been so difficult in releasing the 2014 mandate for the RFS (Renewable Fuel Standard). The RFS ensures that a minimum volume of renewable fuel is included in transportation fuel sold in the United States. Determining the RFS volume requirements involves anticipating market reaction as well as balancing policy objectives. We provide policy alternatives to aid in setting these volume obligations that are applicable to a wide variety of climate and energy market settings and explain why the RFS is not an optimal policy for reducing emissions.

1. Introduction

Climate market policy, in the form of taxes, cap and trade, and other policy instruments, will play an essential part in reducing GHG (greenhouse gas) emissions. Lowering fossil fuel production, increasing renewable fuel production, promoting clean technology, and supporting sustainability and conservation can all be accomplished with the correct policy structure [5,31,43]. Explicit models and quantitative assessments have the advantage of clarifying underlying assumptions and providing specific predictions. Thus, mathematical models allow policy makers to assimilate knowledge from different domains, which is essential for tackling energy sustainability issues [1,27,45].

However, most large-scale equilibrium models (e.g. Ref. [27] do not endogenously determine climate policy, while models that do determine optimal climate policy (e.g. Ref. [30] are often simplified and don't capture complete market dynamics. This paper is the first to provide a practical framework to endogenously determine climate policy while accounting for detailed market dynamics by capturing all relevant players in a bilevel optimization framework, and providing relevant policy choices along with tradeoff through multiobjective optimization. In addition to this contribution, the paper explicitly applies this framework to the Renewable Fuel Standard.

The gap between policy and mathematical modeling often relates to mathematical modeling not being flexible under assumptions, and policy makers requiring more than one "answer" to make an informed decision. MOPECs (Multiobjective Programs with Equilibrium Constraints) solve both of these problems by providing a series of interpretable policy alternatives (the Pareto surface), while making sure the mathematical modeling accounts for the characteristics that make up policy study (Fig. 1). MOPECs have a number of useful applications [6,13,37] including energy, environment, health, and transportation, but they have not been applied to yet permit markets and climate policy. Note that our acronym MOPEC stands for multiobjective programs with equilibrium

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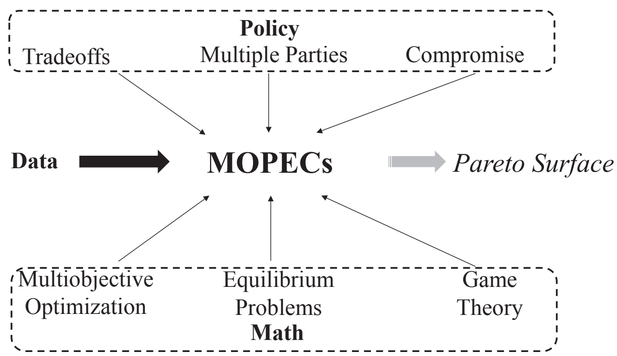

Fig. 1. MOPECs combine mathematical structure that allows the study of policy and provides viable alternatives as opposed to a single answer.

constraints while [6] use MOPEC to mean a different type of problem structure (Multiple Optimization Problems with Equilibrium Constraints). Nonetheless, their structure is relevant to solving equilibrium problems in general. Ref. [37] used the acronym to mean Multiobjective Optimization Problems with Equilibrium Constraints, which is the same structure we have used in this paper.

Energy market equilibria under policy often involve decisions by producers, traders, transporters, and consumers at multiple levels [2,4]. A government (or many) is involved in regulation, regarding emissions, extraction, and delivery. Markets have long been modeled using equilibrium problems formulated as complementarity problems [49], and many modeling techniques exist for representing market power [7,22] and integer restrictions [20,21]. However, modeling policy has often, as with earlier applications, only been performed with one objective. One reason is the large computational cost of bilevel, multiobjective optimization problems [11,44]. With recent algorithmic developments, a multi-objective analysis with equilibrium constraints can now be implemented [41,42].

We look at the current biofuel policy in the United States, which is a good example to consider given the current debate about its usefulness and implementation. The policy is also localized to the United States, making it easily adaptable to the ideas in this paper. Furthermore, we can make a significant contribution to this debate through our framework as we can analyze the tradeoffs between emissions and welfare, while accounting for individual participants in this market. Policies pertaining to biofuels also have to deal with both taxes and caps, so we can display the flexibility of our framework.

Due to climate change, energy security concerns, international politics, and a focus on renewable and sustainable sources of energy, biofuels have taken a central place in sustainable energy debates. In contrast to other renewables, such as wind and solar, that have problems of intermittency, storage, and transportation; the final products of liquid biofuels can potentially be drop-in replacements for liquid fossil fuels. First generation biofuels from seeds, grains, or sugars are widely produced now, but are unsustainable for future production [39]. Large-scale production of those biofuels requires large amounts of arable land, competing with foodcrops. Moreover, many of these biofuels are inefficient on a lifecycle basis, e.g., corn ethanol, which cannot provide much more than a 20% reduction in greenhouse gas emissions. Hence, promoting biofuel production requires an aggressive policy, which the United States implements with a wide variety of overlapping instruments including the RFS (Renewable Fuel Standard), tax credits, and import tariffs. There have been government policies and R&D support directed at increasing biofuel production, lowering its cost, and improving its efficiency. The US produces an average of 16 billion gallons of biofuels (mostly corn ethanol and biodiesel) annually and with the passage of the EISA (Energy Independence and Security Act) of 2007, aims to produce 36 billion gal/yr by 2022, including 21 billion gal/yr from *second generation* advanced biofuels that have much lower greenhouse gas emissions [16]. Federal biofuel subsidies were over $6 billion in 2010, not counting R&D [15].

In order to comply with the RFS oil refiners must hold the mandated number of tradable compliance certificates called RINs (renewable identification numbers). RINs are the liquid fuel equivalent of a REC (renewable energy certificate) used in electricity markets to comply with a RPS (renewable portfolio standard). A RIN is generated by the producer of biofuel, who sells the attached RIN and biofuel to the blender. The blender then separates the RIN from the biofuel and sells it to an obligated party (refiner). Refiners can sell excess RINs they accumulate to other obligated parties. Along with this cap and trade system where RIN credits are tradable/bankable/deficit-able, there are a number of overlapping policies such as production tax credits directed to multiple points in the supply chain depending on fuel type, the Blend Wall (ethanol is limited to 10% of demand of gasoline), import tariffs and tax rates, which are different for each fuel [8,9]. Hence, biofuel markets in the US are difficult to model exemplified by the fact that at the time of this writing, EPA (Environmental Protection Agency) had decided to pull back the proposed rule that established volume obligations in 2014;[1] this rule was released over a year late in July 2015. In the current climate, we need new methods and insights for sufficient production of sustainable biofuels to meet society's energy and environmental needs.

The paper proceeds as follows. The next section describes the problem definition and terminology for MOPECs. After a short introduction on US Biofuel policy in Section 3, we then formulate this policy as a MOPEC in Section 4 and provide numerical results in Section 5. We conclude with comments about our results and the usefulness of MOPECs in informing policy.

2. Background terminology, problem definition, and a solution algorithm for MOPECs

Table 1 describes the mathematical terminology used in this paper for MOPECs.

Multiobjective optimization problems [50] allow the study of tradeoff between conflicting policy decisions, while equilibrium problems model the networks over which these policies are chosen. Combining these two types of optimization problems produces a MOPEC, mathematically shown below.

$$\begin{aligned} \min F(x,y) = [&f_1(x,y), f_2(x,y), f_3(x,y), \ldots, f_n(x,y)] \\ &\text{s.t. } (x,y) \in \Omega \\ &\quad y \in S(x) \end{aligned} \tag{1}$$

where the continuous variables $x \in \Re^{n_x}$, $y \in \Re^{n_y}$ are, respectively, the vector of upper-level, lower-level variables, $\{f_i(x,y)\}_{i=1}^{n}$ in C^2 are the upper-level objective functions, Ω is the joint feasible region between these sets of variables and $S(x)$ is the solution set of the lower-level problem that can be an optimization problem, a NCP (nonlinear complementarity problem) or a VI (variational inequality) problem [18]. In this paper, we focus on $S(x)$ as an NCP [10]: Having a C^2 function $g : \Re^{n_z} \to \Re^{n_z}$, a NCP is to find a vector $z \in \Re^{n_z}$ such that (componentwise):

[1] See http://www.gpo.gov/fdsys/pkg/FR-2014-12-09/pdf/2014-28163.pdf.

Table 1
Definition of terms.

Symbol	Interpretation
x	Vector of continuous upper-level decision variables (taxes, caps, and other climate policy instruments)
y	Vector of continuous lower-level decision variables (production, consumption, prices of energy markets)
f_i	Objective functions to be optimized at the upper-level (social welfare, greenhouse gas (GHG) emissions, producer profit)
$g_j(x,y)$	Constraint functions for the energy and climate policies and markets

$$z \geq 0, ; g(z) \geq 0, ; z^T g(z) = 0 \tag{2}$$

The structure of (2) has been used extensively to model energy markets (e.g. Ref. [27]. Our contribution is to extend (2) by using the formulation (1) to model such markets and policy interventions within. This is also one of the main extensions from Ref. [9].

For MOPECs, in contrast to single-objective optimization, the output is a set of Pareto optimal solutions (or Pareto frontier). A solution point is *Pareto optimal* if there is no other equilibrium point that improves at least one objective function without detriment to one or more other objective functions [32].

Definition 1. The vector $F(\hat{x},\hat{y})$ is said to *dominate* another vector $F(\bar{x},\bar{y})$, if and only if $f_i(\hat{x},\hat{y}) \leq f_i(\bar{x},\bar{y})$ for all $i = 1, \ldots, n$ and $f_j(\hat{x},\hat{y}) < f_j(\bar{x},\bar{y})$ for at least one j. A point $(x^*, y^*) \in \Omega, y^* \in S(x^*)$ is said to be Pareto optimal or an efficient point for Eq. (1) if and only if there does not exist $(x,y) \in \Omega, y \in S(x)$ satisfying $F(x,y) < F(x^*,y^*)$. The vector $F(x^*,y^*)$ is then called a non-dominated or non-inferior point, and specifically a *Pareto point*. The set of all Pareto points is referred to as the *Pareto frontier*.

While MOPECs are a natural fit for modeling policy in energy markets, their use has been limited mainly because of the high computational cost and lack of efficient algorithms [37]. In particular, constraints (2) often form a disjoint, non-convex feasible region resulting in the inability to obtain global Pareto optimal solutions. Locating efficient Pareto optimal solutions with a convex feasible region has also not been possible as several optimization problems need to be solved to obtain a good representation of the Pareto set. Recent advances in algorithms for MPECs (Mathematical Programs with Equilibrium Constraints) (e.g., [23,24] and MO (multiobjective optimization) problems (e.g. Refs. [12,25] have resulted in overcoming these hurdles, and this paper aims to utilize such recent advances to solve large scale MOPECs.

2.1. Solving the MOPEC

The MOPEC algorithm used in this paper involves combining an efficient, gradient-based MPEC algorithm with a MO (multi-objective) algorithm that generates several Pareto points with one application of the MPEC optimization procedure. This algorithm is developed by combining two existing algorithms, and is the first time that these two algorithms have been combined (Appendix B) to solve a MOPEC. Three different MPEC algorithms were tested: the penalty method [42], a nonlinear method [51], and a smoothing method for $y^T g(x,y) = 0$ by Ref. [44]. We tested two different MO algorithms: a gradient-based computationally efficient modification of the NBI (Normal Boundary Intersection) method [41] and the ε-constraint method [34]. Table 2 provides a summary of the methods used to verify the generation of the Pareto frontier.

The algorithm that provided the most computationally efficient generation of the Pareto set is outlined below. Other methods took more computational time and generated Pareto sets that were a subset of this method. The complementarity problem takes less than 5 s to run, however, it is not successful in generating Pareto optimal points when looped over a number of policy choices. The points generated are feasible equilibria, but not on the border of the Pareto frontier. Note that in bilevel (and equilibrium) problems, multiplicity of solutions (and equilibria) is an issue researchers need to account for. In our formulation, we assume that if we get a Pareto point, there could be several solutions at that point. Since our paper focuses on generating the Pareto frontier, this is not an issue. But in our policy analysis section, we note that there could be several policies that result in the same Pareto point. For simplicity, consider a biobjective problem where $f(x,y) = [f_1(x,y), f_2(x,y)]$. We use the penalty method (for details on choosing $L > 0$, refer to the theorems in Ref. [42] to reformulate the problem to satisfy constraint qualifications.

$$\begin{aligned}
&\min f(x,y) + \sum_{i=1}^{n_y} L_i\left(v_i^+ + v_i^-\right), \text{s.t.}\ (x,y) \in \Omega, y \geq 0, g(x,y) \geq 0 \\
&u - \left(v^+ + v^-\right) = 0, \quad u = \frac{y + g(x,y)}{2}, \left(v^+ - v^-\right) = \frac{y - g(x,y)}{2} \\
&\text{where } v^+, v^- \text{ are non} - \text{negative variables}.
\end{aligned} \tag{3}$$

The next step is to find the individual local minima, (we assume they exist and are finite), and reformulate the MO problem as follows [41]:

$$\begin{aligned}
&\min_{x,y,t \in \Re_+, \beta \in \Re_+} t \quad s.t. \begin{pmatrix} 1 \\ 0 \end{pmatrix} \beta + t \begin{pmatrix} 0 \\ 1 \end{pmatrix} = f(x,y) + \sum_{i=1}^{n_y} L_i(v_i^+ + v_i^-) \\
&(x,y) \in \Omega, y \geq 0, g(x,y) \geq 0 \\
&u - \left(v^+ + v^-\right) = 0, u = \frac{y + g(x,y)}{2}, \left(v^+ - v^-\right) = \frac{y - g(x,y)}{2} \\
&\text{where } v^+, v^- \text{ are non} - \text{negative variables}.
\end{aligned} \tag{4}$$

The goal in the method is to use the history of iterates from problem (4) to obtain the Pareto frontier. Hence, β is a decision variable in Eq. (4), which is solved using a quasi-Newton method. The next step is to control the history of iterates when solving Eq. (4) to obtain the Pareto frontier. Recall the Newton method [3] for finding a local minimum for a single-objective optimization problem. To find where the first derivative of an objective function is zero (assume $z = [x, y]$):

$$f'(z) = f'(z_m) + f''(z_m)(z - z_m) = 0, \quad z = z_m - \left[f''(z_m)\right]^{-1} f'(z_m) \tag{5}$$

where the subscript m represents successive better approximations of the solution z^*, i.e., $z_m \to z^*$. Under favorable conditions [3] convergence is obtained iteratively, where

$$z_{m+1} = z_m - \delta_m \tag{6}$$

$$\delta_m = \left[f''(z_m)\right]^{-1} f'(z_m) = H_m^{-1} g_m \tag{7}$$

Since this is a derivation from the quadratic Taylor series of the objective function, approximating the Hessian H_m can prove

Table 2
Solution approaches to solving the multiobjective program with equilibrium constraints. Pareto points generated and computation time in seconds is also displayed.

		Mathematical programs with equilibrium constraints algorithms		
		[42]	[51]	[44]
Multiobjective Algorithms	[41]	Used to generate Pareto Frontier (36 points, 7231s)	Tested and verified Pareto Frontier (22 points, 12531s)	Tested and verified Pareto Frontier (29 points, 22531s)
	[34]	Tested and verified Pareto Frontier (20 points, 17526s)	Tested and verified Pareto Frontier (21 points, 23526s)	Tested and verified Pareto Frontier (18 points, 35478s)

troublesome. Another step, called the line search method in some cases, is added:

$$z_{m+1} = z_m - \alpha_m \delta_m \tag{8}$$

The α_m above in Eq. (9) is called the steplength, and δ_m is the direction. However, since Eq. (4) is being optimized over three sets of variables, one can rewrite Eq. (8) as follows:

$$\begin{pmatrix} z \\ t \\ \beta \end{pmatrix}_{m+1} = \begin{pmatrix} z \\ t \\ \beta \end{pmatrix}_m - \begin{pmatrix} \alpha_m \delta_x \\ \alpha_m \delta_t \\ \alpha_m \delta_\beta \end{pmatrix}_m \tag{9}$$

To generate a minimum number of points on the Pareto frontier, limiting the magnitude but keeping the same direction of $\begin{pmatrix} \alpha_m \delta_x \\ \alpha_m \delta_t \\ \alpha_m \delta_\beta \end{pmatrix}_m$ will enable the successive approximations of z^* points to have a certain maximum distance in between them. Note that the distance between two successive points on the generated Pareto frontier is given by the size of $\alpha_m \delta_\beta$, which is the amount the variable β "steps" towards the solution. Since it is assumed that all objective functions have been normalized, the magnitude of $\alpha_m \delta_\beta$ can be controlled to generate a desired number of Pareto points. In general, to generate p points, set $V_m = 1/(p-1)$, the quantity varied by the user to help obtain a pre-specified number of Pareto points. Apply a filter [35] to get points that are not Pareto dominated.

$$\begin{pmatrix} z \\ t \\ \beta \end{pmatrix}_{m+1} = \begin{pmatrix} z \\ t \\ \beta \end{pmatrix}_m - \frac{V_m}{\alpha_m |\delta_\beta|} \begin{pmatrix} \alpha_m \delta_x \\ \alpha_m \delta_t \\ \alpha_m \delta_\beta \end{pmatrix}_m \tag{10}$$

Note that this method can handle both non-convex and discontinuous feasible regions [41]. For the Pareto frontiers generated with this method, we verified Pareto optimality by numerical tests and the other methods discussed above. All solution points in the next section have thus been numerically verified.

3. United States biofuel market and renewable fuel standard

This section discusses the place of biofuels in the renewable fuel standard, along with the market issues surrounding the economic viability of biofuels on a large scale. We only present the relevant information to formulate the MOPEC. For detailed information, please refer to Ref. [9,8].

The Energy Independence and Security Act of 2007 (Public Law 110–140) contained a number of programs and incentives for biofuels; indeed, Title II of the act is titled Energy Security through Increased Production of Biofuels. That title redesigned the RFS, which is the primary biofuels policy in the US. The RFS measures fuels on a lifecycle GHG (greenhouse gas) basis as well as having qualifications about what feedstocks can be used. In general, new fuels being incentivized in the RFS are divided into categories each with their own GHG reduction to the average gallon of gasoline sold in 2005: Cellulosic (−60%), Biomass-based Diesel (−50%), Advanced Fuel (−50%), and Renewable Fuel (−20%). Congress defined these new fuel classes in order to create volume obligations for each separate type of fuel. Table 3 shows the requirements under the RFS under the statute (law), 2013, projected for 2014 by the EPA, and actual 2014 volumes released by EPA in July, 2015. Note that the cellulosic fuel category forms a minute part of the mandate, and thus is not modeled in our analysis, but interested readers should refer to [26].

Currently, EPA is using their authority to waive down the overall requirement to use biofuel as a transportation fuel.[2] Opponents of the RFS say that infrastructure doesn't exist to use higher blends of ethanol while supporters of RFS say that it was created to drive market change in transportation fuel and waiving the requirement undermines the original intent of the law.

Any supplier of petroleum-based transportation fuel is considered an obligated party under the RFS. In our model, the obligated parties are refiners of crude oil. Obligated parties demonstrate compliance with the RFS by collecting a mandated number of certificates, referred to as RINs, and retiring them to the EPA (Environmental Protection Agency) at the end of a year. RINs are generated by a producer of biofuel and can be banked for the next year's compliance or traded among obligated parties, similar to other cap-and-trade policies. There are five different types of RINs that can be generated under the RFS and are enumerated as D3–D7, but we only model D4 (biodiesel, RINs), D5 (advanced RINs) and D6 (renewable fuel RINs) as D3 and D7 RINs make up less than 1% of the RINs produced. The RFS is a nested mandate, in that the D4 RIN can be used to satisfy the renewable fuel, advanced fuel, and biomass based diesel mandate. Similarly, the D5 RIN can be used to satisfy the advanced fuel and renewable fuel mandate. The D6 RIN, in our model, only satisfies the renewable fuel mandate.

Another important policy in this model used to promote biofuel production is the Biodiesel Tax Credit [39]. This tax credit, at $1/gallon, is given directly to the biodiesel producer and is decided by the United States Congress.

Both the tax credit and RFS mandated volumes will be upper-level decision variables in our model, unlike previous papers which take these values as given. The next section describes how we will formulate this problem as a MOPEC.

4. Formulation of biofuel market and RFS as a MOPEC

The framework implemented here is general and can be used for any setting, so we encourage the reader to analyze this section as a case study for the utility of MOPECs. As mentioned before, we chose this application because it is simple enough to grasp right away and contains all the components we want to highlight in our model.

The model presented in this paper is an extension of the complementarity model presented in an earlier paper [9] but can be applied to other market models as well (e.g., [48]. The main extension is that while the complementarity model in Ref. [9] took the RFS mandated volumes as inputs, this model uses a MOPEC to

[2] See http://www.gpo.gov/fdsys/pkg/FR-2013-11-29/pdf/2013-28155.pdf, last accessed September 28, 2015.

Table 3
2014 Renewable fuel standard mandate (Billions of gallons of production).

Fuel Category	Statute	2013	2014 (projected)	2014 (Actual)
Cellulosic	1.75		0.008–0.03	0.033
Biomass Based Diesel	1.28	1.28	1.28	1.63
Advanced	3.75	2.75	2–2.51	2.68
Renewable	18.15	16.55	15–15.52	15.93

endogenously determine these volumes based on policy objectives. This model, at the lower-level, contains six types of players: ethanol producers, biodiesel producers, importers of ethanol (from Brazil only) obligated parties (refiners), and blenders. These players act over nine different markets: D4, D5, D6 RIN markets, ethanol and biodiesel markets, gasoline blendstock and diesel blendstock markets, and gasoline and diesel markets. These players are put together in an equilibrium model with no speculation, perfect foresight, and perfectly inelastic demand for gasoline and diesel where prices are endogenously determined. Decision variables include quantities of fuel produced, imported, refined, blended, along with RINs bought, sold, and banked. Fig. 2 shows the structure of this market and the complete KKT (Karush Kuhn Tucker) formulation is given in Appendix A.

With this market at the lower-level, the upper-level conflicting objectives are to 1) maximize GHG emissions reduction and 2) minimize price RIN prices. GHG emission reductions are calculated using the exact substitution of each biofuel as put forth by the EPA while RIN prices are summed up (discounted) and averaged over the time period considered in the model. Note that with the MOPEC structure, we have the flexibility of choosing from several objective functions. For this application, we wanted to choose conflicting objectives that policy makers often grapple with. For example, other natural objective functions include consumer welfare, producer profit, and economic efficiency. For our model, we chose to look at the average RIN price as that is a tangible piece of information that can be utilized to calculate all other measures such as surplus, profit, and welfare. With the importance of RIN prices to policy makers as emission reduction instruments, it also made sense that they would want to make sure the prices stay low. We could have also added the consumer fuel prices as objectives, but then the model would be optimizing over many choices, and results would be difficult to display. In a full implementation though, policy makers and modelers should have to key in which parts of the analysis are essential. Details of the mathematical formulation of the objective functions are given in Appendix A and Fig. 3 shows this structure.

5. Numerical results of the biofuel MOPEC

In this section, we present numerical results from the biofuels market model described in Section 4. As mentioned before, solving the MOPEC is not a trivial task. We employed a number of methods to obtain our numerical results, and one in particular worked best.

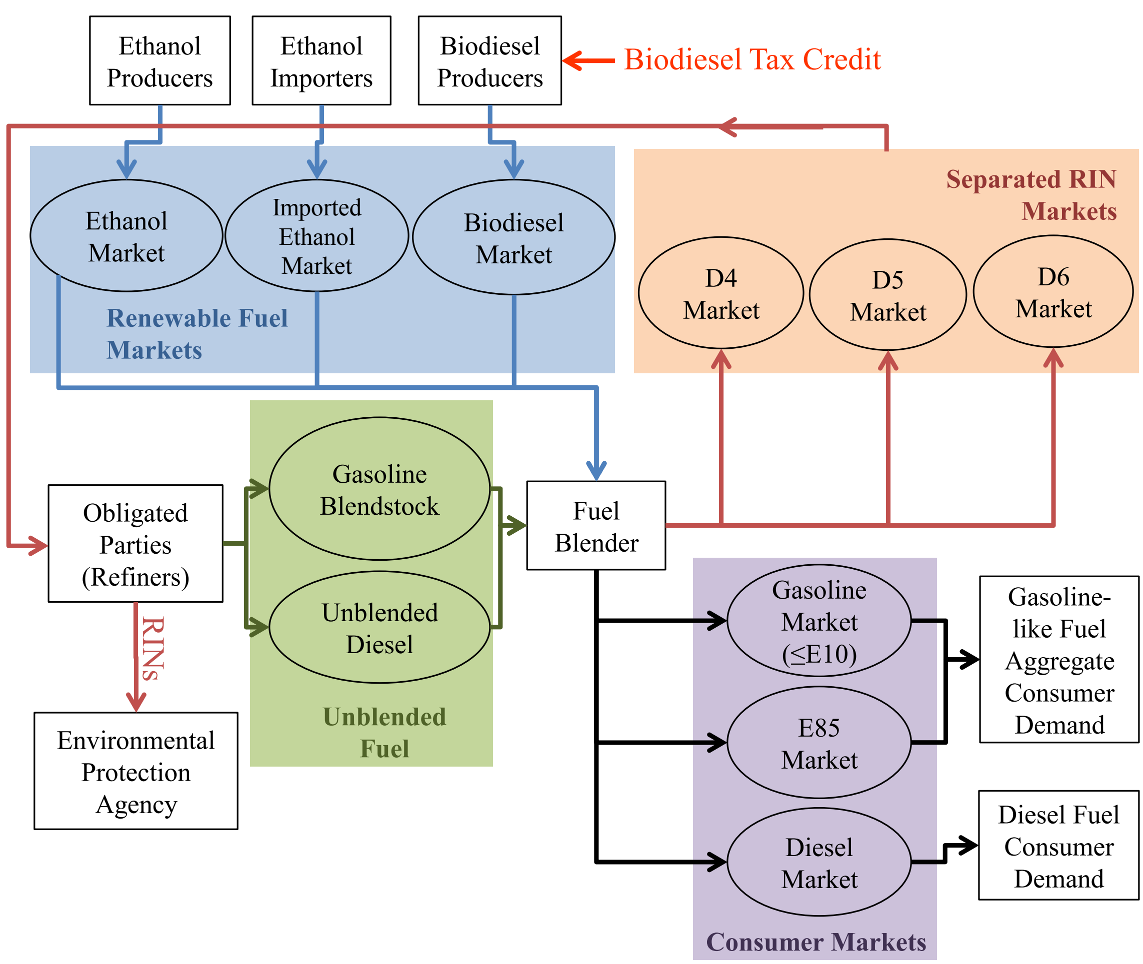

Fig. 2. The lower-level Biofuel and RIN Market Model.

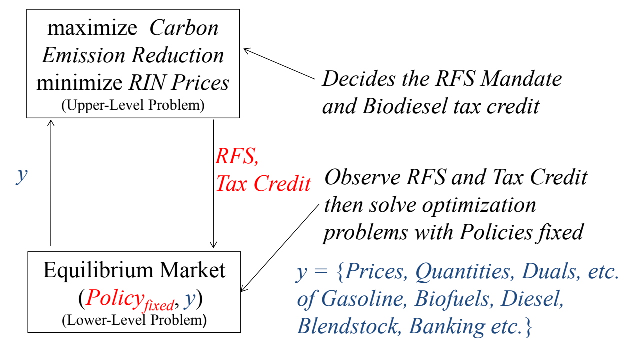

Fig. 3. The MOPEC structure for setting the renewable fuel standard (RFS) in the **US** biofuels market.

The next subsection describes this method and the verification performed to solve the MOPEC.

The goal of this numerical exercise is to show the useful output from a MOPEC. While the MOPEC formulated here can output an incredible amount of useful information that is common to complementarity models, we focus here on the most relevant output. In our example, we want to aid in setting climate policy, specifically the RFS. We want to provide a number of alternatives to set this policy and display output in a way convenient to policy makers. Finally, we hope to provide insight on sensitivity of the policy to changes in the system, as opposed to discrete scenario results. We show that displaying the Pareto frontier of the MOPEC can give additional insight not available from other models.

The model was run for years 2011–2020 (with two extra years ignored in the results to mitigate end of horizon effects). Table 4 details the four different scenarios that were used to put our results in context. Two volume scenarios were proposed by Refs. [28,46]. The other scenarios correspond to the recent proposal released by the [17]. Since the EPA requested comment on a range of biofuel volumes, this scenario includes three separate sub-scenarios that reflect the upper and lower bounds, as well as average, on how many gallons of biofuel must be consumed per annum for each biofuel category. Again, details of data and parameters can be found in Ref. [9]. For the numerical implementation, we chose $L = 0.001$ and $V_m = 0.01$.

Figs. 4 and 5 below show the real insight of the MOPEC. First, we see that the RFS is not a suitable climate market policy to reduce GHG emissions from transportation fuel in the United States by more than about 0.5% over the time period 2011–2020; annualized

Table 4
Volume scenarios used for comparison in this study in Billions of Gallons.

	EPA low *(Base Case)*	EPA mid	EPA high	Irwin	Tyner
Biomass Based Diesel					
2011	0.8	0.8	0.8	0.8	0.8
2012	1	1	1	1	1
2013	1.28	1.28	1.28	1.28	1.28
2014	1.28	1.28	1.28	1.28	1.28
2015	1.28	1.28	1.28	1.28	1.5
Advanced Fuel					
2011	1.35	1.35	1.35	1.35	1.35
2012	2	2	2	2	2
2013	2.75	2.75	2.75	2.75	2.75
2014	2	2.255	2.51	2.75	2.05
2015	2	2.255	2.51	2.75	2.58
Renewable Fuel					
2011	13.95	13.95	13.95	13.95	13.95
2012	15.2	15.2	15.2	15.2	15.2
2013	16.55	16.55	16.55	16.55	16.55
2014	15	15.26	15.52	16.55	15.85
2015	15	15.26	15.52	16.55	16.58

GHG savings are approximately 0.05%/year from 2011 to 2020. This fact is realized once we look at the *x*-axis of both Figs. 4 and 5. The most extreme GHG reduction scenario produces no more than 0.47% reduction over 2011–2020, which was the individual minimum of the objective that maximizes GHG reduction. For scale, the CAFE (Corporate Average Fuel Economy) standards for light duty vehicles from 2017 to 2025 are projected to decrease annual emissions by approximately 6% by 2020; annualized GHG savings are approximately 2%/year. Benefits of CAFE standards also extend well beyond 2020 as the vehicle fleet gradually turns over.[3] The approximate 0.47% reduction in GHG emissions was the maximum feasible Pareto point achievable in our model, showing that even under the best case scenario the impact of the RFS is limited. The average RIN price in this case is around $1.50 for each of the RINs, which is not prohibitive but the gasoline price goes above $6/gallon, which is definitely not sustainable politically. Moreover, there is no difference in prices for the different types of RINs (D4, D5, and D6 are priced all the same), which shows that high emission reductions will lead to no discrimination between RIN categories, implying wasteful design of the RFS.

Second, given the constraints, the Pareto frontier shows that the proposed EPA volumes have been have been picked in the least sensitive range for RIN and fuel prices, i.e., the portions of the Pareto frontier where RIN price changes least with an increase in GHG emission reduction. The ranges from EPA Low to EPA High fall into a flat part of the Pareto frontier, showing less sensitivity to rising RIN price but larger GHG emissions reductions. The 2014 mandate shows that the EPA has chosen a policy with a high GHG emission reduction but not much change in both transportation fuel and RIN prices.

Third, the MOPEC shows numerous policy alternatives for these volume requirements, which result in different price structures and policies. Note that there are multiple solutions, and the MOPEC can help establish various combinations of the RFS that can yield desired prices. For example, Irwin and EPA High focus on high volume obligations for advanced biofuels as opposed to corn ethanol, but such a policy will result in high D5 RIN prices and lower D6 RIN prices. Such a graphic can also help policy makers understand how the RFS can impact the RIN and energy markets. Note that there could be multiple equilibria of different RFS mandates that result in the same Pareto point. Obtaining these equilibria (by using different starting values and desired specific mandated volumes) can help in providing even more options for policymakers.

Overall, our results show that the D4 RIN price is expected to be the most stable of all three, and forms a cap for the other RIN prices. Note that interpolating the Pareto frontier is not bound to give feasible, Pareto optimal points. The gaps in the frontier show that no feasible Pareto solution was found, indicating a discontinuous Pareto frontier. This can have policy implications in that slight changes in policy can very quickly lead to larger changes in the market if the policy is close to an isolated Pareto optimal point. For example, if we want a policy to reduce GHG emissions by around 0.43% but not have the RIN price go above $1, small changes in data and conditions might force the market into the top left Pareto optimal equilibrium (Fig. 4) with RIN prices as high as $1.50.

While the MOPEC was programmed to optimize on RIN price and GHG emission reduction, we can still compare the fuel prices using a similar graphic as shown in Fig. 5. We see that Diesel prices remain relatively stable given various RFS volume obligations. However, gasoline prices are affected much more by the RFS policy. In many ways, this is counterintuitive because biodiesel offers a much greater chance of emission reduction. We can see this by the

[3] http://www.nhtsa.gov/staticfiles/rulemaking/pdf/cafe/FINAL_EIS_Summary.pdf.

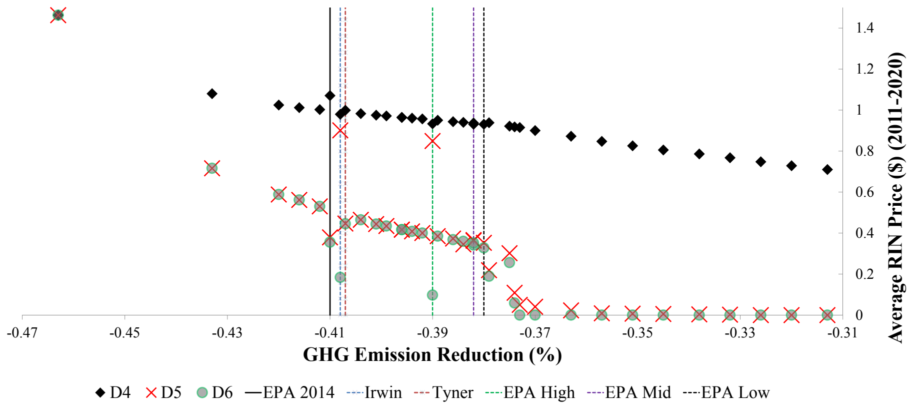

Fig. 4. The Pareto Frontier for the MOPEC showing tradeoff between the two objective functions. Note: Average RIN Price has been broken up into individual components.

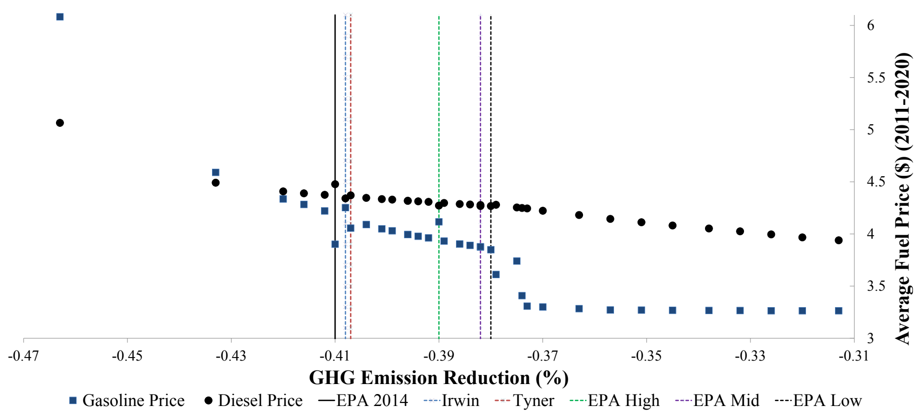

Fig. 5. Output of the MOPEC showing tradeoff between fuel price and greenhouse gas emission reduction. Note: Fuel price was not modeled as an objective to minimize, so this is not a Pareto Frontier.

change in slope of the gasoline price curve at different values of GHG emission reduction. At higher levels of GHG emission reduction, gasoline overtakes the diesel price, showing the pressure that the RFS can place on refiners to blend ethanol once we pass a certain threshold. Note that, again, gasoline prices are most sensitive to changes in RFS policy once we move below or above the current volume obligations being considered; i.e., the gradient of the gasoline price curve is higher below the EPA Low policy and above Irwin's suggested policy.

6. Concluding remarks

Because future energy needs will be fulfilled from a variety of sources, we can expect many policy interventions in an effort to promote sustainability and reduce GHG emissions. As researchers, it is our responsibility to develop tools that can help make these policy interventions and provide input from a number of different angles. Bridging the gap between researchers and policy makers is a role we also have to play. This paper has provided one such tool to aid in decisions and also to make the conversation between researchers and policy makers much easier.

The main conclusion is that we must be careful when developing policy to influence climate and sustainability issues as outcomes can be different because of compromise and tradeoff. Modeling can help us figure out what problems might develop between various players and influence outcomes. Biofuels have an important future in the United States, but taking advantage of them is not easy, and the current RFS might not be the best instrument. We have seen that even under very strict volume scenarios, the RFS induces minimal GHG emission reductions with a danger that gasoline prices might rise too high. It's no wonder that EPA released the 2014 mandate in July 2015.

As shown in this paper, a MOPEC can help see policy in context of its objectives, rather than the objectives in the context of policy as has traditionally been done. The Pareto frontier gives us more insights that we can otherwise not have from a scenario-based analysis. While computational cost has been a big hurdle in solving MOPECs, recent advances in algorithmic development have helped the analysis in this paper, and we believe that these tools can be used in a wide variety of applications.

Future work includes incorporating uncertainty in MOPECs [40] as well as adding state policies and detailed oil and diesel markets and the ability to deal with integer variables [20,21]. We hope that MOPECs get adopted in a wide variety of applications involving energy systems including schematic display [38], data mining, and sustainability [14].

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A. Appendix with mathematical formulation of MOPEC

Model Variables and Parameters [9]

$q^{P,corn}_{eth,t}$	quantity of domestic corn ethanol produced (gal)
$q^{P,oils}_{bbd,t}$	quantity of biodiesel produced (gal)
$q^{P,sugar}_{eth,t}$	quantity of sugar ethanol imported (gal)
$q^{B}_{BOB,t}$	quantity of blendstock for oxygenate blending (BOB) purchased (gal)
$q^{B}_{desb,t}$	quantity of unblended diesel purchased (gal)
$q^{B,corn}_{eth,t}$	quantity of corn ethanol purchased (gal)
$q^{B}_{D6,t}$	quantity of D6 RINs separated (RINs)
$q^{B,oils}_{bbd,t}$	quantity of biodiesel purchased (gal)
$q^{B}_{D4,t}$	quantity of D4 RINs separated (RINs)
$q^{B,sugar}_{eth,t}$	quantity of sugar ethanol purchased (gal)
$q^{B}_{D5,t}$	quantity of D5 RINs separated (RINs)
$q^{B\rightarrow E85}_{BOB,t}$	quantity of BOB purchased for use in E85 (gal)
$q^{B,corn\rightarrow E85}_{eth,t}$	quantity of corn-ethanol purchased for use in E85 (gal)
$q^{B,sugar\rightarrow E85}_{eth,t}$	quantity of imported ethanol purchased for use in E85 (gal)
$q^{B\rightarrow E10}_{BOB,t}$	quantity of BOB purchased for use in E10 (gal)
$q^{B,corn\rightarrow E10}_{eth,t}$	quantity of corn-ethanol purchased for use in E10 (gal)
$q^{B,sugar\rightarrow E10}_{eth,t}$	quantity of imported ethanol purchased for use in E10 (gal)
$q^{B}_{BOB,t}$	quantity of blendstock for oxygenate blending (BOB) produced (gal)
$q^{R}_{desb,t}$	quantity of unblended diesel produced (gal)
$B^{R}_{D4,t}$	quantity of D4 RINs banked in time period t (RINs)
$B^{R}_{D5,t}$	quantity of D5 RINs banked in time period t (RINs)
$B^{R}_{D6,t}$	quantity of D4 RINs banked in time period t (RINs)
$\pi^{corn}_{eth,t}$	price for corn ethanol ($/gal)
$\pi^{sugar}_{eth,t}$	price for imported sugarcane ethanol from Brazil ($/gal)
$\pi^{iols}_{bbd,t}$	price for biodiesel fuel ($/gal)
$\pi_{BOB,t}$	price for gasoline blendstock for oxygenate blending (BOB) ($/gal)
$\pi_{desb,t}$	price for unblended diesel ($/gal)
$\pi_{D4,t}$	price for D4 RINs ($/RIN)
$\pi_{D5,t}$	price for D5 RINs ($/RIN)
$\pi_{D6,t}$	price for D6 RINs ($/RIN)
$\pi_{gas,t}$	price for finished gasoline-like fuels (E10 and E85) ($/gal)
$\pi_{des,t}$	price for finished diesel fuel ($/gal)
$\mu_{bbd,t}$	marginal cost for complying with the biomass-based diesel sub-mandate
$\mu_{adv,t}$	marginal cost for complying with the advanced fuel sub-mandate
$\mu_{rf,t}$	marginal cost for complying with the overall renewable fuel mandate
$\mu^{cap,oils}_{bbd,t}$	dual variable for biomass-based diesel capacity constraint
$\mu^{cap,corn}_{eth,t}$	dual variable for domestic corn-ethanol capacity constraint
$\mu^{cap,sugar}_{eth,t}$	dual variable for imported sugarcane ethanol capacity constraint
$\mu^{cap}_{corn,t}$	dual variable for limit on corn ethanol that can qualify under the RFS
$\mu^{bank}_{bbd,t}$	dual variable for constraint on the number of banked RINs that qualify for the biomass-based diesel sub-mandate
$\mu^{bank}_{adv,t}$	dual variable for constraint on the number of banked RINs that qualify for the advanced fuel sub-mandate
$\mu^{bank}_{rf,t}$	dual variable for constraint on the number of banked RINs that qualify for the overall renewable fuel mandate
$\lambda_{D4,t}$	dual variable for equality constraint for D4 RIN separation
$\lambda_{D5,t}$	dual variable for equality constraint for D5 RIN separation
$\lambda_{D6,t}$	dual variable for equality constraint for D6 RIN separation
$\lambda_{E10,t}$	dual variable for the E10 blend wall constraint
$\lambda_{E85,t}$	dual variable for the E85 blending limit
$\lambda^{bal,sugar}_{eth,t}$	dual variable for the imported ethanol volume balance constraint
$\lambda^{bal,corn}_{eth,t}$	dual variable for the corn ethanol volume balance constraint
$\lambda^{bal}_{BOB,t}$	dual variable for the BOB volume balance constraint
EV_{eth}	equivalence value for ethanol (unitless)
EV_{bbd}	equivalence value for biodiesel (unitless)
$P^{P}_{bbd,t}$	net policy intervention for the biodiesel producer ($/gal)
$P^{P}_{eth,t}$	net policy intervention for the corn ethanol producer ($/gal)
$P^{P,sugar}_{eth,t}$	net policy intervention for the importer sugarcane ethanol ($/gal)

(continued on next page)

(*continued*)

$P^{B}_{bbd,t}$	net policy intervention for the blender to blend biodiesel ($/gal)
$P^{B}_{eth,t}$	net policy intervention for the blender to blend ethanol ($/gal)
$\overline{q}_{des,t}$	perfectly inelastic consumer demand for diesel fuel (gallons)
$\overline{q}_{gas,t}$	perfectly inelastic consumer demand for motor gasoline fuel; E10 & E85 (gallons)
$\overline{q}^{P,corn}_{eth,t}$	total production capacity for corn-ethanol in the United States (gallons)
$\overline{q}^{P,sugar}_{eth,t}$	total import capacity for sugarcane ethanol from Brazil (gallons)
$\overline{q}^{P,oils}_{bbd,t}$	total production capacity for biodiesel in the United States (gallons)
GHG^{corn}	GHG emission reduction percentage for corn ethanol (20%)
GHG^{sug}	GHG emission reduction percentage for sugar cane ethanol (50%)
GHG^{biod}	GHG emission reduction percentage for biodiesel (50%)
GHG^{E85}	GHG emission reduction factor for E85 (78.2%)

Upper-Level Objective Functions

$$\max f_1 = \sum_t \left(\frac{GHG^{corn} q^{B,corn\rightarrow E10}_{eth,t} + GHG^{sug} q^{B,sugar\rightarrow E10}_{eth,t} + GHG^{E85}\left(0.5 q^{B,sugar\rightarrow E85}_{eth,t} + 0.2 q^{B,corn\rightarrow E85}_{eth,t}\right)}{\overline{q}_{gas,t}} + \frac{GHG^{biod} q^{B,oils}_{bbd,t}}{\overline{q}_{des,t}} \right)$$

$$\min f_2 = \frac{\sum_t \beta^t \left(\pi_{D4,t} + \pi_{D6,t} + \pi_{D6,t}\right)}{\sum t}$$

Biodiesel Producer KKT Conditions

$$0 \le q^{P,oils}_{bbd,t} \perp -\pi_{bbd,t} + MC_{bbd,t}\left(q^{P,oils}_{bbd,t}\right) - P^{P}_{bbd,t} + \mu^{cap,oils}_{bbd,t} \ge 0$$

Domestic Ethanol Producer KKT Conditions

$$0 \le q^{P,corn}_{eth,t} \perp -\pi^{corn}_{eth,t} + MC^{corn}_{eth,t}\left(q^{P,corn}_{eth,t}\right) - P^{P}_{eth,t} + \mu^{cap,corn}_{eth,t} \ge 0$$

Ethanol Importer KKT Conditions

$$0 \le q^{P,sugar}_{eth,t} \perp -\pi^{sugar}_{eth,t} + MC^{sugar}_{eth,t}\left(q^{P,sugar}_{eth,t}\right) - P^{P,sugar}_{eth,t} + \mu^{cap,sugar}_{eth,t} \ge 0$$

Refiner KKT Conditions

$$0 \le q^{R}_{BOB,t} \perp MC_{BOB,t}\left(q^{R}_{BOB,t}\right) - \pi_{BOB,t} \ge 0$$
$$0 \le q^{R}_{desb,t} \perp MC_{desb,t}\left(q^{R}_{desb,t}\right) - \pi_{desb,t} \ge 0$$
$$0 \le q^{R}_{D4,t} \perp \pi_{D4,t} - \mu_{bbd,t} - \mu_{adv,t} - \mu_{rf,t} \ge 0$$
$$0 \le q^{R}_{D5,t} \perp \pi_{D5,t} - \mu_{adv,t} - \mu_{rf,t} \ge 0$$
$$0 \le q^{R}_{D6,t} \perp \pi_{D5,t} - \mu_{rf,t} \ge 0$$
$$0 \le B^{R}_{D4,t} \perp \mu^{bank}_{bbd,t} + \mu^{bank}_{adv,t} + \mu^{bank}_{rf,t} + \mu_{bbd,t} - \mu_{bbd,t+1} + \mu_{adv,t} - \mu_{adv,t+1} + \mu_{rf,t} - \mu_{rf,t+1} \ge 0$$
$$0 \le B^{R}_{D5,t} \perp \mu^{bank}_{adv,t} + \mu^{bank}_{rf,t} + \mu_{adv,t} - \mu_{adv,t+1} + \mu_{rf,t} - \mu_{rf,t+1} \ge 0$$
$$0 \le B^{R}_{D6,t} \perp \mu^{bank}_{rf,t} + \mu_{rf,t} - \mu_{rf,t+1} \ge 0$$

Blender KKT Conditions

$$0 \le q^{B}_{D4,t} \perp \lambda_{D4,t} - \pi_{D4,t} \ge 0$$
$$0 \le q^{B}_{D5,t} \perp \lambda_{D5,t} - \pi_{D5,t} \ge 0$$
$$0 \le q^{B}_{D6,t} \perp \lambda_{D6,t} - \pi_{D6,t} \ge 0$$
$$0 \le q^{B}_{BOB,t} \perp \pi_{BOB,t} - \lambda^{bal}_{BOB,t} - \pi_{gas,t} \ge 0$$
$$0 \le q^{B\rightarrow E10}_{BOB,t} \perp -0.10\lambda_{E10,t} + \lambda^{bal}_{BOB,t} \ge 0$$
$$0 \le q^{B\rightarrow E85}_{BOB,t} \perp -0.74\lambda_{E185,t} + \lambda^{bal}_{BOB,t} \ge 0$$
$$0 \le q^{B,corn}_{eth,t} \perp \mu^{cap}_{corn,t} - \lambda^{bal,corn}_{eth,t} - P^{B}_{eth,t} - \pi_{gas,t} + \pi^{corn}_{eth,t} - EV_{eth}\lambda_{D6,t} \ge 0$$
$$0 \le q^{B\rightarrow E10,corn}_{eth,t} \perp \lambda^{bal,corn}_{eth,t} - \lambda_{E10,t}(0.10-1) \ge 0$$
$$0 \le q^{B\rightarrow E85,corn}_{eth,t} \perp \lambda^{bal,corn}_{eth,t} - \lambda_{E85,t}(0.74-1) \ge 0$$
$$0 \le q^{B,sugar}_{eth,t} \perp \pi^{sugar}_{eth,t} - \lambda^{bal,sugar}_{eth,t} - \pi_{gas,t} - P^{B}_{eth,t} - EV_{eth}\lambda_{D5,t} \ge 0$$
$$0 \le q^{B\rightarrow E10,sugar}_{eth,t} \perp \lambda^{bal,sugar}_{eth,t} - \lambda_{E10,t}(0.10-1) \ge 0$$
$$0 \le q^{B\rightarrow E85,sugar}_{eth,t} \perp \lambda^{bal,sugar}_{eth,t} - \lambda_{E85,t}(0.74-1) \ge 0$$
$$0 \le q^{B}_{desb,t} \perp \pi_{desb,t} - \pi_{des,t} \ge 0$$
$$0 \le q^{B,oils}_{bbd,t} \perp \pi_{bbd,t} - P^{B,oils}_{bbd,t} - \pi_{des,t} - EV_{bbd}\lambda_{D4,t} \ge 0$$

Market Clearing Conditions

$$q^{R}_{D4,t} = q^{B}_{D4,t} \quad (\pi_{D4,t})$$
$$q^{R}_{D5,t} = q^{B}_{D5,t} \quad (\pi_{D5,t})$$
$$q^{R}_{D6,t} = q^{B}_{D6,t} \quad (\pi_{D6,t})$$
$$q^{B,corn}_{eth,t} = q^{P,corn}_{eth,t} \quad \left(\pi^{corn}_{eth,t}\right)$$
$$q^{B,sugar}_{eth,t} = q^{P,sugar}_{eth,t} \quad \left(\pi^{sugar}_{eth,t}\right)$$
$$q^{B,oils}_{bbd,t} = q^{B,oils}_{bbd,t} \quad (\pi_{bbd,t})$$
$$q^{B}_{BOB,t} = q^{R}_{BOB,t} \quad (\pi_{BOB,t})$$
$$q^{B}_{desb,t} = q^{R}_{desb,t} \quad (\pi_{desb,t})$$

$$q^{B}_{desb,t} + q^{B,oils}_{bbd,t} - \overline{q}_{des,t} = 0 \quad (\pi_{des,t})$$

$$\left(q^{B\to E10}_{BOB,t} + q^{B,sugar\to E10}_{eth,t} + q^{B,corn\to E10}_{eth,t}\right)\cdots + \rho\left(q^{B\to E85}_{BOB,t} + q^{B,corn\to E85}_{eth,t} + q^{B,sugar\to E85}_{eth,t}\right) - \overline{q}_{gas,t} = 0(\pi_{gas,t})$$

B. Appendix with algorithm steps for solving MOPEC

Start

1) Obtain individual objective function minima for the MPEC [42]. The MPEC method must utilize a quasi-newton method.
2) Normalize all objective functions to have minimum (point of Utopia) at zero and maximum values in the objective space to be 1.
3) Fix $n-2$ objective functions to a fixed value in [0, 1].
4) For each pair, select V_m, the spacing for the generated Pareto points.
5) Initiate the first objective optimization problem with the start point minimum of f_1, $t=1$, $\beta=0$. Use the MPEC solver by Ref. [42] to solve this problem.
6) At the end of the optimization, if $t=0$, $\beta=1$, then move to step 7 − an approximation to the Pareto set is generated.
7) If not, use $t+V_m$ and $\beta+V_m$ as starting points for the next optimization and return to step 5.
8) If the approximation of the Pareto set needs to be more accurate, use smaller V_m for generation of more Pareto points and return to step 4. Otherwise proceed to step 8.
9) For $n>2$, use different values in [0, 1] to fix objective functions values to obtain results for multiple objectives. Then return to step 2. If all combinations of objectives have been fixed, stop. Use the Pareto filter [42] to remove Pareto dominated points from the generated Pareto set.

Stop.

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