Optimal Governmental Incentives for Biomass Cofiring to Reduce Emissions in the Short-Term

Amin Khademi[1] and Sandra Eksioglu[2]

[1]Department of Industrial Engineering, Clemson University

[2]Department of Industrial Engineering, University of Arkansas

Abstract

Several studies showed that biomass cofiring is a viable short-term option for coal-fired power plants to reduce their emissions if supported by appropriate tax incentives. These results suggest a unique opportunity for governments to design monetary incentives such as tax credits which lead to reduction in greenhouse gas emissions in biomass-rich regions. Therefore, a natural question is: what is an optimal tax credit strategy in these regions? To this end, we propose a Stackelberg/Nash game, and solve it algorithmically via reformulating the model as a mixed integer bilinear program (MIBLP) and using a piecewise linear relaxation of bilinear terms. The structure of the optimal solution of special cases is exploited, which helps design efficient heuristics. This study develops a case study using real data about power plants and biomass availability in Mississippi and Arkansas. The results compare the optimal tax credit schemes and plants' cofiring strategies to provide insights on optimal tax credit mechanisms. Results show that a flexible tax credit scheme, which allows a plant-specific tax credit rate, is more efficient than the currently-used flat tax credit rate. This proposed approach uses a smaller budget and targets the plants that need funding support to comply with emissions regulations.

Keywords: Biomass cofiring, Emission reduction, Taxation model, Bilevel optimization, Nash equilibrium.

1 Introduction

Motivation. In the absence of Congressional action to pass a national cap-and-trade policy or a carbon tax to address climate change, the U.S. Environmental Protection Agency (EPA) set regulations through the Clean Air Act. The Climate Action Plan (CAP), issued in 2013, recognizes the harmful impacts of climate change on the environment, the economy, and public health. CAP's goal is to reduce CO_2 emissions from the energy sector up to 30% of 2005 levels by 2030, while maintaining energy reliability and affordability for customers [EPA, 2015]. Coal-fired power plants contribute about a one third of the total energy-related CO_2 emissions in the U.S. [EPA, 2014]. In 2015, the President and the EPA announced the Clean Power Plan to reduce power plants' CO_2 emissions. In particular, the EPA issued the final Carbon Pollution Standards for new, modified, and reconstructed power plants. These standards provide states and utilities ample flexibility and the time needed to reduce emissions, and maintain a reliable and affordable supply of electricity for ratepayers and businesses [EPA, 2015]. However, the Trump administration has announced plans to repeal this plan and its implementation is pending judicial review [The New York Times, 2017]. Despite this fact, states have the freedom to decide how they should proceed about reducing CO_2 emissions. For example, about 30 states have embraced the Renewable Portfolio Standards (RPS) (a regulatory mandate) and the production tax credit (PTC) to encourage increased energy generation from renewable sources. These efforts have resulted in reductions of emissions [National Renewable Energy Laboratory, 2016]. However, most southeastern states have yet to establish RPS standards or targets [National Conference of State Legislatures, 2016]. To comply with the federal emissions standards, officials in the Southeast may consider novel strategies, such as investing in nuclear power or building allowance-trading programs. However, because the Southeast is rich in biomass, promoting biomass cofiring by offering appropriate tax credits could be a viable short-term option to meet the new requirements.

Cofiring has been recognized as a short-term solution to reducing CO_2 emissions from power plants that use conventional fossil fuel. Viable alternatives for long-term CO_2 reduction solutions are technologies, such as CO_2 sequestration, oxy-firing, and carbon loop combustion, which are discussed in the literature [IPCC, 2014]. However, these technologies still remain in the early- to mid-stages of development [Basu et al., 2011]. Cofiring, on the other hand, is a well-proven and relatively inexpensive technology currently used in many countries around the world. During the last 15 years, the European Union led the development of this technology and supported investments in installation capacity [Sullivan and Meijer, 2010, Basu et al., 2011, IEA, 2012, Cleaves, 2014]. According to the International Energy Agency, "the overall policy-setting in the U.S. is not favorable toward biomass/coal cofiring" [IEA, 2012].

Cofiring makes use of existing coal-fired plants' power generation assets and infrastructure.

However, initial investment costs, including the startup research and development expenditures, high biomass collection and transportation costs, and the uncertain nature of biomass supply, are some of the obstacles faced by the industry. Many countries provide tax and financial incentives to help power plants overcome these financial burdens of adopting cofiring. For example, the PTC is a federal incentive that provides financial support to power plants that cofire biomass. This is a flat rate per megawatt-hour (MWh) of renewable energy generated and is provided for the first 10 years of a plant's operations. When this PTC expired at the end of 2013, the Congress extended the bill in 2014, 2015, and 2016; then, the bill was extended again through the end of 2016. These extensions, while helpful, do not guarantee the level of certainty the industry needs to invest in renewable energy. The wide range of policies developed and adopted in a number of Northern European and Asian countries show the extent to which government policies can impact greenhouse gas emissions [Roni et al., 2017].

The objective of this study is to investigate optimal tax incentives in a hypothetical setting where a state government may choose to cap CO_2 emissions at coal-fired power plants. Therefore, this study considers a framework in which the higher level decision maker sets an upper bound on the amount of CO_2 emissions released from power plants. In our setting, which considers a short planning horizon and and coal-fired power plants located in a region rich with biomass, we assume that coal-fired power plants seek cofiring in order to comply with new standards. However, due to inefficiencies of biomass cofiring and the operational challenges that power plants may face, the policymaker provides a tax credit to compensate power plants and avoid rises in electricity prices. Two viewpoints related to this study are presented, however, the proposed framework is flexible enough and can be used with other objective functions and constraints. The first viewpoint considers a policymaker that seeks to maximize renewable energy generation, subject to budgetary and "fairness" constraints. The second viewpoint considers a policymaker that seeks to minimize the budget required to reduce CO_2 emissions, subject to fairness constraints. At the lower level, we assume that each plant identifies a cofiring strategy to maximize its profit, subject to operational and emission requirement constraints. Since the number of biomass suppliers and the biomass supply itself can be limited, we consider a non-cooperative supply chain structure, where each plant seeks to maximize its profit, subject to a set of shared biomass availability constraints, as well as its own set of constraints.

Main Contributions. This paper makes the following contributions: (1) A novel taxation model is proposed in which the higher level decision maker establishes a tax credit, and the self-interested lower level decision makers simultaneously seek to optimize their objectives, subject to a set of shared constraints. The hierarchy in the decision making process is modeled by a Stackelberg game, and the simultaneous decision making in the lower level is modeled by a generalized Nash equilibrium (GNE). In this modeling framework, the objective function and the constraints of the higher level decision maker may be linear or bilinear. The lower level problems may have bilinear objective functions and a set of linear constraints. We apply an algorithmic approach to find the optimal solution to this Stackelberg/Nash game by reformulating the problem as an MIBLP and creating valid bounds using piecewise linear relaxation of the bilinear terms with bivariate partitioning. (2) The Stackelberg/Nash taxation model addresses the challenge of designing efficient and fair tax credit policies in the Southeast that promote the use of biomass cofiring to reduce CO_2 emissions. Two viewpoints are studied here: a policymaker who seeks to (i) minimize the budget or (ii) maximize the total amount of renewable energy generated. A flexible tax credit scheme is introduced, and it provides plant-specific tax credit rates based on plant-specific characteristics. This approach offers a stark contrast to the current tax credit schemes that provide a flat rate to all plants. (3) The structure of the optimal solution is exploited in some special cases in order to design a heuristic solution approach to this problem. Results show that the solutions produced by the heuristic are near-optimal. (4) A case study is developed using data about coal-fired power plants, biomass availability and price in Mississippi and Arkansas. The proposed tax credit schemes are compared based on their efficiency and fairness in distributing taxpayers' money among participating plants.

The remainder of this paper is organized as follows: Section 2 briefly reviews the literature related to tax models and biomass cofiring feasibility studies. Section 3 states the problem setting, explains the modeling assumptions, and provides a Stackelberg/Nash formulation. Section 4 describes an algorithmic approach to derive near-optimal solutions and investigates the structure of the optimal solution in some special cases. These results are utilized to develop a heuristic approach to solve the problem. Section 5 develops a case study using data from Mississippi and Arkansas. Section 6 concludes with novel insights into this problem.

2 Related Work

Streams of work related to this study include biomass cofiring feasibility, tax incentives for biomass cofiring, bilevel optimization, and MIBLPs.

We build our study on the abundant literature that supports the feasibility of biomass cofiring as a short-term option to reduce emissions combined with tax credits. For example, Wils et al. [2012] used a cost-benefit analysis to show that governmental incentives are necessary to make biomass cofiring an attractive investment option. Rahdar et al. [2014] evaluated the impact of RPS and Renewable Fuel Standard on biopower and biofuel generation since both technologies compete for the same biomass resources. Results of these studies provide evidence that cofiring biomass, combined with appropriate tax credits, may be an attractive short-term option to reduce emissions in the energy sector. Broughel [2019] analyzed a dataset of 450 state bioenergy policies and found that from a variety of alternatives in the U.S., governmental tax incentives is associated with higher installed bioenergy capacity. For more on this issue see Young et al. [2018] and references therein. For a review of recent work on policies, challenges, and opportunities for biomass cofiring see Roni et al. [2017], Karimi et al. [2019].

Regarding the optimal tax incentives for biomass cofiring, Eksioglu et al. [2016] developed an integrated production and transportation planning model to investigate the impacts that the existing flat-rate production tax credit has on renewable power generation from a coal-fired power plant's stand point. Karimi et al. [2018] followed a resource allocation perspective and evaluated the impacts of flexible tax schemes on biomass utilization and power plant profit. Different from Eksioglu et al. [2016] and Karimi et al. [2018] this research evaluates the impacts of a number of flexible tax schemes on renewable power generation in a decentralized environment via a Stackelberg/Nash game. Operational aspects of adapting renewable energy technologies have also received attention. For example, Dundar et al. [2019] developed a robust optimization model to minimize the cost of reducing emissions via cofiring considering spatially-explicit biomass availability constraints. Ko and Lautala [2018] integrated supply chain of cofiring and torrefaction process to minimize total cost.

The problem of designing tax schemes, where a leader makes a decision about the tax credit and a follower optimizes its objective function accordingly, is studied via bilevel optimization. Dempe [2003] and Colson et al. [2007] developed comprehensive surveys of bilevel optimization. A general taxation model was provided by Labbé et al. [1998], who proposed a bilevel optimization framework, where the objective function of the leader and the follower is bilinear. Similar frameworks are used for a revenue-maximizing leader who establishes optimal tariffs on the arcs of a network. The follower's problem identifies shipping amounts to meet demand at the minimum cost [Brotcorne et al., 2001]. Bilevel optimization models have also been used to model the following problems in power systems and smart grid: power market equilibrium, power system dispatch and control, demand response, etc [Bai et al., 2014, Yuan et al., 2014, Mei et al., 2017]. However, these studies assume that (i) the followers' decision variables and constraints are independent, and (ii) the leader's set of constraints is linear. In the setting presented here, since followers share constraints, the concurrent decision making faced by the followers is modeled by a GNE. Therefore, the sequential decision making between a leader and followers is modeled by a Stackelberg/Nash framework. Moreover, the set of constraints for the leader contains linear and/or bilinear terms. Therefore, the methods developed in these studies do not apply. Bard et al. [2000] presented a bilevel programming formulation to encourage biofuel production by providing tax credits. Two approximation algorithms were proposed: (i) a grid search over the tax credit variables, and (ii) an approximation of the bilevel program by a nonlinear program. Dempe and Bard [2001] considered a bilevel optimization problem with bilinear terms in the objective function of the leader and follower. They developed a bundle trust-region algorithm and investigated its convergence. However, the methods developed in these studies do not apply to this setting because the problems discussed do not consider interactions between followers and bilinear constraints in the upper level problem.

Our problem is reformulated as an MIBLP and solved via an algorithmic approach based on piecewise linear relaxation of bilinear terms with bivariate partitioning. Computational results for the case study show that this algorithmic approach finds solutions of high quality. In general, finding the global optimal solution for an MIBLP is challenging because it is non-convex [Floudas, 2013, Mitsos et al., 2008]. However, several applications found the piecewise linear relaxation method effective in finding global optimal solutions. For example, Bergamini et al. [2008], Gounaris et al. [2009], and Yue and You [2014] used this technique in an algorithmic approach to solve a variety of synthesis, generalized pooling, and supply chain design problems, respectively. Hasan and Karimi [2010] investigated the computational performance of a variety of piecewise relaxation techniques, such as univariate and bivariate partitioning of several synthesis problems. In particular, our algorithmic approach adapts ideas presented in Yue and You [2014] and Hasan and Karimi [2010] to the formulation presented in this work.

3 Problem Formulation

We consider a policymaker that imposes a limit on the amount of CO_2 emitted by coal-fired power plants. In our case study, we aggregate the power plants at the state level, i.e., we study power plants is MS and AR. However, our modeling framework is flexible to study other types of aggregation. In our setting, the policymaker provides tax credits to compensate power plants for potential profit losses. In particular, we assume that the power plants seek biomass cofiring to comply with these standards in the short-term. Recall that we study two viewpoints: one that minimizes the cost of providing tax incentives and one that maximizes the renewable energy production. Both viewpoints are instances of a tax scheme in which the leader imposes emission limitations on the followers who are competing for shared resources.

Minimizing cost. In this framework, the policymaker seeks to design a tax credit scheme to minimize the budget allocated to encouraging cofiring, subject to a set of constraints ensuring that the net profit of each power plant is greater than a certain threshold. The net profit is calculated based on revenues and costs of displacing coal with biomass and is described in detail in Section 5.1. This framework is flexible in that it allows the policymaker to set different thresholds for the net profit for different "types" of plants, whether based on plant capacity, boiler efficiency, and/or technology used. This consideration is important because larger plants typically operate with higher net profits and can better absorb the risk associated with adopting new technologies, such as cofiring. Thus, policymakers may consider higher threshold values for smaller plants (in general, inefficient plants that cannot take advantage of economies of scale) to encourage their participation in such programs. This policy is inspired by feed-in-tariff (FIT) schemes used in European Union developed to support biomass-related energy generation [Fouquet and Johansson, 2008]. For example, in Germany, small bioenergy systems (<5MW) receive a FIT rate of \$0.1627/kWh and larger systems receive a rate of \$0.1087/kWh [Croucher et al., 2010]. Therefore, the flexibility of choosing threshold net profits and tax credit rates provides the grounds to design "fair" tax schemes. Faced with a restriction about CO_2 emissions, a power plant identifies the amount of coal to displace with biomass in order to maximize profits. However, since the amount of biomass available from suppliers is limited, the power plants compete for this resource. This competition is modeled using a GNE.

Let indices $i \in \{1, 2, \dots, I\}$ and $j \in \{1, 2, \dots, J\}$ denote biomass supplier i and power plant j. Let s_{ij}, e_j, and b_j, respectively, denote the unit profit, in dollars, per ton of biomass purchased from supplier i for plant j, the amount of renewable energy generated in MWh per ton of biomass by plant j, and the initial investment cost, in dollars, to retrofit plant j. The analysis is for a typical year and the annual equivalent of investment costs is calculated based on work by Sondreal et al. [2001], Caputo et al. [2005]. These costs are adjusted to account for inflation. The unit profit equals the difference between unit revenue and cost, and it depends on the tax credit rate, biomass purchasing, and transportation costs from supplier i (see Eksioglu et al. [2016] for details). Also, let l_j denote the minimum amount of biomass that plant j should cofire to meet CO_2 emissions standards. In addition, due to technological constraints, several studies suggest an upper bound on what proportion of coal can be displaced by biomass [Caputo et al., 2005]. Therefore, we let u_j denote the amount of biomass that corresponds to this upper bound for plant j. For biomass availability constraint let $\bar{u}_i$ denote the amount of biomass available at supplier i. Define $T_{n(j)}$ as the tax credit rate per ton of biomass cofired for a plant of type $n(j) \in \{1, 2, \ldots, N\}$, where N is the number of plant types. This notation provides the flexibility to design a broad range of tax schemes. For example, the policymaker can set $T_{n(j)} = T$ for all j to design a flat tax credit rate for all plants, or $T_{n(j)} = T_j$ to design a plant-specific tax credit rate. Define X_{ij} as the amount of biomass plant j purchases from supplier i. The objective function of power plant j is nonlinear and approximated by $\sum_i (s_{ij} + e_j T_{n(j)}) X_{ij} - b_j$ (see Eksioglu et al. [2016] for the derivation and quality of the approximation). Note that this construction assumes that each plant decides to cofire. We will discuss this assumption and model limitations in the next subsection. Work by Eksioglu et al. [2016] derived detailed expressions to estimate revenues and costs of biomass cofiring in coal-fired power plants. The corresponding functions are nonlinear. That research proposed a linear approximation of the nonlinear functions. An extensive numerical analysis indicated that the linear approximation provides quality solutions, and the corresponding approximation errors are within a desired range. Therefore, the policymaker solves the following problem

$$w = \min \sum_{j=1}^{J} e_j T_{n(j)} \sum_{i=1}^{I} X_{ij} \tag{1a}$$

s.t.

$$z_j \geq p_j, \ \ \forall j = 1, \ldots, J, \tag{1b}$$

$$z_j = \max \sum_{i=1}^{I} (s_{ij} + e_j T_{n(j)}) X_{ij} - b_j, \quad \forall j = 1 \ldots J \tag{1c}$$

s.t.

$$l_j \leq \sum_{i=1}^{I} X_{ij} \leq u_j, \tag{1d}$$

$$\sum_{j=1}^{J} X_{ij} \leq \bar{u}_i, \ \ \forall i = 1, \ldots, I, \tag{1e}$$

$$X_{ij} \geq 0, \ \ \forall i = 1, \ldots, I, \tag{1f}$$

where constraints (1b) guarantee that the net profit from cofiring is at least p_j for plant j; constraints (1d) establish lower and upper bounds for the amount of biomass cofired in a plant; and constraints (1e) guarantee that the total amount of biomass delivered from a supplier does not surpass its availability.

Next, we discuss some technicalities regarding formulation (1). Recall that in the lower level we assume that plants react to reach a GNE for a given tax scheme. One natural question is the existence and uniqueness of the GNE in this setting. Rosen [1965, Theorem 1] showed by adopting the Kakutani fixed point theorem that if the payoff function of each player is continuous (over all players' strategies) and concave (for each player fixing other players' strategies) and the set of feasible strategies is convex, closed, and bounded, a GNE exists. In our setting, the objective of each plant is linear on decision variable, then it is continuous and concave. The set of feasible strategies in our setting is a bounded polyhedron. Therefore, it is convex, closed, and bounded and a GNE exists. The question of uniqueness is more subtle. Rosen [1965, Theorem 2] showed that if a specific mapping of payoff functions of all players is diagonally strictly concave, then the GNE is unique. However, this sufficient condition does not hold in our setting. For counterexamples, Sudermann-Merx [2016, Example 1.4.2] showed that the set of GNE for a setting that players solve a linear program with shared constraint (similar to our setting) can be non-convex and even non-connected [Sudermann-Merx, 2016, Example 1.4.3], and thus not unique. Furthermore, Rosen [1965] proposed the concept of normalized Nash equilibrium (NNE), which is a subset of GNE solutions. In particular, in a NNE the Lagrange multipliers associated with shared constraints are the same for each player. We also consider a NNE for the concurrent decision making of power plants. The implication of this assumption is as follows: because the Lagrangian multiplier (shadow price) of the shared constraint (1e) is the unit price of biomass that supplier i provides, normalization means that each supplier sets the same unit purchase price of biomass for different power plants. The conditions for existence and uniquness of NNE is similar to GNE and is presented in Rosen [1965, Theorem 3, Theorem 4]. Similar arguments show that NNE for our setting exists but may not be unique. Therefore, in the upper level of formulation (1) we assume an optimistic Stackelberg game in which the solution to the leader's favor is chosen if the NNE is non-unique: see Wiesemann et al. [2013] for a discussion on the pessimistic approach. The optimistic Stackelberg game is frequently used in literature because it is difficult to analyze the pessimistic approach [Colson et al., 2005].

Next, we provide a lower bound on the optimal objective of formulation (1). In particular, one can show that a lower bound on w is given by

$$w \geq \sum_{j=1}^{J}(p_j + b_j) - w_t, \tag{2}$$

where w_t is the solution to the following transportation problem

$$w_t = \min \sum_{i=1}^{I} \sum_{j=1}^{J} s_{ij} X_{ij}$$

s.t.

$$l_j \leq \sum_{i=1}^{I} X_{ij} \leq u_j, \ \ j = 1, 2, \ldots, J,$$

$$\sum_{j=1}^{J} X_{ij} \leq \bar{u}_i, \ \ i = 1, 2, \ldots, I,$$

$$X_{ij} \geq 0, \ \ i = 1, 2, \ldots, I; j = 1, 2, \ldots, J.$$

Maximizing renewable energy generation. In this framework, the policymaker seeks to maximize renewable energy generation by providing tax credits for biomass cofiring, subject to a budgetary constraint. The formulation of the problem solved by the power plants is similar to framework 1. Let b denote the budget available to the leader. Therefore, the policymaker solves for

$$\max \sum_{j=1}^{J} e_j \sum_{i=1}^{I} X_{ij} \tag{3a}$$

s.t.

$$\sum_{j=1}^{J} e_j T_{n(j)} \sum_{i=1}^{I} X_{ij} \leq b, \tag{3b}$$

$$z_j \geq p_j, \ \ \forall j = 1, \ldots, J, \tag{3c}$$

$$z_j = \max \sum_{i=1}^{I} (s_{ij} + e_j T_{n(j)}) X_{ij} - b_j, \quad \forall j = 1, \ldots, J \tag{3d}$$

s.t.

$$l_j \leq \sum_{i=1}^{I} X_{ij} \leq u_j, \tag{3e}$$

$$\sum_{j=1}^{J} X_{ij} \leq \bar{u}_i, \ \ \forall i = 1, \ldots, I, \tag{3f}$$

$$X_{ij} \geq 0, \ \ \forall i = 1, \ldots, I. \tag{3g}$$

Discussion on modeling assumptions. For modeling purposes we impose three important assumptions. First, we assume that the number of plants in the lower level game is fixed over the analysis time period. This assumption is reasonable in our setting because the time frame for our study is short and the likelihood that a new coal-fired power plant enters to the competition is slim. Statistics and predictions by US DOE [2016] show that, while coal-fired energy was in a steady rise since 1980, this trend has changed since 2007 due to availability of natural gas, renewable power, and stringent environmental regulations. Specifically, the projections show that the share of coal in generating electricity will decrease in the future. Therefore, based on these trends, it is expected that new investments in the energy sector will focus on natural gas and renewables. Thus, the chances that there will be investments in new coal-fired power plants are slim.

Second, in our model the policymaker (i) limits the amount of emission for each power plant and (ii) assumes that the power plants adopt cofiring to comply with the new emission standards. Premise (i) is inspired by prior efforts to legislate CO_2 reduction in several countries: see the Introduction. Premise (ii) is motivated by the observation that cofiring is the most economically viable option in the short-term in regions rich with biomass. In general, plants may use other options to comply with the proposed reduction in emissions. In this case, the model should allow the plants to choose what technology to adopt. This is an interesting extension, however, it is beyond the scope of this study.

Finally, our model does not consider seasonality since the focus is in woody biomass. However, adding biomass seasonality into the models is straightforward. One can append time index t to decision variables and parameters and introduce a decision variable to keep track of inventory of biomass over time [Ko and Lautala, 2018]. The resulting optimization problem for each plant still preserves an LP structure and all the methods presented in this study still hold true. We did not pursue this extension because the focus of this study is on a number of woody biomass feedstocks such as poplar, pine, and softwood residues for which seasonality is not significant.

4 Solution Approach

This section first provides an algorithmic approach to solve formulation (1) based on a piecewise linear relaxation of bilinear terms. In particular, we adapt and apply the algorithmic approach presented in Yue and You [2014] and bivariate partitioning of bilinear terms presented in Hasan and Karimi [2010] into our formulation. Next, the optimal solution for some special cases is investigated. The structure of the optimal solution to a special case of the problem motivated the design of an efficient heuristic. This heuristic provides near-optimal solutions in our numerical study.

4.1 An Algorithmic Approach

Formulations (1) and (3) are nonlinear and non-convex. Thus, an algorithmic approach is developed to solve them. To ease the exposition, we begin by presenting the algorithm for formulation (1), but a similar approach can be used for formulation (3). In the first step, we convert formulation (1), a bilevel optimization problem, into a single-level problem. For a fixed tax credit rate $(T_{n(1)}, T_{n(2)}, \ldots, T_{n(J)})$, each follower's optimization problem is an LP and it can be replaced by its KKT counterpart. However, because a NNE is considered, the Lagrange multipliers associated with shared constraints (1e) must only depend on supplier i. Therefore, formulation (1) is reformulated as

$$\min \sum_{j=1}^{J} e_j T_{n(j)} \sum_{i=1}^{I} X_{ij} \tag{4a}$$

s.t.

$$\sum_{i=1}^{I} (s_{ij} + e_j T_{n(j)}) X_{ij} - b_j \geq p_j, \;\; \forall j = 1, 2, \ldots, J, \tag{4b}$$

$$l_j \leq \sum_{i=1}^{I} X_{ij} \leq u_j, \;\; \forall j = 1, 2, \ldots, J, \tag{4c}$$

$$\sum_{j=1}^{J} X_{ij} \leq \bar{u}_i, \;\; \forall i = 1, 2, \ldots, I, \tag{4d}$$

$$\gamma_j + \mu_i + \lambda_j \geq s_{ij} + e_j T_{n(j)}, \;\; \forall i = 1, 2, \ldots, I, j = 1, 2, \ldots, J, \tag{4e}$$

$$\lambda_j \left[\sum_{i=1}^{I} X_{ij} - l_j \right] = 0, \;\; \forall j = 1, 2, \ldots, J, \tag{4f}$$

$$\gamma_j \left[\sum_{i=1}^{I} X_{ij} - \bar{u}_j \right] = 0, \;\; \forall j = 1, 2, \ldots, J, \tag{4g}$$

$$\mu_i \left[\sum_{j=1}^{J} X_{ij} - u_i \right] = 0, \;\; \forall i = 1, 2, \ldots, I, \tag{4h}$$

$$X_{ij} \geq 0, \lambda_j \leq 0, \gamma_j \geq 0, \mu_i \geq 0 \;\; \forall i = 1, 2, \ldots, I, j = 1, 2, \ldots, J. \tag{4i}$$

Formulation (4) has bilinear terms in the objective function and constraints. Next, the complementary slackness constraints (4f)-(4h) are linearized by introducing binary variables. For example, by introducing $A_j, B_j, C_i \in \{0, 1\}$, constraints (4f)-(4h) are reformulated as

$$-\lambda_j \leq M\, A_j, \;\; \forall j = 1, 2, \ldots, J, \tag{5a}$$

$$\sum_{i=1}^{I} X_{ij} - l_j \leq M(1 - A_j), \ \ \forall j = 1, 2, \ldots, J, \tag{5b}$$

$$\gamma_j \leq M\, B_j, \ \ \forall j = 1, 2, \ldots, J, \tag{5c}$$

$$-(\sum_{i=1}^{I} X_{ij} - \bar{u}_j) \leq M(1 - B_j), \ \ \forall j = 1, 2, \ldots, J, \tag{5d}$$

$$\mu_i \leq M\, C_i, \ \ \forall i = 1, 2, \ldots, I, \tag{5e}$$

$$-(\sum_{j=1}^{J} X_{ij} - u_i) \leq M(1 - C_i), \ \ \forall i = 1, 2, \ldots, I, \tag{5f}$$

where M is a sufficiently large number. After linearizing the complementary slackness constraints, formulation (4) remains bilinear in the objective function and constraints. An algorithm is proposed to solve such a problem based on a piecewise linear relaxation of bilinear terms using bivariate partitioning [Hasan and Karimi, 2010].

With the bilinear terms of type $T_{n(j)}X_{ij}$, with $0 \leq X_{ij} \leq \bar{U}$ and $0 \leq T_{n(j)} \leq \bar{T}$, $\bar{U}$ and $\bar{T}$ are upper bounds on the variables. $\bar{U}$ can be calculated by optimizing X over the feasible region of formulation (4), and $\bar{T}$ is set according to budgetary consideration. To create a piecewise linear relaxation, partition X_{ij} into N_{ij} equal and exclusive segments using $N_{ij}+1$ grid points, and let d_{ij} denote the length of each segment. Similarly, partition $T_{n(j)}$ into $N_{n(j)}+1$ grid points, and let $d_{n(j)}$ denote the length of each segment. Also, let $\mathcal{N} := \{(N_{ij}, N_{n(j)}) : \forall i, j, n(j)\}$ denote the collection of the number of grid points. Note that index $n(j)$ is completely identified by index j but we keep it that way in order to remove repetition in notation. For example, we may have plants 1 and 2 belong to type 3, which reads $n(1) = n(2) = 3$. The following MILP provides a relaxation to formulation (4) and its optimal solution provides a lower bound for the optimal objective.

$$\min w(\mathcal{N}) = \sum_{j=1}^{J} e_j \sum_{i=1}^{I} W_{ij} \tag{6}$$

$$\begin{aligned}
&\text{s.t.}\\
&(4c) - (4e), (5a) - (5f),\\
&\sum_{i=1}^{I} s_{ij} X_{ij} + e_j W_{ij} - b_j \geq p_j, \ \ \forall j,\\
&X_{ij} = \sum_{n=1}^{N_{ij}} d_{ijn} Z_{ijn}, \ \ \forall i, j,\\
&T_{n(j)} = \sum_{m=1}^{N_{n(j)}} d_{n(j)m} Z_{n(j)m}, \ \ \forall n(j),
\end{aligned}$$

$$W_{ij} = \sum_{n=1}^{N_{ij}} \sum_{m=1}^{N_{n(j)}} d_{ijn} d_{n(j)m} \Omega_{ijn(j)nm}, \ \ \forall i, j, n(j),$$

$$\sum_{m=0}^{N_{n(j)}} \Omega_{ijn(j)nm} = Z_{ijn}, \ \ \forall i, j, n(j), n,$$

$$\sum_{n=0}^{N_{ij}} \Omega_{ijnm} = Z_{n(j)m}, \ \ \forall i, j, n(j), m,$$

$$\sum_{n=0}^{N_{ij}-1} E_{ijn} = 1, \ \ \forall i, j,$$

$$\sum_{m=0}^{N_{n(j)}-1} E_{n(j)m} = 1, \ \ \forall n(j),$$

$$Z_{ij0} \leq E_{ij0}, \ \ \forall i, j,$$

$$Z_{n(j)0} \leq E_{n(j)0}, \ \ \forall n(j),$$

$$Z_{ijn} \leq E_{ij(n-1)} + E_{ijn}, \ \ \forall i, j, n = 1, \ldots, N_{ij} - 1,$$

$$Z_{n(j)m} \leq E_{n(j)(m-1)} + E_{n(j)m}, \ \ \forall n(j), m = 1, \ldots, N_{n(j)} - 1,$$

$$Z_{ijN_{ij}} \leq E_{ij(N_{ij}-1)}, \ \ \forall i, j,$$

$$Z_{n(j)N_{n(j)}} \leq E_{n(j)(N_{n(j)}-1)}, \ \ \forall j,$$

$$E_{ijn}, E_{n(j)m}, A_j, B_j, C_i \in \{0, 1\}, \forall i, j, n(j), m,$$

$$X_{ij}, W_{ij}, \Omega_{ijn(j)nm} \geq 0, \lambda_j \leq 0, \gamma_j \geq 0, \mu_i \geq 0, \ \ \forall i, j, n(j), n, m.$$

The quality of the lower bound depends on the total number and placement of grid points. The numerical analyses used in this study test the performance of several strategies, including uniform placement of grid points and increasing their number. Results show that increasing the grid points by one, placing the new grid point on the current optimal solution for $T_{n(j)}$ variables, and uniform placement of grid points to X_{ij} variables is the most efficient strategy.

A feasible solution to formulation (4) provides an upper bound for the original problem. The proposed algorithm is an approach which solves iteratively relaxation (6) to find T^* and X^*. If T^* and X^* are feasible to (4), update the upper bound by plugging T^* and X^* into the objective function of formulation (4). If the gap between the upper and lower bound is smaller than a desired threshold, the optimal solution to the original problem is found. Otherwise, refine the grid points and continue this procedure. To boost the convergence rate, T^* is perturbed in each iteration to find feasible solutions to the original problem. Note that, although the lower bound is nondecreasing and upper bound is non-increasing, the algorithm may not converge due to numerical issues. However, our computational results show that the algorithm converges, on average, within 5 iterations. A similar convergence behavior is observed for this type of algorithm in the literature: see, e.g., Yue and You [2014]. Algorithm 1 formalizes this approach.

Algorithm 1 An algorithmic approach to solve (1)

Set $\epsilon > 0$, $UB = +\infty$, and $LB = -\infty$.
Set $N_{ij} = 2$, $N_{n(j)} = 2$, for all $i, j, n(j)$.
while $\left|\frac{UB-LB}{LB}\right| > \epsilon$ and the number of iterations is less than a threshold **do**
  Refine the grid points, e.g., $N_{ij} \leftarrow N_{ij} + 1$ and $N_{n(j)} \leftarrow N_{n(j)} + 1$ for all $i, j, n(j)$.
  Solve the MILP (6), find its optimal solution (T^*, X^*) and set $LB \leftarrow \max\{LB, w^*\}$.
  if (T^*, X^*) is feasible for (4) **then**
    $UB \leftarrow \min\{UB, y^*\}$.
Return (T^*, X^*).

4.2 A Heuristic Approach

This section presents two special cases of the problem for which the optimal solution can be derived analytically. A lower bound is also provided for a special case of the problem with one supplier, and this bound is shown to be tighter than the one presented in (2). In addition, a heuristic approach is designed, based on the structure of the optimal solution for one of the special cases. This heuristic provides high-quality solutions in our case study.

Case 1. This case studies a setting with only one power plant and one supplier. Adapting formulation (1) into this setting and dropping indices i and j results in

$$\begin{aligned}
&\min eTX \\
&\quad \text{s.t.} \quad z \geq p, \\
&\quad \max z = (s + eT)X - b \\
&\quad \text{s.t.} \quad l \leq X \leq \min\{u, \bar{u}\}.
\end{aligned}$$

Because b denotes the investment cost and p denotes the threshold for net profit that the leader seeks to impose, assume that $b, p \geq 0$ and $b + p > 0$. For the follower's problem and fixed T, if $(s + eT) > 0$, $X^* = \min\{u, \bar{u}\}$; if $(s + eT) < 0$, $X^* = l$; and if $(s + eT) = 0$, $X^* \in [l, \min\{u, \bar{u}\}]$, the leader's constraint implies that $(s + eT)X \geq b + p > 0$. Therefore, $X^* = \min\{u, \bar{u}\}$, and $T^* = \frac{p+b-sX^*}{eX^*}$.

Case 2. This case studies a setting with only one supplier. Similar to Case 1, assume that $b_j, p_j \geq 0$ for all j, and $p_j + b_j > 0$. If $\sum_j u_j \leq \bar{u}$; then, the shared constraint among plants becomes redundant. Therefore, the problem decouples and the optimal solution can be analyzed for each power plant based on the results of Case 1. Specifically, consider a flexible tax credit rate, $X_j^* = u_j$ for all j, and $T_j^* = \frac{p_j+b_j-s_ju_j}{e_ju_j}$. In addition, consider a flat tax credit rate, $X_j^* = u_j$ for all j, and $T^* = \max_j\{\frac{p_j+b_j-s_ju_j}{e_ju_j}\}$. Let $w(T)$ and $w(T_j)$ denote respectively the objective function of formulation (1) with flat and flexible tax credit rate. Recall that, in the flexible tax credit setting, the policymaker considers a plant-specific tax credit rate. Clearly, $w(T) \geq w(T_j)$ in general, and the total savings, due to considering flexible tax credit rates, are $w(T) - w(T_j)$. Savings equal

$$(\sum_j e_j u_j) \max_j\{\frac{p_j + b_j - s_j u_j}{e_j u_j}\} - \sum_j p_j + b_j - s_j u_j.$$

This analysis provides heuristic estimates for the optimal values of T^* and X^* in this case study.

Finally, a lower bound is derived from the objective function of formulation (1) when there is one supplier. This lower bound is tighter than that proposed in (2) because the optimal solution is applied to the lower level problems in this special case to derive the bound. Without loss of generality, assume that plants are indexed by an increasing order of s_j, i.e., $s_1 \leq s_2 \leq \cdots \leq s_J$.

Proposition 1. *If* $b_j, p_j \geq 0$ *and* $b_j + p_j > 0$*, then*

$$w \geq \sum_{j=1}^{J}(p_j + b_j) - \sum_{j=1}^{k-1} s_j u_j - \sum_{j=k+1}^{J} s_j l_j - s_k(\bar{u} - \sum_{j=1}^{k-1} u_j - \sum_{j=k+1}^{J} l_j),$$

where

$$k = \min\{q : \sum_{j=1}^{q} u_j > \bar{u}\}.$$

The assumptions of Proposition (1) are perfectly satisfied in this setting because b_j denotes the investment cost for biomass cofiring, and p_j is the minimum net profit threshold for plant j.

5 Case Study

This section develops a case study using real-world data from Mississippi and Arkansas because both states are rich with biomass and have not yet established RPS goals. Mississippi has 5.01 million tons of forest products and residues, as well as five power plants. Arkansas has 4.91 million tons of forest products and residues, along with four power plants.

The parameters of our optimization models are estimated, and the performance of the algorithm is tested considering both frameworks: minimizing the budget and maximizing renewable energy generation. To explore the effects of taxation schemes, consider two extreme cases: the government sets (1) a flat tax credit rate for every MWh energy generated by biomass, which is current practice, and (2) a tax credit rate for every MWh energy generated by biomass based on plant-specific characteristics such as plant capacity, boiler efficiency and technology used (our proposal). In addition to these extreme cases, the plants are categorized as small- or large-sized and a flat tax credit rate is considered for each category and iterates the analysis. We report the optimal tax credit rates for both states and the optimal biomass cofiring strategy in each power plant. We conduct a sensitivity analysis based on costs and other factors in order to determine the robustness of the results presented.

5.1 Model Setup and Parameter Estimation

Biomass availability data by state and county is extracted from the Knowledge Discovery Framework database, an outcome of the U.S. Billion Ton Study led by the Oak Ridge National Laboratory. This database provides the amount of biomass available at the county level in the form of forest products, forest residues, agricultural residues, etc. The database also provides the amount of biomass available at different market prices. From this data set, the data about forest products and residues is extracted since these types of biomass are likely to be used for cofiring. In particular, Figure 1 shows the biomass availability in all counties of AR and MS in addition to the locations of power plants. The data for coal-fired power plant names, locations, nameplate capacities, types of coal used, boiler efficiency, and annual heat input rates is collected from the U.S. Energy Information Administration (2013). Specifically, AR has four coal-fired power plants and MS has five. Their detailed relevant specifications are presented in Tables 1 and 2 for AR and MS, respectively.

Table 1: Plant specification for the state of Arkansas

Plant name	Flint Creek	Plum Point Energy Station	White Bluff	Independence
Plant number	1	2	3	4
Primary fuel	Subbituminous	Subbituminous	Subbituminous	Subbituminous
α_j: LHV (BTU/Ton)	21,000,000	21,000,000	21,000,000	21,000,000
Capacity factor	0.750	0.200	0.621	0.674
Nameplate capacity (MW)	558	720	1,700	1,700
Plant longitude	-94.5241	-89.9489	-92.1392	-91.4083
Plant latitude	36.2561	35.6644	34.4236	35.6733
Boiler Efficiency	0.93	0.93	0.93	0.93
Other process efficiencies	0.43	0.43	0.43	0.43

Another component of the model is suppliers. We create potential suppliers as follows noting

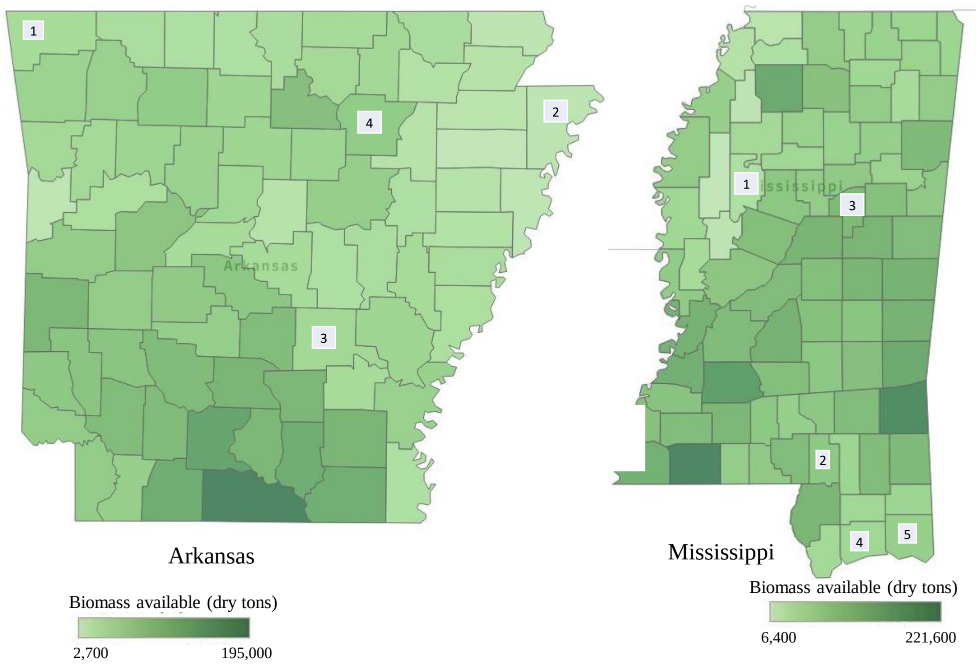

Figure 1: Biomass density and plant locations in MS and AR.

that our model needs the geographical location of each potential supplier, as well as the amount of biomass available. In order to estimate the coordinates of suppliers, we create potential suppliers by clustering the counties in the state. In particular, we group the counties in each state into 10 suppliers using the $k-$means clustering method. The coordinate of each supplier is the center of the cluster, which is calculated by an average of the (center) coordinates of each county contained in the cluster weighted by its biomass availability. Such a supplier construction takes the geographical availability of biomass into consideration as well as proximity. For the biomass availability, we assume that the amount of biomass available from a supplier is equal to the total amount available in the counties included in the cluster. Mississippi has 82 counties and Arkansas has 75 counties. For each state we create 10 suppliers as discussed. We also assume that power plants purchase biomass from suppliers within the state in order to reduce transportation costs and corresponding emissions, i.e., AR (MS) plants purchase biomass from AR (MS) suppliers.

In order to estimate model parameters, we consider the additional revenues and costs from biomass cofiring. Recall that s_{ij} is the unit profit per ton of biomass cofired at plant j and purchased from supplier i. Two sources of revenues are considered, revenues from the displacement of coal and revenues from the tax credit. The revenues from displacing coal with biomass

Table 2: Plant specification for the state of Mississippi

Plant name	Henderson	R D Morrow	Red Hills G F	Jack Watson	Victor J Daniel Jr
Plant number	1	2	3	4	5
Primary fuel	Bituminous	Bituminous	Lignite	Bituminous	Bituminous
α_j: LHV (BTU/Ton)	22,460,600	22,460,600	15,000,000	22,460,600	22460600
Capacity factor	0.107	0.728	0.721	0.354	0.498
Nameplate capacity (MW)	59	400	514	1,216	2229
Plant longitude	-90.2775	-89.3933	-89.2183	-89.0265	-88.5574
Plant latitude	33.5305	31.2194	33.3761	30.4408	30.5335
Boiler Efficiency	0.93	0.93	0.93	0.93	0.93
Other process efficiencies	0.43	0.43	0.43	0.43	0.43

include savings due to not purchasing and transporting coal. The heating values of coal and biomass are different, thus, to maintain the same energy output in a power plant, additional biomass is needed. Costs are calculated based on the amount of biomass required to generate the same amount of energy. Historical market prices of coal are provided by the U.S. Energy Information Administration.

The costs of displacing coal with biomass include: (i) biomass unit purchasing cost, (ii) biomass unit transportation cost, and (iii) biomass cofiring unit variable cost, which includes inventory and handling, among others, and increases linearly with the amount of biomass used. Assume that the unit transportation cost is a linear function of the distance traveled from a supplier to the coal-fired plant and use the corresponding geographical coordinates to calculate transportation distances. The coefficient b_j represents the one-time investment costs when 4% of coal is replaced with biomass. These investments are a function of plant capacity, utilization rate, and rate of cofiring. Considering all these factors results in a nonlinear function for profit formula and as discussed earlier we use a linear approximation to construct our model. For a detailed discussion, formulas, estimations, quality of approximation, and numerical values for those parameters, see Eksioglu et al. [2016].

The focus of this study is direct cofiring since this method is easy to implement, requires less capital investments, and is easier to adopt by coal plants. Studies that analyzed direct cofiring recommend that, at most, 50% of coal could be replaced by biomass. Therefore, set u_j, the maximum amount of biomass cofired at plant j, to be the amount of biomass required to displace coal. The minimum amount of biomass cofired at plant j, l_j, is set to be 4% [International Renewable Energy Agency, 2013].

5.2 Numerical Results

The proposed formulations were programmed in Julia 0.4.6 using the modeling language JuMP. Commercial nonlinear solvers IpOpt and Couenne are used as a benchmark to our algorithm to solve formulation (4). CPLEX 12.6.2 is used in the algorithmic approach to solve the MILP formulation (6). All models are run on an Intel(R) Core(TM) $i7 - 5960X$ CPU @ $3.00GHz$ processor with 16.00 GB of RAM.

Table 3 compares the running time and performance of Algorithm 1 with IpOpt and Couenne in solving MINLP formulation (4) when the tax credit rate is flexible. Problem instances were created by varying p ($p = p_j$ for all j). Similar results are observed when the tax credit rate is flat. The stopping criteria is a run time of about 3,600 CPU seconds, or a relative optimality gap less than or equal to 1%. For all the instances solved, IpOpt stopped within a few seconds reporting that no feasible solution existed. Couenne provided suboptimal solutions within 3,600 CPU seconds only for few instances when the tax credit rates were flat. The proposed algorithm provided an optimal solution, within the 1% optimality gap, in just a few seconds for all instances.

Table 3: Comparing the Proposed Algorithm to Commercial Solvers

	Algorithm 1		IpOpt		Couenne	
$p_j = p$ ($\$10^6$)	Obj Val ($\$10^6$)	CPU (sec)	Obj Val ($\$10^6$)	CPU (sec)	Obj Val ($\$10^6$)	CPU (sec)
0	2,070	53.63	Infeasible	6.94	NA	3,621
1	2,075	2.15	Infeasible	1.56	NA	3,615
2	2,080	2.35	Infeasible	1.58	NA	3,616
3	2,085	2.18	Infeasible	1.86	NA	3,613
4	2,090	1.94	Infeasible	1.08	NA	3,613
5	2,095	15.44	Infeasible	0.97	NA	3,616

The state of Mississippi. This section reports the results for Mississippi in both frameworks - minimization of budget and maximization of renewable energy generation - as well as the results for a variety of tax credit schemes. In particular, Table 4 shows the results when the objective is to minimize the total budget (formulation (6)) for flat and flexible tax credit rates and a variety of net profit thresholds. This experiment assumes the net profit for each plant is the same, i.e., $p = p_j$ for all j. When the tax credit rate is flexible, Plant 1 receives a significant tax credit, but Plants 2, 3, 4, and 5 receive few tax credits, which allows them to achieve the threshold of net profit. This outcome occurs because Plants 2, 3, 4, and 5 are large plants (relative to Plant 1) that can achieve the profit threshold with little monetary support from the government. The heterogeneity of power plants results in inefficiencies of flat tax credit scheme. This is because the constraints of the governmental agency ensures that each plant reaches a net profit threshold. Assuming that the threshold is the same for all plants, the bottleneck constraint corresponds to the least efficient plant in terms of biomass cofiring. That is, the tax credit should be high enough to make the least efficient plant reach its net profit threshold. Therefore, if a flat tax credit scheme is in place, efficient plans can significantly benefit by cofiring more with this high tax credit. However, in a flexible tax credit, all constraints can be binding, which results in less implementation cost for the governmental agency. Our results measure the benefit of deviating from flat tax credit schemes in this case study.

Results show that the amount of biomass cofired by each plant is at its maximum possible value because the total amount of biomass available from suppliers located in Mississippi is greater than the amount required to achieve the maximum cofiring threshold over all plants. This fact, however, does not decouple the problem by plant or supplier because the transportation cost depends on the distance between the plant and supplier. This cost impacts the decision about how much biomass to purchase from each supplier.

The problem setting where the tax credit rate is flat results in 10 times higher governmental spending but similar biomass utilization in renewable energy production as compared to problem setting where the tax credit rate is flexible. When the tax credit rate is flat, every plant receives the same tax credit, which is the tax credit necessary for Plant 1 to achieve its net profit threshold. Thus, the rest of the plants gain from the extra credit. To summarize, the flexible tax credit scheme uses a much smaller budget than the flat tax scheme, but the flexible scheme contributes the same amount of renewable energy.

Table 4: Comparing Costs and Biomass Usage for Flat and Flexible Tax Rates: Mississippi

$p = p_j$	Flat Rate Model			Flexible Rate Model						
value	Total Cost	BM Used	T	Total Cost	BM Used	Tax Credit per Plant (\$/MWh)				
(\$$10^6$)	(\$$10^6$)	(10^6tons)	(\$/MWh)	(\$$10^6$)	(10^6tons)	1	2	3	4	5
0	18,650	4.91	3.80	2,070	4.91	3.80	0.59	0.62	0.48	0.27
1	18,878	4.91	3.87	2,075	4.91	3.87	0.59	0.62	0.48	0.27
2	19,227	4.91	3.94	2,080	4.91	3.94	0.59	0.62	0.48	0.27
3	19,618	4.91	4.02	2,085	4.91	4.02	0.59	0.62	0.48	0.27
4	19,923	4.91	4.08	2,090	4.91	4.08	0.59	0.63	0.48	0.27
5	20,280	4.91	4.16	2,095	4.91	4.16	0.60	0.63	0.48	0.27

Note: BM stands for biomass and Total Cost refers to the objective function in (4).

Recall that Section 4.2 derives analytical results for a special case of the problem when (i) only one supplier is available, and (ii) the total amount of available biomass is greater than the sum of the upper bounds on biomass usage of all plants. The analytical solution to this special case provides only a heuristic for these problems and may not represent the real business. For example, Goerndt et al. [2013] showed that there is a maximum biomass transport distance, which may be violated by having one supplier. However, if biomass is shipped in high volume via trains/barge this distance can be longer [Roni et al., 2014]. Therefore, in our single-supplier scenario, our consideration is that this single supplier has large quantities of biomass available. In this case, the supplier can use the rail transportation system coal plants use currently to deliver coal, for the delivery of biomass. For the state of Mississippi, property (ii) holds true. Therefore, to use the heuristic, consider one single supplier with biomass supply that equals the amount available in Mississippi. We use the weighted gravity location model to identify a location for this supplier. Results show that the heuristic is efficient and the gap between the solution provided by the heuristic, and the optimal solution for flat and flexible schemes is respectively 0.6% and 0.7%. For Arkansas, neither assumption (i) nor (ii) hold true. However, similar to Mississippi, the suppliers in Arkansas were combined as one supplier, and the heuristic was used to find solutions. Results show that the heuristic still provides near-optimal solutions with an optimality gap of 0.4% and 1.2% for the flat and flexible schemes, respectively. These results indicate that grouping of suppliers into 10 clusters, as described in Section 5.1, has minimal impacts on the solutions' quality.

The results in Table 4, where a flexible tax scheme is considered, provide performance bounds on all 2-type tax credit mechanisms a policymaker may design. For example, a policymaker can categorize the plants into two groups of "small" and "large" plants and assign a tax credit rate to each group. Let $\mathcal{P}_1$ and $\mathcal{P}_2$ respectively denote the set of small and large plants. Table 5 summarizes the results of a few variations of such a 2-type tax credit mechanism. The objective of the policymaker in this analysis is to minimize the total budget. Results show that plants which belong to $\mathcal{P}_1$ benefit from the high tax credit rate needed at Plant 1 to achieve the established net profit. These mechanisms are more expensive than the flexible tax scheme and provide no additional benefits to plants for generating renewable energy.

Next are the results for the setting where the policymaker seeks to maximize renewable energy generation. Consider a total budget of $2.1 billion based on the results from minimizing the total budget. The results for the flexible tax credit setting suggest trends similar to those observed for the flat tax credit setting. Table 6 shows that Plant 1 has a significantly higher tax credit rate compared to other plants. Thus, to ensure that Plant 1 will achieve a certain net profit, which could be as low as zero, the policymaker needs to provide a significant incentive.

Table 5: Results From the 2-type tax Rates Mechanisms: Mississippi

		$p = \$0$				$p = \$10^6$			
$\mathcal{P}_1$	$\mathcal{P}_2$	Total Cost ($\$10^6$)	BM Used (10^6tons)	T_1 (\$/MWh)	T_2 (\$/MWh)	Total Cost ($\$10^6$)	BM Used (10^6tons)	T_1 (\$/MWh)	T_2 (\$/MWh)
1	2-5	3,094	4.91	3.80	0.62	3,101	4.91	3.87	0.62
1-2	3-5	5,151	4.91	3.80	0.62	5,203	4.91	3.87	0.62
1-3	4-5	7,269	4.91	3.80	0.48	7,379	4.91	3.87	0.48
1-4	5	9,946	4.91	3.80	0.27	10,120	4.91	3.87	0.27

The amount of biomass used by all the plants in this setting equals the maximum amount of biomass that a plant can cofire.

Table 6: Results from Renewable Energy Maximization Model: Mississippi

Budget ($\$10^6$)	$p = p_j$ ($\$10^6$)	Total Cost ($\$10^6$)	BM Used (10^6tons)	T_1 (\$/MWh)	T_2 (\$/MWh)	T_3 (\$/MWh)	T_4 (\$/MWh)	T_5 (\$/MWh)
2,100	0	2,095	4.91	4.17	0.60	0.63	0.48	0.27
	1	2,096	4.91	4.17	0.60	0.63	0.48	0.27
	2	2,097	4.91	4.17	0.60	0.63	0.48	0.27
	3	2,098	4.91	4.18	0.60	0.63	0.48	0.27
	4	2,098	4.91	4.19	0.60	0.63	0.48	0.27
	5	2,100	4.91	4.21	0.60	0.63	0.48	0.27

The state of Arkansas. Table 7 summarizes the results of similar sets of experiments for Arkansas. The results show that a flat tax rate scheme requires a much higher budget - almost three times higher - than the flexible scheme and results in the same amount of biomass cofired. This observation echoes that of Mississippi; however, the difference in total cost between a flexible and flat tax scheme in Mississippi is much higher because Plant 1 in Mississippi needs more incentives to break even than the others. For reasons similar to those cited in Mississippi, all the biomass available in Arkansas is used in both flat and flexible tax credit schemes. However, the distribution of biomass among plants is different because the amount of biomass available in Arkansas is smaller than the maximum amount of biomass that all plants could cofire.

5.3 Sensitivity Analysis

This section investigates the effects that changes in model parameters may have on optimal tax credit schemes, as well as on the amount of biomass cofired by plants. In particular, a one-way sensitivity analysis is conducted on model parameters, such as the unit biomass transportation cost. A two-way sensitivity analysis is conducted by changing the amount of biomass available and the unit biomass purchasing cost, since they are highly correlated. Most results of the

Table 7: Comparing Costs and Biomass Usage for Flat and Flexible Tax Rates: Arkansas

$p = p_j$ value ($\$10^6$)	Flat Tax Rate Total Cost ($\$10^6$)	BM Used (10^6tons)	T ($/MWh)	Flexible Tax Rate Total Cost ($\$10^6$)	BM Used (10^6tons)	T_1 ($/MWh)	T_2	T_3	T_4
0	1,657	4.29	0.432	708	4.29	0.432	0.203	0.009	0.012
1	1,670	4.29	0.436	712	4.29	0.436	0.205	0.010	0.013
2	1,684	4.29	0.440	716	4.29	0.440	0.206	0.010	0.013
3	1,697	4.29	0.444	720	4.29	0.444	0.207	0.010	0.013
4	1,696	4.29	0.448	724	4.29	0.448	0.209	0.010	0.013
5	1,724	4.29	0.452	728	4.29	0.452	0.210	0.010	0.013

sensitivity analysis focus on Mississippi because the plants are more heterogeneous, and similar trends are observed for Arkansas. The results in this section are for framework 1, where the policymaker seeks to minimize the budget.

Results show that a change (± 20%) in unit transportation cost did not not impact the strategies adopted by the plants. This change, however, had a marginal impact in the tax credit rate and total cost (see Table 8).

Table 8: Analyzing Sensitivity to Unit Transportation Cost ($p = 0$): Mississippi

Change	Flat Tax Rate Total Cost ($\$10^6$)	BM Used (10^6tons)	T ($/MWh)	Flexible Tax Rate Total Cost ($\$10^6$)	BM Used (10^6tons)	T_1 ($/MWh)
-20%	18,536	4.91	3.870	2,066	4.91	3.870
-10%	18,648	4.91	3.870	2,068	4.91	3.870
0%	18,650	4.91	3.871	2,070	4.91	3.871
10%	18,652	4.91	3.871	2,071	4.91	3.871
20%	18,652	4.91	3.871	2,073	4.91	3.871

Table 9: Analyzing Sensitivity to Biomass Availability and Price ($p = \$0$): Mississippi

Price ($/ton)	Available BM (10^6tons)	Flat Tax Rate Total Cost ($\$10^6$)	BM Used (10^6tons)	Flexible Tax Rate Total Cost ($\$10^6$)	BM Used (10^6tons)
20.00	2.04	18,616	2.04	2,006	2.04
28.68	4.91	18,650	4.91	2,070	4.91

Finally, a two-way sensitivity analysis was conducted for purchasing price and availability of biomass. Increasing the price of biomass, while biomass availability is intact, increases the total cost. The data set on biomass availability and its price shows they are positively correlated, i.e., if a plant wants more biomass, it needs to pay more per unit. To increase the supply of biomass, plants will need to use forest products (in addition to using forest residues) and pay the higher price of timber. Alternatively, biomass availability can increase by using arable land to produce biomass. In this case, plants would have to pay the higher land price. The results in Table 9 indicate that a 50% decrease in biomass availability, due to a decrease in purchasing price, has only marginal impacts on the total budget. This is because a higher tax credit rate must be provided to satisfy the minimum net profit threshold.

6 Conclusions and Insights

This study formulated a taxation model to evaluate the impact of governmental incentives for renewable energy generation via biomass cofiring in coal-fired power plants. A Stackelberg game was proposed to model the hierarchy in the decision making process and a generalized Nash equilibrium to model the simultaneous decision making among lower level players. In this setting, the state/federal government is the higher level decision maker that sets a minimum CO_2 emissions reduction strategy for power plants and provides them tax credits to avoid monetary losses at coal-fired power plants which could otherwise lead to rises in electricity prices. Two viewpoints are presented, in which the decision maker seeks to (i) minimize the budget, or (ii) maximize the total amount of renewable energy generated. Power plants are the lower level decision makers that identify how much biomass to cofire to maximize profits. An algorithmic approach was used to find the optimal solution to the proposed Stacklerberg/Nash game by providing a MIBLP reformulation of the problem and creating bounds based on a piecewise linear relaxation of bilinear terms. This framework designed efficient and fair tax credit schemes for biomass cofiring in the Southeast U.S., as studies show that biomass cofiring, coupled with appropriate governmental incentives, can be an attractive short-term solution to reduce CO_2 emissions in coal-fired power plants. An efficient heuristic was designed by exploiting the characteristics of an optimal solution in a special case of the problem. This heuristic provided near-optimal solutions in our numerical study.

A case study was presented using real-world data from Mississippi and Arkansas. The results of this study provided insights summarized below:

1. The current flat tax credit scheme for renewable energy generation is notably inefficient in some states of Southeast U.S. This statement is based on the assumptions that the government imposes restrictions on CO_2 emissions and renewable energy is generated via biomass cofiring. In particular, the current flat PTC is \$1.2 per MWh for open-loop biomass. However, our analysis shows that it must be \$3.80 per MWh in Mississippi and

$0.43 per MWh in Arkansas.

2. The flexible tax credit scheme provides a plant-specific tax credit rate and has advantages over the existing flat-rate schemes. Numerical analysis indicate that both schemes generate the same amount of renewable energy, but the flat-rate scheme is much more expensive. In particular, in Mississippi and Arkansas, the flat tax credit scheme is, respectively, 10 and almost 3 times more expensive than the flexible scheme.
3. By implementing a flat tax credit rate, large plants benefit much more than small plants because they can displace more coal with biomass and take advantage of the economies of scale. The ethics of this disproportionate allocation of tax payers' money should be carefully considered in designing fair allocation policies.

Although a flexible tax credit scheme is cost efficient and ensures that small plants participate in cofiring, its implementation faces ethical concerns as well. A flexible scheme may discriminate against power plants based on certain factors, such as the plant's capacity or the technology it uses. Highly efficient power plants may receive minimal to no financial support. The study of ethics of such allocation of tax payers' money is beyond the scope of this study. However, the results of this study measure the benefits that may be obtained from deviating from the traditional approach to taxation. This work provides bounds on the efficiency of such allocation policies.

References

IPCC. Mitigation of climate change. *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 1454, 2014.

Lihui Bai, Guangyang Xu, and Qipeng P Zheng. A game theoretical approach to modeling energy consumption with consumer preference. In *PES General Meeting— Conference & Exposition, 2014 IEEE*, pages 1–5. IEEE, 2014.

Jonathan F Bard, John Plummer, and Jean Claude Sourie. A bilevel programming approach to determining tax credits for biofuel production. *European Journal of Operational Research*, 120(1):30–46, 2000.

Prabir Basu, James Butler, and Mathias A Leon. Biomass co-firing options on the emissions reduction and electricity generation costs in coal-fired power plants. *Renewable Energy*, 36 (1):282–288, 2011.

María Lorena Bergamini, Ignacio Grossmann, Nicolás Scenna, and Pío Aguirre. An improved piecewise outer-approximation algorithm for the global optimization of MINLP models involving concave and bilinear terms. *Computers & Chemical Engineering*, 32(3):477–493, 2008.

Luce Brotcorne, Martine Labbé, Patrice Marcotte, and Gilles Savard. A bilevel model for toll optimization on a multicommodity transportation network. *Transportation Science*, 35(4): 345–358, 2001.

Anna Ebers Broughel. Impact of state policies on generating capacity for production of electricity and combined heat and power from forest biomass in the united states. *Renewable Energy*, 134:1163–1172, 2019.

Antonio C Caputo, Mario Palumbo, Pacifico M Pelagagge, and Federica Scacchia. Economics of biomass energy utilization in combustion and gasification plants: effects of logistic variables. *Biomass and Bioenergy*, 28(1):35–51, 2005.

Bob Cleaves. Biomass cofiring: Opportunities to expand the industry, 2014. URL `http://biomassmagazine.com/articles/10854/biomass-cofiring-opportunities-to-expand-the-industry`.

Benoît Colson, Patrice Marcotte, and Gilles Savard. Bilevel programming: A survey. *4OR*, 3 (2):87–107, 2005.

Benoît Colson, Patrice Marcotte, and Gilles Savard. An overview of bilevel optimization. *Annals of Operations Research*, 153(1):235–256, 2007.

Matt Croucher, Ant Evans, Tim James, and Jessica Raasch. Market-based incentives. *Seidman Research Institute. WP Carey School of Business*, 2010.

Stephan Dempe. Annotated bibliography on bilevel programming and mathematical programs with equilibrium constraints. *Optimization*, 52(3):333–359, 2003.

Stephan Dempe and Jonathan F Bard. Bundle trust-region algorithm for bilinear bilevel programming. *Journal of Optimization Theory and Applications*, 110(2):265–288, 2001.

Bayram Dundar, Ronald G McGarvey, and Francisco X Aguilar. A robust optimisation approach for identifying multi-state collaborations to reduce CO2 emissions. *Journal of the Operational Research Society*, 70(4):601–619, 2019.

Sandra Duni Eksioglu, Hadi Karimi, and Burak Eksioglu. Optimization models to integrate production and transportation planning for biomass co-firing in coal-fired power plants. *IIE Transactions*, 48(10):901–920, 2016.

EPA. U.S. Greenhouse Gas Inventory Report: 1990-2014, October 2014. URL https://www.epa.gov/ghgemissions/us-greenhouse-gas-inventory-report-1990-2014.

EPA. 40 CFR Part 60 Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units; Final Rule, October 2015. URL https://www.gpo.gov/fdsys/pkg/FR-2015-10-23/pdf/2015-22842.pdf.

Christodoulos A Floudas. *Deterministic Global Optimization: Theory, Methods and Applications*, volume 37. Springer Science & Business Media, 2013.

Doerte Fouquet and Thomas B Johansson. European renewable energy policy at crossroads–focus on electricity support mechanisms. *Energy policy*, 36(11):4079–4092, 2008.

Michael E Goerndt, Francisco X Aguilar, and Kenneth Skog. Resource potential for renewable energy generation from co-firing of woody biomass with coal in the Northern US. *Biomass and Bioenergy*, 59:348–361, 2013.

Chrysanthos E Gounaris, Ruth Misener, and Christodoulos A Floudas. Computational comparison of piecewise- linear relaxations for pooling problems. *Industrial & Engineering Chemistry Research*, 48(12):5742–5766, 2009.

MM Hasan and IA Karimi. Piecewise linear relaxation of bilinear programs using bivariate partitioning. *AIChE Journal*, 56(7):1880–1893, 2010.

IEA. Support mechanisms for cofiring secondary fuels, 2012. URL http://www.iea-coal.org.uk/documents/83114/8679/Support-mechanisms-for-cofiring-secondary-fuels,

International Renewable Energy Agency. Biomass co-firing, 2013. URL https://www.irena.org/DocumentDownloads/Publications.

Hadi Karimi, Sandra Duni Ekşioğlu, and Amin Khademi. Analyzing tax incentives for producing renewable energy by biomass cofiring. *IISE Transactions*, 50(4):332–344, 2018.

Hadi Karimi, Sandra D Ekşioğlu, and Michael Carbajales-Dale. A biobjective chance constrained optimization model to evaluate the economic and environmental impacts of biopower supply chains. *Annals of Operations Research*, pages 1–36, 2019.

Sangpil Ko and Pasi Lautala. Optimal level of woody biomass co-firing with coal power plant considering advanced feedstock logistics system. *Agriculture*, 8(6):74, 2018.

Martine Labbé, Patrice Marcotte, and Gilles Savard. A bilevel model of taxation and its application to optimal highway pricing. *Management Science*, 44(12-part-1):1608–1622, 1998.

Shengwei Mei, Wei Wei, and Feng Liu. On engineering game theory with its application in power systems. *Control Theory and Technology*, 15(1):1–12, 2017. ISSN 2198-0942. doi: 10.1007/s11768-017-6186-y. URL http://dx.doi.org/10.1007/s11768-017-6186-y.

Alexander Mitsos, Panayiotis Lemonidis, and Paul I Barton. Global solution of bilevel programs with a nonconvex inner program. *Journal of Global Optimization*, 42(4):475–513, 2008.

National Conference of State Legislatures. State renewable portfolio standards and goals, 2016. URL http://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx.

National Renewable Energy Laboratory. Renewable portfolio standards, 2016. URL http://www.nrel.gov/tech_deployment/state_local_governments/basics_portfolio_standards.html.

Mohammad Rahdar, Lizhi Wang, and Guiping Hu. Potential competition for biomass between biopower and biofuel under RPS and RFS2. *Applied Energy*, 119(C):10–20, 2014. URL http://EconPapers.repec.org/RePEc:eee:appene:v:119:y:2014:i:c:p:10-20.

Md S Roni, Sandra D Eksioglu, Erin Searcy, and Krishna Jha. A supply chain network design model for biomass co-firing in coal-fired power plants. *Transportation Research Part E: Logistics and Transportation Review*, 61:115–134, 2014.

Mohammad S Roni, Sudipta Chowdhury, Saleh Mamun, Mohammad Marufuzzaman, William Lein, and Samuel Johnson. Biomass co-firing technology with policies, challenges, and opportunities: a global review. *Renewable and Sustainable Energy Reviews*, 78:1089–1101, 2017.

J Ben Rosen. Existence and uniqueness of equilibrium points for concave n-person games. *Econometrica: Journal of the Econometric Society*, pages 520–534, 1965.

Everett A Sondreal, Steven A Benson, John P Hurley, Michael D Mann, John H Pavlish, Michael L Swanson, Greg F Weber, and Christopher J Zygarlicke. Review of advances in combustion technology and biomass cofiring. *Fuel Processing Technology*, 71(1-3):7–38, 2001.

Nathan Georg Sudermann-Merx. *Linear generalized Nash equilibrium problems.* PhD thesis, Karlsruher Institut für Technologie (KIT), 2016.

K. Sullivan and R. Meijer. Co-firing biomass with coal, 2010. URL http://www.renewableenergyworld.com/articles/print/rewna/volume-2/issue-3/bioenergy/co-firing-bi

The New York Times. E.P.A. Announces Repeal of Major Obama-Era Carbon Emissions Rule, 2017. URL https://www.nytimes.com/2017/10/09/climate/clean-power-plan.html.

US DOE. 2016 BILLION-TON REPORT, 2016. URL https://www.energy.gov/sites/prod/files/2016/12/f34/2016_billion_ton_report_12.2.16_0.pdf.

US Energy Information Administration. Electricity generation capacity. http://www.eia.gov/electricity/capacity/, 2013.

Wolfram Wiesemann, Angelos Tsoukalas, Polyxeni-Margarita Kleniati, and Berç Rustem. Pessimistic bilevel optimization. *SIAM Journal on Optimization*, 23(1):353–380, 2013.

Andrea Wils, Wolfgang Calmano, Peter Dettmann, Martin Kaltschmitt, and Holger Ecke. Reduction of fuel side costs due to biomass co-combustion. *Journal of Hazardous Materials*, 207: 147–151, 2012.

Jesse Young, Nathaniel Anderson, and Helen Naughton. Influence of policy, air quality, and local attitudes toward renewable energy on the adoption of woody biomass heating systems. *Energies*, 11(11):2873, 2018.

Wei Yuan, Long Zhao, and Bo Zeng. Optimal power grid protection through a defender–attacker–defender model. *Reliability Engineering & System Safety*, 121:83–89, 2014.

Dajun Yue and Fengqi You. Game-theoretic modeling and optimization of multi-echelon supply chain design and operation under Stackelberg game and market equilibrium. *Computers & Chemical Engineering*, 71:347–361, 2014.

Appendix

Proof of Proposition 1 Problem (1) with one supplier is given by

$$\begin{aligned}
&\min \sum_{j=1}^{J} e_j T_{n(j)} X_j \\
&\text{s.t.} \\
&z_j \geq p_j, \ \ \forall j = 1, \dots, J \\
&z_j = \max (s_j + e_j T_{n(j)}) X_j - b_j, \forall j = 1 \dots J, \\
&\quad \text{s.t.} \\
&\quad l_j \leq X_j \leq u_j, \\
&\quad \sum_{j=1}^{J} X_j \leq \bar{u}, \\
&\quad X_j \geq 0.
\end{aligned}$$

The upper level constraints are of the form $(s_j + e_j T_{n(j)}) X_j \geq p_j + b_j$. By this assumption, the right-hand side is strictly positive and $X_j \geq 0$. Therefore, $s_j + e_j T_{n(j)} > 0$ for all j. If $s_j + e_j T_{n(j)} > 0$, the optimal value for X_j equals u_j in the absence of a biomass availability constraint. Therefore, a Nash equilibrium gives

$$\begin{aligned}
&\sum_{j=1}^{J} X_j = \bar{u}, \\
&l_j \leq X_j \leq u_j, \ \ \forall j = 1 \dots J.
\end{aligned}$$

Now consider the feasible region given by

$$\begin{aligned}
&(s_j + e_j T_{n(j)}) X_j \geq p_j + b_j, \ \ \forall j = 1 \dots J, \\
&\sum_{j=1}^{J} X_j = \bar{u}, \\
&l_j \leq X_j \leq u_j, \ \ \forall j = 1 \dots J.
\end{aligned}$$

Summing up the first Jth constraints result in

$$\sum_{j=1}^{J} e_j T_{n(j)} X_j \geq \sum_{j=1}^{J} (p_j + b_j) - \sum_{j=1}^{J} s_j X_j.$$

The left-hand side is the objective function. To determine the largest lower bound, the right-hand side of the above equation must be maximized, which is equivalent to the following optimization problem:

$$\begin{aligned}
&\min \sum_{j=1}^{J} s_j X_j \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{J} X_j = \bar{u}, \\
&\quad l_j \leq X_j \leq u_j, \;\; \forall j = 1 \dots J.
\end{aligned}$$

This problem is a continuous bounded knapsack problem with a greedy solution. Since $s_1 \leq s_2 \leq \cdots \leq s_J$, take

$$k = \min\{q : \sum_{j=1}^{q} u_j > \bar{u}\}.$$

The optimal solution to the knapsack is therefore $X_1^* = u_1$, $X_2^* = u_2, \dots X_{k-1}^* = u_{k-1}$, $X_k^* = \bar{u} - \sum_{j=1}^{k-1} u_j - \sum_{j=k+1}^{J} l_j$, $X_{k+1}^* = l_{k+1}, \dots, X_J^* = l_J$, the desired bound.