Analyzing Tax Incentives for Producing Renewable Energy by Biomass Cofiring

Hadi Karimi,[1] Sandra Duni Ekşioğlu,[1] Amin Khademi[1]

[1]Department of Industrial Engineering, Clemson University,

Freeman Hall, Clemson, SC 29634

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Abstract

This paper examines the impacts of governmental incentives for coal-fired power plants to generate renewable energy via biomass cofiring technology. The most common incentive is the production tax credit (PTC), a flat rate reimbursement for each unit of renewable energy generated. The work presented here proposes PTC alternatives, incentives that are functions of plant capacity and the biomass cofiring ratio. The capacity-based incentives favor plants of small capacity, while the ratio-based incentives favor plants that cofire larger amounts of biomass. Following a resource allocation perspective, this paper evaluates the impacts of alternative PTC schemes on biomass utilization and power plants' profit-earning potentials. The efficiency of these incentive schemes are evaluated by comparing with the results of utilitarian solution, an approach that finds a distribution of credits which maximizes the total profits in the system. To evaluate the fairness of the proposed schemes, the results of the max-min fairness solution is used as a basis. A realistic case study, developed with data pertaining to the southeastern U.S., suggests how total system costs and efforts to generate renewable energy are impacted both by the existing and the proposed incentives. The observations presented in this study provide helpful insights to policymakers in designing effective incentive schemes that promote biomass cofiring.

Key words: Biomass cofiring; Renewable energy production, Mixed integer programming, Resource allocation; Production tax credit

1 Introduction

Concerns about the impacts of Greenhouse Gas (GHG) emissions on the environment, human health, and the worldwide economy brought many nations leaders together during the 2015 United Nations (UN) Climate Change Conference in Paris (2015). UN members reached an agreement, committing to control GHG emissions. Coal is the single largest contributor to GHG emissions, totaling as much as 25% of the GHG released into the environment. This paper focuses on tax incentives for biomass cofiring, the direct co-combustion of biomass with coal in plants using coal to generate heat and electricity. In the U.S., coal contributes to 71% of the total carbon dioxide (CO_2) emissions from the energy sector (U.S. Energy Information Administration (EIA), 2015). Among all the GHG-reduction technologies, biomass cofiring has been shown to be one of the least expensive and relatively easy to implement (Basua et al. 2011).

The Clean Power Plan, finalized by the U.S. Environmental Protection Agency in 2015, established CO_2 pollution standards for new and existing coal-fired power plants. As a result, researchers estimated that 17% of coal-fired power plants that fail to comply with existing regulations may close over the next few years (Bloomberg New Energy Finance 2015). These plant closings would result in job losses and higher electricity prices. While governmental support mechanisms in European Union (EU) countries offer many incentives for biomass cofiring, the U.S. is different. At the federal level, the PTC is the only tax incentive offered to support biomass cofiring. At the state level, regulations such as Renewable Portfolio Standards (RPS), mandate that power plants generate more renewable energy by using sources like biomass.

While many researchers agree that cofiring biomass with coal in power plants is an option for RPS compliance and a near-term solution for introducing biomass into today's renewable energy market, only 40 of the 560 power plants in the U.S. currently do so (Basua et al. 2011). At least two reasons disincentivize the use of cofiring in power plants: First, cofiring is not cost effective because the cost of collecting, transporting, and storing biomass is high, and burning biomass increases slagging and boiler corrosion. Therefore, overall plant efficiency drops. Second, limited state and federal support for cofiring decreases the likelihood that power plants will cofire biomass. Indeed, many researchers believe that a comprehensive governmental support system is needed to make biomass cofiring economically attractive (Smith and Rousaki 2002, Kangas et al. 2009, McIlveen-Wright et al. 2011, Moiseyev et al. 2014, Montgomery, J. 2015, Ekşioğlu et al. 2016).

This study develops models that (a) support federal- or state-level design of efficient tax incentives for biomass cofiring, and (b) optimize the performance of individual plants corresponding supply chains. These models suggest approaches that policymakers may use to make the best use of their limited budgets. The optimization models presented are extensions of resource allocation problems, which provide insights into how to allocate scarce resources among competing players and achieve the best possible overall system performance (Katoh et al. 2013). This research identifies federal or state funding as the scarce resource to be distributed among coal-fired power plants via renewable energy subsidies similar to the PTC. Depending on the definition of performance used and the conditions under which optimal performance is achieved, different types of resource allocation models can be developed. A *utilitarian* resource allocation model distributes the resources in such a way that the total profit, or utility, of the supply chain is maximized (Bertsimas et al. 2011). Considering the systems total profit as the efficiency measure, this resource allocation model provides the solution for a fully efficient system. Such an approach, however, may favor large-capacity plants, which typically have higher profit margins than their smaller counterparts. Clearly, identifying a fair distribution of resources among supply chain members is desired, but literature reviews reveal that researchers have not agreed upon criteria for defining fairness (Kumar and Kleinberg 2006, Bertsimas et al. 2011). Some models detailed in the literature include the max-min fairness (Radunović and le Boudec 2007), the proportional fairness (Kelly et al. 1998), and the total equity models (Luss 1999). Attaining fairness often comes at the price of losing system efficiencies, so the efficiency loss is estimated by comparing the results with those obtained from the utilitarian model (Bertsimas et al. 2011).

This paper makes two major contributions to the literature: First, this research introduces a novel framework to aid the design of governmental tax incentives, such as the PTC. The resource allocation model proposed identifies how a government might distribute its budget among power plants that cofire biomass. The utilitarian approach focuses on maximizing the utility of the system, but, to balance equity and fairness in systems, this paper proposes policies that can distribute monetary funds to the advantage small-capacity plants or plants that generate the most renewable energy. This research also investigates a budget distribution that maximizes the minimum utility of the system through a max-min fairness model. Such a scheme is considered to result in the worst-case degradation of the utilitarian objective. Thus, the utilitarian and max-min schemes provide the bounds within which lay the fair allocation schemes proposed by this research. The resulting resource allocation models are mixed integer bilinear programs (MIBLP) which are reformulated using McCormick relaxation to provide efficient solution methods. The second major contribution this paper presents is the case study, based on data gathered from the southeastern U.S. The analysis provides novel insights on the efficiency and fairness of various allocation schemes. For example, the existing, flat PTC maximizes a systems utility; however, the model results in the fewest kWh of renewable energy generated. Capacity-based schemes maximize the number of plants that cofire, and they generate the most kWh of renewable energy. Ratio-based schemes provide balanced outcomes in terms of profitability and renewable energy generation. These observations provide helpful insights to policymakers in designing effective incentive schemes that promote biomass cofiring.

2 Related Work

Our study relates to three main streams of literature: techno-economic studies on biomass cofiring, incentive mechanisms and regulations in renewable energy, and fairness studies in resource allocation problems.

Previous literature establishes the technical feasibility of biomass and coal co-combustion in coal-fired power plants (Baxter 2005, Goerndt et al. 2013, Koppejan and Van Loo 2012). While most of this research focuses on the techno-economic analysis of cofiring at certain power plants, a few studies extend the scope by considering biomass supply chain costs (Roni et al. 2014, Sharma et al. 2013, Ekşioğlu et al. 2015). Studies by Hansson et al. (2009) and Al-Mansour and Zuwala (2010) demonstrate the potential of biomass cofiring as an affordable near-term solution to comply with GHG regulations in the EU. Most of the techno-economic assessments of biomass cofiring suggest that financial support is essential to encourage existing plants to utilize biomass power (Tharakan et al. 2005, De and Assadi 2009, McIlveen-Wright et al. 2011, Cuellar 2012). Dong (2012) details environmental concerns that providing plants financial incentives for biomass cofiring may lead to increased use of coal to generate power. However, Lintunen and Kangas (2010) show that cofiring does not result in significant increase of fossil fuel use, despite the fact that subsidizing biomass cofiring does use funds that could otherwise be invested in pure renewable technology. Ekşioğlu et al. (2016) propose an integrated transportation and production planning model that captures the impacts of biomass cofiring decisions on supply chain costs. This paper, by developing a case study using southeastern U.S. coal plants, shows that biomass cofiring in some states is not profitable. Therefore, providing a PTC as low as $0.7¢/kWh$ could increase power plants efforts to generate renewable energy in their respective regions. This paper also proposes a variety of governmental incentives that may increase companies generating renewable energy via biomass cofiring. The performance of the presented incentives are evaluated via an extensive numerical analysis based on a fact-based case study.

Some papers in sustainable operations management literature address the impacts of environmental policies and tax incentives on production and operational decisions (Park et al. 2015, Drake et al. 2016, Krass et al. 2013, Kroes et al. 2012). Works by Garcia et al. (2012), Shrimali and Baker (2012), Alizamir et al. (2016), Zhou et al. (2011) focus on the design and assessment of incentive mechanisms that promote renewable energy generation. Kim and Lee (2012) propose an optimization model that helps policymakers identify feed-in tariffs (FIT), which maximize the incorporation of renewable energy into the regions overall energy supply. Because of the wide-spread usage and proven effectiveness of FIT (Fouquet and Johansson 2008), this support mechanism has received the most attention in the literature. Wiser et al. (2007) analyze the efficiency of the PTC applied to companies generating renewable electricity from wind. A few studies focus on the design and analysis of incentives for biomass cofiring technolog (Lintunen and Kangas 2010, Kangas et al. 2009, Moiseyev et al. 2014, Ekşioğlu et al. 2016). For example, Moiseyev et al. (2014) analyze the impact of subsidies and carbon pricing on woody biomass cofiring in EU markets. Luo and Miller (2013) use a game theoretic approach to design and manage a biofuel supply chain. Their study develops an optimization model that captures the impact of monetary incentives that support biofuel producers.

Similar to those studies, this work proposes models that help policymakers identify PTCs that maximize plants efforts to generate renewable energy. In addition, the models proposed in this work ensure a fair allocation of the PTC among participating plants and compare these models performance, using an extensive numerical analysis, to determine their profitability and fairness.

Finally, we use a resource allocation modeling framework to design PTC allocation schemes

(Katoh et al. 2013). Resource allocation models provide the appropriate setting to aid decision makers in allocating scarce resources among self-interested parties. These models are used to analyze the efficiency and fairness of different allocation schemes (Bertsimas et al. 2011, 2012). This modeling framework has been used on a broad range of applications in operations management literature, such as, healthcare management (McCoy and Lee 2014, Atasu et al. 2016), supply chain management (Cui et al. 2007, Wu and Niederhoff 2014), and recycling network design (Gui et al. 2015) to name a few. There are very few studies in the literature that use resource allocation models to design support mechanisms for renewable energy systems. For example, Dai et al. (2014) propose proportional resource allocation models to address how tradable emission permits can be allocated among a set of entities.

Finally, this research uses a resource allocation modeling framework to design PTC allocation schemes (Katoh et al. 2013). Very few studies in the literature use resource allocation models to design support mechanisms for renewable energy systems. However, Dai et al. (2014) propose proportional resource allocation models to address how tradable emission permits can be allocated among a set of entities. Overall, resource allocation models provide the appropriate setting to aid decision makers in allocating scarce resources among self-interested parties. These models analyze the efficiency and fairness of different allocation schemes (Bertsimas et al. 2011, 2012), and this modeling framework has been used on a broad range of applications in operations management literature, such as healthcare management (McCoy and Lee 2014, Atasu et al. 2016), supply chain management (Cui et al. 2007, Wu and Niederhoff 2014), and recycling network design (Gui et al. 2015), among others. Using a resource allocation model to address profitability and fairness questions will provide new insights to determining the best ways to incentivize plants generating renewable energy.

3 Problem Description

Consider a supply chain consisting of biomass suppliers and coal-fired power plants. Plants face the issue of determining whether or not to cofire biomass, and if a plant decides to cofire, this plant must also decide how much biomass to use. Using coal to produce energy is cheaper than using biomass because the cost of collecting, transporting, and storing biomass is high, and biomass cofiring reduces plant efficiency. Consider that the supply chain is influenced by the policies established by a governmental entity, which faces a limited budget and the challenge of designing efficient and fair polices to encourage plants to generate renewable energy via biomass cofiring. The flexible approach proposed here presents policies that may (a) maximize system-wide profits, (b) ensure a fair distribution of budget to participating plants, or (c) maximize the kWh of renewable energy generated. The models developed here are used to evaluate the trade-offs that exist among a variety of policies.

These approaches are inspired by current U.S. and EU practices. For example, in the U.S., the PTC provides a flat tax credit per unit of renewable energy generated to facilities that implement either full-scale biomass firing or closed-loop biomass cofiring. However, plants that implement only partial cofiring are excluded and do not benefit from the PTC (Internal Revenue Code, §45). The EU uses FIT schemes to support biomass-related energy generation (Menanteau et al. 2003, Ragwitz et al. 2007, Fouquet and Johansson 2008). Finland has the largest number of biomass cofiring installations in the EU (>78). Finland offers tax exemptions for the energy produced from biomass, provides investment subsidies for cofiring related projects, and offers an FIT of 133.5 €/MWh for combined heat and power (CHP) generation. A study by Ragwitz et al. (2007) evaluates the advantages of step-wise FIT schemes, in which plants are compensated based on capacity and fuel types. Based on these observations, this paper extends these policies in the following directions: A ratio-based biomass-to-coal PTC allows plants with the highest biomass-to-coal ratios to receive higher tax credits. The capacity-based PTC provides a tax credit based on plant capacity, so smaller plants receive increased tax credit rates.

These models capture two sides of this decision making process: First, the governmental entity decides the PTCs structure, if funds are allocated for cofiring. On the other side, power plants choose a cofiring strategy that maximizes profits because they depend on supply chain-related costs and revenues from the PTC.

The criteria that governments use to identify the best allocation of resources has been the subject of extensive studies in welfare economics (Mas-Colell et al. 1995, Young 1995, Sen and Foster 1997). The utilitarian approach refers to the common policy of a governmental entity identifying a distribution of resources that will maximize the sum of the utilities of all participants. Under the fairness principle, the governmental entity identifies a distribution of resources which optimizes some system fairness measure. Due to the subjective nature of fairness, no one principle is universally accepted as "the most fair." Thus, depending on the specific problem at hand and the fairness scheme definition applied, different fair solutions may apply. In this context, a scheme is a set of rules and properties that results in a specific distribution of resources. For instance, a solution to the max-min fairness scheme finds a distribution of resources that will maximize the minimum utility of all participants. Such a scheme results in the worst-case degradation of the utilitarian objective (Bertsimas et al. 2011). In the context of this problem, a fair policy ensures a maximum number of small- and large-capacity power plants participate. Without fairness policies, only large-capacity plants may take advantage of tax incentives because large-capacity plants typically have large profit margins with the necessary cushion against uncertainties associated with investments in biomass cofiring. A fair policy also compensates based on the ratio of biomass-to-coal because the relationship between costs and the amount of biomass cofired is not linear.

Definitions: Let $\mathcal{C} = \{1, \ldots, C\}$ represent the set of plants in the supply chain. Let B_j represent the biomass cofiring strategy (the heat input ratio) adopted by plant j and the function $M_j^b(B_j)$ represent the amount of biomass required annually (in tons) to displace coal in plant j. Cofiring decisions at coal plants are impacted by biomass availability in the region, denoted by b. The set $\mathbf{B} := \{B_j | \sum_{j \in \mathcal{C}} M_j^b(B_j) \leq b\}$ represents all of the feasible cofiring strategies.

Let $\mathcal{T}$ represent the *resource set*, which is the set of all feasible allocations of PTC, i.e., each allocation that satisfies physical and monetary limitations that plants and the government face. Let $\mathbf{T} \in \mathcal{T}$ represent one of these PTC allocations where T_j is a tax rate reduction in the form of $\$T_j$ per mega-watt hour (MWh) of electricity generated from biomass in plant j and $\mathbf{T} := \{T_j | \forall j \in \mathcal{C}\}$. The corresponding annual savings from tax credits for each plant is a function $S_j^t(T_j, B_j)$ of the size of tax reduction and cofiring strategy. Let g represent the available annual assigned budget to support biomass cofiring through PTC, and let t^l, t^u represent a lower and an upper bound on the size of the tax rate. The resource set is defined as follows

$$\mathcal{T} := \{\mathbf{T} \in \mathbb{R}_+^n \mid \sum_{j \in \mathcal{C}} S_j^t(T_j, B_j) \leq g, B_j \in \mathbf{B}, t^l \leq T_j \leq t^u, \forall j \in \mathcal{C}\}.$$

For a given $\mathbf{T} \in \mathcal{T}$, assume that each coal plant can achieve a known utility level U_j, and $\mathbf{U} := \{U_j | \forall j \in \mathcal{C}\}$. The achievable utility, in this context, is the average annual profit that each plant can obtain via cofiring. Plants' utility is a function of provided PTC and cofiring strategy adopted by the plants ($U_j : (T_j, B_j) \to \mathbb{R}_+$). Section 4.1 details the approach followed to derive the utility function.

Utilitarian approach: Under the utilitarian approach, the government selects a $\mathbf{T} \in \mathcal{T}$ to maximize the sum of utilities of all participating plants:

$$U^* = \max_{\mathbf{T} \in \mathcal{T}} \quad \sum_{j \in \mathcal{C}} U_j(T_j, B_j). \tag{1}$$

In practice, a utilitarian approach is not always favored since it may result in an unequal distribution of resources among the participating power plants. As a result, some of the plants may not receive a fair share of the available budget. Furthermore, a utilitarian approach focuses on profit maximization, which may not increase power plants efforts to generate renewable electricity.

Fairness approach: The utilitarian approach focuses on maximizing the total profits and, thus, maximizing the efficiency of the supply chain. While identifying a fair distribution of resources among supply chain members is desired, no agreed-upon set of criteria define "fairness" in the literature. To quantify and compare the fairness of different allocation schemes, researchers use metrics such as the minimum system utility, the gap between minimum and maximum utility, and the Jain and Theil indices. The fairness metric used in this study is the minimum guarantee of utility to all players (Rawls 1971). Thus, provided the utility set $\mathcal{U}$, the fairness metric is equal to

$$\overline{U} = \max_{\mathbf{T} \in \mathcal{T}} \min_{j \in \mathcal{C}} U_j(T_j, B_j). \tag{2}$$

As mentioned earlier the practical PTC schemes proposed and analyzed here are based on plant capacity and cofiring ratios. Let $\mathbb{S}$ represent the PTC scheme to be implemented by the government and $U_j^{\mathbb{S}}$ represent the optimal utility of plant j achieved under this scheme and $\mathbf{U}^{\mathbb{S}} := \{U_j^{\mathbb{S}} | \forall j \in \mathcal{C}\}$. Let $\underline{U}^{\mathbb{S}} = \min_{j \in \mathcal{C}} U_j^{\mathbb{S}}$ denote the minimum utility imposed by scheme $\mathbb{S}$. Bertsimas et al. (2012) define *fairness loss* of any scheme $\mathbb{S}$ as the difference between the fairness metric $\overline{U}$ and the resulted minimum utility $\underline{U}^{\mathbb{S}}$. Then, the relative loss in the minimum utility achieved under $\mathbb{S}$, as compared to the maximized minimum utility under max-min scheme, is the *price of efficiency* (PoE) and calculated as $PoE = \frac{\overline{U} - \underline{U}^{\mathbb{S}}}{\overline{U}}$. A fair allocation of resources leads to a loss of efficiency in the supply chain. The *price of fairness* (PoF) is a measure of efficiency loss due to implementing the fairness scheme, and is given by $PoF = \frac{U^* - \sum_{j \in \mathcal{C}} U_j^{\mathbb{S}}}{U^*}$. A PoF value equal to 0 indicates that both of the utilitarian and fair approaches have equal system efficiencies.

4 Developing the Optimization Models

4.1 Calculating Plant Utility

Revenues are obtained via savings from the PTC, plus savings due to displacing coal with biomass. Recall S_j^t, which represents savings due to PTC. Let S_j^c represent the annual savings due to cofiring, and let M_j^c represent the amount of coal substituted by biomass at plant j. Both S_j^c and M_j^c are functions of cofiring ratio B_j. If p_j^c is the unit purchase cost of coal in plant j, then, the corresponding annual saving (in \$) from coal displacement is equal to $S_j^c(B_j) = p_j^c M_j^c(B_j)$.

Costs of biomass cofiring include biomass delivery, ash disposal, coal plant retrofitting investments, and operations and maintenance (O&M) (IEA-ETSAP and IRENA 2013). Biomass *delivery* cost accounts for the cost of purchasing and transportation. The unit delivery cost is denoted by c^d (in \$/ton). Ash generated from burning coal alone is a byproduct with a market value; however, ash generated from cofiring with biomass is not suitable and should be disposed at some cost (Tharakan et al. 2005). The unit ash disposal cost is denoted by c^a (in \$/ton). Let V_j denote the total annual costs due to biomass delivery and ash disposal: $V_j(B_j) = \left(c^b + c^a\right) M_j^b(B_j)$. The investment costs consist of the fixed annual operating O&M costs $\mathcal{F}_j$ (in \$ per MW) and the overnight capital costs I_j (in \$ per MW). Capital costs occur at the beginning of a cofiring project. Let c^f be the capital charge factor used to calculate the annual equivalent cost over the project's lifetime. Parameter N_j represents the plant's capacity in MW. Equation (3) presents the annual investment costs at plant j.

$$\mathcal{I}_j(B_j) = \Big(B_j \mathcal{F}_j + c^f I(B_j)\Big) N_j. \tag{3}$$

The utility achieved at plant j is calculated by subtracting total revenues from total costs as

$$U_j(T_j, B_j) = S_j^t(T_j, B_j) + S_j^c(B_j) - \mathcal{I}_j(B_j) - V_j(B_j). \tag{4}$$

4.2 Utilitarian Optimization Model

Following a utilitarian approach, the governmental entity uses model (1) to identify a credit allocation that will maximize the total utility of power plants. The optimization model developed here identifies allocations that maximize the total utility. Let the ordered set $L := \{\beta_1, \beta_2, \ldots, \beta_{|L|}\}$ contain all the potential values for cofiring strategy B_j. This assumption is not restrictive, since, in real-world decision making about cofiring strategies, only certain cofiring strategies (e.g. 5%, 10%, or 20%) are implemented in a plant (see, for axample, DEBCO (2013)). Moreover, if needed, additional cofiring strategies can be evaluated by simply increasing the size of L. Accordingly, let the binary variable Y_{lj} ($\forall l \in L; j \in \mathcal{C}$) take the value 1 if $B_j = \beta_l$ and 0 otherwise. The binary variables Y_{lj} represents the cofiring strategy $\beta_l, l \in L$ adopted by plant j, therefore, $B_j = \sum_{l \in L} \beta_l Y_{lj}$, where $\sum_{l \in L} Y_{lj} = 1$. Furthermore, in order to ease exposition we let $m_{lj} := M_j^b(B_j = \beta_l)$, $v_{lj} := V_j(B_j = \beta_l)$, $\mathcal{I}_{lj} := \mathcal{I}(B_j = \beta_l)$, and $s_{lj}^c := S_j^c(B_j = \beta_l)$. The optimization model for the utilitarian approach can be formulated by the following mixed integer bilinear program (MIBP). We refer to this as model (UB).

$$\text{(UB)} \qquad \max : U(\mathbf{T}, \mathbf{Y}) = \sum_{l \in L} \sum_{j \in \mathcal{C}} m'_{lj} T_j Y_{lj} + \sum_{l \in L} \sum_{j \in \mathcal{C}} (s_{lj}^c - v_{lj} - \mathcal{I}_{lj}) Y_l j \tag{5a}$$

s.t.

$$\sum_{l \in L} Y_{lj} = 1, \ \ \forall j \in \mathcal{C}, \tag{5b}$$

$$\sum_{l \in L} \sum_{j \in \mathcal{C}} m_{lj} Y_{lj} \leq b, \tag{5c}$$

$$\sum_{l \in L} \sum_{j \in \mathcal{C}} m'_{lj} T_j Y_{lj} \leq g, \tag{5d}$$

$$T_j \in [t^{min}, t^{max}], \ \ \forall j \in \mathcal{C}, \tag{5e}$$

$$Y_{lj} \in \{0, 1\}, \ \ \forall l \in L, j \in \mathcal{C}, \tag{5f}$$

where m'_{lj} is the amount of renewable energy produced at plant j under strategy β_l and $m'_{lj} = H^b m_{lj}$ (H^b is the heating value of biomass feedstock). In this formulation, constraints (5b) guarantee that each plant will select exactly one cofiring strategy, and constraint (5c) sets an upper bound on the total amount of biomass available for cofiring. Constraint (5d) limits the total revenues when tax savings are less than or equal to the available budget, and constraints (5e) set bounds for $\mathbf{T}$, while constraints (5f) are the binary variables.

Model (UB) is non-convex due to the presence of mixed integer bilinear terms T_jY_{lj} in the objective function and constraints. Now, we provide a tight linear relaxation of the model using the McCormick relaxation technique (McCormick 1976). This relaxation converts model (UB) into a mixed integer linear program (MILP). Furthermore, since Y_{lj}'s are binary variables, this relaxation is tight (Adams and Sherali 1993). Based on this method, a convex relaxation of a non-convex functions is obtained using convex over-estimators and under-estimators of the function over its domain. Accordingly, the MILP formulation for the utilitarian model is

$$\text{(UL)} \qquad \max : U(\mathbf{T}, \mathbf{Y}, \mathbf{W}) = \sum_{l \in L} \sum_{j \in \mathcal{C}} m'_{lj} W_{lj} + \sum_{l \in L} \sum_{j \in \mathcal{C}} (s^c_{lj} - v_{lj} - \mathcal{I}_{lj}) Y_l j \tag{6a}$$

s.t.

$$(5b), (5c), (5e), (5f),$$

$$\sum_{l \in L} \sum_{j \in \mathcal{C}} m'_{lj} W_{lj} \leq g, \tag{6b}$$

$$W_{lj} \geq t^{min} Y_{lj}, \ \ \forall l \in L, j \in \mathcal{C}, \tag{6c}$$

$$W_{lj} \geq t^{max} Y_{lj} + T_j - t^{max}, \ \ \forall l \in L, j \in \mathcal{C}, \tag{6d}$$

$$W_{lj} \leq t^{max} Y_{lj}, \ \ \forall l \in L, j \in \mathcal{C}, \tag{6e}$$

$$W_{lj} \leq t^{min} Y_{lj} + T_j - t^{min}, \ \ \forall l \in L, j \in \mathcal{C}, \tag{6f}$$

$$W_{lj} \in \mathbb{R}^n_+, \ \ \forall l \in L, j \in \mathcal{C}, \tag{6g}$$

where the optimal solution of the model (UL) provides an optimal solution to the model (UB).

4.3 Max-Min Optimization Model

In this section we propose an optimization model for the max-min fairness scheme, which identifies a tax incentive to maximize the minimum utility of participating plants. That is,

$$\max \min_{j \in \mathcal{C}} \sum_{l \in L} m'_{lj} W_{lj} + \sum_{l \in L} (s^c_{lj} - v_{lj} - \mathcal{I}_{lj}) Y_l j, \tag{7}$$

s.t.

$$(5b), (5c), (5e), (5f), (6b) - (6g).$$

We can transform this model into an MILP model as follows:

$$(\text{MM}) \qquad \max Z, \tag{8a}$$

s.t.

$$Z \le \sum_{l \in L} m'_{lj} W_{lj} + \sum_{l \in L} (s^c_{lj} - v_{lj} - \mathcal{I}_{lj}) Y_l j, \;\; j \in \mathcal{C}, \tag{8b}$$

$$(5b), (5c), (5e), (5f), (6b) - (6g).$$

The optimal solution of the model (MM) will provide the necessary information to evaluate the relative fairness loss for the proposed PTC schemes.

5 Designing Flexible PTC Schemes

This section proposes flexible tax incentive schemes with respective optimization models. These flexible incentives are step-wise schemes that are functions of plant capacity and the cofiring ratio. The capacity-based scheme for compensation could provide more support for small-capacity plants to help manage uncertainties associated with adopting new technologies. The ratio-based scheme compensates plants based on the ratio of biomass-to-coal used. Since high-ratio cofiring is known to be more expensive than small-ratio cofiring and plants often need to undergo some infrastructural changes for high ratio cofiring, the ratio-based scheme provides greater support for such decisions.

5.1 Ratio-Based Scheme

This scheme rewards plants based on the cofiring strategy selected. Under such a scheme, the tax credit received by plant j, T_j, is proportional to the cofiring strategy adopted, B_j. We start with partitioning the set of cofiring strategies L into K subsets, such that $L_k = \{l \in L | \delta_{k-1} \le \beta_l < \delta_k\}$ for $k = 1, \ldots, K$ and $0 = \delta_0 < \delta_1 < \ldots < \delta_K$. This scheme could provide larger incentives to plants that adopt higher cofiring ratios (see Figure 1).

In order to capture the structure of PTC under the ratio-based scheme, we introduce variables

$\mathcal{T}_k, k = 1, \ldots, K$ as follows

$$T_j = \begin{cases} \mathcal{T}_1 & 0 \leq B_j < \delta_1 \\ \vdots & \\ \mathcal{T}_K & \delta_{K-1} \leq B_j < \delta_K \end{cases} \qquad \forall j \in \mathcal{C}$$

where $t_k^{min} \leq \mathcal{T}_k \leq t_k^{max}$ for $k = 1, \ldots, K$, and $t_{k-1}^{max} \leq t_k^{min}$ for $k = 2, \ldots, K$. Also note that $t_1^{min} = t^{min}$ and $t_K^{max} = t^{max}$ to keep the values for PTCs within the limits defined by resource set T. The optimization model for the ratio-based PTC scheme is

$$\text{(RS)} \qquad \max : U^{\mathbb{S}}(\boldsymbol{\mathcal{T}}, \mathbf{Y}, \mathbf{W}) = \sum_{l \in L} \sum_{j \in \mathcal{C}} m'_{lj} W_{lj} + \sum_{l \in L} \sum_{j \in \mathcal{C}} (s_{lj}^c - v_{lj} - \mathcal{I}_{lj}) Y_l j \tag{9a}$$

s.t.

$$(5b), (5c), (5f), (6g),$$

$$W_{lj} \geq t_k^{min} Y_{lj}, \;\; \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{9b}$$

$$W_{lj} \geq t_k^{max} Y_{lj} + \mathcal{T}_k - t_k^{max}, \;\; \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{9c}$$

$$W_{lj} \leq t_k^{max} Y_{lj}, \;\; \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{9d}$$

$$W_{lj} \leq t_k^{min} Y_{lj} + \mathcal{T}_k - t_k^{min}, \;\; \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{9e}$$

$$\mathcal{T}_k \in [t_k^{min}, t_k^{max}], \;\; k = 1, \ldots, K. \tag{9f}$$

Note that this scheme is simpler to implement compared to the utilitarian approach since, instead of deciding a separate PTC for each plant, each plant will have K options (i.e. $K = 2, 3, \ldots$) for PTC, depending on the levels of renewable energy generated.

Proposition 1. The optimal objective function value of (RS) is a lower bound to the optimal objective function value of the utilitarian model (UL).

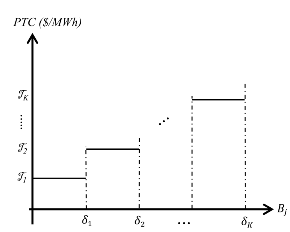


Figure 1: PTC versus cofiring ratio in the ratio-based scheme

Proof: See the Appendix B.

5.2 Capacity-Based Scheme

This scheme rewards plants based on their capacity, i.e. small-sized plants receive a higher PTC than large-sized plants, so smaller-capacity plants have an incentive to participate in cofiring. It is often observed that smaller plants can hardly overcome the burdens of implementing cofiring technology (Toke 2005). Considering the significant number of small and average coal plants in the U.S. 48% of coal plants in the country have less than 250 MW capacity (see Appendix B.) encouraging these plants to utilize biomass resources would help with nationwide demands to increase renewable energy production. Similar capacity-based incentives are in place in some European countries. For instance, in Ireland, small biomass CHP plants receive about 16% higher FITs compared to larger facilities (IEA-ETSAP and IRENA 2013).

Following an approach similar to the ratio-based schemes discussed above, coal plants are classified by partitioning the set C into K subsets $C_k = \{j \in \mathcal{C} | \nu_{k-1} \leq N_j < \nu_k\}$ for $k = 1, \ldots, K$ and $0 = \nu_0 < \nu_1 < \ldots < \nu_K$. As depicted in Figure 2, the biggest PTCs are provided in descending order, with the smallest power plants receiving the largest credits and the largest accepting the smallest.

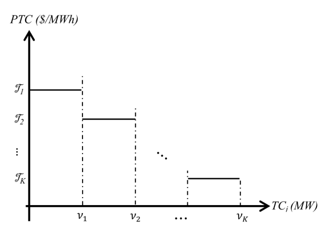


Figure 2: PTC versus plants' capacity in the capacity-based scheme

The variables $\mathcal{T}_k, k = 1, \ldots, K$ are defined to capture the proposed scheme in the optimization model:

$$T_j = \begin{cases} \mathcal{T}_1 & 0 \leq N_j < \nu_1 \\ \vdots & \\ \mathcal{T}_K & \nu_{K-1} \leq N_j < \nu_K \end{cases} \qquad \forall j \in \mathcal{C}$$

where $t_k^{min} \leq \mathcal{T}_k \leq t_k^{max}$ for $k = 1, \ldots, K$, and $t_{k-1}^{max} \geq t_k^{min}$ for $k = 2, \ldots, K$. Also, $t_K^{min} = t^{min}$ and

$t_1^{max} = t^{max}$. The optimization model for the capacity-based PTC scheme can be represented as

$$\text{(CS)} \quad \max : U^{\mathbb{S}}(\mathbf{\mathfrak{T}}, \mathbf{Y}, \mathbf{W}) = \sum_{l \in L} \sum_{j \in \mathcal{C}} m'_{lj} W_{lj} + \sum_{l \in L} \sum_{j \in \mathcal{C}} (s^c_{lj} - v_{lj} - \mathcal{I}_{lj}) Y_l j \tag{10a}$$

s.t.

$(5b), (5c), (5f), (6g)$,

$$W_{lj} \geq t_k^{min} Y_{lj}, \ \ \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{10b}$$

$$W_{lj} \geq t_k^{max} Y_{lj} + \mathfrak{T}_k - t_k^{max}, \ \ \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{10c}$$

$$W_{lj} \leq t_k^{max} Y_{lj}, \ \ \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{10d}$$

$$W_{lj} \leq t_k^{min} Y_{lj} + \mathfrak{T}_k - t_k^{min}, \ \ \forall l \in L_k, k = 1, \ldots, K, \forall j \in \mathcal{C}, \tag{10e}$$

$$\mathfrak{T}_k \in [t_k^{min}, t_k^{max}], \ \ k = 1, \ldots, K. \tag{10f}$$

Proposition 2. The optimal objective function value of (CS) is a lower bound to the optimal objective function value of the utilitarian model (UL).

Proof: See Proposition 1 proof.

6 Numerical Results

In this section we design a case study and provide managerial insights into tax incentives for biomass cofiring. First, we present the case study which is developed using data from nine southeastern U.S. states because the region is rich in biomass. Next, we compare the computational performance of the linear relaxation of bilinear models. Finally, the results of the sensitivity analysis on the PTC schemes are summarized, and managerial insights are provided.

6.1 Case Study Development

This case study focuses on the following nine states located in the southeast U.S.: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Tennessee. The data about biomass availability comes from the Knowledge Discovery Framework (KDF) database provided by the Oak Ridge National Laboratory (Oak Ridge National Laboratory 2013). The database provides detailed, county-level information about the availability of different types of biomass feedstock, such as forest products and residues, as well as agricultural products and residues. This study only focuses on woody biomass since it is shown to be the biomass of choice for cofiring projects (Fernando 2005). The data about the characteristics of existing coal-fired power plants, such as nameplate capacity, capacity factor, and operational hours, is provided by the U.S. Energy Information Administration (EIA, 2010).

The data about capital and O&M costs are collected from related articles in the literature. Different references in the literature estimate capital costs for biomass power that range between \$50 and \$400 per kW of installed capacity. The main reason for this variability in cost estimation is the difference among the quality of energy fuels analyzed and the status of the existing infrastructures at respective power plants (IEA-ETSAP and IRENA 2013). These costs do not seem to be significant when cofiring ratio is 5% -10% because the existing infrastructure of the coal plants can efficiently be utilized without additional investments. According to Sondreal et al. (2001), the expected capital cost is usually close to \$50 per kW of installed capacity when cofiring ratio is less than 5%. These costs are typically between \$150 and \$300 per kW of installed capacity when cofiring ratio is 10-20% (Zhang et al. 2009). Cofiring at a ratio higher than 20% typically impacts negatively because of increased risk to the boilers' fouling and slagging. For cofiring ratios greater than or equal to 25%, coal plants typically invest in new boilers to reduce the impacts of slagging and corrosion (Basua et al. 2011). We assume that capital costs are \$400 per kW of installed capacity when cofiring is at a ratio between 25% and 50%. Most of the existing cofiring projects have adopted strategies which displace up to 50% coal (IEA-ETSAP and IRENA 2013). Equation (11) presents capital costs as a function of cofiring ratio. The O&M costs are estimated to be 2.5-3.5% of the overall capital costs.

$$\mathcal{C}(B_j) = \begin{cases} \$50/kW & 0.00 < B_j \leq 0.05 \\ \$150/kW & 0.05 < B_j \leq 0.15 \\ \$300/kW & 0.15 < B_j \leq 0.25 \\ \$400/kW & 0.25 < B_j \leq 0.50 \end{cases} \qquad \forall j \in \mathcal{C}. \tag{11}$$

Using biomass results in an efficiency loss and reduces the plants' nameplate capacity. The plants' nameplate capacity is used to calculate the investment costs since the retrofit costs are calculated based on nameplate capacity (Cuellar 2012).

We set $t^{min} = 0\$/MWh$ and $t^{max} = \$20/MWh$. We use the same bounds for all schemes. In order to keep the proposed fair schemes simple, the following setups are considered. For the step-wise schemes proposed, we only consider $K = 2$ and $K = 3$. This approach is inspired by common practices in step-wise FIT schemes (see, for example, Germany's FIT policies in Couture et al. (2010)). The corresponding (RS) models developed are referred to as the *2-level* and *3-level* ratio-based schemes. The selected ranges for 2-level ratio-based schemes are

$$T_j = \begin{cases} \mathcal{T}_1 & 0 \le B_j < 0.05, \\ \mathcal{T}_2 & 0.05 \le B_j < 0.5, \end{cases} \qquad \forall j \in \mathcal{C},$$

where $\$0 \le \mathcal{T}_1 \le \$10$, and $\$10.01 \le \mathcal{T}_2 \le \$20$. And for the 3-level ratio-based schemes,

$$T_j = \begin{cases} \mathcal{T}_1 & 0 \le B_j < 0.05 \\ \mathcal{T}_2 & 0.05 \le B_j < 0.25 \\ \mathcal{T}_3 & 0.25 \le B_j < 0.5 \end{cases} \qquad \forall j \in \mathcal{C},$$

where $\$0 \le \mathcal{T}_1 \le \$10$, $\$10.01 \le \mathcal{T}_2 \le \$15$, and $\$15.1 \le \mathcal{T}_3 \le \$20$.

Similarly, for the *capacity-based schemes*, we partition the set of coal plants $\mathcal{C}$ into two and three subsets based on capacity by setting $K = 2$ and $K = 3$. The corresponding (CS) models developed are referred to as the *2-level* and *3-level* capacity-based schemes. The corresponding ranges for 2-level and 3-level capacity-based schemes are, respectively,

$$T_j = \begin{cases} \mathcal{T}_1 & 0 \le N_j < 500 \\ \mathcal{T}_2 & 500 \le N_j \end{cases} \qquad \forall j \in \mathcal{C},$$

where $\$10.01 \le \mathcal{T}_1 \le \$20$, and $\$0 \le \mathcal{T}_2 \le \$10$,

$$T_j = \begin{cases} \mathcal{T}_1 & 0 \le N_j < 500 \\ \mathcal{T}_2 & 500 \le N_j < 2000 \\ \mathcal{T}_3 & 2000 \le N_j \end{cases} \qquad \forall j \in \mathcal{C},$$

where $\$15.1 \le \mathcal{T}_1 \le \$20$, $\$10.01 \le \mathcal{T}_2 \le \$15$, and $\$0 \le \mathcal{T}_3 \le \$10$.

The total number of potential cofiring strategies in all cases is set to $|L| = 201$, thus, each plant can potentially cofire at ratios of $B_j \in L = \{0, 0.0025, 0.005, \dots, 0.5\}$.

6.2 Computational Results

We model the MIBP problem (UB) in GAMS 23.7 and solve the problem using BONMIN and COUENNE solver packages. We model the corresponding MIP approximation, model (UL), in AMPL 20141128 and solve it using GUROBI 6.5.0. The computations are done in a Dell personal computer with Intel(R) Core(TM) $i5-4300U$ CPU 2.50 GHz processor, and with 8.00 GB of RAM.

The performance measures used for models (UB) and (UL) are presented in Table 1. This table summarizes the size of the problems solved, the running time in CPU seconds, and the optimality gap reported by each solver. Each problem corresponds to one of the states in the southeastern U.S. The last problem set (SE), corresponds to the whole Southeast. Two stopping criteria apply: (i) CPU running time of no more than 4,000 seconds, and (ii) relative optimality gap of no more than e^{-06}. The results from Table 1 indicate that using McCormick relaxation leads to finding the

Table 1: The performance of the solution approaches proposed

		Model (UB)						Model (UL)			
	Nr. of	Number of		BONMIN		COUENNE		Number of		Gurobi	
Problem	Plants	Variables	Constraints	CPU	Gap	CPU	Gap	Variables	Constraints	CPU	Gap
AL	11	4,000	2,211	13	$4.06e^{-01}$	124	e^{-06}	4,411	8,813	0.4	e^{-06}
AR	4	352	804	6	$1.00e^{-06}$	40	e^{-06}	1,604	3,206	0.2	e^{-06}
FL	15	4,000	3,015	17	$3.76e^{-01}$	309	e^{-06}	6,015	12,017	0.9	e^{-06}
GA	12	2,965	2,814	16	$1.00e^{-06}$	253	e^{-06}	5,614	11,216	0.3	e^{-06}
LA	4	4,000	804	6	$8.19e^{-01}$	29	e^{-06}	1,604	3,206	0.8	e^{-06}
MS	5	4,000	1,005	7	$4.66e^{-01}$	51	e^{-06}	2,005	4,007	0.3	e^{-06}
NC	23	1,531	5,025	27	$5.00e^{-06}$	157	e^{-06}	10,025	20,027	0.4	e^{-06}
SC	16	4,000	3,216	18	$8.79e^{-01}$	925	e^{-06}	6,416	12,818	0.4	e^{-06}
TN	9	4,000	2,010	12	$4.92e^{-01}$	138	e^{-06}	4,010	8,012	0.3	e^{-06}
SE	99	4,000	20,904	106	$5.00e^{-03}$	4,000	$8e^{-03}$	41,704	83,306	2.5	e^{-06}

optimal solution for all problems in less than 3 CPU seconds, an approach which is much more efficient than using off-the-shelf nonlinear solvers. Additionally, for the majority of the problems solved, BONMIN stopped because it reached the maximum running time without providing the optimal solution.

6.3 Comparing the PTC Schemes

This section uses numerical analyses to evaluate the impacts that the utilitarian, max-min and other PTC schemes have on profitability and renewable energy production. Table 2 summarizes the total profits, and Table 3 summarizes the total biomass utilized when solving the models proposed (maximum values are in bold). For these instances the available budget of individual states is set to $\$300M$. For the SE problem set, the budget is set at $\$3,000M$. Since these numbers may not reflect the budgets actually available, sensitivity analyses are also conducted based on a broad range of available budgets (Figures 3 and 4).

Results show that a utilitarian approach maximizes the total profits in the supply chain. Similar results are found when solving the flat rate model. The profits of the capacity-based models are typically lower, with very few exceptions, than the profits from the ratio-based models. Therefore, the relative loss in profits, as indicated by the PoF, is greatest for the capacity-based model: The average PoF is 18%, and the maximum PoF is 70%, compared to the PoF for ratio-based models of only 3.3%. For a few problems, the ratio-based model gives the same results as the utilitarian approach. The average PoF for flat rate models is 0%. Table 3 presents the optimal

Table 2: Total profits under the utilitarian approach and other schemes ($\$10^6$)

Problem	(UL)	(MM)	(CS)		(RS)		Flat rate
			2-level	3-level	2-level	3-level	
AL	**268.53**	173.43	240.01	251.36	265.03	256.33	**268.53**
AR	**163.53**	141.33	48.43	118.31	**163.53**	144.56	**163.53**
FL	**273.69**	106.42	234.84	260.38	269.85	255.32	**273.69**
GA	**271.40**	145.83	247.02	258.12	268.62	260.85	**271.40**
LA	**176.07**	146.08	64.98	134.90	175.24	157.82	**176.07**
MS	**227.96**	**227.96**	176.45	184.26	**227.96**	218.71	**227.96**
NC	**275.80**	16.52	256.60	265.11	272.33	265.13	**275.80**
SC	**270.68**	16.60	251.10	263.05	269.53	259.27	**270.68**
TN	**268.57**	25.16	186.46	232.63	268.15	253.36	**268.57**
SE	**2,675.18**	1,235.45	2,347.55	2,490.96	2,666.20	2,551.38	**2,675.18**

solution of the problems in terms of the percentage of the biomass available and how much is being used. The maximum values for each problem appear in bold. While a utilitarian approach maximizes profits, such an approach does not necessarily maximize the amount of biomass used at a plant or, consequently, the amount of renewable electricity generated. Indeed, the utilitarian approach, compared to the other schemes, uses the least amounts of biomass. Likewise, the flat rate approach does not maximize the amount of biomass nor renewable energy. On the other hand, the capacity-based models use the maximum amount of biomass. Two problem instances in the 3-level capacity-based model, AR and SC, use 100% of the biomass available in the region. The average biomass usage for 2-level capacity-based models is about 80% of the total amount available. On average, biomass usage for the 2-level and 3-level ratio-based models is 56% and 67%, respectively, of the total amount available. These results indicate that the flat rate model, while easy to implement, is not as effective as the capacity-based or ratio-based models in encouraging power plants to generate renewable energy. The ratio-based schemes are sensitive to the value

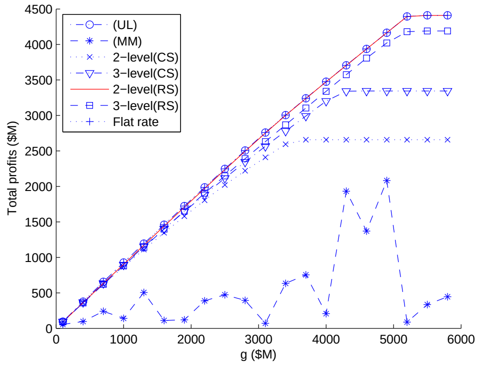
Table 3: Optimal biomass usage under utilitarian approach and other schemes (in %)

Problem	(UL)	(MM)	(CS)		(RS)		Flat rate
			2-level	3-level	2-level	3-level	
AL	48.68	**94.73**	79.45	65.08	48.73	62.67	48.68
AR	54.05	56.72	**90.09**	66.67	54.05	54.05	54.05
FL	84.62	98.19	**100.00**	**100.00**	84.62	99.99	84.62
GA	48.29	71.77	**79.34**	62.19	48.38	62.74	48.29
LA	35.34	35.37	**50.56**	44.18	35.32	39.70	35.34
MS	41.91	41.91	**62.86**	55.21	41.91	43.17	41.91
NC	42.32	**99.87**	65.50	54.23	42.32	54.94	42.32
SC	66.43	**98.85**	89.29	78.02	66.61	83.59	66.43
TN	84.78	81.36	**100.00**	**100.00**	84.80	98.66	84.78
SE	57.46	**90.78**	85.09	74.73	57.49	69.56	57.46
Average	56.39	76.96	**80.22**	70.03	56.42	66.91	56.39

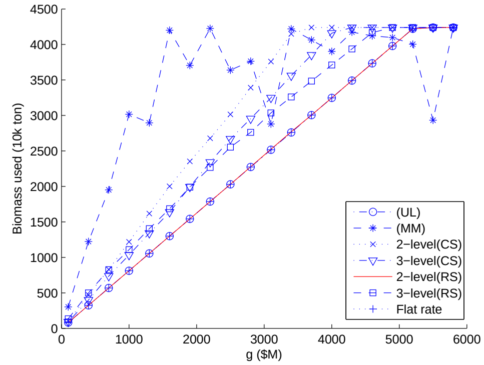
of cofiring ratio B_j, which is directly related to the decision variable Y_{lj} (recall that $Y_{lj} = 1$ if $B_j = \beta_l$). This decision variable appears in the profit maximizing objective function along with the constraints (5b)-(5d), and when higher incentives T_j are provided for bigger cofiring ratios, profits are maximized rather than enforcing more participation or renewable energy generation (the term $T_j Y_{lj}$ positively impacts the objective function). Note that, B_j is not a direct measure of plant characteristics, i.e. two plants with equal cofiring strategies may have different sizes, capacity factors, etc. On the other hand, the capacity-based schemes are directly related to the plants installed capacity N_j, a parameter that only appears in the objective function and biomass limit constraint (5c) (recall that the biomass amount m_{lj} is a function of N_j, F_j, and O_j - Appendix B.). Fixing the incentive value for different ranges of N_j does not help improve the objective function, unlike the case for the ratio-based approach.However, providing higher incentives for plants with smaller capacities better increases the utilization of the biomass limit constraint, which leads to increased renewable energy production. The capacity-based approach more accurately represents power plant characteristics, and effective capacity-based schemes may encourage more plants to participate and produce more renewable energy.(See Appendix A. for a simple numerical example).

Our analysis show that the total budget available to fund incentives such as the PTC can significantly impact renewable energy generation and plant profitability. In Figure 3(a) we plot profits versus budget limit, and in Figure 3(b) we plot the amount of biomass used versus budget limit. These plots correspond to the SE problem set, and for all the proposed schemes. Based on these results, the utilitarian, the flat-rate and 2-level ratio-based schemes maximize profits. The 2-level capacity-based scheme results in largest biomass usage; and the utilitarian, flat-rate, and 2-level ratio-based schemes use the least amount of biomass. The results indicate that, the profits of the 2-level capacity-based model do not change for a budget greater than \$3,500M. This is mainly because the plants have used all the available biomass in the region. A similar observation is made for the utilitarian, flat rate and 2-level ratio-based schemes. However, these schemes reach this point when the budget equals \$5,300M. That is, the same amount of renewable electricity is generated when implementing the 2-level ratio-based scheme -as compare to the utilitarian, flat rate and 2-level ratio-based schemes- for about \$1,500M less.

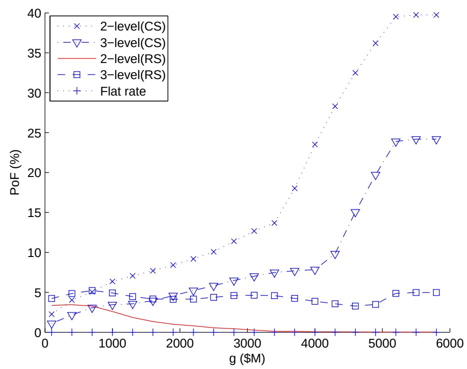
The analysis presented here shows that the total budget available to fund incentives like the PTC can significantly impact renewable energy generation and plant profitability. Figure 3(a) plots profits against budget limits, and Figure 3(b) shows the amount of biomass used versus budget limits. These plots correspond to the SE problem set and all the proposed schemes. Based on these results, the utilitarian, flat rate, and 2-level ratio-based schemes maximize profits. The 2-level capacity-based scheme results in the largest biomass usage, and the utilitarian, flat rate, and 2-level ratio-based schemes use the least amount of biomass. The results indicate that the profits of the 2-level capacity-based model do not change for a budget greater than \$3,500M because the plants will have used all the available biomass in the region. A similar observation is made for the utilitarian, flat rate, and 2-level ratio-based schemes. However, these schemes reach this point when the budget equals \$5,300M. The same renewable amount of renewable electricity is generated when implementing the 2-level ratio-based scheme, as compared to the utilitarian, flat rate, and 2-level ratio-based schemes, for about \$1,500M less. Figure 3(c) plots the PoF against budget availability. This graph shows that the values of PoF are sensitive to the available budget. When the budget is less than $\$800M$, the ratio-based schemes result in the highest PoF. When the budget is greater than $\$800M$, the capacity-based schemes result in the highest PoF. Recall that PoF measures the relative gap between the utilitarian and fairness schemes, so as PoF increases, the relative gap between these two approaches increases as well. On the other hand, capacity-based schemes result in plants using the most biomass, as demonstrated above. These results could help policy makers



(a)



(b)

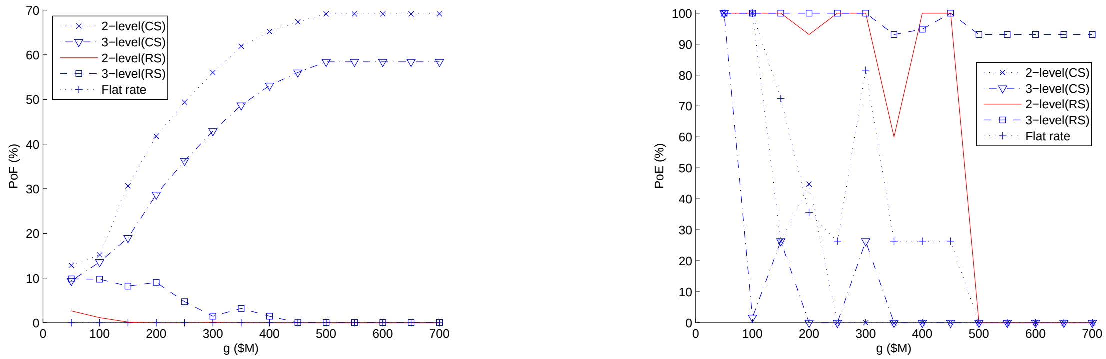


(c)

Figure 3: (a) Total profits, (b) biomass usage, and (c) PoF, versus the total budget for SE

design credit allocation policies that balance efficiency and fairness. Capacity-based schemes result in the most renewable energy generated, while ratio-based schemes balance profitability and biomass utilization. PoE values for the SE problem set were 100% because at least one plant decided not to cofire ($\underline{U}^{\mathbb{S}} = 0$) no matter what budget level was tested. However, not all of the individual states embraced such a policy (for instance, see Mississippi's results below).

The PoF and PoE values for different levels of budget availability in Mississippi are depicted in 4. Similar to the case of problem set SE, by increasing the available budget, the capacity-based schemes tend to result in a larger loss of profits (48% on average) than the flat rate (0%) and ratio-based schemes (2% on average). However, capacity-based schemes lead to smaller PoE than other schemes. For a budget level of $\$250M$, both the 2-level and 3-level capacity-based schemes result in zero PoE, while the ratio-based schemes both lead to highest relative PoE of 100%. Table



(a) (b)

Figure 4: (a) The PoF, and (b) PoE, versus the total budget for the state of Mississippi

4 summarizes the optimal values of T_j and biomass cofiring strategy B_j for each of the plants in Mississippi. These results suggest: (i) All the plants participate in cofiring in the 3-level capacity-based model, but plant participation is lowest in this model, followed by the utilitarian and flat rate models. (ii) High rate tax incentives do not guarantee that every plant participates in cofiring. The flat rate model provides the same incentive ($19.99 per MWh) to all plants; however, only a few plants participate since the savings from such an incentive do not cover their expenses. Plant

Table 4: Optimal PTCs and cofiring strategies for MS

Plant	Capacity (in MW)	(UL)		(MM)		(CS)				(RS)				Flat rate	
						2 level		3 level		2 level		3 level			
		T^*	B^*	T^*	B^*	T^*	B^*	T^*	B^*	T^*	B^*	T^*	B^*	T^*	B^*
1	513	18.48	0.00	8.03	0.10	10.00	0.00	15.00	0.04	0.00	0.00	0.00	0.00	19.99	0.00
2	59	0.00	0.00	20.00	0.15	20.00	0.03	20.00	0.15	0.00	0.00	0.00	0.00	19.99	0.00
3	400	20.00	0.15	16.45	0.40	20.00	0.50	20.00	0.50	20.00	0.15	20.00	0.35	19.99	0.15
4	2229	20.00	0.15	3.73	0.10	10.00	0.14	10.00	0.04	20.00	0.14	15.00	0.15	19.99	0.15
5	1215	20.00	0.04	10.41	0.43	10.00	0.04	15.00	0.15	20.00	0.06	0.00	0.00	19.99	0.04

1, although of greater capacity than plant 3, participates only in the 3-level capacity-based scheme because the plant currently uses lignite coal, and other plants use bituminous coal (see Appendix B.). Lignite coal has a smaller heating value and is cheaper than bituminous coal, so the savings from displacing coal are not significant. Thus, this plant does not find biomass cofiring economically attractive.

6.4 Managerial Insights

We now summarize some observations and insights produced by our case study. Provided that there is a limited budget to support biomass cofiring through PTC:

- *The flat rate model leads to the fewest kWh of renewable energy produced and favors large-sized plants.* The flat rate model behaves similar to the utilitarian model. Such a model maximizes system's efficiency, that is, total profits. However, these profits are collected by the large-sized plants mainly.

- *Capacity-based models lead to the most renewable energy produced and increased number of participating plants in cofiring.* The 2-level and/or 3-level capacity-based models result in plants utilizing the greatest amount of biomass in all the problems solved, which implies that plants will generate the most renewable energy if these incentive models are implemented. All the plants, smallest to largest, participate in the 3-level capacity-based model. While this scheme does not maximize a systems efficiency, it distributes the assigned budget more fairly to all the plants in the region.

- *Ratio-based models balance the PoF.* Under these models, smaller amounts of renew- able energy are produced, but more profits are obtained than from the capacity-based models. These models generate more renewable energy than flat rate and utilitarian models, but the proposed models also produce lower profits.

- *The size of the budget influences biomass cofiring decisions both for power plants and governments.* Ratio- based models lead to plants using more biomass than capacity-based models when budgets are relatively small; capacity-based models lead to plants using more biomass when budgets are larger. This fact impacts governmental decisions about which allocation scheme to use and the size of tax rates. From the plants point of view, the selected scheme and the size of tax rates impact decisions about whether to participate in cofiring and, if so, how much biomass to cofire.

7 Conclusions

This study investigates the impacts of governmental incentives on renewable energy generation via biomass cofiring in coal-fired power plants. The literature indicates that biomass cofiring is readily available technology that is relatively easy to implement and will significantly reduce CO_2 emissions among existing coal-fired power plants.

This paper considers a resource allocation framework that allows the government to encourage power plants to cofire by providing credits in the form of the PTC to help plants absorb the additional costs incurred from biomass cofiring. We start with developing the utilitarian and max-min models which guarantee to find an allocation scheme to maximize achievable total profits and highest minimum profit of participating plants, respectively. These approaches provide a basis for evaluating the proposed schemes in terms of relative loss in system's efficiency and fairness. Next, flexible PTC schemes are proposed, based both on plants capacity and the cofiring strategies used, to incorporate fairness in these allocation problems. The capacity-based and ratio-based schemes offer more financial support to smaller plants and those adopting higher cofiring ratios, respectively. The corresponding optimization models are non-convex, which are computationally difficult to solve. We reformulate the non-convex MIP as a linear MIP by using the McCormick relaxation of bilinear terms with binary variables.

Computational experiments are conducted using case studies based on information from nine southeastern U.S. states. We first compare the computational performance of solving linear MIPs by using Gurobi and non-convex MIPs by using BONMIN and COUENNE. Results show that the MIP solver outperforms the other two solvers in terms of CPU time and optimality gap for all of the instances. Then, we solve the case studies when ratio-based and capacity-based scheme are applied in utility optimization models.

This study demonstrates the potential of different governmental incentives to promote renewable energy production via biomass cofiring. Our results indicate that the existing flat PTC could maximizes system's efficiency, but does not make the best use of the available biomass to generate renewable energy. One the other hand, capacity-based schemes result in highest levels of biomass utilization in most of the cases. Roughly speaking, it seems that ratio-based schemes provide a good balance between profitability and renewable energy production. However, the ratio-based schemes do not necessarily offer an economically attractive option for some plants (see the results from Mississippi). These observations provide insights to policy makers in state and federal levels to assist them in designing better tax scheme frameworks, considering available budgets and emission reduction goals.

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Appendix A

Note on the increased biomass utilization under capacity-based schemes. The results of Tables 2. and 3. indicate that capacity-based schemes lead to higher levels of biomass utilization than with the ratio-based schemes, in most cases. This increased use of biomass seems counter-intuitive since, under the ratio-based schemes, plants that adopt higher cofiring ratios have the opportunity to receive higher incentives and may, we hypothesize, use more biomass overall because of the optimization models structure. This phenomenon can be illustrated with an example of a single power plant model. Model (UB) for a single plant can be represented as follows:

$$\max : \alpha^1 TB - \alpha^2 B \tag{1a}$$

s.t.

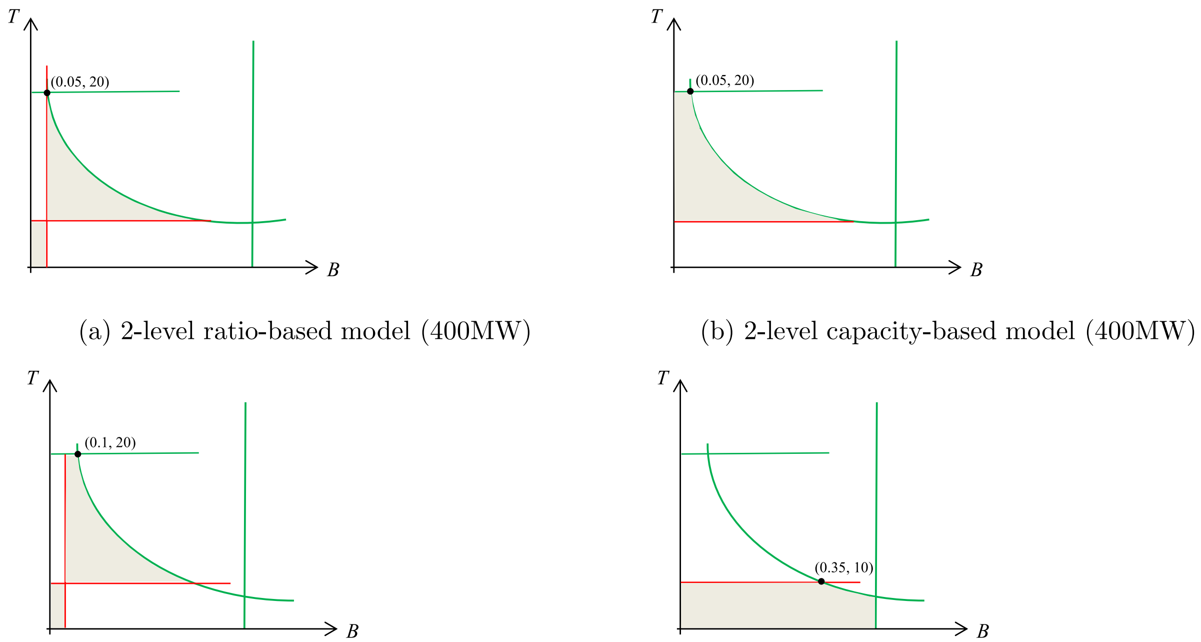
$$\sum_{j \in \mathcal{C}} \alpha^3 B \leq b, \tag{1b}$$

$$\alpha^1 TB \leq g, \tag{1c}$$

$$T \in [t^{min}, t^{max}], \tag{1d}$$

$$B \in [0, 0.5]. \tag{1e}$$

Using the 2-level capacity-based and ratio-based schemes explained in Section 6.1., also assume two plants, with capacities 400MW and 2229MW, respectively, falling under the first and second levels of capacity ranges in the 2-level capacity-based scheme. Figure (1) illustrates the feasible region of the model (1) under these schemes and for the two plants. The marked point on each graph represents the optimal solution for the corresponding model. For the smaller plant, T is allowed to chose amounts greater than \$10.01 (Section 6.1.) under the capacity-based scheme, which allows the optimal points for both schemes to be the same values. However, for larger-sized plant, under the capacity-based scheme, T is only allowed to chose amounts less than \$10 and this provides a larger feasibility range for B. Consequently, the optimal point under the ratio-based model results in a smaller value for cofiring ratio. Therefore, a capacity-based model leads to greater B^* than the ratio-based model, despite the fact that ratio-based model provides greater incentive for high-ratio biomass cofiring.



(a) 2-level ratio-based model (400MW)

(b) 2-level capacity-based model (400MW)

(c) 2-level ratio-based model (2229MW)

(d) 2-level capacity-based model (2229MW)

Figure 1: Feasible regions and optimal points for two plants under PTC scheme models

Appendix B

Proposition 1. Proof: The utilitarian approach identifies a PTC rate for each plant that maximizes system-wide profits, accounting for the existing limitations on budget (g) and the biomass supply in the region (b). Note that, for each plant j, T_j can take values within $[t^{min}, t^{max}]$. The proposed ratio-based scheme adds additional constraints to the model. These constraints limit PTC to taking values within smaller subintervals which are all contained within $[t^{min}, t^{max}]$. These additional limitations reduce the size of the feasible region for model (RS). Thus, its objective function value is a lower bound for model (UL). ■

Tax saving function. Each plant $j \in \mathcal{C}$ is characterized by its installed capacity N_j, the plant's capacity factor F_j, and the annual operating hours O_j. These characteristics define the amount of energy (in MWh) generated annually at a plant. The amount of energy, denoted with E_j, is function of N_j, F_j, O_j. Given these plants characteristics the amount of energy generated at a plant is equal to $E_j = N_j * F_j * O_j$. Then, if plant j is to cofire at a ratio of B_j, the amount of renewable energy generated would equal to $E_j * B_j$. Note that, the lower heating values for coal and biomass are not the same. If H^b represents the lower heating value of biomass (in kWh per ton), then the amount of biomass required annually (in tons) to displace coal equals

$$M_j^b(B_j) = \frac{B_j * E_j}{10^{-3} * H^b}. \tag{2}$$

Finally, if T_j represent the amount of PTC received by coal-fired power plant j, the annual saving due to PTC equals

$$S_j^t(T_j, B_j) = T_j * H^b * M_j(B_j).$$

Parameters values.

Table 1: Values assigned for the main parameters used in the study (Wang (2008), IEA-ETSAP and IRENA (2013), US Energy Information Administration (EIA) (2010), Cuellar (2012), US National Renewable Energy Laboratory (NREL) (2004))

Parameter	Unit	Value
FOM	(\$/kWh yr)	12
TPC	(\$/ton)	50
c_f	(/yr)	0.15
c^{ash}	(\$/ton)	10
A	(%)	2
c^{coal} -Bituminous-	(\$/ton)	64.92
c^{coal} -Subbituminous-	(\$/ton)	14.28
c^{coal} -Lignite-	(\$/ton)	20.18
LHV^{bm}	(kWh/ton)	4926.8
LHV^{coal} -Bituminous-	(kWh/ton)	6582.5
LHV^{coal} -Subbituminous-	(kWh/ton)	6154.5
LHV^{coal} -Lignite-	(kWh/ton)	4396.1

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