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# Feasibility of an Adaptable Biorefinery Platform: Addressing the Delivery Scale Dilemma under Drought Risk

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Conversion of biomass to electricity is often not economically feasible as a result of large transportation costs and low output prices. We build a model of an adaptable biorefinery situated at an agri-processing facility that already has biomass on-site and consider the optimal scale of the plant to achieve a price premium by selling peaking power given uncertain biomass deliveries year over year as a result of climatic variability. We find that, for conservative electricity prices, a plant situated near cotton gins in Texas could operate with positive expected net revenue while converting on average only 38% of available biomass for peak electricity prices.

*Key Words:* biomass, biorefinery, drought

**JEL Classifications:** Q4, Q16

Successful conversion of biomass to energy requires the right size, the right price, and the right transportation process. A central economic problem for biomass to energy conversion concerns the conflict between right size and right transportation process—the so-called "delivery scale" dilemma. Large, low average cost processing plants with large feedstock demands often require high transport costs, at least at the margin. By virtue of selling into a commodity market such as gasoline or diesel, there are low prices for the bioenergy output, which makes the process vulnerable to high-cost feedstock requirements in recurrent droughts for still only modest returns. In this article, we explore an alternative bioenergy production process that seeks the "right price" and the "right transportation cost" at the expense of large economies of scale in small-capacity bioenergy plants.

The purpose of this analysis is to determine whether agricultural processing plants that currently dispose of waste biomass can convert that biomass into electricity or other products profitably (as a biorefinery) as an option to increase revenue streams for agricultural producers. In particular, we analyze distributed bioelectricity power plants, primarily in the 8–20 megawatt (MW) size range, that convert biomass on-site at existing agricultural

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processing plants. By targeting production to enter peaking power electricity markets, producers can achieve a considerable price premium. Timing production in this way avoids competition with the electricity pricing market that is driven by very low marginal costs of power from coal. The biomass is centered at an agricultural processing plant (a cotton gin in this example) where waste biomass (in the form of cotton gin residuals) is already transported to the plant along with the commodity to be processed. The use of biomass on hand largely eliminates the transport costs of biomass for bioenergy production. Also peaking power demands are quite local and prices can vary from minute to minute and from node to node (the access points for power delivery) across a single power grid region. At their local supply points, gins may enjoy local niche price advantages in peaking power markets compared with less targeted and typically larger natural gas and liquid fuel plant competitors. Natural gas plants locate nearer to population centers and manage peak demands at a somewhat larger size, yet the highest peak prices in this market area emerge from summer irrigation at rural nodes closer to gins. The peak electric power demanded at these prices is smaller than what is normally supplied by natural gas plants of average size. This makes adding this value stream to a ginning operation attractive to gins located in the area for other economic reasons and at a size where full operating capacity can be used to achieve these prices with no idled potential. The low transportation cost–high niche market price of output overcomes engineering size inefficiencies to secure a robustly profitable power island at a rural cotton gin.

Finally, the flexible size choice in this model directly addresses concerns for drought, which we assert is an obvious problem for any biomass-dependent operation. By accounting for potential regional feedstock shortages, the power island at the gin is sized to produce electricity at a high peaking price target for approximately 3000 hours per year. So plant size fits the local market and can be sized to irregular biomass availability. A larger plant designed so that average costs are low must operate for longer periods and generate revenue almost continuously to recoup fixed costs. That means, at the margin, these plants must sell into a lower valued, undifferentiated product market to be viable. This need to recoup fixed costs by more continuous operation carries a risk that the plant be required to import biomass during periods of low biomass availability. The smaller size, lower fixed cost, and the latitude to time production of the modeled plant add flexibility. The modeled plant produces during nonpeak hours as long as marginal revenue exceeds marginal costs because peak power sales largely recoup fixed costs.

### *Biomass to Bioenergy*

Most economic studies in the bioenergy area treat the single-site bioenergy processing center as built to a size that approximately minimizes operations costs (see, for example, English et al., 2006). However, this bioenergy model corresponds to very large feedstock requirements, and that pressure tends to induce, at the margin, expensive feedstock acquisition strategies (Richard, 2010). Early assessments of gross biomass availability (Haq, 2002; McCarl, 2000) provided initial optimism that raw biomass supplies can make significant contributions to US energy supply. That baseline however does not dictate a singular economic model for biomass to bioenergy conversion. Indeed, biomass supplies are geographically distributed with considerable local variation (U.S. Department of Agriculture, National Agricultural Statistics Service, 2002–2009). Unsurprisingly, economic cost estimates of an array of feedstock delivery options for bioelectricity production find that marginal delivery costs rise quickly with distance (Curtis et al., 2003). Additionally, some biomass to bioenergy conversion models require market structures that are different from current agricultural markets and would require possibly difficult adjustments for US farmers and processers (Epplin and Haque, 2011).

Where the "right price, right size, right transport" technology balance appears to be satisfied is the distributed electric bioenergy market (Richard, 2010; Singh et al., 2010). In particular, smaller distributed bioelectricity plants are more flexible in the choice of size, either because of favorable processing technologies for bioelectricity production (Bruins and Sanders, 2012) or flexibility in the alternative methods to deliver bioenergy products to the market (Tremel, Gaderer, and Spliethoff, 2012).

As bioenergy for power production by locally distributed power systems evolves, opportunities arise to integrate multiple production processes (Facchinetti et al., 2012; Iakovou, Vlachos, and Toka, 2012); this includes multiple value streams drawn from the biomass feedstocks themselves into fully integrated multiproduct biorefineries (Bruins and Sanders, 2012). A key extension of the work presented in this article is to use the extra biomass available during high biomass production years to products other than low-valued incidental power sold at nonpeak power prices. That is, we recognize that the bioelectricity plant can serve as a base, or platform, of a full multiproduct biorefinery. This is possible because the process that we consider to generate electricity can be easily adapted to produce high-value products like ammonia fertilizer or plastics using the same capital already installed for electricity as part of the fixed asset requirements for these other products. Clearly this literature is still in its early phases, but the initial engineering results for such operations are promising. We move this forward by adding economic insights.

This work adds two key economic observations to the literature. First, at smaller sizes in very local areas, there are more opportunities for higher valued market positioning such as peaking power markets. Second, the choice of size also can be a mechanism to adapt to regionally recurring drought. To our knowledge, choice of installed capital in bioenergy models is typically premised on mean (or median) biomass availability, and although some bioenergy models consider water use requirements of biomass crops (Popp, Nalley, and Vickery, 2010), the drought risk inherent in biomass production has not yet been considered, yet adaptation to drought by considering distribution rather than the average of biomass availability goes to the very heart of managing the costs of feedstock availability by strategically choosing operational size. For the local small distributed bioenergy power plant, drought planning accommodation would seem to be essential.

### *Opportunities for Bioenergy in Electricity Markets*

Electricity utilities currently design and build large power plants to satisfy base load electricity demand—a constant supply of electricity that does not vary. Base load power plants are typically coal-fired or nuclear plants and, on startup, can take many hours to reach capacity output. Fuel for base load plants is inexpensive, but the plants are unable to increase or decrease supply to meet fluctuations in electricity demand. To meet peak demand, therefore, electric utilities must also have the ability to generate smaller quantities of electricity to add to the power generated by the larger plants (along with intermediate "load following" plants). These smaller-capacity facilities are called "peaker plants" and can easily be brought into operation when electricity demand rises. Because of the need to quickly respond to changes in demand, the marginal cost of electricity production is highest in the peaker plants, mostly as a result of the cost of the fuels that can be used in such plants. In the United States, most peaker plants burn natural gas to generate electricity.

Utilities occasionally contract with outside producers to supply peaking power rather than build their own peaker plants, and in this article, we investigate the ability of a small biomass-to-electricity plant to provide peaking power electricity to a utility at prices comparable to natural gas peaker plants. Under a renewable portfolio standard, in which power producers are required to generate a certain quantity of electricity from renewable sources, such an agreement may be more attractive to utilities than contracting with a natural gas peaker plant. For example, in our study area, on the Texas High Plains, Texas has a renewable portfolio standard that includes a requirement to have 500-MW of nonwind renewable energy capacity installed by 2025 (Texas State Energy Conservation Office, 2013).

The plant we consider would operate at a cotton gin using waste generated at the gin along with waste from gins no more than 5 miles from the bioenergy plant. Cotton gin trash comprises roughly 50% of the harvest weight of cotton and is currently either disposed of (at a cost to gin operators) or, when possible, sold as a low-quality, low-price cattle feed supplement. In the process we consider, the biomass waste is stored on-site until it is processed through a combined fluidized bed gasifier/generator into a combustible gas that is immediately used to generate electricity. This process is preferable to simply burning cotton gin waste to fuel a boiler and steam turbine because gasification is more efficient and because the high ash content in the gin trash can cause slagging and corrosion, which significantly increases maintenance costs (LePori and Parnell, 1989).

In addition to renewable portfolio standards, electricity generated from cotton gin trash would qualify for a federal (US) production tax credit of $11/megawatt-hour (MWh) during its first 10 years of operation, whereas electricity from other renewable energy sources such as wind, geothermal, and energy from "closed-loop biomass" processes qualifies for a $23/MWh tax credit (House Bill 8, American Taxpayer Relief Act of 2012, 2011–2012). Since cotton gin trash is waste biomass, rather than a dedicated crop, it is classified as "open-loop" and does not qualify for the larger credit.

To determine the efficient size of this operation (defined as MW installed), we build a stochastic operations programming model to jointly solve for the optimal capacity of the power plant and the optimal commitment the operator will assume to meet a peaking power contract, and we do so at a range of prices and policies. The joint determination of the optimal size and the optimal contract additionally considers the uncertainty that is introduced from biomass shortfalls that result from recurrent droughts in the region. We assess if this system is economically viable on its own, if only modestly, motivated by the potential capacity for this system to function as a platform for other future biorefinery products.[1]

## Material and Methods

Cotton gin trash is a byproduct of cotton harvesting and handling generated through the ginning process, of which the primary product is cotton lint. Gins on the Texas High Plains can be grouped broadly according to capacity: 20, 40, or 60 bales of lint per hour. Gins operate through the ginning season at approximately 80% of capacity, requiring approximately one MWh to gin 20 bales. Gins sort received biomass into lint, seed, and trash. The average bale results from processing 1000 kg of biomass. Ginning has a lint turnout of 28% by weight and also produces approximately 200 kg of cotton seed. This leaves close to 500 kg of gin trash, or almost half the harvest weight.

The energy content of gin trash is estimated at 8758 MJ per metric ton. At a somewhat conservative 25% energy conversion rate in the gasification, combustion, and electricity generation process used here, the trash available from processing one bale can generate approximately one MWh, or approximately 20 times what is needed to operate the gin.

Although our method can apply to other industries, cotton gin trash in the region of the southern high plains is considerable, even in

[1] A key future benefit of this system, which motivates this economic analysis, is that the system can serve as a platform for a biorefinery that potentially produces many other value-added products. The gasification process and the installed capital to preprocess biomass also accommodate the production of other bioproducts beyond electricity; for example, hydrogen stripping from the gasifier and use of bio-oil from an inexpensive mobile pyrolysis unit used to supplement biomass in drought years serve the production of multiple biorefinery products. Some such as ammonia fertilizer can be produced and sold immediately; others such as biodiesel can be produced today but require a stronger market and physical infrastructure to sell the products. Other over-the-horizon technologies could serve, for example, a hydrogen economy if that develops; or specialty fuels, specialty fertilizers, and specialty plastics and adhesives may find local pricing premiums depending on location at the same plant using some of the base equipment required for the modest-sized distributed electric power plant.

drought years (Wilde, Johnson, and Farmer, 2010). On average, between 2001 and 2008, Texas produced 6266 thousand bales of upland cotton annually (U.S. Department of Agriculture, National Agricultural Statistics Service, 2002–2009); so over the state, this equates to approximately 4,791,000 MWh per year potentially produced or for the purpose of context only, the equivalent of a 685-MW plant operating 7000 hours per year in the average year using a 25% energy conversion rate of electricity from gin trash. This number would represent roughly 14% of total current electricity production in Texas but only approximately 4% of current consumption.

Recent biomass tests, ash tests, and efficiency simulations (Capareda, 2010) suggest possible updates: there is likely more BTU content in the biomass but a possibly lower conversion rate under field stress conditions (15%). The net result is that final throughput from biomass to energy output rises approximately 6%. This analysis is based on more initial and more conservative engineering work, but we also include a summary comparison of the higher performance conversion.

The determination of optimal plant capacity depends on the ability of the producer to meet a given peaking power contract in any year. Because gin trash production is stochastic, being significantly affected by spring rainfall, a proper understanding of the distribution of gin trash production is required to set a contract and optimal plant size. So as a first step, the analyst needs to determine the distribution of gin trash. We use a function of gin trash production to annual rainfall fit by Liu, Farmer, and Capareda (2011) and then use that function against rainfall data over the last century to estimate the distribution of gin trash production.

### *Estimation of Interannual Biomass Distribution*

To estimate a production function of gin trash in response to weather, we collect data on ginning production by firm by reconciling the record of bales ginned from the "Red Book" published by the cotton industry (Texas Cotton Ginners' Association [Southwest Edition], 2008) with the USDA National Agricultural Statistics Service (U.S. Department of Agriculture, National Agricultural Statistics Service, 2006), which reports total gin production by county and sorts the share of production into high-yielding irrigated agriculture and dryland cotton production, but marginal difficulties exist with the reliability of the trash total measures and the consistency of measurement processes from year to year (Wilde, Johnson, and Farmer, 2010). Therefore, reliable gin trash data are available for only a single decade. Fortunately, annual plantings to cotton have been stable; so the majority of gin trash variation is attributable to weather variance, predominantly spring rains.

We conduct a sampling with replacement regression analysis that regresses gin trash against the natural log of spring rainfall and the square of the natural log of spring rainfall. Using a Monte Carlo Markov Chain simulation, we then estimate a gin trash to rainfall probability distribution described in Liu, Farmer, and Capareda (2011).

We map the 92-year rainfall record (from the National Climatic Data Center, U.S. Department of Commerce, 2010) to the estimated expected gin trash production function to produce a probability density function for gin trash availability. That is, for every rainfall amount, we calculate an estimated quantity of resulting gin trash. Using the conversion rate described previously, we then convert that gin trash quantity to a quantity of electricity. Figure 1 illustrates the annual electricity probability distribution sorted into eight quantiles from the probability density function expressed in units of electricity available (in MWh) from biomass output. We can discretize the function at a higher resolution than eight quantiles, but it did not affect choices from the subsequent model. Figure 1 is based on data from a group of four gins within five miles of a central gin at which the processing facility would be located. These gins process cotton from roughly 40,000–50,000 acres. We will use this grouping for subsequent economic operations analysis explored subsequently.

### *Theory: Opportunities for Peaking Power Contracts*

We consider groups of two to seven gins in close proximity as a consortium to allow operation at

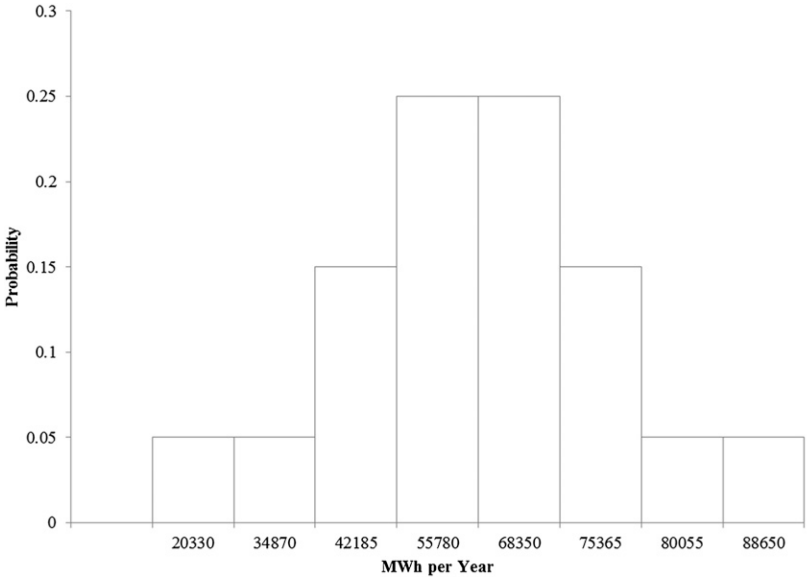


**Figure 1.** Distribution of Electricity Production for an Example Group of Four Gins

a size that would attract the interest of the area full-supply utility to enter into a peaking contract. By choosing the gins in close proximity (within five miles of the plant), we effectively minimize transportation costs faced by the plant. The model consortium has several operational choices. Energy from gin trash can be sold for high peaking power, secondary peaking power, incidental power, or for use on-site. In drought years, when the amount of available biomass is low and the consortium is unable to meet the peaking contract, there is a penalty in the form of purchases of power from other sources, generally being electricity generated by natural gas peaking plants outside of the region. Clearly the highest peaking power deliveries garner the highest prices, whereas the "secondary" peak generates high returns, but not as substantial as the high peak deliveries. Finally, own power demands such as required power during ginning season offer a small premium for on-site production and incidental power, produced at will, returns the lowest prices.

Wholesale price contracts timed to different peaking conditions are somewhat difficult to find because much of the information required to differentiate utility power costs to specific periods is proprietary, commencing with the Public Utility Regulatory Policies Act (PURPA) in the 1970s. These reporting rules also differ by region. Nonetheless, with average 2006 retail energy prices of $128.6/MWh in Texas and daily peaks running over $150/MWh (U.S. Department of Energy, 2008), peaking prices run conservatively at $130/MWh (i.e. 13¢/kWh). There are notorious peaking power spikes over $300, whereas off-peak retail prices fall between $35 and $50 per MWh (U.S. Department of Energy, 2008). Some general plausible pricings are used for this analysis; and we use what we consider reasonable prices for each category. Based on these retail rates, we use $125/MWh delivered at the highest peaking power prices. We allow 945 hours per year, which coincides with deliveries of five hours per day for 27 weeks (17 in the summer and ten in the winter) at this highest peaking price. We also allow another 2000 "secondary peak" hours at a rate of $65/MWh to be available by contract across the year.

Critically, peaking contracts are firm promises of delivery. There are others forms of contract; but we analyze this form. If a contract cannot be met, a biomass processor will likely foresee this shortage at harvest, several months before the shortfall of any delivery. The producer pays a premium for any shortage. This advanced notice should control losses to avoid the risk of very high spot energy purchases in summer; and most processing centers likely will be able to contract for electricity deliveries from outside of the region several months in advance to fulfill these peaking contract shortfalls in the summer. Nonetheless, we assign a penalty price of $145/MWh for any outside purchases to meet shortfalls as they arise[2]; but as shown subsequently, producers avoid this circumstance in most years by committing to a much smaller contract. Finally, power sold off peak as incidental power returns $35/MWh, which is closer to the wholesale price for coal. We assess a small premium to on-site production for immediate use at the gin of $45/MWh. Prices of course will vary from region to region and company to company, so we choose somewhat conservative prices for our analysis.

### *Model to Estimate Optimal Installed Capacity and Power Contract*

The optimization model for the plant operator and agricultural industry processor solves for the operator choices of both electricity generation capacity and the size of the contracts to deliver high peak and secondary peak electricity. Figure 1, recall, shows the probability distribution of available electric output in a given year. That distribution is discretized into eight separate states of gin trash availability expressed as potential electric energy output: so, 20,330 MWh occurs 5% of the time; 34,870 MWh, 5%; 42,185 MWh, 15%; 55,780 MWh, 25%; 68,350 MWh, 25%; 75,360 MWh, 15%; and 80,055 MWh, 5% and 88,650 MWh 5%. The key is to build a plant that uses the biowaste for peaking power sales but avoids penalties from any biomass shortages in low harvest years.

Sales of electricity are sorted into four prices for each MWh of electricity produced: high peak ($125), secondary peak ($65), own power production ($45), and incidental sales ($35). The peaking power contract does not include any obligation to provide any nonpeak power, but there is a small marginal benefit to producing electricity for the plant and gin to use and a smaller benefit to sell nonpeak power back to the utility. A shortage penalty is $145. Fixed costs include capital cost, financing terms, licensing, and machinery to manage biomass handling. Costs follow natural gas installations (Lieuwen and Yang, 2006) adjusted for higher costs as a result of handling but lower costs of environmental compliance resulting from the rural location of these operations; the composition of the biomass; and, finally, the lower costs of capital now available to preprocess and generate electricity (Capareda, 2010). These cost advantages lead to a declining average cost curve mapped against the size of operation capacity (in MW), explained subsequently. Marginal costs follow standard gasification units with a small per-unit premium for biomass handling on-site. Given the practical requirement to dispose of waste biomass, gasification in fact solves a problem for the ginning side of the operation that would in this case reduce total costs, yet we include a modest extra cost for handling on-site as a conservative check in part because handling costs can vary enormously depending on managerial skill.

Plant financing is nested in fixed costs. The financing structure assumes a 12-year payback with a 10% interest rate in which 75% of total fixed costs are financed. This is more generous than the six-year payback of most venture capitalists but is the most likely financing structure if the local utility serves as lender–investor or as guarantor. Utilities under PURPA that must plan to meet full load coverage over time are required to hold large cash reserves for future plant construction and many are facing renewable energy mandates (such as the renewable portfolio standard in Texas, described previously), so the business model assumes local utilities will

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[2] Given recurrent droughts, which cause the low electricity production years described, any firm peaking power contract from distributed power sources likely will incur losses in some years to fulfill power utility contracts. The agro-forestry operator will assess contracting opportunities based on the ability to achieve higher priced deliveries subject to anticipated losses. A potential advantage that agricultural processors have as potential biomass electricity producers is that risk management by forward contracting and hedging is already a core competency, because these operations naturally face this seasonal supply risk in day-to-day operations. Critically, the skill to manage a multiparty contract or cooperative to a single market purchaser is already a core competency of agricultural processors we envision adopting this program.

initially be the financing source. Clearly contracts will differ greatly, but we argue that the structure for pricing and for financing on the whole is conservative and respects the riskiness of the investment. The terms of the peaking contract and financing, including the schedule for 945 and 2000 hours per year of primary and secondary peak, were shaped in part through conversation with a local power supplier (West, 2010).

In any period, installed capacity is fixed and the peaking contract demands are fixed at 945 and 2000 hours. Embedded in the model subsequently is the constraint that the power generation equipment operates at a maximum of 7000 hours a year and that the highest peak only occurs for 23.57 weeks (165 days). The net revenue stream in a given year, $i$, will take the form, using prices from above, of:

$$\begin{aligned} NR_i &= \$125 \cdot HP \cdot C + \$65 \cdot P \cdot C \\ &+ \$45 \cdot Own \cdot C + \$35 \cdot Inc \cdot C \\ &- \$145 \cdot Short - FC(C) - Var \cdot TMW \end{aligned} \tag{1}$$

where $HP$ is number of hours of plant operation devoted to high peak electricity production (fixed at 945), $C$ is capacity of the facility in MW, $P$ is number of hours of plant operation devoted to secondary peak electricity production (fixed at 2000), $Own$ is the number of hours of plant operation devoted of electricity production to satisfy its own onsite power needs, which production is restricted to being less than 17% of total electricity produced, $Inc$ is number of hours of plant operation devoted to production of electricity to sell at will, \$145, $Short$ is the cost to purchase supplemental energy to fulfill peaking contracts, $FC$ is the fixed costs of the system (a function of capacity as illustrated in the equation subsequently), and $Var$ is variable costs per MWh produced. To clarify, the amount of electricity produced in $t$ hours at a plant with capacity of $C$ MW, is $t \cdot C$ MWh, so $TMW$, the total electricity produced at the plant in one year, in MWh, is $TMW = (HP + P + Own + Inc) \cdot C$. High peak and peak are set equal to 945 and 2000, representing the contractual delivery requirements. The fixed cost function of the gasifier/generator is

$$FC = \left(\frac{4000000}{1.2 \cdot C + 5} + 640000\right) \cdot C, \tag{2}$$

which gives an average fixed cost as a function of capacity $C$ (Multer et al., 2010). The ability of the facility to produce the electricity quantity $TMW$ (or the difference between peak electricity produced and the contracted quantity, which is the value $Short$) is determined by the amount of rainfall and associated biomass in year $i$, which is distributed as described previously (with eight possible discrete outcomes).

To summarize, given a chosen capacity level and high peak and secondary peak contracts, total net revenue will depend on the biomass availability in any given year. So each year generates a different revenue value and alters some operating decisions. In a short year, the firm will attempt to first fulfill its peaking power obligations and possibly forego producing any of its own electricity or any incidental deliveries. If very short, the firm may have to purchase supplemental energy and pay the \$145/MWh penalty to satisfy its delivery contracts.

Our representative producer maximizes expected net returns. In this model, expected net returns are the simple inner product of probability of biomass available and the associated net revenue in a period, $i$, and the returns in $i$, $NR_i$; or

$$NR = \sum_{i=1}^{8} \Pr(i) \cdot NR_i, \tag{3}$$

where the probabilities of each outcome are described previously. In other words, equation (3) is the average of the possible net revenue outcomes.

Technical constraints in any period then include the physical amount of biomass available, market requirements, and engineering performance constraints. The biomass constraint simply requires that the total amount of electricity generated be less than or equal to the energy equivalent collected biomass in a given year, $y_i$ (measured in MWh):

$$y_i \geq (HP + P + Own + Inc) \cdot C \tag{4}$$

where $y_i$ is a discrete random variable, distributed according to Figure 1. The value $Short$ is determined by the difference between $y$ and the sum of $HP \cdot C$ and $P \cdot C$ in a drought year. In a normal rainfall year, that is, one in which the available biomass is sufficient to satisfy the contracts, *Short* is zero; otherwise, *Short* is positive; so, formally, we have,

$$(5) \quad Short = \begin{cases} (HP + P) \cdot C - y & y < (HP + P) \cdot C \\ 0 & y \geq (HP + P) \cdot C \end{cases}$$

The full optimization model is then to maximize the expected net revenue by choosing the facility capacity, *C, Own* energy production, and *Inc*, incidental energy production. All other choices such as contract size are embedded in the capacity decision. Formally our model solves the following:

$$(6) \quad \max_{C, Own, Inc} \sum_{i=1}^{8} \Pr(i) \cdot NR_i$$

subject to equations (2) through (5).

Note that the high peak and secondary peak contract sizes are chosen jointly with the capacity of the system. Given that *HP* and *P* are fixed at 945 and 2000, a chosen capacity *C* will give high peak and secondary peak contracts of size $945 \cdot C$ and $2000 \cdot C$, respectively.

## Results and Discussion

We considered six different groups of two to seven gins and solved the previous model for each group. All gins are within 60 miles of Lubbock, Texas. The optimization model is solved using Lingo 12.0. For simplicity, we show results for one group, which achieves about the median profitability, and present results in Table 1.

The results of the base case that uses the prices delineated previously are shown in the top row of the middle column of Table 1. On average, the plant achieves over $1.6 million in net revenue with average annual production at 60,000 MWh of electricity and capacity at 11.8 MW. The contract requirement chosen then is only 34,869 MWh, which reflects, on average, only approximately 65% of the biomass available. Fixed costs averages are close to $825,000/MW at this size for reasons explained previously. These results are favorable suggesting that a biomass to electricity conversion process could operate at a profit while serving as a platform for a small-sized biorefinery. Return on investment for operators who invest 50% of upfront capital falls between 30% and 35%. Even if cash for the entire first year of operating expenses needs to be covered, investors still show a profit in year one. Note also that the total average electricity produced, 60,000 MWh, is close to the median of the distribution of available energy (Figure 1). This suggests that, roughly 50% of the time, the plant will be able to devote the extra biomass to other products.

As a sensitivity analysis, we adjust prices in the optimization model to determine the optimal plant capacity at higher and lower prices. First, we raise prices by 20% for the various electricity products (specifically, we increase the prices for high peak, secondary peak, own, and incidental electricity to $150, $78, $54, and $42, respectively). The results for this case are reported in the upper right corner of Table 1. Here we see that average net revenue increases significantly (46% over the base case), optimal capacity increases by 21%, and average total annual production increases by just more than 1%. Next, we lower prices by 25% (so that high peak, secondary peak, own, and incidental

**Table 1.** Expected Net Returns to Biorefinery Investment—Baseline Case

| Low Prices | Low Prices | Baseline Prices | High Prices |
|---|---|---|---|
| No subsidy | $730,478 | $1,656,704 | $2,438,264 |
| | (10.77/59,530)[a] | (11.84/60,299) | (14.32/61,319) |
| Open-loop subsidy | $1,325,781 | $2,259,805 | $3,051,452 |
| | (10.77/59,530) | (11.94/60,363) | (14.32/61,319) |
| Closed-loop subsidy | $1,980,926 | $2,926,885 | $3,725,958 |
| | (11.43/60,098) | (12.66/60,830) | (14.32/61,318) |

[a] Numbers in parentheses are optimal capacity (in megawatts) and total expected annual power generation (in megawatt-hours).

electricity prices are $94, $49, $34, and $26, respectively). At these lower prices, expected net revenue decreases by 56%, optimal capacity by 10%, and average annual production by 1%. Total production and capacity appear to be more robust to price changes than does expected net revenue.

The second change we impose on the model is the introduction of a production subsidy, which increases (or further increases) prices received for each MWh of electricity generated. In this case we consider two existing subsidies. The first we consider is the federal (US) production tax credit for renewable electricity generation from "open-loop" biomass (i.e., where the biomass is a waste product rather than a dedicated energy crop), which is currently set at $0.011/kWh, or $11/MWh (House Bill 8, American Taxpayer Relief Act of 2012, 2011–2012). The middle row of Table 1 reports the optimal response to the subsidy at the low price case, the base case, and the high price case. The introduction of the subsidy does not change the optimal plant capacity or resulting average production amounts significantly in any of the three price scenarios but does result in large increases in expected net revenue. Depending on the objectives of this subsidy, and depending on the decisions made by investors, this result may indicate that the subsidy would be potentially successful in this instance. Although the subsidy does not increase the amount of electricity generated from a producer who is already operating, an investor who required a larger profit might not invest without the high net revenues achieved with the subsidy, meaning that in absence of the subsidy, no electricity is generated. In such a case, the subsidy would increase renewable electricity generation from zero MWh to 59,000+ MWh.

Finally, we consider the hypothetical case of this system qualifying for the closed-loop biomass (i.e., biomass from a dedicated energy crop) subsidy, which is currently $0.023/kWh or $23/MWh. We do not anticipate this production tax credit program to include biomass waste, but this case illustrates the effects of a drastic increase in the production tax credit available to open-loop biomass-generated electricity (in short, exposes the policy distortion against using biomass waste to produce bioenergy versus dedicated crops that are grown to produce bioenergy directly). The results are reported in the bottom row of Table 1. It is instructive to compare the differences between the results of the low price, no subsidy case and the results of the high-price, high subsidy (closed-loop) case. The increase in average net revenue for the producer (400%) far outweighs the increase in optimal plant capacity (33%) and average annual electricity output (3%).

After completing the initial analysis in the previous paragraphs, new engineering tests revised the rates of converting biomass to electricity upward by a small factor (roughly 1.06 times higher). Given the new information, we ran the model with the updated conversion rates and present the results in Table 2. Comparing

**Table 2.** Expected Net Returns to Biorefinery Investment—Updated Energy Content and Conversion Rate[a]

| | Low Prices | Baseline Prices | High Prices |
|---|---|---|---|
| No subsidy | $795,516 | $1,780,266 | $2,612,312 |
| | (11.43/63,227)[b] | (12.58/64,042) | (15.21/65,126) |
| Open-loop subsidy | $1,427,783 | $2,420,902 | $3,263,574 |
| | (11.43/63,227) | (12.68/64,111) | (15.21/65,126) |
| Closed-loop subsidy | $2,124,251 | $3,130,016 | $3,979,962 |
| | (12.41/63,830) | (13.45/64,607) | (15.21/65,126) |

[a] On net, the new biomass BTU content and energy efficiency rates imply final energy generated per ton of gin waste is 1.0621 times larger than that which generated the results in Table 1.

[b] Numbers in parentheses are optimal capacity (in megawatts) and total expected annual power generation (in megawatt-hours).

Tables 1 and 2 suggests that the 6% increase in energy content and conversion rate results in a 6–9% increase in net revenues for the producer, depending on prices and policies. The optimal capacity of the plant increases by 6–8.5% depending on the specific scenario.

Taken together, the results presented in Tables 1 and 2 suggest that the optimal plant capacity and average annual output are fairly stable with respect to price changes. What drives plant size is the expected distribution of available biomass. This variability of biomass production, we argue, is very important to bear in mind when considering biomass to energy systems, especially those driven by regional biomass supplies from agricultural operations. Given a contract of only 34,868 MWh per year in this case, the plant is short approximately 7% of the time. Therefore, policy alternatives designed to increase output by increasing prices tend to be fairly ineffective to increase size if that is the goal.

However, if greater returns are required to induce investors to produce more, this analysis shows that very modest subsidies (approximately 10% per BTU provided already to other bioenergy sources) increase producer net revenue. This does little to increase output at a given plant but would likely encourage a larger number of modest distributed energy systems to emerge, increasing the impact on total peaking production that could meaningfully offset some of the planned power plant expansions. In the case that a producer must secure financing at a higher rate or shorter term, the higher prices might make the difference between entering the market or not.

*Technology and Competitive Position*

This work is a proof-of-concept study meant to motivate future study into policy reforms and engineering operations studies to combine existing technologies for efficient plant operations in the context of economic prices and bioproducts policies. The economic potential flows from quasi-niche market opportunities of peaking power rather than technical breakthroughs that scientists and engineers might easily identify. So it is the prima facie market case here that justifies further study to a full engineering–economic prototype.

The primary market competitor to an installed power island at an agri-forestry plant is a natural gas power plant. Models represented here adopt an on-site gasifier and generator. Direct combustion (biomass boilers) could be used but the low conversion efficiency of biomass to energy and the reduced ability to flexibly regulate power output across a day to meet the highest peak, or price, spikes favored a small on-site gasifier. The head-to-head cost competition with a natural gas plant is the tradeoff between installing a gas line and then purchasing and transporting natural gas to a natural gas plant versus installing a gasifier to convert the biomass available on-site. Beyond that, marginal processing costs are the same. There is a difference in size because the smaller power island at the gin is limited by local biomass in these scenarios, whereas an installed gas line generally satisfies fuel on demand.[3] However, gins are located closer to remote nodes that can have extraordinarily high peaking prices that require relatively modest power supplements to satisfy. A small plant nearby meets this additional niche market without powering up and idling a much larger gasifier and typically a gas turbine rather than the generator set expected to be used here. A final concern centers on the expectation of new natural gas supplies entering the electric power market.

[3] An anonymous reviewer noted increased efforts at gas storage. Although on-site gas storage is possible, it is very expensive and no nonexperimental, commercial power plant in the United States currently stores natural gas on-site, yet storage by reinjection of harvested gas into already extracted sites (depleted wells for example) or aquifers, usually closer to markets and existing plants, has become an important method to sustain natural gas supply on demand. If a plant plans to draw gas on a given day, a closer supply reinjected underground makes it easier to "pack the line" to the plant the day (night) before. In general, peaker natural gas plants that compete with the power island modeled are smaller and require less storage than base facilities but also require very ready access, a storage need that is not unlimited but has been increasing (U.S. Energy Administration, 2012). So we assume a natural gas plant has supply-on-demand, whereas the syngas at an agroforestry plant is dependent, for this model, on the biomass available over time.

Historically, dramatic shifts in gas prices (high or low) have not much affected the supply of natural gas used in electric power (U.S. Energy Information Administration, 2008), including gas prices from 1995–2002 that were much lower than the currently low gas prices. Our scenarios use at and below historically low peak electricity prices for base and low price scenarios that model possible low future electricity prices as a result of emerging natural gas supply increases.

Analyses of long-term natural gas prices over the next decade and decades vary, but nearly all predict gas price increases after 2015 (U.S. Energy Administration, 2013a). Debate over natural gas impacts on peak power prices centers on the degree to which electricity prices are expected to rise through 2040 (U.S. Energy Administration, 2013b). Several features constrain increasing natural gas supplies from inducing a fall in power prices over today's prices. Coal power prices are quite low, so there is a limit to how far an expanding power demand market can be met wholly by natural gas. Another competition is for the natural gas itself from lucrative liquefied natural gas markets for motor fuels. Also plant operating costs are not expected to change and working natural gas storage capacity is becoming more expensive as gas storage is moving further from primary markets. On balance, the predictions suggest that as natural gas plants cover more and more of the expansion of power production (offsetting plans to expand local coal facilities) in coming decades, that increased use is dedicated to keeping up with increased demand in peak energy use periods. Because gas is more expensive than coal, analysts expect higher peak energy prices even with the expansion of natural gas supplies (Energy Information Administration, 2013).

The two greatest obstacles to very near term commercialization are technical risks and a balance in renewable energy policy that favors large and more centralized operations, often using dedicated crops such as corn for ethanol or soybeans for biodiesel. Technically, gasifier–generator set combinations, which are scalable in 100 kW to 1.5-MW increments, are projected to cost $1000/kW installed (similar to investment costs for natural gas plants) at 25–30% efficiency and cheaper at the 7–10 MW size modeled here (Multer et al., 2010) and are in late precommercial development for instrumentation (Capareda, personal communication). Neither these technologies nor their competitors are especially novel. What is new is the engineering effort to calibrate them at this size. Economic incentives used in our analyses may explain the lack of prior work in this area, i.e., most policies to encourage bioenergy production have been targeted to larger plants and/or to directed crops rather than waste products.

Production subsidies tend to favor other investments. Using $/BTUs as the common unit, with subsidies similar to biodiesel (a technology with a more than 100-year history), returns to the power island are as much as twice as large in terms of percentage returns to cash invested (Tables 1 and 2). Additional attention in public research priorities to these same bioenergy investments, arguably, could skew the technical risks of such investments. A Department of Energy program that often provides half the capital costs to first-generation alternative energy plants such as coal gasification is clearly intended to reduce investment risk. With high returns demanded in venture capital markets, investors in the same industry have had more attractive options. Given the low output prices and onerous venture capital investment terms assumed, we submit there is a compelling prima facie for greater attention to these bioenergy alternatives and, then, the possibility of a next generation biorefinery that uses the power plant as a platform for a multiple value stream biorefinery.

Because the gin could operate a bioelectricity plant or biorefinery profitably, there exists a possibility that refineries could increase profits by choosing an optimal gin waste quantity by purchasing waste from other gins rather than relying on the quantity of waste left over from the ginning process, which is distributed randomly. If a given biorefinery began purchasing gin waste from other gins within the region, this could potentially create a new market for gin waste, which would affect the analysis done here. The addition of a new choice variable, quantity of gin waste, and a price of that waste, which would be determined endogenously, would drastically change this model, which is of a single firm. To adequately model the price of gin trash in such a market, we would necessarily include additional firms that would choose to supply or demand waste. However, this model also generates hypotheses about such a market. In the previously stated model results, the plant only uses a fraction of its biomass in average to high rainfall years, so the gin would likely only be willing to purchase additional biomass in low rainfall years, yet in low rainfall years, a market for gin trash waste already exists, in which it is sold as a low-quality cattle feed supplement. In these periods, prices for gin trash are particularly high because low rainfall correlates with high feed prices regardless of the source. Prices in those years increase beyond $150/ton (Walker, 2012), pushing the price of additional biomass above what the plant would have to pay to buy electricity from outside the region. This effect is partly captured by the high penalty the model imposes for not meeting output targets to meet peak demand in drought years. Effectively, because a plant would only demand additional biomass when prices for that biomass were very high, the likelihood of a market for gin waste biomass developing to support the bioelectricity market is small. In any case, the gin consortium modeled here would remain profitable in the presence of a gin waste market; the question of whether a gin trash biorefinery could increase profits above those simulated here is an open question that will be addressed in future work.

## Conclusions

The summary conclusion is that the biomass to electricity power plant as a small distributed energy source produced from biowastes at agri-industry sites is economically viable in the case studied and, even at very low prices (which are lower than the forecasted lows caused by the natural gas boom; Energy Information Administration, 2013), can provide an additional value stream to agricultural processors. Weather, cropping patterns, and waste residual volume and variability will differ, but a strong a priori case suggests promise. The plant largely avoids some of the unintended consequences of directed crops such as possible commodity price volatility and indirect land use effects and the design ameliorates the transportation cost barrier of biomass movement to a processing center. Additionally, this analysis is extendable to multiple different types of biomass waste, including wood wastes. Moreover, it realizes economic viability without subsidies and performs well above venture capital expectations if current subsidies are applied here. The waste of average total quantity of cotton production, if gasified in this process, represents approximately 14% of current electricity output in the state and would be comprised of 80 plants of the size described in the results.

That this peaking power contract uses only approximately half of the biomass half of the time suggests two future research questions. Future research on optimal supplementation using the mobile pyrolysis technology (Aquino, Capareda, and Parnell, 2010; Multer et al., 2010) might improve profits and, because biomass supply in short years is the critical factor to plant size and peaking power contract provisions, it might expand total output to meet peak demands. This case has been examined initially by Liu, Farmer, and Capareda (2011) with favorable results; and this model will be explored more thoroughly in studies underway.

In our view, the second follow-up research topic will be more significant: that the excess biomass facilitates a multiproduct biorefinery. This is why we label this overall plant model a "biorefinery platform." The capital equipment required is part of the component set for several other products beyond electric power generation. The critical point of this baseline analysis is that it shows that the platform, as a standalone entity, is economically viable. That profit can be even higher than shown here depending on financing terms, but the long-term advantage of the plant is the capacity to bolt on other biorefinery products at reduced capital installation costs. At times, joint production enjoys shared marketing costs. Bio-oils allow conversion to local fertilizers as well as plastics and adhesives if local markets support them, yet it also supports several biofuels from diesel (Capareda, 2010) and even ethanols or butanols. Many of these bioproducts suffer from being perpetually near commercialization because capital costs are a little too high or biomass delivery costs are prohibitive.

The gasification system has similar advantages. In the short run, it accommodates ammonia production as well as electricity production in off-peak hours (Maxwell, 2011). In a possible future hydrogen economy, hydrogen stripping from syngas is a relatively easy add-on that may become profitable because it is produced in a distributed system by design, one obstacle to hydrogen-based products. Future research to calibrate baseline production efficiencies for an array of bolt-on biorefinery products to assess capital cost reduction is a next step with strong future promise for producing power at agri-processing sites.

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