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RESEARCH ARTICLE

Economic Opportunities of Bioelectricity from Cotton Gin Waste

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Abstract

This work shows that direct combustion of cotton gin waste (CGW) at cotton gins can profitably generate electricity. Many bioenergy processing centres emphasise very large-scale operations, which require a large and stable bio-stock supply that is not always available. Similarly, a small biorefinery processing gin trash at a cotton gin must wrestle with the high volatility of cotton yields and price variation in cotton and electricity. Fortunately, the smaller scale allows these risks to be somewhat countervailing. Low cotton yields allow the limited gin trash available to be applied to the highest peak electricity prices in winter. Similarly, high yields with low cotton prices generate revenue from power generation throughout high winter electric prices.

To assess the profitability of an onsite power plant requires high-resolution data. We utilise hourly electricity price data from 2010 to 2021 in West Texas and obtain a small data array of 15 years of gin trash at a medium-sized gin. Prior analyses have had neither. We leverage limited CGW data to better leverage generous electricity price data by generating a Bayesian distribution for CGW. We simulate 10,000 annual CGW outcomes and electricity prices. Using engineering parameters for combustion efficiency, we show the expected internal rates of return of 19–22% for a 1 MWe and a 2 MWe plant at a small gin. Simulations then compare economic returns to the variance of those returns, which allows the analyst to present to investors a frontier of stochastic dominant return outcomes (risk-returns trade-off) for plants of different sizes at different sized gins.

Keywords: Bioenergy; Bayesian simulation; cotton; cotton gin; electricity; IRR; optimisation

JEL classifications: C61; C63; Q12; Q16; Q42

1. Introduction

The more than three decades of cultivating dedicated crops for ethanol and biodiesel production has left a very mixed record. Concerns begin with the observation that corn ethanol and forest biodiesel show no measurable reductions in carbon releases. More serious, critiques show that biofuels from dedicated crops often accelerate environmental degradation by the expansion of corn cultivation onto marginal farmlands and the clearing of forest floors, degrading both prairie and forest soils. Yet the longer history of bioenergy production in the USA before the recent era has not centred on dedicated crops. In the late 19th century, biomass boilers began to chemically process biowaste to generate steam. That steam, in turn, powered an electric turbine used for power to process cultivated crops or forest residuals (Del Rio *et al.*, 2022).

Over the 20th century, food processing industries began to consolidate, and many rural processing plants closed (Dimitri *et al.*, 2005). In addition, falling electricity prices after the 1936

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Rural Electric Act created little incentive to invest in small-scale, local bioelectricity (Kitchens, 2014). By the 1990s, however, trends began to turn. Electricity prices began to rise, especially in rural areas (Sueyoshi and Goto, 2014). Further, the volume of cotton gin waste (CGW) continued to expand as gins grew larger and as cotton yields rose steadily (Gulati and Rollin, 2015; Reddy *et al.*, 2017).

Given the challenges that rural industries face, the addition of new revenue streams through bioenergy production can be an important contribution to the rural economy (see Golden *et al.*, 2024) for a comprehensive review of the economic value and job creation from the biomass industry). The processes examined here also provide local environmental benefits. Biowaste management is cleaner when processed inside a contained system, such as a chemical boiler — a benefit of special significance given the ambient pollutants from CGW (Safferman *et al.*, 2009; Yue *et al.*, 2014). Further, rural electric power generation is now overburdened. The rapid acceleration in peak electric prices in winter, when ginning is most active, means that new production helps to prevent brownouts (Billimoria *et al.*, 2021; Shoreh *et al.*, 2016). Currently, the impediments to biopower appear to be policy driven rather than technical or economic (Batidzirai *et al.*, 2012).

Current bioenergy policy emphasises large, concentrated plants (Roni *et al.*, 2017). To the extent bio-residual waste is used, current processes centre on cofiring forest residuals with coal (Mirzaee *et al.*, 2023) or processing almond and pecan shells at cogeneration plants (Wiltsee, 2000). England's Drax plant is a perfect example. The plant has replaced a large coal combustion chamber entirely with wood pellets. That conversion is telling. This single operation requires a global biomass feedstock collection system, marked by aggressive clear-cutting and forest floor gleaning (Rahman *et al.*, 2022) — all of which have been shown to create severe environmental damages (Blanco-Canqui and Lal, 2009).

The effort to replace fossil fuels with large bioenergy systems has emphasised advances for more efficient combustion — turning a large percentage of the BTUs in the biomass into megawatts of electric power. This effort has stimulated research into gasification and pyrolysis to process biowaste at higher efficiencies (Farmer and Sinquefield, 2007). These technologies clearly show promise; yet over the last 30–40 years, these technologies have remained stubbornly expensive and, mostly, beyond full technical implementation (Capareda, 2023). This situation may improve, and these technologies may become more affordable and feasible. Yet, currently, gasification generates 'slagging' or tars in turbines, a problem that has eluded remedy for half a century (Farmer and Sinquefield, 2007). In the interim, traditional boilers, due largely to progress at US papermills, have become far more efficient, often exceeding 30% conversion efficiency of wood pulp, and they are ready to deploy (Farmer and Sinquefield, 2007). At a time of extreme electricity price spikes, the system proposed can be implemented immediately.

This work models the economic benefits of a supplemental 'single cycle' electric power system, meaning the system delivers power on short notice during peak use hours. This marks an important distinction from the much larger, utility-scaled combined cycle bioenergy systems that supplement 'base' load through continuous operation. So, the proposed bioelectric system examined here is supplementary to core power generation systems. This supplemental power is easier to operate for food and fibre processing centres whose primary activity is not power generation, and, critically, that power can be timed to relieve very high use (high price) periods by selling to utilities through 'day ahead' power market sales, which as the name suggests, schedules power delivery a day ahead at a high contracted price to meet peak demand (Martelli *et al.*, 2021).

Using the example of CGW, this work shows that onsite power production at food and fibre processing facilities can be very profitable. Establishing a power plant on the same site as the processing facility renders feedstock transport costs effectively zero because, of course, CGW is already delivered with cottonseed and fibre. It adds needed revenue to rural processing plants and to producer cooperatives. Critically, investment choices also allow great flexibility. Rather than 'one size fits all', investments of large-scale optimally scaled biotechnology operations, these investments can be tailored to investor risk preferences and to gin size. The analytic approach

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presented herein examines investments at different scales. We isolate stochastically undominated plant size alternatives for each size gin — a unique contribution to this literature. So, investors make choices that suit their risk preferences rather than force fit a single optimal investment scale.

This work provides a unique treatment of the risks in bioenergy production. It simultaneously examines variation in cotton yields, cotton fibre prices and peak, subpeak and base electricity prices. Investors can elect risk levels for a given level of return based on different investment scales. We know of no bioenergy analysis that adopts this flexible approach.

The scope of application of this single bioenergy suggestion is significant. Across Texas, over 200 gins operate (Wade and Hudson, 2017). Wilde *et al.* (2010) report that across the 30 counties in the Texas High Plains alone, during the years from 2000 to 2006, each county averaged 33,158 tonnes of gin trash — enough to support one medium-sized gin in each county. There is also a concentration of CGW in the seven largest counties, each producing 60,000 tonnes of CGW annually, enough to support one large gin in those counties. The added electric power output, especially when delivered at very expensive peak times in winter, is both a substantive needed supply for winter power and a substantial economic support for rural cotton gins.

2. Previous work of bioenergy from CGW

Prior explorations into the use of CGW as a bioenergy feedstock goes back half a century. In 1972, gin trash was labelled a public health threat due to ambient air pollutants (Wilmot *et al.*, 1974). A decade later, Lacewell *et al.* (1982) proposed to use CGW for bioenergy to generate electricity and, simultaneously, to remove the health threat. Lacewell noted that the energy content in 1 tonne of CGW is about 14 million BTU, which Le Pori *et al.* (1982) noted could meet the entire energy needs of a gin in stripper harvesting areas. As Texas launched its renewable energy push in 2008, Capareda (2010) calculated that a tonne of CGW also could produce 120 gallons of motor fuel using an updated version of Lacewell *et al.*'s (1982) fluidized bed gasifier. Finally, as environmental challenges from CGW mounted, Multer *et al.* (2010) noted that conversion of CGW to biopower could greatly reduce existing dust, small particle and lint fly emissions, all of which contain at least trace amounts of arsenic, bacteria and pesticides (Multer *et al.*, 2010). Due to the 2010–11 drought, industry leaders found that CGW can be used as a cattle feed supplement, reliably valued between \$9 and \$12/tonne (Mullenix *et al.*, 2021).

Works also have considered bioenergy from CGW directly in the form of bioelectricity. Liu *et al.* (2009) completed a proof-of-concept to establish baseline profitability. Tangaoui and Michael (2014) examined cross-correlations of prices of cottonseed oil to soybean oil, to palm oil and to biodiesel, which demonstrate enough long-run price stability in cottonseed oil to prevent widespread gin shutdowns that might strand a bioenergy investment. Farmer *et al.* (2014) made the first attempt to consider stochastic processes that would affect a biorefinery from CGW. Yet data limitations, primarily from mandated *non*-reporting of hourly electricity prices have prevented full analyses of complex stochasticity: drought, cotton price risk and changing electricity prices.

This is the first study to examine the joint sources of variability in cotton yields, cotton fibre prices and daily peak, subpeak and base electricity prices. Analyses generate plausible risk-return predictions across biopower investments from 1 to 6 MWe each for a small- and medium-sized gin by repeated draws from the distributions of these multiple risks.

This work then estimates returns and variance of power plants at gins for these various sizes from 1 to 6 MWe installed capacity. This work also presents a very realistic picture of the risk-return trade-off options from various onsite power plant investments. We examine multiple biopower options available both to small and medium-sized gins. Specifically, we generate a mean return and variance Frontier (or EV Frontier) that reveals the multiple power plant sizes available to each sized gin. The Frontier defines the set of second-order stochastic undominated alternatives, which accounts for the uncertainties above.

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This is an important point of departure from works that estimate a single optimal output scale under average conditions, which dominates engineering and economic literature on this subject. Though some works do treat uncertainty, it is often relegated to parameter sensitivity analyses. Even in cases that have applied stochastic dominance (Domínguez *et al.*, 2021; or, much earlier, Lesser, 1990), the objective is to identify the *single* choice whereby the central planner can maximise average power output without accepting undue risk at that maximal output level.

We know of no work in any bioenergy assessment which is conducted at this level of data resolution and that allows for a more realistic risk presentation. We know of no other work that presents this level of flexibility in risk-return trade-off information for investors. We expect subsequent works to improve on the multi-pronged model strategy introduced here.

3. Overview of modelling process[1]

The modelling process is straightforward but does integrate many moving parts. We simulate the annual profitability of onsite power plants from one to six megawatts of installed capacity at cotton gins. We also consider two different sized gins — a small and a medium-sized gin. We add up all the sources of annual revenue generated from CGW and subtract the annual marginal and financing costs of operation. We employ 10,000 simulated annual decisions.

Most of the revenue comes from the sale of electric power generated from the combustion of CGW. The annual decision of how and when to allocate a year's CGW to electric power is modelled as nine sequential monthly choices, starting in mid-December. The gin operator makes this decision in any given month to allocate some portion of on-hand (or remaining) gin trash to deliver power during peak, subpeak and base electricity price periods during that month. Current month prices are observed as future monthly electricity prices remain stochastic.

Most electricity sales occur during winter, timed to daily peak prices when possible. If the CGW supply is moderately large, sales also occur during subpeak and base power hours.

CGW is also expensive to store, especially because environmental hazards from CGW grow larger the longer CGW is stored on site. Fortunately, gin trash now can be sold as cattle feed. In our simulations, the choice to sell CGW directly as feed generally occurs at winter's end (March). CGW is rarely held over for very high-priced summer power demand unless the CGW supply is exceptionally large. In most years what CGW is left after winter is sold as cattle feed in March.

The costs of operation are discussed below. Labour is the largest expense. Labour applied directly to power production and delivery is captured as marginal costs. We also assume higher fixed labour costs for a professional plant manager dedicated to harmonising gin and power plant operations. Based on an annual median income of around $90,000 in Texas,[2] we impose a $75,000 fixed cost for 9 months out of a year effort to oversee power plant operations. We also model high annual financing costs. We adopt plant depreciation at 12 years rather than the more common 20–30-year life of the plant. Finally, we limit the total operating time per year for power generation, and, at times, this is an occasional binding constraint. Our purpose for these conservative assumptions is to capture better the inevitable learning curve costs for early adopters as they struggle to meet the requirements of the procedural plan filed by a licenced power evaluator.

The largest contribution of this work, however, emerges from integrating multiple stochastic processes. Electricity prices in each price category for each month are stochastic as is annual CGW volume.

We contrast this strategy to other bioenergy models which lean strongly on the adoption of a one, singular representative optimal scale operation. Our analyses allow the decision environment to differ in numerous ways from year to year. What makes this more realistic risk modelling process possible is due to recent changes in public reporting of hourly electricity prices. We use a

[1]We thank an anonymous reviewer for suggesting this section.

[2]Bureau of Labor Statistics.

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record of over 105,000 reported electricity prices — each hour for each calendar day for 12 years, allowing for a much richer presentation of the multiple sources of uncertainty.

To simulate the annual decision to allocate CGW, we organise observed hourly prices from mid-December to mid-September into peak, subpeak and base electricity prices for each of the nine months — 27 variables in all.

For each month, we randomly draw one peak price, one subpeak price and one base price from the extensive price record available. We repeat this 10,000 times to generate 10,000 simulated decision years. Simulation results then provide an average annual return and a standard deviation. This process repeats for each of the six power plant sizes available for each sized gin. This allows us to organise results into risk-return graphs or the outer envelope of an EV Frontier to visually compare risk-return outcomes: from a 'small-low risk' scaled plant to a 'large-high risk' scaled plant. In this way, investors can make informed risk-return choices from an array of options.

The greatest uncertainty in the simulations is the year-to-year variation in CGW. This deserves special attention. We have a very short CGW record: only 15 years at a small to medium-sized gin as gins are reluctant to provide this information. Of benefit to us, that 15-year period includes two years of very high rainfall and severe 2-year drought (2011–2012). Given more than a century of rainfall data, this wide range allows for a more realistic simulated CGW distribution.

Of note, CGW volume is modelled as a quadratic response to rainfall, which has limitations. Yet, we follow several decades of existing literature to estimate cotton yields based on a quadratic rainfall function and cotton prices. As farmers and cotton co-op investors use our information, we need it to match the large body of extension and academic work on cotton production (see Mitchell-McCallister *et al*., 2021). Presumably, many producers or larger co-ops have experience adjusting their own conditions to those estimates. What we do add is a Gibbs-sampled estimation of the parameters to estimate CGW. That lone extension generates a multi-modal CGW distribution rather than a single peaked estimate, which mimics the distribution in the raw data.

The remaining constraints on the model are right-hand side production constraints on choices to allocate CGW in a given year; conversion efficiency of 1 tonne of gin trash to megawatts of electricity; adding up conditions for the several uses of CGW; constraints by the number of peak hours, subpeak hours and base supply hours available in a given month; and other material balance constraints. We do conduct sensitivity analyses

We conduct three separate sensitivity analyses: a lower conversion efficiency rate (less electricity per tonne of CGW), a 40% drop in base period electricity prices (to conform to historic rates prior to 2010) and following trends, a 10% increase in all electricity prices. Profitability remains high in all cases.

As a final consideration, we attempt to address the possibility of plant obsolescence in a future energy economy, in particular the transition to a 'hydrogen-based' economy. Much of that hydrogen would be generated through electrolysis. So, for completeness, we model a bolt-on anhydrous ammonia technology, which is one existing technology that employs electrolysis. Adding ammonia production to the array of choices for CGW use is currently less profitable than a stand-alone power plant, but this is largely due to the very high cost of safety protocols in ammonia handling. The technical feasibility serves only as a proof-of-concept scenario to suggest an electric power plant would survive anticipated technology shifts, at least at first, though may become even more profitable than these scenarios show.

The analytic model is detailed in the Appendix A. The main text includes the mechanics of the CGW allocation decision process, the method for draws from electricity prices, the Gibbs sampling process to build distributions for annual CGW and a distribution for ammonia prices from a regression analysis. The results are presented as financial outcomes, primarily as the return on invested capital (ROIC) for different levels of investment and borrowing. Finally, two graphs map a Frontier that plots all second-order stochastic undominated alternatives as a risk-return graph: one for each size gin. Each graph plots the risk-return outcomes for six different power plant sizes.

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4. Data for stochastic analyses

Cotton Gin Waste (CGW): We obtain CGW data from the Ropes Farmers Co-Op Gin in Lubbock County, Texas, between 2004 and 2018. Fortunately, this period includes two of the top five 2-year records for drought and one of the three highest 2 years rainfall events since 1908. We also obtain rainfall data for the same years from the ASOS-AWOS-METAR database (Iowa State University, 2022). Further, cotton fibre price data is obtained from (USDA, 2022). We use these data to generate an estimated sampling distribution of CGW by regressing CGW in a Gibbs-sampled Bayesian regression on rainfall and cotton price.

Electricity Prices: Electricity prices are obtained from Electric Reliability Council of Texas (ERCOT) (ERCOT, 2022). We report 'Day-Ahead Market' prices on an hourly and daily basis for 2010–2021 for the ERCOT West Hub and Load Zone, recording more than 105,000 price points. For convenience, we sort electricity prices by daily intervals of peak, subpeak electricity prices and base electricity prices. In the analyses below, we estimate sampling distributions of peak, subpeak and base prices for each month. These monthly price distributions are obtained by regressing *hourly* electricity prices on *hourly* temperature data (from the ASOS-AWOS-METAR database; Iowa State University, 2022) in each month over 12 years. This allows a Bayesian draw for the separate distribution estimates of daily peak, subpeak and base electric prices for each of nine months of analysis.

Anhydrous Ammonia Prices: We use monthly anhydrous ammonia price data from 2014 to 2021, collected from the DTN Progressive Farmer database (Progress Farmer, 2021). Anhydrous prices movements are tied to seasonal cycles rather than month-to-month fluctuations, so we follow the modelling approach in the established literature and group prices into intervals: (i) winter, December to February; (ii) spring, March to May; and (iii) summer, June to September. Ammonia prices are regressed on the prices and lagged prices of major crops and oil (USDA National Agricultural Statistics Service, USDA, 2022) to generate an estimated distribution of seasonal ammonia prices, following Schnitkey (2021).

5. Decision process

Figure 1 below illustrates the decision process across the nine-month decision period from January through September. The gin allocates CGW in any given year to biopower and to cattle feed sales (at $10/tonne). At the start of the decision period, the volume of gin trash is known. Electric prices for the immediate month are also known, so on January 1, the peak, subpeak and base prices for that January draw are known, while prices in all future months are stochastic.

Using Figure 1, given CGW on hand (*Total CGW)*, the ginner maximises expected profits across a year and confronts stochastic electricity prices for each future month (μp_{i+n}, in Figure 1). In panel A, we show that the ginner observes current monthly electricity prices (*Obs.* P_i; the red 'E' in Figure 1, Panel A) as the rest remain uncertain. The manager decides how much CGW to use in any month by maximising expected profit for the year using current prices and the expected mean price (μ_p) in each electricity price category (peak, subpeak and base power) for future months. In the next month, the process repeats with a draw of electricity prices from the then-drawn peak, subpeak and base prices.

Once a decision is made, the available gin trash remaining is known and is to be allocated over the remaining 8 months in the same fashion. The second panel in Figure 1 shows electricity price information updates be the information in red in period 2. The decision to maximise expected returns now takes place over the 7 months. An option always open to the gin is to sell a portion or all the remaining CGW as cattle feed at $10/tonne, a stable price since the 2010–2011 drought. There is no explicit risk aversion within the annual CGW allocation as investors and day-to-day managers operate consistent with investor preferences. Yet to carry gin trash forward is expensive.

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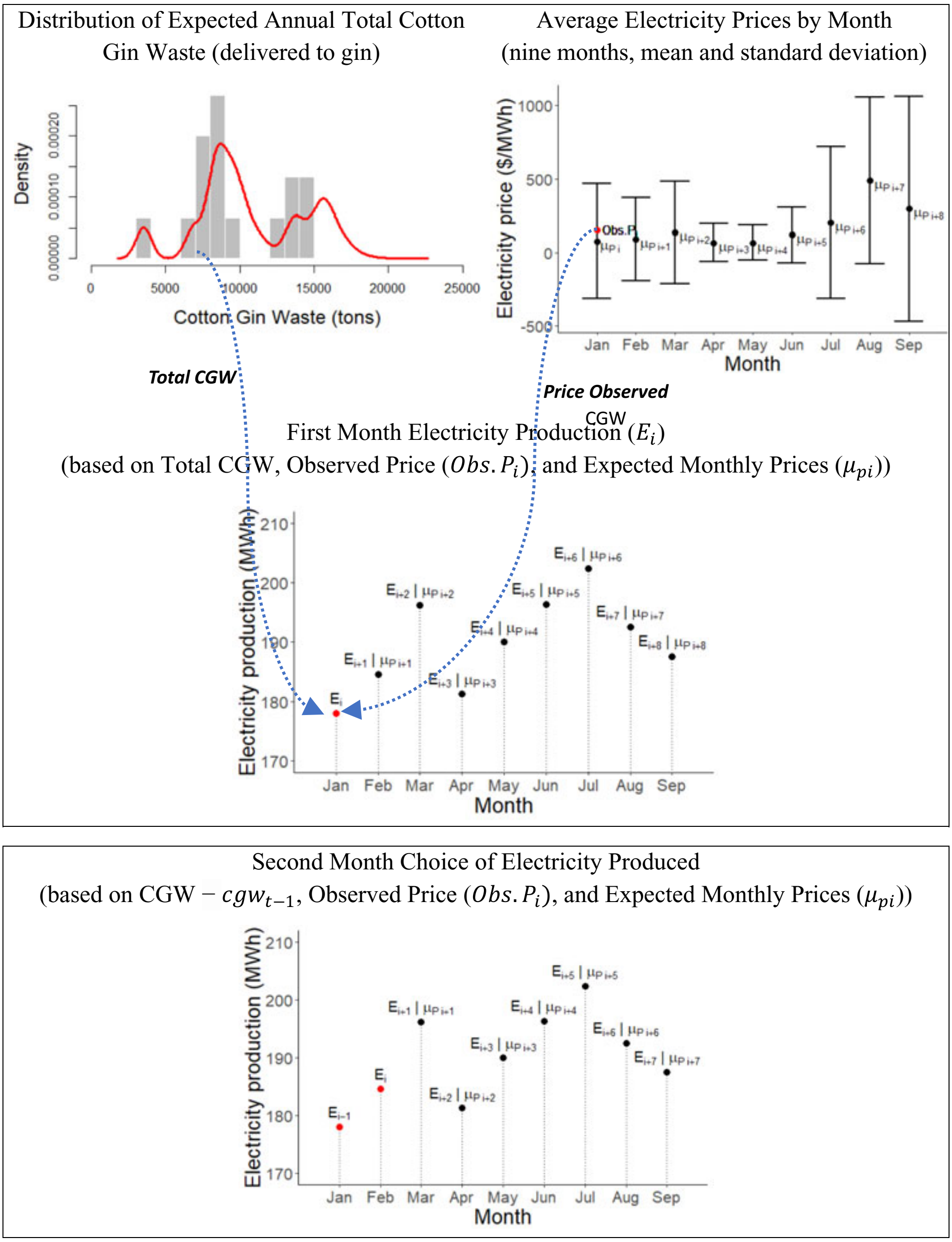

Figure 1. Decision process to allocate cotton gin waste.

Holding over gin trash during the low electric prices of April and May (and early June) to sell in late June, July and August is expensive. So, we assess a $2/tonne per month storage charge to store the remaining CGW (suggested by site managers at *Ropes*, a small gin, and by *Plains Cotton Growers*, a large co-op gin). In low or medium volume years, gins will sell the remaining CGW at the end of March. Nonetheless, given very high expected summer electricity prices, plotted in Figure 1, years where there is an exceptionally large CGW volume, it is profitable to generate electric power through the summer and to skip power generation in April and May.

We model power sold to local utilities through 'day ahead' pricing. So, a sale has a guaranteed price to produce the next day, often a little higher than the actual price, especially in winter. Though produced power also may be used to service onsite ginning needs, it is advantageous to sell at least some electricity to the local utility for some hours most winter days. Utilities routinely offer a price premium to ensure power delivery during the next day's peak use, and peaking power can last 10 hours or more on the highest demand periods of winter.

6. Model parameters

We generate a distribution for each of the 28 distinct sales decisions a power plant operator makes: peak, subpeak and base electricity generation in each of nine months and sales of CGW as cattle feed. Operating expenses are dominated by fixed and quasi-fixed costs: fixed costs include a chemical boiler, steam turbine, loan payments if not fully financed and affixtures to plant operations; quasi-fixed costs are annual labour expenses dedicated to manage operations. Finally, marginal costs include per unit costs of electricity generation and storage costs for CGW.

Appendix A details the model as the summed difference between all revenue streams and annual costs — subject to constraints on plant size, conversion efficiency, limits on hours of operation and material balance constraints. On the cost side, both fixed and quasi-fixed costs exceed existing engineering reports on the costs of installation of similar sized plants (U.S. Department of Energy, 2016). Plant costs also exceed those in engineering reports: our modelled costs are 15% higher for a 1 MWe plant and 8% for a 5 MWe plant. We include financing costs with a 25% investment in installation costs with the remaining 75% amortised at 8.5% over a 12-year loan, both of which are higher than typical market rates. The fixed cost of the ammonia processor is $350,000, though only one has ever been built and includes costs of natural gas installations, which include costs of a feeding system and gas turbine. The financing structure of the ammonia processor follows that of the power plant. We also report the internal rate of return of a fully financed investment. Overall, our costs are higher and returns lower than most engineering reports.

6.1. Simulation methods: sources of uncertainty

We conduct profitability analyses on 10,000 simulated annual decisions. This requires the use of existing data to simulate distributions of CGW and of 27 different electricity prices.

Cotton Gin Waste: To simulate the distribution of annual CGW, a regression of CGW against precipitation and its square is estimated by a Gibbs sampling of the model:

$$CGW = \beta_0 + \beta_1 PPT + \beta_2 PPT^2 + \varepsilon \tag{10}$$

where CGW is an annual production of CGW in tonnes, PPT is annual precipitation in cm and β_0, β_1 and β_2 are the regression coefficients to be estimated.

To estimate a posterior distribution for the coefficients (β) and the error variance (σ^2), we specify the number of model iterations (11,000 herein), of which 1,000 are used to burn in the sample and then discarded. Each iteration alternates between sample draws for the two beta coefficients and the error variance. The 'betas' are sampled from a multivariate normal distribution, using the covariance matrix and mean parameters. 'Sigma' values are drawn from an inverse gamma distribution as this allows great flexibility in the shape of the CGW distribution. Each sampling draw is stored, and the corresponding value of CGW (10,000 in all) is assigned from these sampled coefficients (Lacombe, 2022). We employ the same Gibbs sampling regression for each of the three seasons of anhydrous ammonia.

Electricity Prices: Electricity price distributions are based on over 105,000 observations of hourly electricity prices, which sort into more than 3,600 observations for peak prices for every month, more than 5,000 subpeak prices for each of 9 months and 2,900 observations of base prices

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for each of 9 months. To simulate distributions, we randomly draw 10,000 times from these data for each electricity price category (peak, subpeak and base) in each month. This generates 27 electricity price distributions, each with 10,000 draws based on 105,000 direct observations of hourly electricity prices.

So, simulations are reports from 10,000 random draws of *annual cotton gin trash* and 10,000 draws of *peak, subpeak* and *base electricity prices* for each month (December–September).

When adding ammonia processing, three seasonal *anhydrous ammonia price* distributions are added. The ammonia simulation model is derived from Ibendahl (2021) and Schnitkey (2021) in which demand is determined by the price of corn and a lagged oil price. Our formal regression model uses the price of major crops including corn, cotton and oats, their squared prices and 9-month lagged oil prices. Table B1 in the Appendix presents the summary statistics of the observed and simulated values.

6.2. Distributions

Panel A, Figure 2 presents a distribution of draws of annual CGW against cotton prices and annual rainfall by the Gibbs sampled Bayesian regressors, described above. The flexibility of the simulation process is represented in the triple peaked distribution of CGW, which closely matches the variable weather in the study area.

Panels B, C and D show distributions of hourly electricity prices for every hour over 9 months for 12 years, sorted by peak (4–7 hours/day), subpeak (8–14 hours/day) or base (10 hours/day) electricity prices. The distributions reflect a secular trend of increasing peak prices, frequently exceeding \$100/ MWe and higher base prices for off-peak hours, well above the \$25–\$30 15 years earlier (US Bureau of Labor Statistics, 2021). For profitability analysis, we extract 10,000 draws of these 27 prices to solve a revenue maximisation problem that allocates annual CGW according to Figure 1.

7. Risk-returns

Simulations address two sized gins. The CGW represented in Figure 2: Panel A is based on a known record of CGW from Ropes Gin. The medium-sized gin is premised on *Plains Cotton Growers*, a local co-op gin with total revenues close to three times those of Ropes — in the same area. Plains Cotton Growers co-op in fact reports an overall average gin size of 28,000 tonnes of gin waste, close to 2.9 times the size of Ropes Gin. The distributions of all are identically scaled to Figure 2: Panel A.

We evaluate investment success through several financial benchmarks. First, simulations provide 10,000 simulated annual profit or loss outcomes for a power plant of a given size at a given sized gin. That variation also generates a standard deviation from the expected annual profit. ROIC tracks two scenarios where an investor makes a 25% down payment and borrows the rest and a 100% self-financed.

The average returns over 10,000 simulations compared to the cash investment drive the ROIC percentages. These are converted to annual returns on invested capital rather than the entire 12-year life of the plant. In addition, over the 12-year life of the plant, we report the probability that the investment shows an overall loss and report the probability of a 100% return or greater on invested capital (annualized).

7.1. Small gin options

Table 1 summarises results for bioproducts produced at a small gin. Presented are two types of plants: electric power only or with ammonia processors. Profit is represented as cash flow — all revenue from electric power minus operating costs, and estimated returns to a small gin are reported in Table 1. As shown in Table 1, plants where 25% of the installation costs (\$321,000 and

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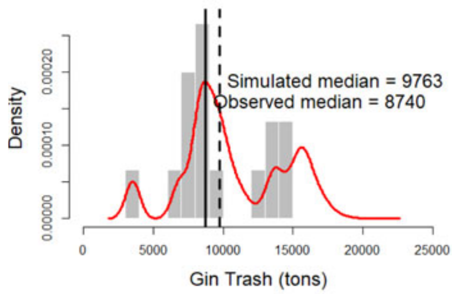
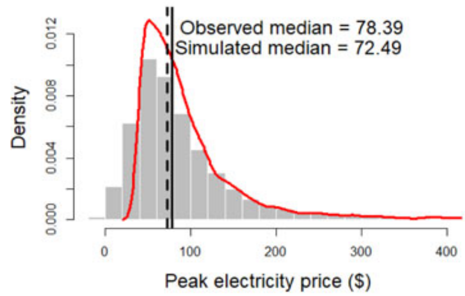
Panel A: Distribution of Gin Trash



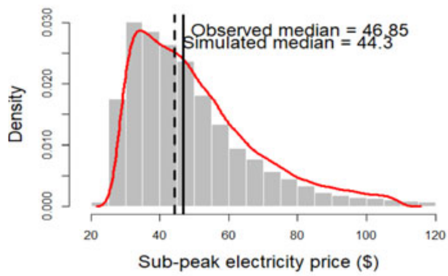
Minimum:	3,342
Median:	9,763
Mean:	10,752
St. Dev.:	3,662
Maximum:	21,093

Panel B: Distribution of Peak Electricity



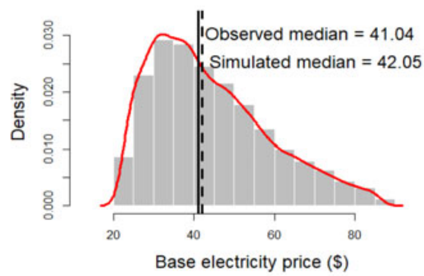
Minimum:	-407.02
Median:	72.49
Mean:	184.91
St. Dev.:	849.82
Maximum:	23,259.35

Panel C: Distribution of Sub-Peak Electricity



Minimum:	4.14
Median:	44.30
Mean:	52.35
St. Dev.:	56.35
Maximum:	3,910.65

Panel D: Distribution of Base Electricity



Minimum	-2.04
Median	42.05
Mean	48.41
St. Dev.	53.04
Maximum	3,152.99

Figure 2. Distribution of simulated and observed cotton gin waste and electricity prices.
Note: Top and bottom 5% of the distributions were truncated for better scaling on the axes (except gin trash); grey bars represent observed values and red density plots represent simulated values).

$590,000) are self financed and the remainder borrowed ($0.963 million and $1.770 million). Financing of course lowers average annual cash flow and elevates annual ROIC.

Both the 1 MWe and 2 MWe plants appear very attractive. In an average year, the 1 MWe plant is expected to return 58.8% of initial invested capital and a 2 MWe plant to return 51.2% of invested capital. Yet the very high standard deviation around annual cash flows is worthy of note.

The key source of variability in annual cash returns is the variation in the quantity of gin trash, but the ratio of standard deviation to average annual returns is due to principal and interest financing payments and the annual fixed labour costs we added for first-time investors. This is why we present outcomes as cash flows to highlight this concern.

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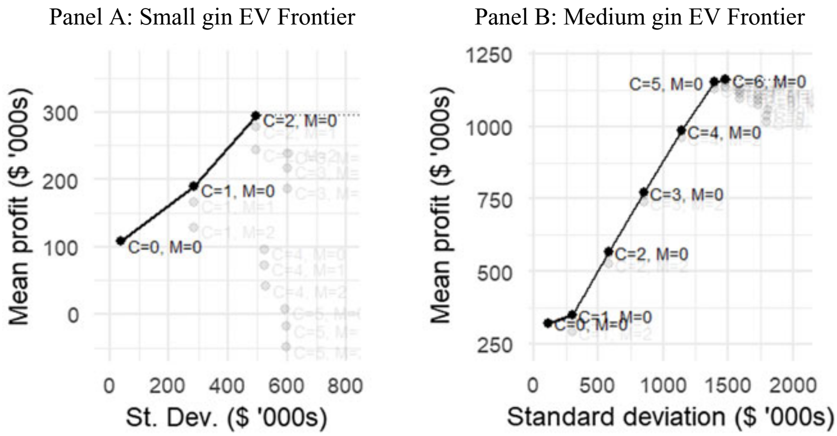

Figure 3. EV Frontier. The standard deviation (SD) represents the SD of net profit across 10,000 simulation runs, with each iteration using different input values generated through Bayesian regressions. The mean profit is plotted on the *y*-axis, and the standard deviation of profit is plotted on the *x*-axis.

Real average profits of the 1 MWe plant have to add back the $80,000 average annual principal outlays and for the 2 MWe plant add back $130,000 average principal payments. These returns are very high even with added annual fixed labour costs of $75,000 for new investors. Even with intermittent cash flow concerns, the chance of negative cash flow over the entire 12-year period is only 5.6% for a 1 MWe plant and 9.6% for a 2 MWe plant, each with very high expected returns on invested capital. If we consider self-financed options, the more conventional internal rate of return is 22.2% annually for the 1 MWe plant and 18.0% annually for the 2 MWe plant.

Figure 3, Panel A graphs the outcomes of Table 1 labelled EV: the set of second-order stochastic dominant investments for the 1 MWe plant for a small gin. The do-nothing option is always on the frontier as it presents virtually no risk for the expected revenues of CGW sales as cattle feed. This Frontier is slightly bowed right given the cash flow risks from fixed expenses that advantage the 2 MWe plant investment. Nonetheless, all are stochastically dominant. Only the risk preference of an investor can choose among these options.

7.2. Medium-size gin options

The medium-sized gin is modelled as three times the size of the small gin, processing 29,000 tonnes in an average year.[3] Results continue to reflect a 25% investment with a 75% loan. Table 2 shows modestly increasing scale returns. First, greater size reduces the cost per MWe of quasi-fixed labour of $75,000; yet it is the declining average cost in plant construction that contributes most to scale economies.[4] This is clearly evident when comparing Table 2 to Table 1.

75% financing of a medium gin returns an average annual return of more than 90% of the invested capital; and this ROIC continues at every scale up to the 5 MWe plant for a medium gin. Conversely, in a fully financed power plant, the internal rates of return (IRR) of installing a 1 MWe, 2 MWe and 4 MWe are 41, 37 and 36% respectively.

[3]The medium-sized gin is modelled as 3× larger than the small-sized gin: 9,700 tonnes versus 29,000 tonnes on average.
[4]Installation costs herein commence at $1.285 million/MWe for a 1 MWe plan — well above engineering reports of $1 million. Modelled costs of $1.010 million/MWe for a 4 MWe plant is still 12% higher than reports of $0.9 million/MWe at this scale. At the 6 MWe scale — the largest plant on the EV frontier, our costs ($0.921/MWe) compares to $0.850–0.900 million/MWe in engineering reports. Finally, our lowest cost plant of $0.865 million/MWe for a 9 MWe plant finally falls close to engineering reports (U.S. Department of Energy, 2016; Frontiers, 2021).

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Table 1. Analyses for small gin

Models	Avg. ROIC (%)	Prob. loss (%)	Prob. ROIC >100%	Avg. annual profit (cash flow, $)	SD profit (cash flow, $)
$C = 0$, $M = 0$ EV*	0.00	0.00	0.00	107,516	36,626
$C = 1$, $M = 0$ EV	58.83	5.60	12.99	189,011	284,846
$C = 2$, $M = 0$ EV	51.25	9.50	11.04	294,700	494,065
$C = 3$, $M = 0$	29.51	30.39	6.17	238,519	602,822
$C = 1$, $M = 1$	40.73	9.06	8.94	166,505	284,887
$C = 2$, $M = 1$	41.86	12.05	8.72	277,330	493,492
$C = 3$, $M = 1$	24.21	35.52	5.22	216,900	600,695
$C = 1$, $M = 2$	25.96	22.46	7.11	128,860	284,887
$C = 2$, $M = 2$	32.40	17.38	6.87	242,992	493,718
$C = 3$, $M = 2$	18.93	42.23	4.27	186,189	602,075

* C = installed power capacity in MWe; M = number of ammonia plants (550 tonnes/plant); when $C = 0$ and $M = 0$, all CGW is sold as feed at $10/tonne; for each incremental increase in C, installed power capacity increases by 1 MWe, and for each incremental increase in M, installed ammonia capacity increases by 550 tonnes; EV = models on the Efficient Frontier; ROIC is calculated by dividing net profit [revenue – (marginal cost + fixed cost)] by invested capital [debt + equity]; Prob. loss represents the number of simulations (out of 10,000) where net profit is less than 0; Prob. ROIC >100% refers to the number of simulations (out of 10,000) where ROIC exceeds 100%; all results are based on 10,000 simulations; full results in Appendix Tables B2 and B3; output combination in Appendix Table B10.

Table 2. Analyses for medium gin

Models	Avg. ROIC (%)	Prob. loss (%)	Prob. ROIC >100%	Avg. annual profit (cash flow, $)	SD profit (cash flow, $)
$C = 0$, $M = 0$ EV, *	0.00	0.00	0.00	322,549	109,878
$C = 1$, $M = 0$ EV	108.79	0.01	37.39	349,517	297,249
$C = 2$, $M = 0$ EV	98.96	0.02	23.52	569,104	577,942
$C = 3$, $M = 0$ EV	95.41	0.54	21.83	771,254	854,539
$C = 4$, $M = 0$ EV	96.01	3.09	22.16	986,196	1,140,497
$C = 5$, $M = 0$ EV	92.91	4.90	21.21	1,152,070	1,391,770
$C = 6$, $M = 0$ EV	80.56	5.81	17.35	1,162,195	1,482,193
$C = 7$, $M = 0$	68.44	6.59	13.75	1,122,302	1,592,251

* C = installed power capacity in MWe; M = number of ammonia plants (550 tonnes/plant); when $C = 0$ and $M = 0$, all CGW is sold as feed at $10/tonne; for each incremental increase in C, installed power capacity increases by 1 MWe, and for each incremental increase in M, installed ammonia capacity increases by 550 tonnes; EV = models on the Efficient Frontier; ROIC is calculated by dividing net profit [revenue – (marginal cost + fixed cost)] by invested capital [debt + equity]; Prob. loss represents the number of simulations (out of 10,000) where net profit is less than 0; Prob. ROIC >100% refers to the number of simulations (out of 10,000) where ROIC exceeds 100%; all results are based on 10,000 simulations; full results in Appendix Tables B4 and B5 and output combination in Appendix Table B12.

The EV Frontier on Panel B, Figure 3 shows considerable flexibility for an investor. A gin this size choosing to install a boiler-steam turbine power plant faces a very low probability of loss. The simulated probability of loss over 12 years is less than one percent up to a 3 MWe installation. Not until installation reaches a 5 MWe scale is the probability of loss nearly equal to the probability of loss to the 1 MWe plant at a small gin.

What provides security to a risk-averse manager of a medium gin is volume of CGW. On average, the gin with a smaller power plant can cover the hours of peaking electricity prices across the early months during ginning. The smaller plant at a medium-sized gin can offset some loss of a low harvest year by selling all gin trash at very high peaking prices. A small gin with the same size plant will have greater exposure to years in which they exhaust CGW before they satisfy winter peaking power.

Investors in the medium-sized plant can secure very high returns coupled — an elevated ROIC — with very modest risk. Conversely, an investor with a higher risk tolerance and a strong cash position can support, say, a 5 MWe plant with very high returns over time. The EV Frontiers in Figure 3 illustrate that investors of different risk preferences and different cash positions can fashion their investment choice to their own needs, rather than face a take-it-or-leave-it option of a singular 'optimal' scaled system.

7.3. Sensitivity analyses

Though we elevate installation costs by 5–20% across plant options, use somewhat low conversion efficiency (25% rather than 28%) and increase labour commitments, simulations still show strong returns and modest risk, especially for larger sized gins. We summarise sensitivity analyses below. The appendix details even more conservative results. Sensitivity analyses for the small gin are recorded in Tables 6 and 7; results for the medium gin are presented in Tables 8 and 9; and combined outputs using an ammonia plant are recorded om Tables 11 and 13.

7.3.1. Lower base electricity price

As a first sensitivity analysis, we lower base electricity prices from the $48/MWe we found in the 12-year record to $25/Mwe, which is more in line with historical base prices. Critically, the EV Frontier is slightly lower although optimal plant capacity does not change.

Though we have not found the addition of an ammonia plant more profitable than electric power only, a drop in base prices would encourage the diversion of power from electricity sold to a local utility to ammonia production via electrolysis during nonpeak hours If a small gin installed $C = 1$ and $M = 1$ (not on the Frontier), electric power *sold* would decrease from 3,771 MWh to 3,314 MWe as ammonia production rose from 138 tonnes to 179 tonnes. The medium gin realises a similar pattern.

7.3.2. Lower marginal cost of ammonia plant

The chief reason ammonia production is currently unprofitable is the high price of electricity sold to power utilities and the very high marginal cost of production of ammonia due to safety concerns. If we lower the marginal cost of ammonia production by 34.8% — from $130.34/tonne to $85/tonne — this drop in marginal cost does not alter optimal plant composition; plants with no complementary ammonia processor remain a little more profitable.

If the policy seeking to reduce the size of ammonia plants for safety concerns subsidised an ammonia processor by 10%, adding this marginal cost reduction would almost match the EV Frontiers presented. The effect would decrease the amount of electricity *sold*, especially in base price markets, and divert power generation to ammonia output. What this simulation does show is that electrolysis-based products, such as hydrogen fuel, can be produced in the future as technology makes these systems more efficient. These are easily 'located' onto an existing power plant.

7.3.3. Lower conversion rate

We now reduce the conversion rate efficiency of CGW into electricity. We initially employed a conversion rate of 25%, which is only slightly below the current 28% efficiencies reported for a modern boiler. If conversion efficiency falls to 18% from suboptimal operation and maintenance, the benchmark 2 MWe plant at the small gin is still the plant size with the highest expected profit for the small gin, but 12-year cumulative cash flow falls by 72%.

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The same conversion efficiency drop for the medium gin reduces the 12-year cumulative profit of a 5 MWe plant by 53%. The operational adjustment of lower efficiency is to almost eliminate holding any CGW to summer months, selling CGW as cattle feed in March instead.

7.3.4. Higher electricity prices

As a final sensitivity analysis, we increase all electricity prices by 10%. For each sized gin, this increase does not change the optimal plant composition, nor the timing of electricity sold over the seasons. Of course, IRR and ROIC increase with increasing electricity prices.

The next step is a formal operational assessment by a power evaluator. Even with the advice of engineers, implementation involves multiple licences and process plans that match to rigid design and operation standards. While many dual biomass processors with biopower operations have been licenced, each is different. The final plant will differ from this in some fashion. Our conservative orientation here suggests the evaluation is warranted and shows enough residual profits to realise a reliable second value stream for independent and co-op gins.

8. Conclusion

This work illustrates profitable pathways to develop bioelectricity plants at rural food and fibre processing centres using biowaste feedstocks. First, the power plant uses existing technology. The operation of a chemical boiler to generate heat to power a steam turbine has been used for more than 130 years, and the technology has improved continuously over that period. As a secondary benefit, this system can be upgraded as more efficient gasification or pyrolysis technologies become commercially available. The system can also adapt to new electrolysis-based products if a hydrogen-based economy evolves. The investment options are also highly profitable under conservative parameters. Compared to existing engineering studies, these analyses overstate the costs of plant installation, abbreviate the useful life of a plant to replacement and elevate the operational costs to manage the plant.

A central benefit of this work is to demonstrate that investment choices are highly flexible. The scale of investment, forms of financing and level of leveraging exposure support very different levels of investment. Critical to this work is that we presented a structured method to allow more flexibility in bioenergy production and investment. By presenting a realistic risk-return (EV) Frontier, investors make informed risk-return choices on their own without facing a narrow set of researchers or policymakers who presented optimal investments. This flexibility we assert is central to elevate the adoption of alternative energy sources.

This flexible presentation emerges from the manner of economic estimation itself. As bioenergy has often been dominated by technical advances, applied at utility scale to accelerate conversion, the presentations may not resolve the question of real investors. The presentation of average prices and average conditions for bio-feedstocks, and often little more, presents investments that may fit only a few investors and pressure public entities to subsidise investments that, under more flexible conditions, are profitable for investors in current markets.

Unique to this study, risk and uncertainty are analysed and communicated by the simultaneous variation of electricity prices (varying peak, subpeak prices and base prices), variations in feedstock availability due to variations in rainfall, heat and commodity prices themselves. Risk presentation is supplemented by specific sensitivity analyses, such as the biomass conversion efficiency. Though policymakers seek continuous provision, the marginal investor also may need to optimise the timing of power output across a day and across seasons. Communicating risk is also important.

This return-variance information is also presented graphically in the form of a frontier of these stochastic dominant outcomes, or an EV Frontier mapped onto expected returns and variance axes. All of this assists the investor (gin, cooperative, or independent investor) match their risk

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tolerance against each separate investment level. We have not seen this in the extensive bioenergy literature.

Two final advantages include the direct environmental benefits of managing and processing CGW to avoid long-term problems. CGW starts to release arsenic and attract beetles that carry diseases after long periods. With nearly all gin waste processed during winter ginning and only a small volume held over in exceptional years for summer combustion, these local environmental risks are virtually eliminated.

Second, this diversification contributes to the economic viability of rural industry while also easing some of the most dangerous periods of power supply shortage. This process also allows other products to be made, from ammonia fertiliser to hydrogen fuels from electrolysis. A rural power plant may be an attractive bolt-on technology contributing to viable rural economies, especially as electricity demand is projected to increase as more electric vehicles are deployed. The possibility for a multi-product biorefinery may be more open to smaller operations, outfitted with more versatile uses than large, complex single-use systems such as a combined cycle power plant.

Finally, bioenergy literature itself may need a more holistic perspective. To assess this resource use process as a bioenergy project misses the multifaceted benefits to resilient rural economic development. The energy and climate challenge clearly will require some large single-purpose operations. Yet such a large complex, comprehensive conversion of an economy will need to be buttressed by numerous, small retrofitted multi-use systems such as those suggested here. These programmes require a different analytic approach. Similarly, rural development and agricultural economic analyses should not ignore energy and climate impacts. When a credible opportunity for meaningful overlap does appear, we risk obsolescence of single-purpose investment and policy analysis.

Data availability statement. CGW data in this study are collected from Ropes Farmers Co-Op Gin. The other data that support the findings of this study are openly available on the Electric Reliability Council of Texas (ERCOT) website (https://www.ercot.com/mktinfo/prices); ASOS Network: ASOS-AWOS-METAR Database (https://mesonet.agron.iastate.edu/request/download.phtml); DTN Progressive Farmer website (https://www.mydtn.com/); Federal Reserve Bank of St Louis Economic Data website (https://fred.stlouisfed.org/); and USDA National Agricultural Statistics Service website (https://www.nass.usda.gov/index.php).

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Appendix A

The optimisation model for the plant operator and processor solves for the operator choices of electricity generation capacity, the amount of biomass available and expected prices of electricity and ammonia. Expected profit is defined below as:

$$\begin{aligned} &MAX\ P_pE_p + P_{UB}E_{UB} + P_{LB}E_{LB} + P_MM - 5.5\left(E_p + E_{UB} + E_{LB} + E_M\right) \\ &- 130.34 * M - 37645 * ME - 0.100385 * \left[640000 + \frac{4000000}{1.2 * C + 5}\right] * C - FC + 10 * GW_f \end{aligned} \tag{1}$$

- P_p is the peak electricity price; E_p is the MWe of electricity sold each month at peak prices;
- P_{UB} is the subpeak electricity price; E_{UB} is the MWe of electricity sold each month at subpeak prices;
- P_{LB} is the price of base electricity; E_{LB} is the MWe of electricity each month at base prices;
- P_M is the price of ammonia, M, per tonne; E_M is electricity in MWe required to produce a tonne of M (11 MWe is needed to produce every tonne of ammonia, M);
- ME is the number of ammonia processors, which ranges from 0 to 2;
- C is installed power capacity, which ranges from 1 to 5 MWe for the small gin and 1 to 9 MWe for medium gins;
- FC is the annual labour cost, fixed at $75,000;
- GW_f is gin waste, in tonnes, sold as cattle feed.

Equation (1) can be rewritten as:

$$\begin{aligned} &MAX\ P_pE_p + P_{UB}E_{UB} + P_{LB}E_{LB} + P_M\frac{E_M}{11} + 10 * GW_f - 5.5\left(E_p + E_{UB} + E_{LB} + E_M\right) \\ &- 130.34 * \frac{E_M}{11} - 0.100385 * \left[640000 + \frac{4000000}{1.2 * C + 5}\right] * C - FC - 37645 * ME \end{aligned} \tag{2}$$ [5]

Subject to:

$$(E_p + E_{UB} + E_{LB} + E_M + GW_f) \le CGW \tag{3}$$

$$(E_p + E_{UB} + E_{LB} + E_M) \le 5403 * C \tag{4}$$

$$0 \le E_P \le 1072 \tag{5}$$

$$0 \le E_{UB} \le 2426 \tag{6}$$

$$0 \le E_{LB} \le 1905 \tag{7}$$

$$0 \le ME \le 550 \tag{8}$$

$$0 \le E_M \le 6050 \tag{9}$$

[5] Revenue $\left[P_pE_p + P_{UB}E_{UB} + P_{LB}E_{LB} + P_M\frac{E_M}{11} + 10 * GW_f\right]$ – Marginal Costs $\left[5.5\left(E_p + E_{UB} + E_{LB} + E_M\right) + 130.34 * \frac{E_M}{11}\right]$ – Fixed Costs $\left[0.100385 * \left[640000 + \frac{4000000}{1.2*C+5}\right] * C + FC + 37645 * ME\right]$.

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In equation (2), $0.100385*\left[640000+\frac{4000000}{1.2*C+5}\right]*C$ is the fixed cost function of the gasifier/generator and gives an average (amortized) fixed cost as a function of capacity C (see Multer *et al.*, 2010); 37645*ME is the (amortized) fixed cost for ammonia processor and gives an average fixed cost as a function of number of processors (ME) each with fixed capacity of 550 tonnes/year. Ammonia production in particular is given very high marginal production costs ($130.34/tonne) because of the potential risks involved. Limited information from boilers at paper mills suggests low marginal costs to generate electric power ($5.5/MWe) as paper mills, in time, integrated power generation more seamlessly into operations (see Farmer *et al.*, 2014). Finally, FC is the annual labour cost fixed at $75,000 for both small and medium gin, though the operator is not committed all year.[6] While profits change as marginal costs change, in general for an asset composition mix, the volume of products sold to ammonia, peak power, subpeak power and base power change very little over the ranges of marginal costs simulated.

Installed capacity is fixed. Equation (3) is the efficiency constraint, stating that 1 tonne of CGW produces approximately 1 MWe of electricity at 25% efficiency (see Farmer *et al.*, 2014). Total electricity power output is constrained by total CGW in tonnes less gin waste sold as feed. GW_f; equation (4) restricts the maximum hours of operations to 5,403 hours over 9 months, reflecting the possible hours of operation. Equations (5) to (7) account for electricity sold at peak prices, subpeak and base prices respectively for specific hours of the day for each. (The breakdown of the total annual hours of operation is provided in Appendix Table B14.) Equation (8) constrains ammonia production to 550 tonnes in 9 months, which is equivalent to 6,050 MWe dedicated to its production (equation (9)), since 11 MWe is required for every tonne of ammonia.

The sum of the RHS of equations (5) to (7) equals total electricity production in (4) allocated to peak, subpeak, base electricity and ammonia production.

Appendix B

Table B1. Summary statistics

	Obs.	Median	Mean	Min	Max	St. dev.
Peak price (observed)	10,757	78.39	197.24	15.59	23,224.67	776.05
Peak price (simulated)	80,000	72.48	184.91	−407.02	23,259.35	849.82
Subpeak price (observed)	25,099	46.85	56.68	6.60	3,884.34	61.44
Subpeak price (simulated)	100,000	44.29	52.35	4.14	3,910.65	56.35
Base price (observed)	19,039	41.04	47.71	−0.86	3,119.24	51.47
Base price (simulated)	100,000	42.05	48.41	−2.04	3,152.99	53.04
Ammonia price (observed)	75	537.0	562.1	413.0	750.0	95.39
Ammonia price (simulated)	30,000	507.4	536.1	358.7	808.8	88.92
Small CGW (observed)	15	8,740	9,704	3,442	14,988	3,312.44
Small CGW (simulated)	10,000	9,763	10,752	3,342	21,093	3,662.59
Medium CGW (observed)	15	26,221	29,113	10,326	44,964	9,937.32
Medium CGW (simulated)	10,000	29,290	32,255	10,025	63,278	10,987.79

*Peak price data shows cumulative data from 8 months, subpeak and base from 10 months and ammonia price from three seasons (winter, spring, summer).

[6]For the labour cost assumptions, such as the $75,000 figure used for the professional staff, we based these on our knowledge of typical compensation levels for this type of work. As mentioned, we know that professionals in this field (power plant operators) in Texas earn a median income of around $90,000 per year. Given this is a new application of the technology, we took a conservative approach and assumed the need for a dedicated manager to oversee operations for at least the first 12 years. This full-time or near-full-time staffing requirement contributed to the $75,000 per year estimate for labour costs. Our intent with these assumptions was to err on the side of caution, as this would be the first time implementing this technology. We wanted to account for the additional management and oversight that may be required during the initial deployment phase, even if these labour costs could potentially be lower in the long run as the operations become more established.

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Table B2. Baseline analyses for small gin

Models	Avg. ROIC (%)	Prob. loss (%)	Prob. ROIC >100%	Avg. annual profit (cash flow, $)	SD profit (cash flow, $)
C = 0, M = 0 EV*	0.00	0.00	0.00	107,516	36,626
C = 1, M = 0 EV	58.83	5.60	12.99	189,011	284,846
C = 2, M = 0 EV	51.25	9.50	11.04	294,700	494,065
C = 3, M = 0	29.51	30.39	6.17	238,519	602,822
C = 4, M = 0	9.28	50.01	2.09	95,302	523,131
C = 5, M = 0	0.59	62.83	1.40	7,289	594,257
C = 1, M = 1	40.73	9.06	8.94	166,505	284,887
C = 2, M = 1	41.86	12.05	8.72	277,330	493,492
C = 3, M = 1	24.21	35.52	5.22	216,900	600,695
C = 4, M = 1	6.44	53.75	1.69	71,800	524,745
C = 5, M = 1	−1.41	65.35	1.21	−18,692	595,214
C = 1, M = 2	25.96	22.46	7.11	128,860	284,887
C = 2, M = 2	32.40	17.38	6.87	242,992	493,718
C = 3, M = 2	18.93	42.23	4.27	186,189	602,075
C = 4, M = 2	3.40	57.57	1.46	40,922	525,505
C = 5, M = 2	−3.49	68.79	1.10	−49,316	595,749

*C = 0, M = 0 where all gin trash sold at $10/tonne; a = 10,000 simulations for each combination; EV = models on EV frontier.

Table B3. Extended analyses for small gin

Models	Disc. avg. profit 12 yrs.	SD disc. profit 12 yrs.	Disc. avg. ROIC 12 yrs.	Prob. ROIC <0	Prob. ROIC between 0 and 250	Prob. ROIC between 250 and 500	Prob. ROIC >500
C = 0, M = 0 EV*	484,920	44,933	0.00	0.00	0.00	0.00	0.00
C = 1, M = 0 EV	852,478	366,294	265.33	0.00	52.58	43.46	3.96
C = 2, M = 0 EV	1,329,158	632,613	231.13	0.00	65.19	32.17	2.64
C = 3, M = 0	1,075,770	765,202	133.08	0.12	88.36	10.92	0.60
C = 4, M = 0	429,830	652,641	41.85	21.61	76.71	1.68	0.00
C = 5, M = 0	32,875	742,402	2.65	62.30	36.37	1.32	0.00
C = 1, M = 1	750,972	366,107	183.71	0.00	78.99	20.53	0.48
C = 2, M = 1	1,250,814	630,693	188.78	0.00	76.95	22.09	0.96
C = 3, M = 1	978,265	762,912	109.20	1.44	91.72	6.48	0.36
C = 4, M = 1	323,831	654,115	29.05	30.73	67.95	1.32	0.00
C = 5, M = 1	−84,305	743,722	−6.35	71.07	27.85	1.08	0.00
C = 1, M = 2	581,185	366,107	117.11	0.00	94.12	5.88	0.00
C = 2, M = 2	1,095,942	630,828	146.11	0.00	88.12	11.76	0.12
C = 3, M = 2	839,751	764,295	85.39	6.12	89.44	4.44	0.00
C = 4, M = 2	184,566	654,875	15.35	45.74	53.18	1.08	0.00
C = 5, M = 2	−222,425	744,538	−15.72	79.71	19.33	0.96	0.00

*C = 0, M = 0; all gin trash sold at $10/tonne; EV = models on EV frontier.

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Table B4. Baseline analyses for medium gin

Models	Avg. ROIC (%)	Prob. loss (%)	Prob. ROIC >100%	Avg. annual profit (cash flow, $)	SD profit (cash flow, $)
$C = 0$, $M = 0$ EV, *	0.00	0.00	0.00	322,549	109,878
$C = 1$, $M = 0$ EV	108.79	0.02	37.39	349,517	297,249
$C = 2$, $M = 0$ EV	98.96	0.01	23.52	569,104	577,942
$C = 3$, $M = 0$ EV	95.41	0.54	21.83	771,254	854,539
$C = 4$, $M = 0$ EV	96.01	3.09	22.16	986,196	1,140,497
$C = 5$, $M = 0$ EV	92.91	4.90	21.21	1,152,070	1,391,770
$C = 6$, $M = 0$ EV	80.56	5.81	17.35	1,162,195	1,482,193
$C = 7$, $M = 0$	68.44	6.59	13.75	1,122,302	1,592,251
$C = 8$, $M = 0$	60.41	7.51	12.16	1,108,041	1,731,743
$C = 9$, $M = 0$	52.17	9.14	10.25	1,057,049	1,808,466
$C = 1$, $M = 1$	80.12	0.10	17.57	327,514	296,984
$C = 2$, $M = 1$	84.27	0.01	18.11	558,336	577,545
$C = 3$, $M = 1$	85.37	0.83	18.37	764,793	854,580
$C = 4$, $M = 1$	88.00	3.70	19.39	980,860	1,139,546
$C = 5$, $M = 1$	86.31	5.32	18.98	1,145,799	1,392,416
$C = 6$, $M = 1$	75.27	5.99	15.79	1,151,806	1,479,441
$C = 7$, $M = 1$	64.27	6.72	12.74	1,110,122	1,592,734
$C = 8$, $M = 1$	56.86	7.80	11.24	1,092,579	1,733,801
$C = 9$, $M = 1$	49.04	9.78	9.44	1,036,498	1,800,740
$C = 1$, $M = 2$	58.41	1.42	10.77	289,869	296,984
$C = 2$, $M = 2$	69.99	0.09	14.23	524,940	577,435
$C = 3$, $M = 2$	75.23	1.62	15.78	739,788	854,714
$C = 4$, $M = 2$	79.93	4.46	17.17	960,895	1,139,982
$C = 5$, $M = 2$	79.78	5.58	17.03	1,128,895	1,393,265
$C = 6$, $M = 2$	70.16	6.14	14.3	1,134,904	1,479,485
$C = 7$, $M = 2$	60.23	6.89	11.65	1,092,982	1,593,145
$C = 8$, $M = 2$	53.56	8.2	10.32	1,076,046	1,737,079
$C = 9$, $M = 2$	46.20	10.61	8.84	1,017,042	1,799,914

*$C = 0$, $M = 0$; all gin trash sold at $10/tonne; EV = Models on EV frontier.

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Table B5. Extended analyses for medium gin

Models	Disc. avg. profit 12 yrs.	SD disc. profit 12 yrs.	Disc. avg. ROIC 12 yrs.	Prob. ROIC <0	Prob. ROIC between 0 and 250	Prob. ROIC between 250 and 500	Prob. ROIC >500
C = 0, M = 0 [EV, *]	1,454,760	134,800	0.00	0.00	0.00	0.00	0.00
C = 1, M = 0 [EV]	1,576,391	377,960	490.64	0.00	0.00	59.30	40.70
C = 2, M = 0 [EV]	2,566,774	741,181	446.35	0.00	0.24	70.11	29.65
C = 3, M = 0 [EV]	3,478,513	1,098,908	430.31	0.00	2.28	70.83	26.89
C = 4, M = 0 [EV]	4,447,943	1,473,180	433.03	0.00	3.84	68.31	27.85
C = 5, M = 0 [EV]	5,196,070	1,813,341	419.03	0.00	7.20	67.23	25.57
C = 6, M = 0 [EV]	5,241,735	1,898,068	363.33	0.00	18.25	65.79	15.97
C = 7, M = 0	5,061,813	2,040,941	308.69	0.00	39.26	52.22	8.52
C = 8, M = 0	4,997,490	2,229,814	272.48	0.00	54.98	39.02	6.00
C = 9, M = 0	4,767,505	2,295,739	235.29	0.00	65.91	30.49	3.60
C = 1, M = 1	1,477,155	377,352	361.35	0.00	7.68	83.55	8.76
C = 2, M = 1	2,518,207	740,212	380.07	0.00	6.60	79.11	14.29
C = 3, M = 1	3,449,370	1,098,474	385.03	0.00	9.84	72.99	17.17
C = 4, M = 1	4,423,879	1,474,828	396.88	0.00	9.24	70.35	20.41
C = 5, M = 1	5,167,785	1,814,727	389.28	0.00	12.61	67.71	19.69
C = 6, M = 1	5,194,881	1,891,555	339.50	0.00	25.45	63.15	11.40
C = 7, M = 1	5,006,879	2,040,355	289.87	0.00	47.30	46.34	6.36
C = 8, M = 1	4,927,753	2,229,297	256.44	0.00	59.78	35.65	4.56
C = 9, M = 1	4,674,819	2,284,637	221.17	0.00	71.31	26.17	2.52
C = 1, M = 2	1,307,368	377,343	263.43	0.00	50.30	49.10	0.60
C = 2, M = 2	2,367,584	740,046	315.65	0.00	31.09	63.39	5.52
C = 3, M = 2	3,336,594	1,098,318	339.30	0.00	23.17	67.23	9.60
C = 4, M = 2	4,333,833	1,474,939	360.51	0.00	19.33	67.35	13.33
C = 5, M = 2	5,091,545	1,814,649	359.82	0.00	20.77	64.59	14.65
C = 6, M = 2	5,118,650	1,891,890	316.42	0.00	35.05	57.02	7.92
C = 7, M = 2	4,929,570	2,040,801	271.63	0.00	53.42	42.26	4.32
C = 8, M = 2	4,853,186	2,231,881	241.56	0.00	64.59	32.05	3.36
C = 9, M = 2	4,587,068	2,286,605	208.39	0.00	75.27	22.57	2.16

*C = 0, M = 0; all gin trash sold at $10/tonne; EV = models on EV frontier.

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Table B6. Sensitivity analyses for small gin

Models	Avg. ROIC (%)	Prob. loss (%)	Prob. ROIC >100%	Avg. annual profit (cash flow, $)	SD profit (cash flow, $)
Panel A: Lower base electricity price					
C = 1, M = 0	52.44	7.70	11.67	168,487	283,346
C = 2, M = 0	45.12	12.29	9.8	259,497	488,653
C = 3, M = 0	24.45	37.49	5.45	197,617	593,311
Panel B: Lower marginal cost of ammonia plant					
C = 1, M = 1	42.49	7.62	9.12	173,695	284,943
C = 2, M = 1	43.37	10.85	8.87	287,383	494,158
C = 3, M = 1	25.20	33.88	5.28	225,761	601,975
Panel C: Lower conversion rate					
C = 1, M = 0	19.34	43.13	6.93	62,126	191,089
C = 2, M = 0	14.27	48.19	5.3	82,035	328,990
C = 3, M = 0	1.22	66.82	2.92	9,847	398,163
Panel D: Higher electricity prices					
C = 1, M = 0	71.57	4.12	15.58	229,938	313,080
C = 2, M = 0	63.21	7.31	13.18	363,520	543,967
C = 3, M = 0	38.71	19.85	7.81	312,919	665,178

Table B7. Extended sensitivity analyses for small gin

Models	Disc. avg. profit 12 yrs.	SD disc. profit 12 yrs.	Disc. avg. ROIC 12 yrs.	Prob. ROIC <0	Prob. ROIC between 0 and 250	Prob. ROIC between 250 and 500	Prob. ROIC >500
Panel A: Lower base electricity price							
$C = 1, M = 0$	759,909	364,915	236.52	0.00	60.74	36.61	2.64
$C = 2, M = 0$	1,170,384	628,194	203.52	0.00	71.07	27.01	1.92
$C = 3, M = 0$	891,294	756,695	110.26	2.88	89.08	7.44	0.60
Panel B: Lower marginal cost of ammonia plant							
$C = 1, M = 1$	783,401	366,202	191.64	0.00	76.95	22.57	0.48
$C = 2, M = 1$	1,296,155	631,325	195.63	0.00	75.27	23.53	1.20
$C = 3, M = 1$	1,018,227	764,227	113.66	0.96	91.60	7.08	0.36
Panel C: Lower conversion rate							
$C = 1, M = 0$	280,200	245,015	87.21	8.76	87.64	3.60	0.00
$C = 2, M = 0$	369,993	421,096	64.34	17.77	79.95	2.28	0.00
$C = 3, M = 0$	44,412	505,977	5.49	58.58	40.70	0.72	0.00
Panel D: Higher electricity prices							
$C = 1, M = 0$	1,037,069	402,813	322.78	0.00	34.45	55.94	9.60
$C = 2, M = 0$	1,639,549	696,492	285.11	0.00	47.66	46.46	5.88
$C = 3, M = 0$	1,411,327	844,000	174.59	0.12	81.03	17.41	1.44

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Table B8. Sensitivity analyses for medium gin

Models	Avg. ROIC (%)	Prob. loss (%)	Prob. ROIC >100%	Avg. annual profit (cash flow, \$)	SD profit (cash flow, \$)
Panel A: Lower base electricity price					
$C=1, M=0$	102.21	0.12	32.08	328,395	296,175
$C=2, M=0$	91.62	0.05	20.4	526,885	575,876
$C=3, M=0$	87.79	1.11	18.9	709,681	850,037
$C=4, M=0$	88.09	4.01	19.26	904,845	1,133,853
$C=5, M=0$	85.07	5.33	18.4	1,054,829	1,381,562
$C=6, M=0$	73.24	6.07	15.03	1,056,585	1,465,958
$C=7, M=0$	61.67	7.09	11.92	1,011,202	1,569,375
Panel B: Lower marginal cost of ammonia plant					
$C=1, M=1$	81.92	0.08	18.22	334,898	296,907
$C=2, M=1$	86.08	0.01	18.53	570,363	577,425
$C=3, M=1$	86.86	0.66	18.78	778,165	854,677
$C=4, M=1$	89.27	3.52	19.88	995,100	1,139,793
$C=5, M=1$	87.37	5.22	19.33	1,159,837	1,392,870
$C=6, M=1$	76.11	5.98	16.00	1,164,649	1,480,222
$C=7, M=1$	64.95	6.62	12.89	1,121,919	1,593,849
Panel C: Lower conversion rate					
$C=1, M=0$	68.06	2.99	14.39	218,682	206,708
$C=2, M=0$	53.48	2.60	10.57	307,538	389,924
$C=3, M=0$	48.32	5.95	9.78	390,599	573,267
$C=4, M=0$	47.21	7.06	10.04	484,905	762,191
$C=5, M=0$	44.49	8.83	9.5	551,732	928,249
$C=6, M=0$	36.34	13.68	7.48	524,198	986,970
$C=7, M=0$	28.52	21.99	5.68	467,588	1,057,092
Panel D: Higher electricity prices					
$C=1, M=0$	121.91	0.00	46.72	391,695	324,945
$C=2, M=0$	113.63	0.00	30.95	653,424	634,654
$C=3, M=0$	110.60	0.11	28.37	894,037	939,239
$C=4, M=0$	111.75	1.59	28.95	1,147,867	1,254,446
$C=5, M=0$	108.53	3.97	27.99	1,345,784	1,531,516
$C=6, M=0$	94.87	5.24	23.16	1,368,654	1,631,901
$C=7, M=0$	81.33	6.08	18.82	1,333,689	1,750,837

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Table B9. Extended sensitivity analyses for medium gin

Models	Disc. avg. profit 12 yrs.	SD disc. profit 12 yrs.	Disc. avg. ROIC 12 yrs.	Prob. ROIC <0	Prob. ROIC between 0 and 250	Prob. ROIC between 250 and 500	Prob. ROIC >500
Panel A: Lower base electricity price							
$C = 1, M = 0$	1,481,129	377,212	460.99	0.00	0.24	66.51	33.25
$C = 2, M = 0$	2,376,358	740,010	413.23	0.00	3.96	73.71	22.33
$C = 3, M = 0$	3,200,807	1,094,780	395.95	0.00	10.56	69.39	20.05
$C = 4, M = 0$	4,081,035	1,467,255	397.31	0.00	13.45	64.71	21.85
$C = 5, M = 0$	4,757,494	1,806,227	383.67	0.00	17.77	61.94	20.29
$C = 6, M = 0$	4,765,414	1,884,815	330.32	0.00	33.49	55.34	11.16
$C = 7, M = 0$	4,560,729	2,025,123	278.13	0.00	52.82	41.06	6.12
Panel B: Lower marginal cost of ammonia plant							
$C = 1, M = 1$	1,510,457	377,319	369.49	0.00	4.44	85.83	9.72
$C = 2, M = 1$	2,572,453	740,088	388.26	0.00	4.80	79.71	15.49
$C = 3, M = 1$	3,509,683	1,098,521	391.76	0.00	7.44	74.55	18.01
$C = 4, M = 1$	4,488,102	1,475,010	402.64	0.00	7.80	70.95	21.25
$C = 5, M = 1$	5,231,103	1,815,142	394.05	0.00	10.44	69.03	20.53
$C = 6, M = 1$	5,252,804	1,892,178	343.28	0.00	24.49	63.75	11.76
$C = 7, M = 1$	5,060,085	2,041,324	292.95	0.00	45.50	47.90	6.60
Panel C: Lower conversion rate							
$C = 1, M = 0$	986,300	260,520	306.98	0.00	27.13	70.35	2.52
$C = 2, M = 0$	1,387,058	497,920	241.20	0.00	60.86	38.42	0.72
$C = 3, M = 0$	1,761,680	735,048	217.93	0.00	68.67	30.61	0.72
$C = 4, M = 0$	2,187,021	982,521	212.92	0.00	69.75	29.41	0.84
$C = 5, M = 0$	2,488,426	1,207,993	200.68	0.00	72.99	26.05	0.96
$C = 6, M = 0$	2,364,240	1,263,469	163.88	0.00	83.31	16.45	0.24
$C = 7, M = 0$	2,108,919	1,355,612	128.61	0.12	90.76	9.00	0.12
Panel D: Higher electricity prices							
$C = 1, M = 0$	1,766,623	413,849	549.85	0.00	0.00	41.30	58.70
$C = 2, M = 0$	2,947,078	814,534	512.48	0.00	0.00	54.14	45.86
$C = 3, M = 0$	4,032,288	1,208,472	498.81	0.00	0.00	57.50	42.50
$C = 4, M = 0$	5,177,116	1,620,984	504.02	0.00	0.00	56.54	43.46
$C = 5, M = 0$	6,069,759	1,995,721	489.49	0.00	0.96	59.42	39.62
$C = 6, M = 0$	6,172,909	2,089,713	427.88	0.00	4.44	68.91	26.65
$C = 7, M = 0$	6,015,209	2,246,261	366.83	0.00	16.93	66.99	16.09

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Table B10. Output combination for small gin

Capacity	Electricity (MWh)	Ammonia (tons)	Total electricity (MWh)
$C = 1, M = 0$	5,225	–	5,225
$C = 2, M = 0$	9,192	–	9,192
$C = 3, M = 0$	10,677	–	10,677
$C = 4, M = 0$	10,752	–	10,752
$C = 5, M = 0$	10,752	–	10,752
$C = 1, M = 1$	3,771	138	5,288
$C = 2, M = 1$	7,102	195	9,245
$C = 3, M = 1$	8,792	173	10,696
$C = 4, M = 1$	9,157	145	10,752
$C = 5, M = 1$	9,400	123	10,752
$C = 1, M = 2$	3,771	138	5,288
$C = 2, M = 2$	6,666	234	9,245
$C = 3, M = 2$	7,910	253	10,696
$C = 4, M = 2$	8,259	227	10,752
$C = 5, M = 2$	8,495	205	10,752

Table B11. Output combination with sensitivity analysis for small gin

Capacity	Electricity (MWh)	Ammonia (tons)	Total electricity (MWh)
Panel A: Lower base electricity price			
$C = 1, M = 0$	5,226	–	5,226
$C = 2, M = 0$	9,192	–	9,192
$C = 3, M = 0$	10,677	–	10,677
Panel B: Lower marginal cost of ammonia plant			
$C = 1, M = 1$	3,314	179	5,288
$C = 2, M = 1$	6,515	248	9,245
$C = 3, M = 1$	8,310	217	10,696
Panel C: Lower conversion rate			
$C = 1, M = 0$	3,484	–	3,484
$C = 2, M = 0$	6,128	–	6,128
$C = 3, M = 0$	7,118	–	7,118
Panel D: Higher electricity prices			
$C = 1, M = 0$	5,226	–	5,226
$C = 2, M = 0$	9,193	–	9,193
$C = 3, M = 0$	10,678	–	10,678

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Table B12. Output combination for medium gin

Capacity	Electricity (MWh)	Ammonia (tons)	Total electricity (MWh)
$C = 1, M = 0$	5,346	–	5,346
$C = 2, M = 0$	10,683	–	10,683
$C = 3, M = 0$	15,676	–	15,676
$C = 4, M = 0$	20,614	–	20,614
$C = 5, M = 0$	24,890	–	24,890
$C = 6, M = 0$	27,575	–	27,575
$C = 7, M = 0$	29,490	–	29,490
$C = 8, M = 0$	31,090	–	31,090
$C = 9, M = 0$	32,031	–	32,031
$C = 1, M = 1$	3,854	142	5,413
$C = 2, M = 1$	8,234	234	10,811
$C = 3, M = 1$	12,968	263	15,863
$C = 4, M = 1$	17,744	281	20,841
$C = 5, M = 1$	22,020	278	25,074
$C = 6, M = 1$	24,906	253	27,693
$C = 7, M = 1$	27,030	233	29,590
$C = 8, M = 1$	28,804	215	31,165
$C = 9, M = 1$	29,907	196	32,063
$C = 1, M = 2$	3,854	142	5,413
$C = 2, M = 2$	7,700	283	10,811
$C = 3, M = 2$	11,544	393	15,863
$C = 4, M = 2$	15,887	451	20,847
$C = 5, M = 2$	19,945	469	25,105
$C = 6, M = 2$	22,769	451	27,735
$C = 7, M = 2$	24,897	432	29,644
$C = 8, M = 2$	26,676	413	31,215
$C = 9, M = 2$	27,829	387	32,084

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Table B13. Output combination with sensitivity analysis for medium gin

Capacity	Electricity (MWh)	Ammonia (tons)	Total electricity (MWh)
Panel A: Lower base electricity price			
$C = 1, M = 0$	5,347	–	5,347
$C = 2, M = 0$	10,684	–	10,684
$C = 3, M = 0$	15,677	–	15,677
$C = 4, M = 0$	20,615	–	20,615
$C = 5, M = 0$	24,891	–	24,891
$C = 6, M = 0$	27,577	–	27,577
$C = 7, M = 0$	29,491	–	29,491
Panel B: Lower marginal cost of ammonia plant			
$C = 1, M = 1$	3,387	184	5,413
$C = 2, M = 1$	7,557	296	10,811
$C = 3, M = 1$	12,281	326	15,863
$C = 4, M = 1$	17,044	345	20,841
$C = 5, M = 1$	21,331	340	25,074
$C = 6, M = 1$	24,262	312	27,693
$C = 7, M = 1$	26,441	286	29,590
Panel C: Lower conversion rate			
$C = 1, M = 0$	3,564	–	3,564
$C = 2, M = 0$	7,122	–	7,122
$C = 3, M = 0$	10,451	–	10,451
$C = 4, M = 0$	13,743	–	13,743
$C = 5, M = 0$	16,593	–	16,593
$C = 6, M = 0$	18,384	–	18,384
Panel D: Higher electricity prices			
$C = 1, M = 0$	5,347	–	5,347
$C = 2, M = 0$	10,685	–	10,685
$C = 3, M = 0$	15,679	–	15,679
$C = 4, M = 0$	20,617	–	20,617
$C = 5, M = 0$	24,893	–	24,893
$C = 6, M = 0$	27,578	–	27,578

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Table B14. Breakdown of operation hours

	Date	Hours of operation	Total hours
Peak electricity	Dec 16–Dec 31	5am–9am (4 hr)	16 × 4
	Jan 01–Feb 28	5am–9am and 5 pm–8 pm (7 hr)	59 × 7
	Mar 01–Mar 15	5am–9am (4 hr)	15 × 4
	Jun 01–Sept 15	1 pm–6 pm (5 hr)	107 × 5
Total peak		1,072 MWe	
Subpeak electricity	Dec 16–Dec 31	9am–8 pm (11 hr)	16 × 11
	Jan 01–Feb 28	9am–5 pm (8 hr)	59 × 8
	Mar 01–Mar 15	9am–8 pm (11 hr)	15 × 11
	Mar 16–May 31	6am–8 pm (14 hr)	77 × 14
	Jun 01–Sept 15	8am–1 pm (5 hr)	107 × 5
Total subpeak		2,426 MWe	
Base electricity	Dec 15–May 31	8 pm–12am and 4am (5 hr)	167 × 5
	Jun 01–Sept 15	6 pm–12am and 4am–8am (10 hr)	107 × 10
Total base		1,905 MWe	
Total		5403 MWe	

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