Optimization of On-site Renewable Energy Generation for Industrial Sites

Suriya Ruangpattana, Diego Klabjan, Jorge Arinez, *Member, IEEE,* and Stephan Biller, *Member, IEEE*

***Abstract*—We consider the energy sourcing decision problem faced by industrial power consumers who must determine their long-term electricity procurement plan and need to evaluate various options to meet load requirements for their facilities including those which may involve on-site renewable generation. Other than sourcing from on-site renewable generation such as solar photovoltaic or wind, power can be purchased from spot markets or through a power purchase agreement, i.e. energy supply contract. We develop a mixed-integer linear model to make decisions that include investments in renewable generation, power purchases from spot markets, and amount sourced from supply contracts. Taking into account renewable energy certificates, the model's objective is to maximize revenue from trading renewable certificates minus the expected total costs of investing and operating on-site renewable generation, and purchasing from electricity markets. Real load data from manufacturing plants are used to illustrate a numerical case study for our model.**

***Index Terms*—mixed integer linear programming, renewable energy, sustainability, on-site generation, industrial consumers.**

I. Introduction

THE powerful forces of competition that exist in all manufacturing sectors are causing management to examine all the major contributors to operational costs. In automotive manufacturing, the strong pressure to reduce costs has brought plant energy costs under closer scrutiny than ever before. According to a 2008 report by Galitsky et al. [1], the U.S. automotive industry as a whole spends about $3.6 billion dollars on energy annually. Clearly, for companies in this industry in particular, efforts to reduce energy consumption can have a significant financial benefit. There are various approaches to identify and implement measures to both improve energy efficiency and reduce consumption. These measures range from short-term operational modifications to equipment to longer term facility investments in more energy efficient technologies. However, energy efficiency and consumption are not the only aspects that contribute to a plant's total energy costs. The energy rates and charges associated with usage and demand represent other factors, which can be targeted for improvements through more effective energy procurement strategies.

Furthermore, a good energy procurement plan can potentially do more than just reduce a plant's overall energy-related costs; it can offer flexibility to respond to potential increases in costs from energy providers or even help sustainable manufacturing initiatives. The high volatility of energy and electricity prices, along with the potential for new stricter environmental regulations may impose risks to overall energy procurement costs. This paper develops a decision framework that can be used by management to help make decisions when analyzing energy procurement plans for manufacturing operations. Selected energy sources in such a plan would be able to meet long-term load requirements while minimizing expected total costs due to investments and operations of on-site renewable energy generation.

We focus on industrial consumers faced with the problem of having to make an investment decision on on-site renewable generation while still engaged with the power markets through spot purchases and purchase agreements. Our approach is to formulate this problem as a mixed integer linear programming (MILP) model. Relatively limited work exists in the literature that combines on-site renewable generation, contract decisions, and spot purchases for making long-term energy decisions as the work described herein. Predicting long-term electricity prices for the purpose of making projections of operational costs several years out to evaluate today's investments in renewable projects can be difficult, if not impossible. Future energy prices are unknown though probabilistic forecasts can be made [2]. A prior approach to long-term generation planning can be found in Bloom [3] where an MILP method integrated with a probabilistic simulation for production costing and reliability calculations was developed. David [4] presents optimization methods by categorizing consumer load types to optimize consumer response and maximize benefits to consumers in any short-range marginal tariff scheme. Forward contracts as hedges against spot price risk for electricity industries are discussed in Kaye et al. [2]. Arroyo [5] addresses the optimal response of a thermal unit to electricity spot market maximizing the unit profits from selling both energy and spinning reserve in the market. An energy system linear optimization model developed by Cormio et al. [6] based on the energy flow is adopted and detailed by exploiting renewable energy sources for power and heat. This model takes into account the location specifics required for the plant installation of combined cycle, wind power and biomass.

An optimization model to minimize the overall energy supply costs for mid-term (one year) management of a thermal and electricity supply system of an industrial consumer is presented by Gomez-Villalva and Ramos [7] where electricity is supplied from the grid or a gas turbine engine. Liu and Guan [8] consider price volatility in purchase allocation problems

S. Ruangpattana, Postdoctoral Fellow, and D. Klabjan, Associate Professor, are with the Department of Industrial Engineering and Management Sciences, Northwestern University, Evanston, Illinois, 60208 USA. e-mail: suriya@northwestern.edu.

J. Arinez, Staff Researcher, and S. Biller, Technical Fellow and Lab Group Manager, are with the Manufacturing Systems Research Laboratory, General Motors R&D Center, Warren, Michigan, 48090 USA.

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and model the sequential nature using a stochastic method. An analytical solution for the optimal allocation is derived and numerical simulations are demonstrated using actual data of the U.S. market. The recent work of Conejo et al. [9] and Carrion et al. [10] provides a framework for large consumers to decide optimal mixes of purchases from different electricity sources that include bilateral contracts, self-production, and the pool. Muis et al. [11] develop an MILP model for planning of electricity generation for Malaysia, where the plan is to meet the carbon reduction goal and predict potentials to produce electricity from renewable energy. An MILP is developed by Ren and Gao [12] for evaluating an integrated plan for distributed energy resource (DER) systems. A case is used to illustrate that a gas engine is the most economical DER system and that renewable energy is not competitive at the moment. A multi-objective approach to distributed generation is proposed by Zangeneh et al. [13]. Uncertain parameters for distributed generation long-term planning such as the peak load factor and electricity market price are considered and studied how they affect the selection of the best plan.

The main contribution of this paper and a major distinction from the above work review is the formulation of an MILP that incorporates investments in renewable energy generation for a long-term procurement plan for large consumers. The model includes investment decisions and generation profiles of renewable energy sources such as wind and solar, allowing the matching of consumer demand with self-generation, power purchases from a contract, and spot markets on an hourly basis. In addition, the model takes into account potential savings and revenue from selling power to the grid and trading renewable energy credits (RECs). The model uniquely combines the operational (short-term) problem with the strategic (long-term) problem by matching, on an hourly basis, each load with on-site renewable generation and power purchases, and representing it as an annuity through the aggregation of all expected costs and benefits. The annuities of expected costs and benefits include annual cash inflows and outflows of investments into renewable energy generation so that they may be financially evaluated using discounted cash flow or net present value (NPV) methods.

Problem Statement

Consider the problem of an industrial-type power consumer analyzing its strategic energy procurement plan. The consumer needs an analytical framework to support decision making, especially investments in on-site renewable energy generation and power purchases for its manufacturing facilities. A framework considers existing bilateral power purchase contracts, energy spot prices, a rate schedule, and potential credits due to tradable environmental credits. Once investment and purchase choices are made the resulting plan will achieve a cost reduction and risk mitigation resulting from energy price fluctuations, load uncertainty, and potential regulations that impact energy costs. Power purchase agreements exist as a hedge against volatility of electricity market prices. However, satisfying all energy needs by contracts might not be beneficial in situations where market prices fall well below contract

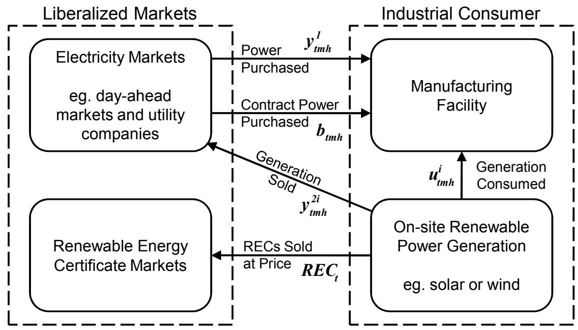

Fig. 1. Power flows considered in the MILP model include renewable self-generation, power purchase, and REC trading

rates. Other than reducing exposure to risks from market prices, renewable self-generation helps ensure environmental requirements will be partly or completely satisfied. Trading excess renewable credits can also be a source of revenue. Mixes of electrical power from the energy sources are to meet its long-term forecast load requirements for its manufacturing facility. We present a profit-maximization model that takes into consideration overall expected costs and credits from power procurement including fixed capital and variable operating costs, RECs, and power purchases from the grid and through a bilateral agreement. Solutions provide investment decisions that meet long-term demand for power and other requirements related to energy supply and regulation. Figure 1 illustrates power flows for power consumers who operate on-site generation and trade RECs.

II. Mathematical Formulation

We present an MILP model for deciding on investment of renewable generation and power purchase in existence of capital expenses, operational and maintenance costs, a contract rate schedule, revenue from trading RECs, and uncertainty in demand and market price for electricity. The model's objective is to maximize the expected total discounted revenue from RECs minus costs from power purchase and investing in renewable generation guaranteeing that the selected mixes of power have enough capacity to meet projected load in each hour of the planning timeframe. Investment in renewable generation decisions, variable costs due to operating and maintaining generating facilities, the power purchase agreement, a.k.a. supply contract, and tradable RECs are explicitly integrated in the model. Generation resource acquisition decisions are modeled as binary variables and operation-type decisions are modeled as continuous variables. Renewable generation resources are acquired in an all-or-nothing fashion such that the corresponding fixed costs associated with construction and installation, e.g. land, equipment, generating unit, materials, etc. are lumped together. Different generation technologies' costs and economies of scale are reflected in the expected lump sum fixed capital costs. Real-valued variables include decisions to determine power generation from selected resources, power purchase from electricity markets, and power that is generated but sold back to the grid, all with respect to hour, month, and year. Power consumed by own manufacturing facility comes from the bilateral contract and self-generation, which correspond to real-valued decision variables. In this context if power from on-site generation is enough for own consumption there should not be any power purchased from the markets.

A. Nomenclature

1) Decision Variables:

x^i_{tmh} = power generation from energy source i, in year t, month m, hour h (in kW)

y^1_{tmh} = power purchased from spot market in year t, month m, hour h (in kW)

y^{2i}_{tmh} = power sold to grid from source i, in year t, month m, hour h (in kW)

z_i = binary variable specifying whether renewable energy source i is selected or installed

u^i_{tmh} = power generated from source i and consumed by the site in year t, month m, hour h (in kW)

b_{tmh} = power consumed by the site from the bilateral contract in year t, month m, hour h (in kW)

α_t = energy in year t below the contracted agreement (in kWh)

β_t = energy in year t above the contracted agreement (in kWh)

$\bar{\alpha}_{tmh}$ = demand in year t, month m, hour h below contracted agreement (in kW)

$\bar{\beta}_{tmh}$ = demand in year t, month m, hour h above contracted agreement (in kW)

2) Parameters:

REC_t = expected price for RECs in year t (in \$/kWh)

p_{tm} = expected spot price for energy in year t, month m (in \$/kWh)

V^i_t = expected variable operational and maintenance costs for energy source i in year t (in \$/kWh)

C_i = expected capital costs for energy source i (in \$)

$B^{min,d}_{tmh}$ = minimum contract demand quantity in year t, month m, hour h without incurring a penalty (in kW)

$B^{max,d}_{tmh}$ = maximum contract demand quantity in year t, month m, hour h without incurring a penalty (in kW)

$B^{min,e}_t$ = minimum contract energy quantity in year t without incurring a penalty (in kWh)

$B^{max,e}_t$ = maximum contract energy quantity in year t without incurring a penalty (in kWh)

d_{tmh} = demand in year t, month m, hour h (in kW)

w_m = days or working days in month m

$H^{under,d}_{tmh}$ = penalty for contract demand under performance in year t, month m, hour h (in \$/kW)

$H^{over,d}_{tmh}$ = penalty for contract demand over per - formance in year t, month m, hour h (in \$/kW)

$H^{under,e}_t$ = penalty for contract energy under performance in year t (in \$/kWh)

$H^{over,e}_t$ = penalty for contract energy over performance in year t (in \$/kWh)

Cap_i = capacity for generation from energy source i (in kW)

r_{tmh} = energy rate in year t, month m, hour h based on the contract (in \$/kWh)

3) Sets:

$\mathcal{T}$ = planning horizon years

$\mathcal{M}$ = months in a year

$\mathcal{H}$ = hours of the day

$\mathcal{I}$ = candidate renewable energy sources

Variables x^i_{tmh} represent power generation in each hour, month, and year. They are indexed in this way to capture each renewable generation profile on the hourly basis.

B. Objective Function

The objective function is to maximize the total expected revenue from on-site renewable generation after total expected costs to procure energy are subtracted. In (1), the first term represents expected revenue from selling RECs in year t. The second and third terms define the expected revenue from selling excess power from on-site renewable generation source i or expected costs from power purchased from the grid due to generation deficit. The next term describes expected variable operational and maintenance costs from on-site generation. The next four terms define penalties due to over and under contract consumptions. The last term under summation over years captures the contracted energy rated. The very last term represents the lump sum capital investment costs.

$$\begin{aligned}
\max \sum_{t\in\mathcal{T}} \frac{1}{(1+r)^t}[\ & REC_t \sum_{i\in\mathcal{I}}\sum_{m\in\mathcal{M}}\sum_{h\in\mathcal{H}} w_m x^i_{tmh} \\
&+ \sum_{i\in\mathcal{I}}\sum_{m\in\mathcal{M}}\sum_{h\in\mathcal{H}} w_m p_{tm} y^{2i}_{tmh} - \sum_{m\in\mathcal{M}}\sum_{h\in\mathcal{H}} w_m p_{tm} y^1_{tmh} \\
&- \sum_{i\in\mathcal{I}}\sum_{m\in\mathcal{M}}\sum_{h\in\mathcal{H}} V^i_t w_m x^i_{tmh} - \sum_{m\in\mathcal{M}}\sum_{h\in\mathcal{H}} H^{under,d}_{tmh}\bar{\alpha}_{tmh} \\
&- \sum_{m\in\mathcal{M}}\sum_{h\in\mathcal{H}} H^{over,d}_{tmh}\bar{\beta}_{tmh} - H^{under,e}_t\alpha_t - H^{over,e}_t\beta_t \\
&- \sum_{m\in\mathcal{M}}\sum_{h\in\mathcal{H}} w_m r_{tmh} b_{tmh}\ ] - \sum_{i\in\mathcal{I}} C_i z_i
\end{aligned} \tag{1}$$

Note that we made the assumption of constant load within each hour. To get energy within each month m, we multiply daily demand by working days in month w_m.

C. Constraints

1) Self Generation: Generation from energy source i cannot exceed its capacity.

$$0 \leq x^i_{tmh} \leq Cap_i z_i, \quad \forall i, \forall h, \forall m, \forall t \tag{2}$$

Next constraints govern that the total generation from all energy sources is either sold or consumed. All of the on-site generation must sum to the power that is sold to the grid and the total power that is consumed by own manufacturing facility, at the hourly level.

$$x^i_{tmh} = y^{2i}_{tmh} + u^i_{tmh}, \quad \forall i, \forall h, \forall m, \forall t \tag{3}$$

2) Demand Balance: Demand is satisfied by consuming on-site generation, purchase from spot markets, and bilateral contract with utility. It is assumed that the demand is deterministic since industrial site's load profiles do not fluctuate. Demand is satisfied by the summation of all on-site generation that is consumed plus the power that is purchased from the grid and through the bilateral contract.

$$\sum_{i \in \mathcal{I}} u^i_{tmh} + y^1_{tmh} + b_{tmh} = d_{tmh}, \quad \forall h, \forall m, \forall t \tag{4}$$

3) Contract: Energy obtained from the utility power contract must be no less than the minimum and no greater than the maximum. Demand must be in the range of maximum and minimum contracted; otherwise, a penalty is incurred.

$$\sum_{m \in \mathcal{M}} \sum_{h \in \mathcal{H}} w_m b_{tmh} + \alpha_t \geq B^{min,e}_t, \quad \forall t \tag{5}$$

$$\sum_{m \in \mathcal{M}} \sum_{h \in \mathcal{H}} w_m b_{tmh} - \beta_t \leq B^{max,e}_t, \quad \forall t \tag{6}$$

We have similar constraints for demand, except that they are hourly based.

$$b_{tmh} + \bar{\alpha}_{tmh} \geq B^{min,d}_{tmh}, \quad \forall h, \forall m, \forall t \tag{7}$$

$$b_{tmh} - \bar{\beta}_{tmh} \leq B^{max,d}_{tmh}, \quad \forall h, \forall m, \forall t \tag{8}$$

Other than that, the decision variables are nonnegative numbers and integers.

$$x^i_{tmh},\ y^{2i}_{tmh},\ u^i_{tmh} \geq 0, \quad \forall i, \forall h, \forall m, \forall t \tag{9}$$

$$y^1_{tmh},\ \bar{\alpha}_{tmh},\ \bar{\beta}_{tmh},\ b_{tmh} \geq 0, \quad \forall h, \forall m, \forall t \tag{10}$$

$$\alpha_t,\ \beta_t \geq 0, \quad \forall t \tag{11}$$

$$z_i \in \{0, 1\}, \quad \forall i \tag{12}$$

When both power purchase y^1_{tmh} and power sold $\sum_{i \in \mathcal{I}} y^{2i}_{tmh}$ are positive, it implies purchasing and selling happen at the same time. An alternative solution with only one being positive can be derived as follows. If $y^1_{tmh} < \sum_{i \in \mathcal{I}} y^{2i}_{tmh}$, then we can set $y^1_{tmh} = 0,\ y^{2i}_{tmh} = y^{2i}_{tmh} - \delta_i$, for δ_i with properties $\sum_{i \in \mathcal{I}} \delta_i = y^1_{tmh},\ \delta_i \leq y^{2i}_{tmh}$. Since $\sum_{i \in \mathcal{I}} y^{2i}_{tmh} > y^1_{tmh}$, it is easy to find such δ_i's, for example, by using a greedy algorithm. We also increase self consumption u^i_{tmh} by δ_i. In case $y^1_{tmh} \geq \sum_{i \in \mathcal{I}} y^{2i}_{tmh}$, an alternative solution can be derived in a similar manner.

III. Risks in renewable generation portfolios

Two major types of risk have a significant impact for industrial consumers looking into investing in on-site renewable generation: electricity price risk and regulatory compliance risk, such as a potential carbon emission regulation. High energy prices and increasing risks in fossil-fuel generation have helped with improvements in renewable energy economics and motivated the additions of renewable power facilities in recent years. Governmental mandates for a renewable portfolio standard and carbon emission restriction policy create incentives for utilities to invest in renewable projects and participate in markets for RECs.

Renewable energy projects such as solar or wind require substantial capital investments. In a weakening economy with tight bank lending policies obtaining new funding for capital intensive projects can be difficult. This is certainly the case for long-term renewable projects because return on investment can be hard to predict. Oil and natural gas prices have a recent history of high volatility. Such volatile energy prices have so far supported the argument for including renewable energy in power generation portfolios. However, if the prices steadily decrease, it can jeopardize the incentives for utilities and consumers to buy more expensive renewable energy. Therefore, continual support from government in the form of investment and production tax credits for investment in renewable energy to stay competitive with conventional fuel technologies can be even more important. Another risk may arise from potential technological advances in competing energy resources. These are very hard to capture and could also influence energy prices.

In determining which sources bring the greatest potential to the consumers, an enhancement to the model presented next highlights benefits and risks from the use of the renewable resources for on-site generation technologies. The rationale to select sources includes expected costs, availability, reliability of supply, technology maturity, potential to reach grid parity, environmental location, and installed base. External factors may include customer sentiment towards new environmentally friendly products, manufacturing sustainability, a potential government legislation, global environmental issues, and regulatory implications.

Risk Formulation

To diversify risks in portfolios of power generation assets, i.e. fuel diversifcation [14], it is customary to take variations in fuel prices as the source of portfolio risks so covariances between different prices of fuel sources become a risk term in the objective function. Suppose we are interested in risks due to variations in REC prices, the electricity spot prices, and contract rates. We can assess portfolio risk by the variations of monetary values related to RECs and power purchase. To this end, let

1) Ω_{tm} be the correlation between the REC price REC_t and spot price p_{tm} in year t, month m,
2) Σ_t be the correlation between the REC price REC_t and contracted price r_t in year t, and
3) Υ_{tm} be the correlation between the spot price p_{tm} and the contracted price r_{tm} in year t, month m.

The risk based model has the objective function

$$\min \sum_{t\in\mathcal{T}} [\ REC_t \sum_{m\in\mathcal{M}} w_m^2 p_{tm} \Omega_{tm} \sum_{i\in\mathcal{I}} \sum_{h\in\mathcal{H}} x_{tmh}^i \sum_{i\in\mathcal{I}} \sum_{h\in\mathcal{H}} y_{tmh}^{2i}$$
$$+ REC_t \Sigma_t \sum_{m\in\mathcal{M}} \sum_{i\in\mathcal{I}} \sum_{h\in\mathcal{H}} w_m x_{tmh}^i \sum_{m\in\mathcal{M}} \sum_{h\in\mathcal{H}} w_m r_{tmh} b_{tmh}$$
$$+ \sum_{m\in\mathcal{M}} \Upsilon_{tm} \sum_{h\in\mathcal{H}} w_m r_{tmh} b_{tmh} \sum_{i\in\mathcal{I}} \sum_{h\in\mathcal{H}} w_m p_{tm} y_{tmh}^{2i}\ ] \quad (13)$$

and constraints (2)-(12). In addition, a constraint is added that allows the value of the original objective function to be more than or equal to a certain percentage of the optimal value.

IV. Numerical Experiment

We study a case [1] of an industrial consumer with a given specific location and plant type, and energy sources consisting of solar and wind. A part of the sensitivity analysis includes a sensitivity for the physical scale of investment, such as the roof surface area for solar PV and the number of turbines for wind energy.

After inputting all factors related to the available energy sources, we utilize actual hourly data from an automotive assembly plant to determine an optimal selection of energy sources given constraints of renewable generation and incentives. The decisions optimize a 20 years NPV calculation.

We implemented the model in Excel by using Solver as the optimization solver. The model parameters include the availability of each energy source, best/average/worst case for sensitivity analysis, and the available land and roof space can be chosen. The preliminary model does not include risk, and thus it is based on equations (1)-(12). We also do not include contract penalties since the utility in question does not have them. The demand profile of the assembly plant is the average profile for the next year. For all subsequent years, an escalating factor is used. Additional input includes, cost of capital, tax rate, working days per year, electricity cost growth assumption, electricity rate information, hourly electricity demand (load profile), and available energy supplied for each hour per energy source.

Net present value for renewable equipment selections is based on an upfront investment cost (also known as capital expenditures or CAPEX) and the depreciation schedule in line with the tax law. Electricity generated from each chosen source per year is used to calculate the electricity savings based on grid energy prices that would have otherwise been incurred. Incentives and fees are also entered into the NPV calculation, taken at the kWh level and uniformly distributed throughout a year.

A. Renewable Generation

In this study, we look at two types of renewable energy sources: solar and wind.

[1]The analysis described in this section is based on actual plant data. For reasons of confidentiality, the real numbers have been modified; however, the results, trends, and conclusions though slightly distorted still hold true.

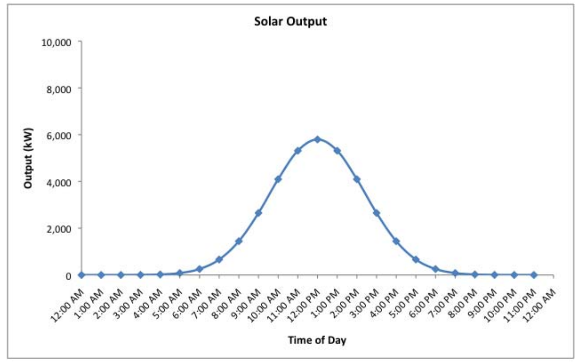

Fig. 2. Hourly solar PV generation (kW) based on average intensity of solar radiation assuming 500,000 sq.ft. roof surface area

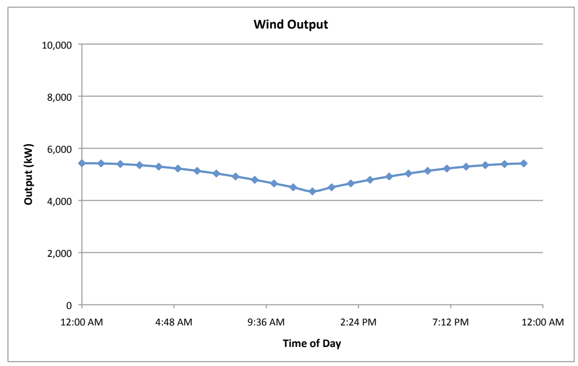

Fig. 3. Hourly wind generation (kW) based on 200 turbines with 6,031 kW total max capacity assuming 50 m.-diameter blades at 5 m/s wind speed

1) Solar photovoltaic: Solar photovoltaic energy generates electric power by converting energy from the sun into electricity. The southwest region of the United States is an ideal location for solar energy use due to its radiance levels in the area. Solar photovoltaic costs are declining as solar energy technology continues to improve. Potential advancements in this area include cost and efficiency improvements in current silicon based cells, the upcoming 3rd generation non-semiconductor based cells exploiting nano-structure materials, and a shift in materials that enable more rapid manufacturing of thin film solar cells. Figure 2 illustrates solar generation by hour.

2) Wind: Wind energy producing farms require substantial capital to construct and install. A significant part of total investment costs are spent on equipment, peripherals, land, and legal process fees, which depend on site specific conditions. Wind energy costs are expected to decrease as technology becomes more efficient. Figure 3 illustrates typical wind generation by hour.

In general, the unit costs of electricity from onshore wind and solar PV technologies are highly sensitive to the load factor variation, and to a less extent than the construction costs. Assuming a 10% discount rate, the unit cost for wind ranges from \$70 to \$140 per MWh, and the cost for solar is from \$333 to \$600 per MWh depending on assumptions on the load factor [15].

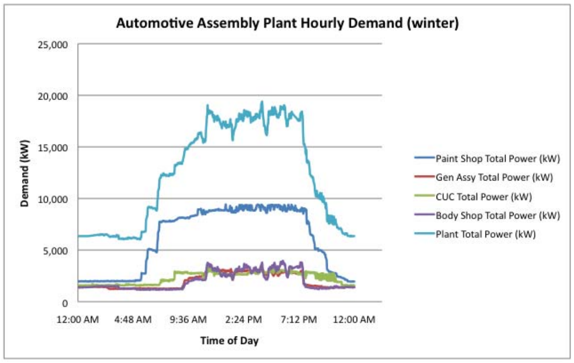

Fig. 4. Model input data - winter demand for power

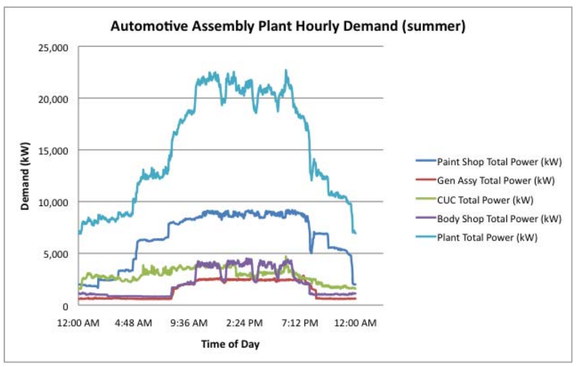

Fig. 5. Model input data - summer demand for power

B. Demand for Power

We illustrate our model by using demand data from an automotive assembly plant, see Figures 4 and 5 for daily demand profiles for winter and summer respectively.

Assuming deterministic demand and a projection from historical demand data can be made, once optimized, the model recommends what renewable generation options should be selected. Table I displays a typical demand-supply matching and, in its last column, amount of electricity purchased from the grid, i.e. electricity markets. Figure 6 displays a graph of daily power demand matched with generation from selected renewable sources that include solar and wind. Purchase from grid is necessary when there is not enough on-site generation to match with the demand from assembly plant.

C. Baseline Model

The experiment incudes three solar and three wind options. Table III shows solar option configurations that vary by the available surface areas, kW/panel, installation costs, and maximum kWs. All assume a 30% investment tax credit, \$0.011 per kWh production tax credit, and a 20 years useful life. Table II displays standard wind option configurations that vary by the number of turbines, swept area, capacity and installation costs. All assume 5 m/s wind speed, 80% rotor efficiency, 40% turbine efficiency, and \$0.02 per kWh production tax credit. Since our model's objective is to maximize NPV and a large portion of the costs come from capital expenditure, the model

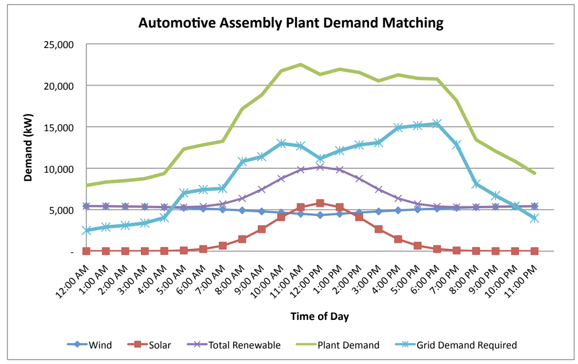

Fig. 6. Model results: demand matching with power generation from solar and wind energy

TABLE I
POWER DEMAND AND RENEWABLE GENERATION SUPPLY MATCHING (kW)

Hour	Demand	Solar	Wind	Grid
12:00 AM	13,246	0	5,429	2,498
1:00 AM	17,158	0	5,420	2,911
2:00 AM	18,881	1	5,395	3,106
3:00 AM	21,700	5	5,354	3,388
4:00 AM	22,567	22	5,296	4,041
5:00 AM	21,271	82	5,223	7,010
6:00 AM	21,998	255	5,135	7,428
7:00 AM	21,485	661	5,033	7,559
8:00 AM	20,522	1,445	4,918	10,803
9:00 AM	21,279	2,653	4,791	11,392
10:00 AM	20,859	4,095	4,652	12,987
11:00 AM	20,716	5,313	4,504	12,688
12:00 PM	18,233	5,794	4,347	11,169
1:00 PM	13,512	5,313	4,504	12,121
2:00 PM	12,020	4,095	4,652	12,807
3:00 PM	10,916	2,653	4,791	13,087
4:00 PM	21,259	1,445	4,918	14,896
5:00 PM	20,841	661	5,033	15,146
6:00 PM	20,759	255	5,135	15,369
7:00 PM	18,148	82	5,223	12,842
8:00 PM	13,432	22	5,296	8,113
9:00 PM	12,056	5	5,354	6,697
10:00 PM	10,836	1	5,395	5,440
11:00 PM	9,402	0	5,420	3,982
Total	423,095	34,858	121,221	217,480

will tend to choose a renewable generation option with the most efficient power-to-cost. For solar power, it chooses the one with the highest kW per panel, regardless of the roof space availability. Similarly for wind power, comparing between two projects with the same number of turbines, it chooses the one with the larger blade diameter. Therefore, our model confirms the fact that the economy of scale is an important factor in investing in renewable generation.

TABLE II
WIND POWER GENERATION OPTIONS

Description	Diameter (m)	Swept Area (m^2)	Nameplate (kW)	Actual (kW)	Installed Cost (\$)	Max (kW)
Standard 50 turbines	50	1,963.50	698.26	75.40	62,843,665	1,507.96
200 turbines	50	1,963.50	698.26	75.40	251,374,662	6,031.86
Smaller 1,011 turbines	20	314.16	111.72	12.06	203,306,090	4,879.72

The model selected each one of the wind and solar options. The 7,154 kW solar project of 500,000 sq.ft. roof surface

TABLE III
SOLAR POWER GENERATION OPTIONS

Description	Surface (m^2)	kW/panel	Installed Cost ($)	DC Rating (kW)	Max (kW)
Standard option	46,452	0.15	47,500,000	6,968	5,365
Higher cost & efficiency	46,452	0.20	60,000,000	9,290	7,154
Lower cost & efficiency	4,645	0.10	3,750,000	465	358

area resulting in 46,452 sq.m. of solar panel area with an installation cost alone of $60 million is selected. For wind, it selects a 6,031 kW wind farm of 200 turbines costing $251 millions to install. A negative NPV (-$170 millions) suggests that owning an on-site renewable energy generation is not yet financially viable, in the case of an automotive assembly plant. Due to the large up-front capital expense, this is true even with the investment and production tax benefits adopted from state incentives.

D. Sensitivity to REC Price

Although the model was able to provide some baseline conclusions and recommendations, it is of interest to conduct a sensitivity analysis to different parameters. We start with RECs where we want to analyze how varying REC prices can have an effect on the model the project selection or NPV. We assumed an excessively large roof surface area (3 million sq.ft.) because we would like to observe how excess generation capacity would help with increasing revenue from trading RECs. Wind capacity and its parameters are kept the same as in the base case. REC prices are varied in step size of $0.02 from zero to $0.20 per kWh while fixing the electricity rate sold to the grid at $0.05 per kWh. The objective NPV continues to increase (from -$298 to -$190 millions) due to the increased revenue from RECs but has no effect on the amount of energy sold to the grid. This is due to the monetary benefits from RECs that have been absorbed through power generation. Renewable generation and power purchase combined exceed demand at all times, suggesting that the model tries to compensate the large investment cost with more power generation. Table IV shows decreasing NPVs as REC prices are increased, but the quantity of electricity sold to the grid becomes stagnant.

TABLE IV
REC PRICES, NPVS ($), AND AMOUNT OF ELECTRICITY SOLD (KW)

REC ($/kWh)	NPV ($)	Grid Electricity	Gen Sold
0.00	-298,125,762	225,089	5,365
0.02	-287,372,672	225,089	5,365
0.04	-276,619,582	225,089	5,365
0.06	-265,866,493	225,089	5,365
0.08	-255,113,403	225,089	5,365
0.10	-244,360,314	225,089	5,365
0.12	-233,607,224	225,089	5,365
0.14	-222,854,135	225,089	5,365
0.16	-212,101,045	225,089	5,365
0.18	-201,347,955	225,089	5,365
0.20	-190,594,866	225,089	5,365

E. Sensitivity to Economy of Scale

We have carried out additional experiments by changing parameters regarding the available roof surface area and the number of wind turbines. Both variations were to test how consistent our model responds to renewable generation economies of scale. That is, we want to verify that our model continues to select the right investment regarding project or investment costs, which are known to have a significant impact on the financial outcome of renewable energy projects.

1) Roof Surface for Solar PV: By keeping other parameters such as the number of turbines, costs, and tax incentives constant, we varied the available area roof surface from 500,000 to 3 million sq.ft. The results in Table V show that the NPV decreases from $61 to $198 million. The quantity of electricity purchased from the grid in a day does not change and remains at 324,671 kWh. This holds because we assumed static demand for power from the plant. The quantity of electricity sold to the grid increased from 65,164 to 239,455 kWh.

TABLE V
INCREASING ROOF SURFACE AREA AND RESULTING NPVS

Roof Surface (sq.ft.)	NPV ($)
500,000	-61,032,293
1,000,000	-127,453,662
1,500,000	-145,148,867
2,000,000	-162,844,072
3,000,000	-198,234,482

2) Number of Wind Turbines: Similar to the case of solar generation, we keep other parameters unchanged and vary the number of wind turbines from 50 to 200. The results show that the NPV decreases from $109 to $170 millions. The electricity sold to the grid went from 65,163 to 156,079 kWh. Table VI summarizes the experimental results when the number of wind turbines is varied.

TABLE VI
INCREASING THE NUMBER OF WIND TURBINES AND RESULTING NPVS

Number of Turbines	NPV ($)
50	-109,758,457
100	-129,923,211
150	-150,087,964
200	-170,252,718

V. CONCLUSION

This paper presented an MILP model as a decision-making framework for investments in long-term on-site renewable generation while participating in power purchase contracts and purchases from spot markets. The model includes renewable investment decisions, generation costs, renewable generation profiles, contracts and RECs. The objective is to maximize revenue and benefits of having an on-site renewable facility less generation costs, power purchases, plus selling excess generation and incentives due to the participation in a renewable energy program. Results from a case study suggest that REC price increases have no effect on the amount of power sold to the grid. Due to the static nature of our demand assumptions increasing the sizes of wind or solar projects did not affect the quantity of electricity sold. The model is capable of consistently selecting high efficiency renewable generation investments. The model also provides the basis for evaluating more complex financing structures and inclusion of other incentives for investment into on-site renewable generation.

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Suriya Ruangpattana is a Postdoctoral Fellow at Northwestern University, Department of Industrial Engineering and Management Sciences. He obtained his Ph.D. in Industrial Engineering (2010) from Purdue University, where he worked as graduate research assistant with the State Utility Forecasting Group. He holds a BEME from Chiang Mai University, Thailand, MSISE from Colorado State University–Pueblo, and MBA from the University of Colorado at Colorado Springs.

Diego Klabjan is an associate professor at Northwestern University, Department of Industrial Engineering and Management Sciences. Professor Klabjan obtained his doctorate from the School of Industrial and Systems Engineering of the Georgia Institute of Technology in 1999. In the same year he joined the University of Illinois at Urbana-Champaign, and in 2007 became an associate professor at Northwestern. His research is focused on business intelligence and analytics in the areas of electric vehicles, smart grid, renewable energy, and sustainable transportation.

Jorge Arinez (M'09) received his Ph.D. (2000) and Masters (1995) degrees in Mechanical Engineering from the Massachusetts Institute of Technology and his B.A.Sc. (1993) from the University of Toronto. He is currently a staff researcher in the Manufacturing Systems Research Lab at the General Motors R&D Center. His research interests include the real-time monitoring, control, and quality of manufacturing systems with a focus on energy efficiency of plant operations.

Stephan Biller (M'07) received a Dipl.-Ing. degree in electrical engineering from the RWTH Aachen, Germany, a Ph.D. in Industrial Engineering and Management Science from Northwestern University and an MBA from the University of Michigan. He is a currently a Group Manager and Technical Fellow at the General Motors R&D Center where he has responsibility for innovations in plant floor systems and controls. He is currently focusing on the digital factory, the real-time information enterprise and the interoperability of the two.