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A Two-Stage Stochastic Aggregate Production Planning Model with Renewable Energy Prosumers

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Abstract

This study presents a two-stage stochastic aggregate production planning model to determine the optimal renewable generation capacity, production plan, workforce levels, and machine hours that minimize a production system's operational cost. The model considers various uncertainties, including demand for final products, machine and labor hours available, and renewable power supply. The goal is to evaluate the feasibility of decarbonizing the manufacturing, transportation, and warehousing operations by adopting onsite wind turbines and solar photovoltaics coupled with battery systems assuming the facilities are energy prosumers. First-stage decisions are the siting and sizing of wind and solar generation, battery capacity, production quantities, hours of labor to keep, hire, or layoff, and regular, overtime, and idle machine hours to allocate over the planning horizon. Second-stage recourse actions include storing products in inventory, subcontracting or backorder, purchasing or selling energy to the main grid, and daily charging or discharging energy in the batteries in response to variable generation. Climate analytics performed in San Francisco and Phoenix permit to derive capacity factors for the renewable energy technologies and test their implementation feasibility. Numerical experiments are presented for three instances: island microgrid without batteries, island microgrid with batteries, and grid-tied microgrid for energy prosumer. Results show favorable levelized costs of energy that are equal to \$48.37/MWh, \$64.91/MWh, and \$36.40/MWh, respectively. The model is relevant to manufacturing companies because it can accelerate the transition towards eco-friendly operations through distributed generation.

Keywords
Stochastic Programming, Aggregate Production Planning, Renewable Energy, Climate Analytics, Energy Prosumer

1. Introduction

Aggregate production planning (APP) determines optimum production levels, machine hours, and workforce usage for each period over a planning horizon to satisfy customers' demands and minimize production costs [1]. APP permits developing the master production schedule and planning for other production resources, such as capacity and raw material. In [1], authors found that attention to stochastic APP models has recently increased due to the need to address practical issues not included previously. However, [1] did not identify any APP contributions considering microgrids integration or another type of distributed generation (DG) systems as an alternative energy source. Renewable energy integration is a critical issue to address in manufacturing due to climate change and the need to attain the United Nations sustainable global goal of affordable and clean energy. The contribution of this research work is to fill this existing gap in the APP literature by developing a two-stage stochastic (TSS) model that incorporates renewable energy (RE) adoption decisions into APP. The goal of this research work is to contribute to accelerate the cost-efficient adoption of RE in production systems striving to operate as net-zero carbon manufacturing (N-ZCM) facilities. N-ZCM facilities have all energy consumed over the year offset with the RE generated.

This paper presents a two-stage stochastic APP model for a manufacturing system that faces uncertainties in final products' demand and machine and labor hours availability. The model aims to determine the optimum size of microgrids comprised of wind turbines (WT), solar photovoltaics (PV), and batteries, and the optimum production plan, machine hours, and workforce levels that minimize the system expected operational cost. Capital investment and maintenance of RE systems are part of the cost. The manufacturing system consists of factories and warehouses planning to install a microgrid in each facility. The microgrids can operate in island mode or connected to the main grid. If connected, the facilities become energy prosumers (EP) to perform bidirectional energy exchange (i.e., buy conventional power or sell RE energy) with the main grid. The RE supply is also stochastic due to the intermittent wind speed and uncertain weather conditions. The paper is organized as follows. Section 2 presents a literature review on mathematical programming models to integrate RE into production planning, a topic closer to APP. Section 3 provides the WT and PV power generation models. Section 4 formulates the two-stage stochastic APP model. Section 5 describes the numerical experiments and discusses the results. Section 6 summarizes the conclusions.

2. Literature Review

The study in [2] develops a multi-period, multistage stochastic production-inventory planning model for a multi-plant manufacturing system powered with onsite RE, grid RE, and grid conventional energy . The goal is to minimize the total annualized cost comprised of production and energy costs and satisfy the target levels for the green energy coefficient (i.e., the ratio of RE over total energy consumed). The system studied includes two RE technologies, WT and PV. It excludes batteries and the operation of facilities as EP. The work in [3] implements a two-step, deterministic optimization framework for determining the optimal production plan and the microgrids sizes in a multi-facility system considering variation in energy supply due to random wind speed and weather conditions. The microgrids include batteries and are connected to the main grid only to purchase energy. Experimental results show that net-zero energy operation is cost-effective in geographical areas where the WT capacity factor is above 0.25 or the PV capacity factor exceeds 0.45, respectively. Reference [4] introduces a TSS programming model for minimizing APP cost for a multi-site garment company considering product demand uncertainty and excluding energy aspects. To the best of our knowledge, there are few publications on production planning with RE adoption. This research would be among the first endeavors on implementing a two-stage stochastic APP model integrating WT, PV, batteries, and the EP paradigm to achieve low-carbon manufacturing operations with minimum cost.

3. Methodology for Modeling WT and PV Power Generation

Wind speed usually increases with height. Equation (1) below estimates the wind speed at any height h, denoted as v_h. It is a function of the wind speed v_g recorded by the observing system at the height above the ground h_g and the Hellman exponent k, which considers seaside location, air stability, and terrain shape.

$$v_h = v_g \left(\frac{h}{h_g}\right)^k \tag{1}$$

Equation (2) presents a cubic model used to determine WT output power, $P_w\,(v_h)$, as a function of the wind speed at height h. The equation shows that the power curve has four operating phases: standby ($0 < v < v_c$), nonlinear production ($v_c \le v \le v_r$), rated power region ($v_r \le v \le v_s$) and cut-off ($v > v_s$).

$$P_w\,(v_h) = \begin{cases} 0 & 0 < v < v_c, v > v_s \\ P_m\,(\frac{v_h}{v_r})^3 & v_c \le v \le v_r \\ P_m & v_r \le v \le v_s \end{cases} \tag{2}$$

The capacity factor of a WT, λ, measures the WT utilization and is a number in the [0,1] range. Equation (3) computes λ when $v_c \le v \le v_r$. If the wind speed is less than v_c or larger than v_s, then λ is 0. For wind speeds above v_r, λ is 1.

$$\lambda = \frac{P_m\,(\frac{v_h}{v_r})^3}{P_m} \tag{3}$$

Under weather uncertainty, the actual power output of a PV system, denoted as $P_{pv}(t)$ at time t in day d, is given by

$$P_{pv}(t) = W_t \eta A I_{pv}(t)\,[1 - 0.005(T_0 - 25)] \tag{4}$$

where W_t is a random variable representing the stochastic weather condition at time t in day d. Besides, η is the PV efficiency, A is the PV size or area (m^2), $I_{pv}(t)$ is the actual solar irradiance incident on PV at time t in day d (W/m^2), and T_0 is the PV operating temperature (ºC). Equation (5) computes the capacity factor of a PV system, λ_{PV}.

$$\lambda_{PV} = \frac{1}{P_{PV}^{Max} T} \sum_{t=1}^{T} P_{PV}\,(t) \tag{5}$$

In Equation (5), P_{PV}^{Max} is the rated capacity or PV maximum output power. In the numerical experiments discussed in Section 5, computations of capacity factors assume P_{PV}^{Max}, η, A, and T_0 as 160W, 0.2, 1m^2, and 45ºC, respectively.

4. Two-Stage Stochastic APP Model

This paper researches a manufacturing system consisting of multiple factories and warehouses. The system is adopting microgrids to generate the energy to produce, transport, and store the products over a planning horizon comprised of multiple production periods, which are assumed to be months. The factories produce multiple products, and there is uncertainty in final products' demands and available machine hours and labor hours. The microgrids operate under uncertain wind speed and weather conditions and can be connected or disconnected from the main grid. In the grid-connected case, the facilities acting as EP can buy energy or sell extra RE generated to preserve the environment, drive economic development, and realize net-zero carbon manufacturing operations. The model used to solve the APP problem with RE integration is a TSS program.

The TSS program aims to simultaneously determine: (1) the optimal sizing of three RE generation technologies (i.e., WT, PV, and batteries) and (2) the optimum production plan, machine hours, and workforce levels to minimize the total expected cost of the system. The first stage occurs at time zero. The main first-stage decisions taken for all periods in the time horizon are the amounts to produce for each product and the size of the WT, PV, and batteries to install in each factory and warehouse. Other first-stage decisions include defective and rectification amounts, hours of labor allocated, hired and layoff, and regular, overtime, and idle machine hours. First-stage decisions do not change over the periods. Recourse actions are based only on the realized uncertainty. They include: (1) the amount of product stored in inventory, backordered, or subcontracted in each period, (2) the daily energy stored in the batteries, and (3) the daily energy sold to or purchased from the main grid. In the mathematical programming model, *I* represents the set of products, *T* represents the set of production periods, *T'* represents the set of previous production periods, *S* represents the scenarios. Besides, *G* represents the set of generation technologies, *K* represents the set of factories, *N* represents the set of warehouses, and *J* represents the set of days in the planning horizon. Tables 1 and 2 present the model's notation, definition, units. Some rows in the tables provide more than one notation due to similar definitions.

Table 1: Decision variables

Notation	Definition	Units
x_{ikt}	Amount of product *i* produced at factory *k* in period *t*	item
m_{ikt}, r_{ikt}	Amount of product *i* defective (rectified) at factory *k* in period *t*	item
y_{ints}	Amount of inventory of product *i* stored at warehouse *n* in period *t* under scenario *s*	item
b_{ikts}	Amount of product *i* backordered at factory *k* in period *t* under scenario *s*	item
q_{ikts}	Amount of product *i* subcontracted at factory *k* in period *t* under scenario *s*	item
l_{kt}	Labor hours kept at factory *k* in period *t*	h/period
$h_{kt,}f_{kt}$	Labor hours hired (layoff) at factory *k* in period *t,*	h/period
$w_{kt,}o_{kt}, p_{kt}$	Regular, overtime, and idle machine hours, respectively, at factory *k* in period *t*	h/period
P_{kg}^c, P_{ng}^c	Capacity of generation technology *g* in factory *k* (warehouse n)	MW
$Q_{kjs}^- Q_{njs}^-$	Energy sold by factory *k* (warehouse *n*) at day *j* under scenario *s*	MWh/day
Q_{kjs}^+, Q_{njs}^+	Energy bought from main grid at factory *k* (at warehouse *n*) at day *j* in scenario *s*	MWh/day
B_k^c, B_n^c	Battery capacity installed in factory *k* (in warehouse *n*)	MWh/day
B_{kjs}^f, B_{njs}^f	Energy stored in battery at factory *k* (at warehouse *n*) at day *j* under scenario *s*	MWh/day

Table 2: Model parameters (Note: units not applicable (N/A) for some notation).

Notation	Definition	Unit
$c_{it}^x, c_{it}^w, c_{it}^q$	Materials, transportation, and subcontracting cost, respectively, for product *i* in period *t*	\$/item
c_{it}^y, c_{it}^b	Inventory holding cost and backorder cost, respectively, for product *i* in period *t*	\$/item
c_{it}^m, c_{it}^r	Defective and rectification cost, respectively, for product *i* in period *t*	\$/item
c_t^l	Regular time labor hour cost in period *t*	\$/h
c_t^h, c_t^f	Labor hiring and labor layoff cost, respectively, in period *t*	\$/h

D_{ikts}	Demand of product *i* in factory *k* in period *t* under scenario *s*	item/period
m_{it}^{max}	Maximum defective amount of product *i* in period *t*	item/period
WH_t^{max}	Maximum inventory capacity in period *t*	item/period
$LH_{kts}^{max}, MH_{kts}^{max}$	Maximum labor (machine) hours in factory *k* in period *t* and scenario *s*	h/period
a_i, u_i	Unit labor hour and unit machine hour, respectively, required by product *i*	h/item
α	Percentage of allowable workforce variation	%
υ	Allowable defective percentage from production	%
η	Percentage of defective product produced that is rectified	%
Φ_g, Φ_b	Capital recovery factor of generation technology *g* and battery *b*, respectively	N/A
c_g	Penalty cost or tax incentive of generation technology *g*	\$/MWh
b_g	Operating and maintenance (O&M) cost of generation technology *g*	\$/MWh
a_g, a_b	Capacity cost for generation technology *g* and battery *b*, respectively	\$/MW
τ_{gj}	Number of generation hours in day *j* for generation technology *g*	h/day
τ_g^*	Generation hours for generation technology *g* over the entire production periods	h
e_i^x, e_i^f	Energy consumed for producing and storing one unit of product *i,* respectively	MWh/item
q^v	Electric vehicle energy intensity rate	MWh/kg/km
m^v	Vehicle self-weight	kg
d_{kn}, d_{nk}	Distance between factory *k* and warehouse *n* (warehouse *n* and factory *k*)	km
β	Number of daily trips	trip/day
$L_k,\ L_n$	Base electricity load of factory *k* and warehouse *n,* respectively	MW
w_i	Unit weight of product *i*	kg/item
$\|J\|, \|J_t\|$	Size of the set of days over the entire horizon and in period *t*, respectively	day
$\lambda_{gkjs}, \lambda_{gnjs}$	Capacity factor for generation technology *g* in factory *k* (warehouse *n*) in day *j* under scenario *s*	N/A
χ	Number of hours in a day	h
u^-, u^+	Profit from selling energy and cost of buying energy, respectively	\$/MWh
δ	Daily operating hours of a facility (warehouse or factory)	h/day
p(s)	Probability of scenario *s*	

The two-stage stochastic, aggregate production planning model is presented below

Minimize

$$\begin{aligned} Z = &\sum_{i\in I}\sum_{k\in K}\sum_{t\in T}(c_{it}^{x} + c_{it}^{w})\, x_{ikt} + \sum_{i\in I}\sum_{k\in K}\sum_{t\in T}(c_{it}^{m}\, m_{ikt} + c_{it}^{r} r_{ikt}) + \sum_{k\in K}\sum_{t\in T}(c_l l_{kt} + c_h h_{kt} + c_f f_{kt}) + \\ &\sum_{i\in I}\sum_{k\in K}\sum_{t\in T}\sum_{s\in S} p(s)\ (c_{it}^{b}\, b_{ikts} + c_{it}^{q}\, q_{ikts}) + \sum_{i\in I}\sum_{n\in N}\sum_{t\in T}\sum_{s\in S} p(s)\, c_{it}^{y}\, y_{ints} + \sum_{k\in K}\sum_{g\in G} \Phi_g a_g P_{kg}^{c} + \\ &\sum_{n\in N}\sum_{g\in G}\Phi_g a_g P_{ng}^{c} + \sum_{k\in K}\frac{\Phi_b a_b B_k^c}{\chi} + \sum_{n\in N}\frac{\Phi_b a_b B_n^c}{\chi} - \sum_{k\in K}\sum_{j\in J}\sum_{s\in S} p(s)\, u^{-}\frac{Q_{kjs}^{-}}{\chi} + \sum_{k\in K}\sum_{j\in J}\sum_{s\in S} p(s)\, u^{+}\frac{Q_{kjs}^{+}}{\chi} - \\ &\sum_{n\in N}\sum_{j\in J}\sum_{s\in S} p(s)\, u^{-}\frac{Q_{njs}^{-}}{\chi} + \sum_{n\in N}\sum_{j\in J}\sum_{s\in S} p(s)\, u^{+}\frac{Q_{njs}^{+}}{\chi} + \sum_{k\in K}\sum_{g\in G}\sum_{s\in S} p(s)(b_g - c_g)\tau_g^{*}(\sum_{j\in J}\frac{\lambda_{gkjs}}{|J|})P_{kg}^{c} + \\ &\sum_{n\in K}\sum_{g\in G}\sum_{s\in S} p(s)(b_g - c_g)\tau_g^{*}(\sum_{j\in J}\frac{\lambda_{gnjs}}{|J|})P_{ng}^{c} \end{aligned} \quad (6)$$

Subject to:

$$y_{int-1s} - y_{ints} + x_{ikt} + q_{ikts} - b_{ikt-1s} + b_{ikts} - m_{ikt} + r_{ikt} = D_{ikts} \quad (7)$$

$$\forall i \in I, \forall t \in T\backslash\{1\}, \forall k \in K, \forall n \in N, \forall s \in S$$

$$\sum_{i\in I}(e_i^x + q^v d_{kn} w_i)\frac{x_{ikt}}{|J_t|} + \delta L_k + q^v \beta d_{kn} m^v + B_{kjs}^f - B_{kj-1s}^f + Q_{kjs}^- = \sum_{g\in G}\tau_{gj}\lambda_{gkjs}P_{kg}^c + Q_{kjs}^+ \tag{8}$$
$$\forall t \in T, \forall j \in J\backslash\{1\}, \forall k \in K, \forall n \in N, \forall s \in S$$

$$\sum_{i\in I} e_i^f y_{ints}\left(\frac{j - \sum_{t\in T'}|J_{t'}|}{|J_t|}\right) + \delta L_n + q^v \beta d_{nk} m^v + B_{njs}^f - B_{nj-1s}^f + Q_{njs}^- = \sum_{g\in G}\tau_{gj}\lambda_{gnjs}P_{ng}^c + Q_{njs}^+ \tag{9}$$
$$\forall t \in T, \forall j \in J\backslash\{1\}, \forall k \in K, \forall n \in N, \forall s \in S$$

$$\sum_{i\in I} a_i x_{ikt} = l_{kt} \qquad \forall k \in K, \forall t \in T \tag{10}$$

$$l_{kt} = l_{kt-1} + h_{kt} - f_{kt} \qquad \forall k \in K, \forall t \in T \tag{11}$$

$$h_{kt} + f_{kt} \le \alpha l_{kt-1} \qquad \forall k \in K, \forall t \in T \tag{12}$$

$$\sum_{i\in I} u_i x_{ikt} = w_{kt} \qquad \forall k \in K, \forall t \in T \tag{13}$$

$$w_{kt} = w_{kt-1} + o_{kt} - p_{kt} \qquad \forall k \in K, \forall t \in T \tag{14}$$

$$l_{kt} \le LH_{kts}^{max}, \; w_{kt} \le MH_{kts}^{max} \qquad \forall k \in K, \forall t \in T, \forall s \in S \tag{15}$$

$$\upsilon x_{ikt} = m_{ikt} \qquad \forall i \in I, \forall k \in K, \forall t \in T \tag{16}$$

$$\eta m_{ikt} = r_{ikt} \qquad \forall i \in I, \forall k \in K, \forall t \in T \tag{17}$$

$$0 \le m_{ikt} - r_{ikt} \le m_{ikt}^{max} \qquad \forall i \in I, \forall k \in K, \forall t \in T \tag{18}$$

$$\sum_{i\in I} y_{ints} \le WH_t^{max} \qquad \forall n \in N, \forall t \in T, \forall s \in S \tag{19}$$

$$0 \le B_{kjs}^f \le B_k^c \qquad \forall k \in K, j \in J, \forall s \in S \tag{20}$$

The objective function (6) minimizes the expected annual cost considering all production and energy costs. Constraint (7) assures product demands are satisfied in all scenarios and periods and it varies slightly for the first period, Constraints (8) and (9) represent the daily energy balance kept in the factory and warehouse in days different from the first one in which the equations vary slightly. Constraint (10) indicates that the labor hour consumed to produce the products must be equal to the labor hours kept in each period. Constraint (11) updates the workforce level from one period to the next one. Constraint (12) satisfies norms regarding the maximum amount of labor hired and fired in each period. Constraint (13) states that the total machine hours used in production of all products must equal the machine hours allocated in each period. Constraint (14) updates the machine hours from one period to the next one considering overtime and downtime hours. Constraints listed in (15) guarantee that labor and machine hours do not exceed the corresponding maximum available hours in each scenario. Constraints (16)-(17) define the amounts of production defective and to be rectified. Constraint (18) limits the amount of defective product. Constraint (19) is the inventory capacity constraint. Constraint (20) is for the factory, and it ensures that the daily energy stored or discharged should not exceed the battery capacity. A similar constraint applies to the warehouse.

The model in (6)-(20) represents the APP model instance with EP and battery adopted. The APP model with island microgrid (IM) and battery and the one for IM without battery result from dropping terms in (6), (8), (9), and (20). The model was coded using the AMPL mathematical programming language and solved through the CPLEX solver.

5. Numerical Experiment and Results

In the numerical experiment, the manufacturing system consists of one factory located in San Francisco and one warehouse in Phoenix. The factory makes two products with two demand levels, i.e., high and low. The maximum labor and machine hours available can be at any three levels, i.e., low, medium, and high. The specific values assumed for all the model input parameters are in [5]. The variation over the years for the daily WT and PV capacity factors (CF) is accounted by selecting three years (2013, 2014, and 2015) of hourly wind and weather profiles, applying the methodology in Section 3, and averaging the hourly CF in each day. Hence, the random parameters of the model produce a set of size $|S|=108$ scenarios ($2\times2\times3\times3\times3$). The scenarios are classified into three equally probable categories (i.e., 1=low, 2=medium, 3=high) by assigning the corresponding numerical score to low, medium, and high product demands, machine, and labor hours available and adding those scores. There are 22, 64, and 22 scenarios in the low, medium, and high category. WT and PV CF are computed for 26,280 observations (365days×24 hours/day×3 sets) of wind speed and weather conditions. The San Francisco and Phoenix mean CF for the WT are 0.4142 and 0.1541, respectively, while the mean CF for the PV are 0.2959 and 0.3736. In San Francisco, the WT capacity factor is 39.98% higher than the PV one, whereas, in Phoenix, the PV capacity factor is 142.44% higher than the WT one. The energy tariffs are assumed fixed, $130/MWh to buy, and $30/MWh to sell in EP mode.

5.1 Levelized Cost of Energy

Levelized cost of energy (LCOE) represents the cost of producing one MWh of energy. It is an indicator to decide whether a RE project is attractive compared to conventional energy. The LCOE's for the model instances studied are $48.37/MWh for island model (IM) without battery, $64.91/MWh for IM with battery, and $36.40/MWh for EP. These values are below the actual cost of traditional energy sources, which is $50-$100/MWh in the US.

5.2 Expected Cost and Sensitivity Analysis

The expected cost is $28,591,046 for IM without battery, $17,131,084 for IM with battery and $12,727,622 for EP. This result indicates that the EP model instance is the most economically viable. EP results in 55% cost reduction if compared to IM without battery and in 25.70% cost reduction if compared to IM with battery. A preliminary full four-factorial design of experiments was performed to determine if products demand distribution, PV installation cost, tax incentives for installing PV, and the probabilities of each of the 108 scenarios in the TSS model affect the expected cost. The number of levels selected for each of these factors is 4, 3, 3, and 3, respectively. One replication or run in each experimental condition produced 108 ($4\times3\times3\times3$) experimental runs. The statistical analysis of the experiment showed that all factors were significant, with PV installation cost having the largest impact on expected cost.

6. Conclusions

This paper presents and implements a two-stage stochastic optimization model for solving an aggregate production planning problem that involves wind and solar-based microgrid systems with batteries and energy prosumer facilities. The renewable generation daily capacity factors are estimated from hourly climate data for three recent years in San Francisco and Phoenix and input to the model scenarios. The capacity factors capture the variability of wind and solar generation over the planning horizon. Three operating modes are studied: 1) island microgrid without batteries, 2) island microgrid with batteries and 3) grid-tied microgrid with batteries. The numerical experiments show that manufacturing facilities operating with grid-tied microgrid as energy prosumer are the most cost-effective if compared to facilities powered by island microgrids. The expected cost and levelized cost of energy results show that the proposed two-stage stochastic aggregate production planning model can potentially accelerate the manufacturing industry's transition towards an eco-friendly operation. A future work is to input the estimated hourly capacity factors directly into the model, refine the granularity of some of the model constraints so they are satisfied hourly instead of daily, and implement time-varying energy tariffs.

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