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# Optimized Decision Making in the Power Industry Using Machine Learning

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ABSTRACT

To supply power to customers, a power company procures fuel from suppliers while also holding an inventory of such fuel and/or storing a very limited amount of excess power in a battery. Additionally, a power company may directly sell renewable energy sources to customers and exchange power with a neighboring grid to ameliorate shortages. The standard techniques of optimizing profit entail a tedious, human-driven decision-making procedure that results only in local optima. This disclosure optimizes the profit of a power company by automatically making intelligent procurement and selling decisions using machine learning. The decisions are treated as an end-to-end supply-chain problem and jointly optimized, such that optimal trade-offs are achieved amongst supply, demand, system restrictions, and environmental constraints. In particular, the techniques jointly optimize over the end-to-end supply chain, including fuel procurement, fuel and electricity selling, fuel stocking, etc.

KEYWORDS

- Energy procurement
- Energy sales
- Energy optimization
- Energy mix
- Renewable energy
- Machine learning
- Inventory optimization

BACKGROUND
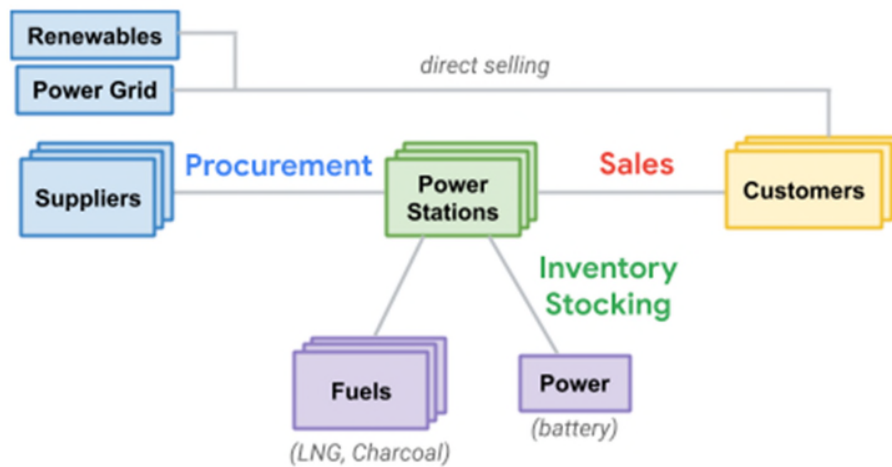
Fig. 1: The ecosystem of a power station

Fig. 1 illustrates the ecosystem of a power station. To supply power to customers, a power company procures fuel (e.g., coal, LNG, etc.) from suppliers while also holding an inventory of such fuel and/or storing a very limited amount of excess power in a battery. Additionally, a power company may own or have access to renewable energy sources, which can be directly sold to customers. Moreover, an excess or shortfall of power can be ameliorated by an exchange of power with a neighboring power grid.

In optimizing profit, a power company seeks to optimize costs, e.g., of procurement, of holding inventory, of having to buy power from another grid to cover a shortfall, etc. The power company also seeks to optimize revenue, e.g., supply to markets with excess demand, use an appropriate renewable-conventional mix, etc.

The standard techniques of optimizing profit entail a multi-stage, human-driven decision-making procedure. Although forecasting tools are used, it is primarily humans who arrive at procurement or sales decisions by applying domain heuristics. For example, operational decisions can be made (e.g., daily electricity production) to minimize operational expenses.

However, merely minimizing operational expenses only optimizes for the production stage, which is only a part of the supply chain. Such an approach does not account for demand fulfillment, nor does it leverage the availability of potential new markets. It also does not account for fuel procurement price trends or supplier availability, which are both stochastic in nature.

Such optimization being local rather than end-to-end, suboptimal decisions can result, and profit remains unmaximized. Separately, the human involvement needed to make decisions is costly, bias-prone, and sub-optimal. Also, a local optimization outcome (e.g., of operational expenses) has to be manually tied in with optimization outcomes in other parts of the supply chain (e.g., supply-side, demand-side factors).

DESCRIPTION

This disclosure describes techniques to optimize the profit of a power company by generating (and in some configurations, automatically making) intelligent procurement and selling decisions using machine learning. The decisions are treated as an end-to-end supply-chain problem. Different parameters are jointly optimized, such that optimal trade-offs are achieved amongst supply, demand, system restrictions, and environmental constraints. In particular, the techniques jointly optimize over the end-to-end supply chain, including fuel procurement, fuel and electricity selling, fuel stocking, etc. The optimization is carried out temporally, e.g., over data obtained over the course of months.

The profit of a power company is given by

$$
\begin{aligned}
\text{Profit} = \quad &\text{Sales revenue} \\
&+ \text{Direct-selling revenue} \\
&- \text{Costs of procurement} \\
&- \text{Costs of procurement shipping or set-up}
\end{aligned}
$$

– Costs of sales shipping or set-up

– Inventory-holding costs.

In mathematical terms, the profit Z_{it} at a time (day-of-year) t and energy item (e.g., LNG, coal, electricity, etc.) i is given by

$$
\begin{aligned}
Z_{it} = {} & \sum_{k} P^{\mathrm{S}}_{k,it} \eta^{\mathrm{out}}_{k,i} x^{\mathrm{S}}_{k,it} \quad \text{(Sales revenue)} \\
& + \sum_{u} \sum_{k} O_{u} \eta^{\mathrm{direct}}_{u,k,i} P^{\mathrm{D}}_{u,k,it} x^{\mathrm{D}}_{u,k,it} \quad \text{(Direct selling revenue)} \\
& - \sum_{u} (1 - O_{u}) P^{\mathrm{P}}_{u,it} x^{\mathrm{P}}_{u,it} \quad \text{(Costs of procurement)} \\
& - \sum_{u} s^{\mathrm{P}}_{u,it} y^{\mathrm{P}}_{u,it} \quad \text{(Costs of procurement shipping or setup)} \\
& - \sum_{k} s^{\mathrm{S}}_{k,it} y^{\mathrm{S}}_{k,it} \quad \text{(Costs of sales shipping or setup)} \\
& - h_{it} I_{i,t+1} \quad \text{(Inventory holding costs)},
\end{aligned}
$$

where the symbols have the following meanings (the symbol i indexes the energy item; t, time; u, supplier; k, market or customer).

$P^{\mathrm{S}}_{k,it}$: sale price for energy item i at time t for market (or customer) k;

$\eta^{\mathrm{out}}_{k,i}$: transmission efficiency for supplying energy item i to market (or customer) k;

$\eta^{\mathrm{direct}}_{u,k,i}$: transmission efficiency for supplying renewable energy item i directly from supplier u to market (or customer) k;

$P^{\mathrm{D}}_{u,k,it}$: sale price for direct sales of renewable energy item i from supplier u to market (or customer) k at time t;

$x^{\mathrm{D}}_{u,k,it}$: quantity of direct sales of renewable energy item i from supplier u to market (or customer) k at time t;

O_{u} : a binary variable; equals 1 if supplier u is owned by the power company, 0 otherwise;

$P^{\mathrm{P}}_{u,it}$: procurement price for energy item i at time t from supplier u;

$x^{\mathrm{P}}_{u,it}$: quantity of procurement of energy item i at time t from supplier u;

$s_{u,it}^{\mathrm{P}}$: cost of shipping energy item i from supplier u at time t;

$s_{k,it}^{\mathrm{S}}$: cost of sales of energy item i to market (or customer) k at time t;

$x_{k,it}^{\mathrm{S}}$: quantity of sales of item i at time t to customer k;

$y_{k,it}^{\mathrm{P}}$: a binary variable; equals 1 if a procurement order is placed for market (or customer) k for energy item i at time t, 0 otherwise;

$y_{k,it}^{\mathrm{S}}$: a binary variable; equals 1 if energy item i is sold to market (or customer) k at time t, 0 otherwise;

h_{it} : unit cost of holding inventory of energy item i at time t;

$I_{i,t+1}$: the inventory level of energy item i at time $t+1$.

The problem is to maximize the sum-profit Z over time and energy item:

$$\max_{x,y} \sum_i \sum_t Z_{it} \tag{1}$$

The variables of optimization are included in the vector $\left[x_{k,it}^{\mathrm{S}}, x_{u,k,it}^{\mathrm{D}}, x_{u,it}^{\mathrm{P}}, y_{u,it}^{\mathrm{P}}, y_{k,it}^{\mathrm{S}}\right]$. The components of the optimal vector indicate an optimal supplier-to-market combination and energy mix and quantity to procure and to sell for each day of the year.

The optimization of equation (1) can be carried out using, e.g., an actor-critic reinforcement-learning neural network, linear programming, multi-stage dynamic programming (Bellman) techniques, etc. The parameters of equation (1), e.g., sale and procurement prices, transmission efficiencies, costs of shipping and sales, costs of holding inventory, fuel and electricity demand, etc., can be made available by the power company.

Based on such input parameters, the described techniques automatically model the supply chain, and output optimal decisions in the vector $\left[x_{k,it}^{\mathrm{S}}, x_{u,k,it}^{\mathrm{D}}, x_{u,it}^{\mathrm{P}}, y_{u,it}^{\mathrm{P}}, y_{k,it}^{\mathrm{S}}\right]$. This can result in optimal energy sourcing, optimal long- and short-term inventory decisions, optimal production planning, rapid response to unexpected incidents, and optimal demand-fulfilling decisions. The

techniques are robust to the stochastic nature of energy parameters, e.g., random fluctuations in energy supply (due to wind velocity, cloud cover, etc.), mix, demand, etc.

	Conventional approach	**This disclosure**
Algorithm	Stochastic dual dynamic programming	Temporal difference learning with value function approximation
Approximation function	Sampling solution in dual problem	Concave piecewise linear regression or deep neural network
Generalizable to new data?	No. With new input, requires the solving of a new problem from scratch.	Yes. Able to generalize to unseen data, robust to small distribution shifts of stochastic variables.
Model-less?	Not model-less. It requires a given distribution of stochastic variables	Model-less. The distribution is learned via sampling data or exploring the environment

Table 1: Differences between the disclosed approach and conventional approaches

Table 1 illustrates some important differences between the disclosed techniques and conventional approaches. In summary, the techniques of this disclosure can improve power-industry optimization as follows:

- The techniques jointly optimize decisions across multiple stages in the supply chain of a power plant, thereby reaching global optima. As mentioned, the stages include fuel sourcing, fuel inventory stocking, electricity production, electricity or fuel-sales decisions, etc.

- The techniques automate decision making across multiple stages, eliminating substantial manual efforts and heuristics.

- In making decisions that encompass the entire (end-to-end) supply chain, the techniques minimize risk and maximize the lifetime value for the power company.

CONCLUSION

This disclosure optimizes the profit of a power company by automatically making intelligent procurement and selling decisions using machine learning. The decisions are treated as an end-to-end supply-chain problem and jointly optimized, such that optimal trade-offs are achieved amongst supply, demand, system restrictions, and environmental constraints. In particular, the techniques jointly optimize over the end-to-end supply chain, including fuel procurement, fuel and electricity selling, fuel stocking, etc.

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