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Design the Capacity of Onsite Generation System with Renewable Sources for Manufacturing Plant

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Abstract

The utilization of onsite generation system with renewable sources in manufacturing plants plays a critical role in improving the resilience, enhancing the sustainability, and bettering the cost effectiveness for manufacturers. When designing the capacity of onsite generation system, the manufacturing energy load needs to be met and the cost for building and operating such onsite system with renewable sources are two critical factors need to be carefully quantified. Due to the randomness of machine failures and the variation of local weather, it is challenging to determine the energy load and onsite generation supply at different time periods. In this paper, we first propose time series models to describe and predict the variation of the energy load of manufacturing system and the irradiation of solar energy. After that, a case study utilizing the predicted data is implemented. The case study includes different scenarios with respect to generation capacities, considering different predicted energy loads from manufacturing system. The cost for building and running such an onsite generation system and its corresponding service level are examined and discussed.

Peer-review under responsibility of the scientific committee of the Complex Adaptive Systems Conference with Theme: Engineering Cyber Physical Systems.

Keywords: Renewable source; Manufacturing; Onsite generation

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1. Introduction

With the increasing concerns of environmental protection and climate changes, the utilization of renewable sources in energy supply mix has drawn wide attention from industry, academia, and government. The penetration of renewable sources in electricity grid has witnessed a significant growth in recent years. It was reported that, in 2015, about 13% and 10% of total U.S. electricity generation and energy consumption are contributed by renewable sources, respectively [1]. This growth trend is expected to be maintained for next several decades, it is projected that renewable sources will account for approximately 80% of total electricity generation mix in the U.S. by 2050 [2].

One important application of renewable sources is to build onsite generation system to mitigate the disturbances of the utility grid because the onsite generation system can continue to operate while the utility grid is down. The primary benefits are the improved reliability, affordability, resilience, and security of energy supply to end use customers. Furthermore, the greenhouse gas (GHG) emissions can be reduced and the stress on transmission and distribution systems can be relieved. Therefore, some pioneer onsite generation system projects have been implemented in residential housing [5-7] and some critical facilities, such as medical centers, financial corporations, military bases, and jails [8-9].

Manufacturing is traditionally not considered a critical facility. However, the industrial sector accounts for one third of total energy consumption in the United States [10], and manufacturing activities dominate energy consumption and GHG emissions in the industrial sector [11]. In an age when it is impossible to conduct manufacturing activities in the absence of electricity, even a short power outage can cause detrimental impacts on manufacturing enterprises. Studies show that manufacturing has been one of the most-affected industries by power outages [14-17]. An outage can bring production lines to an abrupt halt. It may also break supply chains altogether, which leads to huge losses of productivity, material and revenue, as well as negative environmental and societal impacts. For example, the U.S. Northeast blackout on August 14, 2003, led to the shutdown of 19 manufacturing facilities and three parts warehouses of General Motors in Michigan, Ohio, and Ontario and idled more than 47,000 employees [15]. Also, Hurricane Sandy in 2012 destroyed many industrial businesses and left tens of thousands of New York and New Jersey residents unemployed [16]. Hurricane Katrina in 2006 led to a job loss of more than 10,000 workers in the manufacturing industry of New Orleans and Louisiana [17].

The economic effects are enormous because of loss of power for manufacturing enterprises, as shown in the previous analysis. The improved resilience by deploying onsite generation system with renewable sources for manufacturing facilities will greatly reduce such impacts. One challenge of deploying onsite generation system is the randomness of both manufacturing electricity demand due to unreliable manufacturing machines and renewable energy supply. In this paper, classical time series models are applied to the historical data of manufacturing system regarding the energy demand and solar irradiation in order to describe and predict these two stochastic processes from both demand and supply sides. Various scenarios with respect to generation capacities considering different predicted energy demands from manufacturing system are studied to examine the cost for building such an onsite generation system and its corresponding service level.

2. Time Series Model

The model we proposed to predict the future electricity demand is autoregressive-integrated moving average (**ARIMA**) model. In order to illustrate this model, few concepts including the stochastic processes, time series, stationary time series, nonstationary time series, and autoregressive-moving average (**ARMA**) processes are briefly introduced first in this section.

Definition 2.1. Stochastic Process: A stochastic process is a family of random variables $\{X_t, t \in T\}$ defined on a probability space $(\Omega, \mathcal{F}, \mathcal{P})$, where T denotes an index set, which is usually a set of real numbers. If T denotes a set of points in time, then $\{X_t, t \in T\}$ is called a time series. In particular, if $\{T \subseteq \mathbb{Z}\}$, then $\{X_t, t \in T\}$ is called a discrete time series.

Note that $\{X_t\}_{t\in T}$ is sometimes used in place of $\{X_t, t \in T\}$ to denote a time series.

Definition 2.2. Stationary Time Series: The time series $\{X_t, t \in \mathbb{Z}\}$, is said to be stationary if for all $t, r, s \in \mathbb{Z}$,
(i) $E[|X_t|^2] < \infty$;
(ii) $E[X_t] = m$;
(iii) $Cov(X_r, X_s) = \gamma_X(r, s) = \gamma_X(r+t, s+t)$.
Such stationarity is sometimes referred as weak stationarity, covariance stationarity, stationarity in the wide sense, or second-order stationarity. Otherwise, the time series $\{X_t, t \in \mathbb{Z}\}$ is nonstationary.

Definition 2.3. Autoregressive-Moving Average (ARMA(p, q)) Process: A real-valued time series $\{X_t\}_{t\in\mathbb{Z}}$ is said to be an autoregressive-moving average (ARMA(p, q)) process with mean μ if it is stationary and satisfies

$$\Phi(B)(X_t - \mu) = \theta(B)\varepsilon_t, t \in \mathbb{Z},$$

where
$$\Phi(z) = 1 - \Phi_1 z - \Phi_2 z^2 \dots - \Phi_p z^p$$
and
$$\theta(z) = 1 + \theta_1 z + \theta_2 z^2 \dots + \theta_q z^q$$

are autoregressive and moving-average polynomials of orders p and q, respectively, with no common roots; $\{\varepsilon_t\}_{t\in Z}$ is a white noise error (innovations) process with zero-mean and constant variance σ^2; $\mu = E(X_t)$ for all t; B is the back-shift operator defined such that $B^k X_t = X_{t-k}$ for all $k \in \mathbb{N}$, and $B^0 X_t = X_t$. If $p = 0$, $\{X_t\}_{t\in\mathbb{Z}}$ is called a pure moving-average process of order q (MA(q)), and if $q = 0$, the time series is termed a pure autoregressive process of order p (AR(p)).

Frequently, it is necessary to represent a given ARMA time series as an infinite order moving-average of the current and past innovations. When a time series can be represented in this manner, it is called a causal process. The ARMA(p, q) processes can be generalized to include nonstationary behaviors. The traditional generalization of ARMA models leads to the ARIMA(p, d, q) process, which is defined below.

Definition 2.4. Autoregressive-Integrated Moving Average (ARIMA(p, d, q)) process: A real-valued process $\{X_t\}_{t\in\mathbb{Z}}$ is said to be an Autoregressive-Integrated Moving Average (ARIMA(p, d, q)) process if the process $\{Y_t\}_{t\in\mathbb{Z}}$ with

$$Y_t = \nabla^d (X_t - \mu), t \in \mathbb{Z},$$

is a causal ARMA(p, q) process, where $\nabla = 1 - B$ and $d \in N$. Note that if d = 0, it is actually an ARMA process.

In real life, many time series are nonstationary and hence the ARIMA processes are extensively used in various areas, including manufacturing industry. Therefore, in Section 3, we forecast the unknown electricity demand and solar irradiation using the ARIMA model explained above.

3. Case Study

3.1 Time series model for manufacturing load and solar irradiation

The energy demand of a manufacturing system is obtained from a simulation model built on the simulation platform of Plant Simulation as shown in Figure 1. An auto component manufacturing system is built in the simulation model with real parameters. The machine parameters such as the cycle time, rated power, mean time between failures, mean time to repair, etc. are integrated in the model (due to confidentiality agreement, such parameters cannot be given in detail here). The values of power consumption for different working states, i.e., working, idle, failure, etc. are configured for each machine. In addition, the buffer parameters including the initial contents and respective capacities are also configured in the simulation model. Note that mean time between failures and mean time to repair for each machine are modeled by two random distributions. Weibull distribution is used for mean time between failures and exponential distribution is used for mean time to repair based on the actually historical data of each manufacturing machine in the plant. The remaining parameters are modeled as constants.

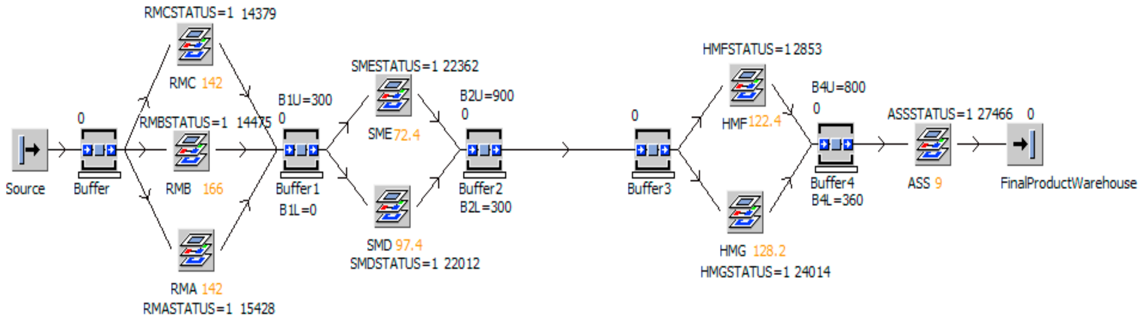

Figure 1. Snapshot of a Manufacturing System in Simulation Model

The time series of monthly power consumption of this manufacturing system is obtained through running the simulation model for 30 days, with three 8-hour shifts per day using the real parameters. Every 15 minutes, the energy consumption is recorded. The format of this simulated high frequency data is shown in Table 1, where the first column is the index of 15-minute intervals and the second column is the average power (kW) consumption.

A scatter plot of the entire data is given in Figure 2 to illustrate the high frequency feature of the data. It shows that the power demand of the manufacturing system fluctuates around a roughly constant mean, which matches the pattern of the real power consumption data of the plant. Thus, the time series model like ARMA can be a candidate tool to model the variation of power demand along the time horizon.

Table 1. A Sample of the Power Consumption Data

Time Interval	Power (kW)
1	190.96
2	256.14
3	259.63
4	285.29
5	244.87
6	368.52
7	294
8	385.81
9	360.86
10	330.08

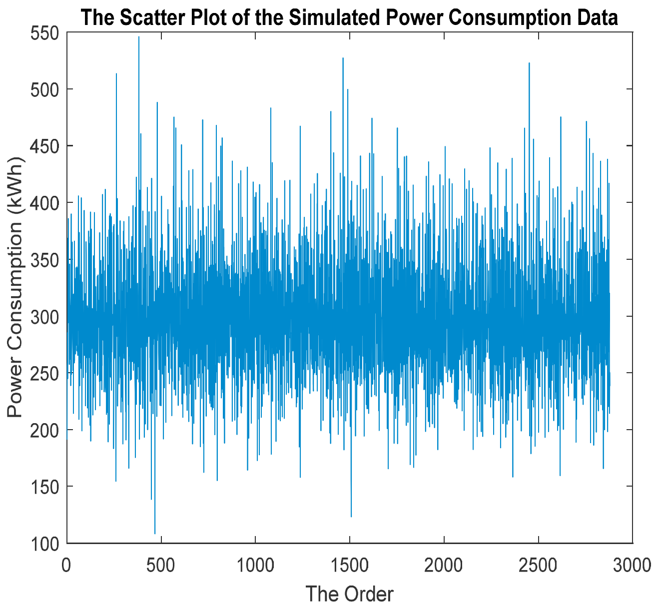

Figure 2. A Scatter Plot of the Solar Irradiation Data

Using MATLAB software, we model this power demand time series and predict the new power demand of the manufacturing system based on the following process.

Step 1: Plot the sample ACF and PACF as shown in Figure 3 to examine the data autocorrelation to further determine if ARMA or ARIMA can be used to model this time series.

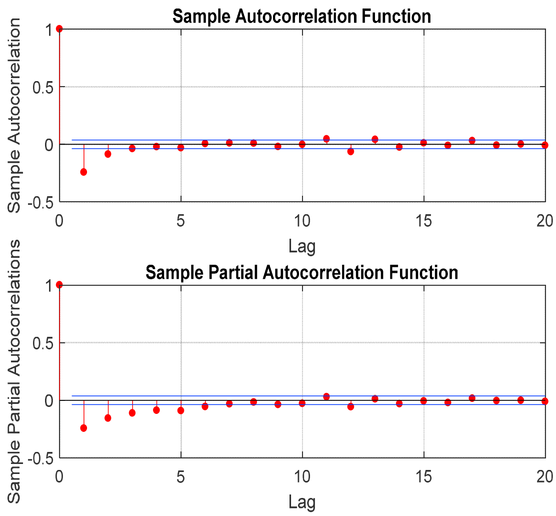

Figure 3. The ACF and PACF Plots of the Electricity Data

Step 2: Since both the sample ACF and PACF decay relatively slowly, it is plausible to consider an ARIMA$(p, 0, q)$ or ARMA(p, q) model. Although the ARMA lags, p and q, cannot be selected solely by looking at the ACF and PACF plots, it is fair enough to estimate them as: p is between 1 and 6, and q is between 1 and 6.

Step 3: To identify the best p and q, we fit total 36 models with different lag choices. That is, fit all combinations of $p = 1, \dots, 6$ and $q = 1, \dots, 6$ to the simulated data. Then choose the best model according to the Bayesian Information Criterion (BIC) and other criteria, such as the difference of the range, maximum, or minimum between the simulated data and their estimates. It turns out ARIMA(2,0,6) is the most appropriate model that can fit to the simulation data.

Step 4: Forecast the new electricity demand for the next month using the trained ARIMA(2,0,6) model based on the 30-days simulated data.

We assume that the electricity demand for different months has same pattern. Therefore, using the predicted monthly data repetitively, we can obtain the predicted demand for an entire year.

Similarly, we use the same procedure aforementioned to model and predict the solar irradiation. The historical data of solar irradiation from May 2015 to May 2016 is obtained from the National Renewable Energy Laboratory (NREL) [18]. A scatter plot of this high frequency data is presented in Figure 4. Following the same steps illustrated above, we find that ARIMA(2,0,0) or AR(2) model is the most appropriate one to describe this time series.

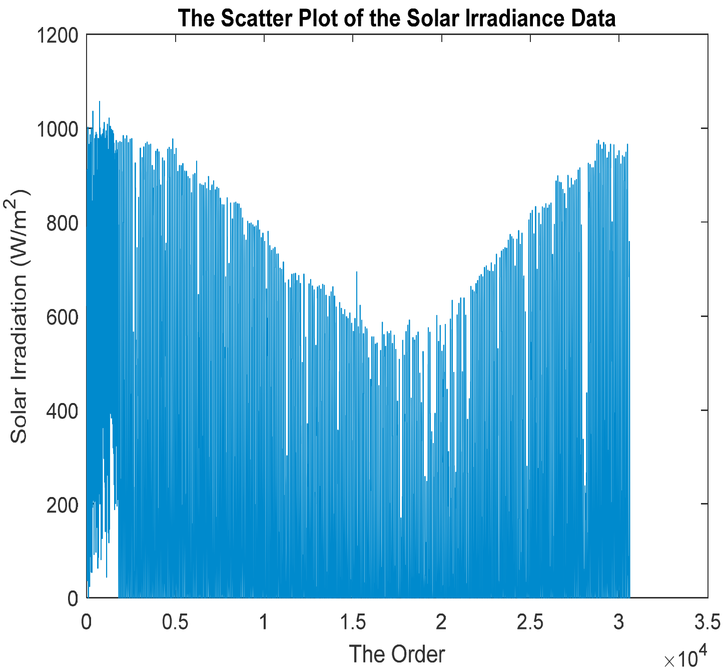

Figure 4. A Scatter Plot of the Solar Irradiance Data

3.2 Cost and service level comparison considering different system capacity

Based on the predicted electricity demand, we consider two scenarios of onsite generation system capacity with maximum and average predicted demand, respectively. Considering the variation of solar irradiation along the time horizon, average value of irradiation is usually used in designing solar PV system [19]. Thus, in this case, the average predicted irradiation is used for both scenarios as shown in Table 2.

Table 2. Two Scenarios of Capacity of Onsite Generation System

Scenario	Capacity of onsite generation system (kW)		Average predicted irradiation (W/m^2)
1	Maximum of the predicted demand	360.90	231.63
2	Mean of the predicted demand	296.67	231.63

For each scenario, the required area of solar panels is calculated by

$$A_{pv} = \frac{1000P}{I_T \times \eta} ,$$

where P is the capacity in kW of solar PV system; A_{pv} is the area of solar PV array in m^2; I_T is the solar irradiation on the solar PV surface in W/m^2; and η is the system efficiency. In this case, η is set as 0.225 [20]. The commercial solar PV installation cost is \$2.13/W [21]. The unit electricity generation cost is \$0.122/kWh [22]. Assuming that the lifetime of the onsite generation system is 20 years, the results of the annual cost and the probability that the demand can be met by the onsite generation system are calculated as shown in Table 3.

Table 3. Cost and Service Level Comparison

	Solar PV area (m^2)	Annuity of initial installation	Annual generation cost	Probability
Scenario 1	6925	\$42599	\$334053	39.3%
Scenario 2	5692	\$35053	\$274601	36.8%

The results of the case shown in Table 3 match the common understanding regarding the relationships among the capacity, cost, and service level. The trade-off between the capacity/cost, and the service level could be further quantitatively modelled so that an optimal capacity can be identified.

Also, it can be seen that the annual value of the initial purchase and installation cost is pretty high. It implies that purely employing the solar energy for the onsite generation system may not be economically optimal to the manufacturer. The probabilities that the demand is met by the onsite generation system with solar PV are less than 40%. This is mainly due to the fact that the manufacturing system in this case runs three 8-hour shifts per day, which also implies that for such a 24-hour working schedule, other renewable sources, like the wind turbine should also be considered since wind energy can be, to some extent, complementary to the solar energy.

4. Conclusion and future work

In the paper, we present two classical stochastic time series models to estimate and forecast the potential demand of electricity based on a set of simulated data of energy load of a manufacturing system as well as the solar irradiation based on a set of true historical data. After that, using the predicted data of the demand and irradiation, we examine the cost and service level for the onsite generation systems with different capacities.

For future work, we can study the predication analysis of high frequency data using Kalman filter or linear quadratic estimation with the consideration of seasonality and long-memory characteristics. In addition, some other sources like the wind turbine and battery system can be integrated into the onsite generation system. The cost items of purchasing the electricity from external grids can also be modeled in cost analysis. An analytical model that can quantitatively balance the trade-off between the capacity and service level can be another research direction.

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