Optimal Energy Management Integration for a Petrochemical Plant Under Considerations of Uncertain Power Supplies

Tung-Yun Wu, Shyan-Shu Shieh, Shi-Shang Jang, and Colin C. L. Liu

***Abstract*—The electric power demands of many petrochemical plants are matched by supplies from an in-house cogeneration system and from the electric grid. However, due to the fluctuations of fuel costs, production, and electricity rates, it is necessary to balance electric supply between these two sources. In reality, uncertain effects play a very important role in this decision-making problem. One of the most important uncertainties is the occurrence of power interruptions from either one of the supply sources, which could endanger operability and reliability of plant operations. To minimize the total energy cost under consideration of unexpected power failures, we break up the solution of the problem into two layers. The outer layer is to determine the optimum contracting of three-section time-of-use rate. We use an artificial neural network regression model as a meta-model to simulate the contour plot of a nonconvex cost function. The occurrences of incidental power failures are simulated by the Monte Carlo method. The inner layer is to determine the optimum operation of the cogeneration system. Since the searching space is huge in the outer layer and the Monte Carlo simulation in the inner layer is time consuming, we implement an interactive sampling search approach to find the optimal contract capacity in this multi-local-optima problem.**

***Index Terms*—Cogeneration, meta-model approach, Monte Carlo simulation, optimal contract, uncertainty factors.**

I. Introduction

THE OPTIMAL strategy for energy management chemical plants has become critical recently due to the increase in the price of fuels such as coal and oil. In-house cogeneration systems are extremely useful in chemical plants due to the availability of high-pressure steam, especially in those countries where the electrical grid system is unstable. Diewekar *et al.* [1] have analyzed several uncertainties, such as fluctuations of production rate, process performance, and fuel cost in designing a power system. Incidental equipment failure, however, is not one of uncertain factors considered in their article. In many petrochemical plants as well as semiconductor industries, a short period of power failure, even as short as a few seconds, could result from several hours to a couple of days of plant shutdown. For many plants, such incidental power failure is almost intolerable. Worse, if the electric power needed during restartup is beyond the contract capacity, then it incurs a large sum of penalty imposed by the power company. Therefore, it is necessary to take power failure into account when determining the design capacity of cogeneration system or for the computation of optimum contracting demand with the power company. In this paper, the terminologies, such as failure, trip, or interruption, interchangeably mean incidental stop of unit operations or power delivery.

Few among those works discussing optimum contracting have considered the significance of power trips. There are three scenarios of power trips: interruption of the electrical grid, turbine failure, and boiler system failure. Each scenario has different responding procedures that have various electrical power demands to restart the plant operation. Due to three-section time-of-use (TOU) rate, the timing of power trip occurrence also results in different economical damages. The formulation of the optimum contracting problem in this paper takes all the above considerations into account.

Material and energy balance modeling of cogeneration system has been addressed in many studies. O'Brien and Bansal [2] conducted a comprehensive review of these works. Zheng and Furimsky [3] presented a complete simulation of the cogeneration system using a commercialized package. Based on these mature modeling techniques, many works focused on the optimal operation of the cogeneration systems. For instance, Arivalagan and Raghavendra [4] optimized fuel resources under various levels of production in a chemical process. Chen and Hong [5] used the Newton method to optimize load allocation of boilers and generators under TOU rates. Tsay and Lin [6] went one step further and solved a TOU problem using evolutionary programming approach that is useful in implementing an input/output regression curve. Besides, some works focused on the general problem formulation for optimal operation of flexible models [7]. Optimal energy management of industrial consumers also attracts lots of attention among the researchers. For instance, Gomez-Villalva and Ramos [8] combined operation optimization and contracting decisions as a whole, although they did not consider the process operation uncertainties. Tsay *et al.* [9] worked on optimal contracting decision without considering the optimal operation of the plant with a cogeneration system.

Fig. 1 shows a general hierarchical operation strategy for a manufacturing plant [10]. At the highest level, the past fluctuation of raw material cost and the forecast of product price in the

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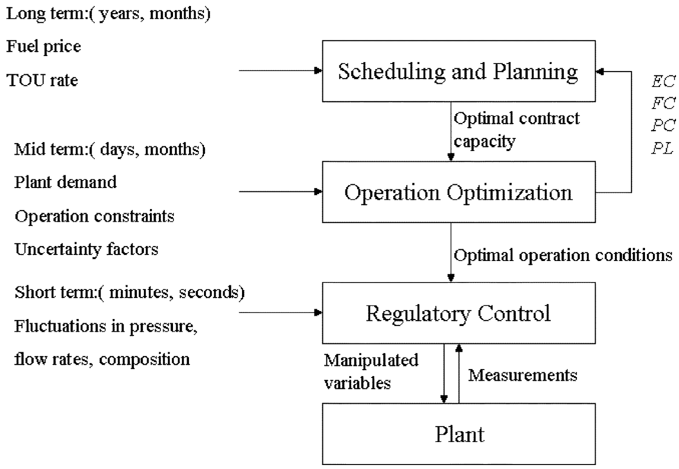

Fig. 1. General hierarchical operation strategy for a manufacturing plant.

future market are considered to determine production capacity or resource allocation. We consider this as the strategic management level. At the second level, it is necessary to optimize detailed operation based on the decision made at the strategic management level. We consider this as the tactical management level. The function of the lowest level is to perform some regulation and servo control requested by the second level. It should be noted that, as described in the literature, the levels in the above hierarchical management/operation structure can sometimes be blurred. In a plant with a cogeneration system, optimizing contract capacity of imported electricity is a decision-making process at the strategic management level, while optimizing operation of a cogeneration system is at tactical management level. The objective of this paper is to solve decision-making problems at both levels at the same time. We also take into consideration the incidental power trips in our decision-making process.

Research on decision making under uncertainties became substantial recently. Diwekar *et al.* [1], [11], [12] developed optimal design of advanced power systems under uncertainty. Their studies included the development of sampling technologies in an uncertainty variable space. Their sampling technology is extremely effective in saving sampling number when a rigorous model is used. However, a rigorous model is not always available in solving optimization problem.

Given a set of contract capacity of the electric power grid, a fixed charge (*FC*) can be easily calculated while the optimum cogeneration plant operation, i.e., minimization of energy cost (*EC*) by balancing thermal energy and electric energy, can be done via conventional optimization techniques. However, incidental failures of power supply causes production loss (*PL*) and various penalty charge (*PC*), which varies with contract capacity. The failures of cogeneration system and the electric power grid system from the utility company are the major uncertain factors in this study. The combination of the incidental trip events are so high that the simulation work is formidable. We implement the well-known Monte Carlo approach to estimate penalty charge and production loss. At the top level of the problem, a general regression model—artificial neural network (ANN) model—is used to take all of *EC*, *FC*, *PC*, and *PL* into account. A rigorous model is not available at this level. The regressive ANN model is a meta-model that is effective in saving sampling number, however, at the expense of solution accuracy. During making strategic decision of optimal contract capacity, tactical decision of optimal operation for a cogeneration system is made. Besides, this paper can be viewed as an extension of our previous meta-model driven experimental design approach [13].

TABLE I
DEFINITIONS OF EACH TIME PERIOD CATEGORY

Period	Summer-season month	Non-summer-season month
Peak	t=1	
Semi-peak	t=2	t=5
Saturday Semi-peak	t=3	t=6
Off-peak	t=4	t=7

The rest of this paper is organized as follows. Section II introduces the optimal operation approach in the second level of the problem. In Section III, the optimal contracting capacity problem in the first level is formulated. The solution method, a meta-model approach, is illustrated in Section IV. We present a real plant case in Section V. The conclusive remark is given in the final section.

II. Problem Formulation for Optimal Plant Operation

In this section, we focus on the problem formulation of the second level, i.e., the optimal operation level for the cogeneration system, which has been discussed in many literatures [4]–[6].

Without loss of any generality, let us assume the following situations: 1) single utility company and 2) constant steam demand for the plant.

It would be convenient to revise the following cost function when considering multiple utility companies. It is also possible to formulate a changeable steam demand problem as long as the demand pattern is known. In the following, boldfaced letters are used to represent a set of variables. Given a set of new $\mathbf{d}$, representing market disturbance variables, such as new demand forecast, new energy price, new fuel price, etc., a set of manipulated variables $\mathbf{m}$ is to be determined at the strategic management level. In this study, $\mathbf{m}$ is a set of contract capacity for peak (*CP*), semi-peak (*CMP*), and off-peak (*COP*) periods, and a set of operation variables $\mathbf{x}$ is determined at the tactical operation level by solving the following optimization problem:

$$\text{Min}EC(\mathbf{x},\mathbf{d},\mathbf{m}) = \sum_{t=1}^{7} HR_t \times \left(c_{1t}\cdot EB_t - c_{2t}\cdot ES_t + \sum_{i=1}^{n} c_i \cdot B_{it} + \sum_{a=1}^{w} c_a \cdot B_{at} \right) \quad (1)$$

where HR_t is the number of hours in the t period in a year, t is the time period category (seven categories of TOU rates in our study; see Table I), c_{1t} is the unit cost of the electrical energy from the grid system in the t period, c_{2t} is the unit price of the electrical energy sold to the grid system in the t period, c_i is the unit cost of fuel for the ith high-pressure boiler, c_a is the unit cost of fuel for the ath medium-pressure auxiliary boiler, EB_t is the total electricity purchased from the grid system in the t period, ES_t is the total electricity sold to the grid system in the t period, B_{it} is the steam output of the ith high-pressure boiler in the t period, n is number of the high-pressure boilers, B_{at} is the total steam output of the ath medium-pressure auxiliary boiler in the t period, and w is the number of medium-pressure auxiliary boilers.

Summarily, $\mathbf{d} = \{c_i, c_a, c_{1t}, c_{2t}\}, \mathbf{m} = \{CP, CMP, COP\}$, and $\mathbf{x}$ represent the rest of the variables. The set $\mathbf{m}$ is determined at the first level, while $\mathbf{x}$ is to be solved as an optimization problem formulated in this section. The following material balances, energy balances, and constraints for the operation units are made for general cases. The detailed formulations of equations are referred to in the literature [4], [5], [20]:

1) operational constraints of high-pressure and medium-pressure auxiliary boilers;
2) mass balance in each pressure steam header;
3) each pressure steam demand for the process;
4) recycled steam from the process to each steam eader;
5) operational constraints of steam turbines;
6) conversion of steam to electricity in a generator;
7) operational constraints of a generator;
8) electrical energy balance of the plant;
9) operational constraints of buying and selling electrical power.

III. Problem Formulation for Optimal Contracting Capacity

An annual cost function can be revised as follows by considering all existing deterministic and stochastic uncertainties in the integrated problem of the strategic management and optimum operation, i.e., the top and second levels in Fig. 1:

$$\min_{\mathbf{x},\mathbf{m}} Q(\mathbf{x}, \mathbf{u}, \mathbf{d}, \mathbf{m}) \tag{2}$$

where $\mathbf{x}$, $\mathbf{d}$, and $\mathbf{m}$ are defined in the previous section, and $\mathbf{u}$ is a set of incidental power failure events. Note that $\mathbf{d}$ is deterministic, but $\mathbf{u}$ is stochastic variable. The objective of this study is to find a set of $\mathbf{m}$ and $\mathbf{x}$ to minimize the objective function Q with a given set of $\mathbf{d}$. In other words, we would solve the following optimization problem by minimizing the sum of *EC*, *FC*, *PC* for overuse beyond the contract capacity, and *PL* due to the power trips on an annual basis:

$$\min_{\mathbf{u},\mathbf{m}} Q = EC(\mathbf{x}, \mathbf{d}, \mathbf{m}) + FC(\mathbf{m}) + PC(\mathbf{m}, \mathbf{u}) + PL(\mathbf{m}, \mathbf{u}). \tag{3}$$

The fixed charge of contract capacity can be calculated by the following formula:

$$FC(\mathbf{m}) = SM \times SS + NSM \times NSS \tag{4}$$

where *SM* is the fixed demand charge of the contract capacity per month during the summer season [*NSM* during the nonsummer-season (*NSS*)]. The summer-season (*SS*) in the TOU tariff in the following case is between June 1 to September 30, and the NSS represents the rest of the year.

In this paper, we address the uncertainty of power failures caused by steam turbine, boiler, or the grid system. Each kind of failure incurred a different degree of damages on the plant operation. The breakdown of turbines and generators in a cogeneration system results in disrupting electric power supply. It may cause total or partial shutdown of the production facility, depending on the amount of electricity loss. Unless the loss of electricity is small enough that it can be compensated by stopping some of the nonurgent units, the whole plant is forced to stop. For most petrochemical plants and semiconductor industries, partial loss of electric power usually forces total shutdown of the plant operation. The disturbance of a boiler system would result in both electric and thermal energy supplies. It usually causes a longer interruption in the operation. The influence of the grid system's failures is similar to that of cogeneration system's failures because both events only result in the loss of partial electric power supply. However, there is a major difference between them. The electric power loss due to the cogeneration system's failure may be made up for by raising power supply from the grid system. However, it does not work in the other way because it needs a certain period of time from increasing the throughput of boilers to that of electric generators in a cogeneration system.

These three kinds of power failure modes have different impacts on business loss. First of all, the restartup procedures are different for different parts of the plant and have different durations of operation loss hours. When the cogeneration system is not working, it is necessary to import enough electric power to start up the operation. The timing of power failure and startup period incurs various electricity costs and penalties imposed by the utility company due to overuse of electric power beyond the contract capacity. Both depend on the TOU rates.

It is almost certain to incur a heavy penalty charge during restartup after an interruption of plant operation. The penalty is two times that of the fixed monthly demand charge when imported electricity is less than 10% beyond the contract capacity, while the penalty is three times when it is over 10%. The formulation of total annual penalty charge equations, i.e., *PC* in (3), is omitted due to its complexity and limited space in this paper. A detailed description is given elsewhere [20] for the benefit of interested readers.

It is impossible to calculate the cost incurred due to business loss analytically because the timing and mode of power failures are stochastic, not deterministic. Therefore, we calculate the business loss via the Monte Carlo method to simulate various incidental failure modes on an annual basis. Fig. 2 illustrates the flowchart of Monte Carlo simulation in this study.

The production loss due to power failures can be described as follows:

$$PL(\mathbf{m}, \mathbf{u}) = PF \times PR \times \sum_{t=1}^{7} (brt_t \times bt_t + grt_t \times pt_t) \tag{5}$$

where *PL* is the production loss, *PF* is the profit of production, *PR* is the production rate, brt_t is the restartup time after an accidental boiler failure in the t period, grt_t is the restartup time after an accidental power failure in the t period, bt_t is the number of boiler trips in the t period, and pt_t is the number of power trips in the t period annually.

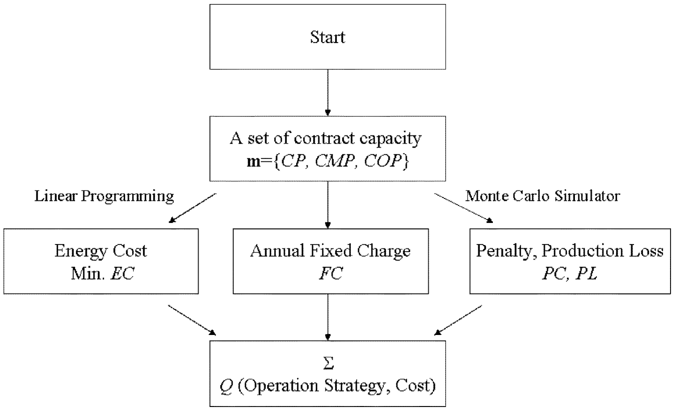

Fig. 2. One "experimental" run given a set of (*CP, CMP, COP*).

IV. Integrated Problem-Solving Algorithm

Given a new condition or a forecast of $\mathbf{d}$, consider the following general case:

$$\min_{\mathbf{x},\mathbf{m}} Q(\mathbf{x},\mathbf{u},\mathbf{m}) \tag{6}$$

subject to

$$EC = \min_{\mathbf{x}} EC(\mathbf{x},\mathbf{m}). \tag{7}$$

Note that in (6), the optimal energy cost *EC* is a function of $\mathbf{m}$ only. In other words, given the new contract capacity, *EC* can be solved by (7). Let the incidental failures $\mathbf{u}$ be stochastic with a known probability distribution $\mathrm{f}(\mathbf{u})$. Then, the effects of u on Q can be determined by Monte Carlo simulation, and the problem solving of (6) can be further reduced to

$$\min_{\mathbf{m}} Q(\mathbf{m}). \tag{8}$$

Theoretically, a complete sampling of $\mathbf{u}$ is necessary to reduce (6) to (8). However, this sampling work, if not impossible, is still formidable. In the case of this study, at least 15 000 runs of Monte Carlo simulation [15] are necessary for the solution of the cost function to reach an accuracy of ± 800 US dollars within 95% confidence level. It is time consuming to find the corresponding Q *with a* given $\mathbf{m}$ and can be treated as an experimental design problem. The basic idea of experimental design is to form a standard response surface via statistical experimental design. Start with a set of experiments (trials), i.e., a set of m, in this case, $\mathrm{X} = \{\mathbf{m} \mid \mathbf{m} = 1,\ldots,N\}$. For each m, a corresponding Q can be obtained by following the computation procedures shown in Fig. 2. Then, get a set of corresponding results $\mathrm{Y} = \{Q \mid Q = 1,\ldots,N\}$. A response surface model $R(\mathbf{m})$ is obtained based on Y and X. An approximate solution of (8) can be found as follows:

$$\mathbf{m}^* = \min R(\mathbf{m}) \tag{9}$$

where function R is usually a polynomial.

In several studies, the above optimization is performed interactively. For example, in this case, with the best approximate solution $\mathbf{m}^*$, a corresponding Q can be computed by following the procedures given in Fig. 2. Now, a new $(\mathbf{m}^*, Q)$ can be added to the trial set X and result set Y. A new response surface model can be constructed, and a new optimum can be obtained based on the new response surface, and so on. This iterative process is termed an interactive sampling approach. The approximate model is used to find the next sampling points in the real model. This response surface model R, which is computed quickly and approximately, is called a meta-model [18]. In this paper, we propose to implement an ANN model instead of a polynomial model due to the complex and nonlinear nature of the problem, as follows:

$$Q = \mathrm{ANN}(\mathbf{m}). \tag{10}$$

The benefits of implementing such a model are as follows.

1) The ANN model has long been recognized as a powerful tool to approximate complex multivariable functions [16], [17].
2) With regression and evolutionary capability, the accuracy of the model can be improved by increasing the size of the training set (sets X and Y) during the interactive sampling.
3) The real response surface of the TOU problem is basically nonconvex, as will be shown in the next section; a polynomial response surface is not suitable to fit this problem.

Another important issue in the interactive sampling of experimental design is how to implement an efficient and effective sampling strategy to locate the real optimum for (6). Especially for a problem such as (6), each sample, i.e., every given $\mathbf{m}$, requires a lot of computation efforts as described above. If a meta-model can completely represent the objective function, then the optimization problem can be simplified as a search problem. Unfortunately, no such perfect meta-model exists in this study. Thus, the purposes of sampling for the objective function (6) are first to improve the meta-model, an ANN model, and second to locate the global optimum in this TOU problem. In order to include these two requirements in the model, we propose an efficient sampling method guided by information theory that is an extension of Shannon's information entropy [19].

Considering any random variable Z taking a value of z, the Shannon information entropy can be denoted by

$$S(Z) = -\int_{-\infty}^{\infty} p(z) \ln\, p(z) dz \tag{11}$$

where p denotes the probability of a random variable Z whose value is assumed a Gaussian distribution

$$p(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-z^2/2\sigma^2} \tag{12}$$

where σ denotes the variance of the random variable. Thus, the information entropy can be solved as

$$S(Z) = \frac{\ln\left(2\pi\sigma^2\right)}{2}. \tag{13}$$

In this study, given a new trial point $\mathbf{m}$ and existing trial set X, the variance can be evaluated by

$$\sigma^2 = \frac{1}{\sum_{r=1}^{N} l\left(\frac{\mathbf{m}}{\mathbf{m}_r}\right)} \tag{14}$$

where $l(\mathbf{m}/\mathbf{m}_r) = |\mathbf{m} - \mathbf{m}_r|$ measures the distance between the new trial point $\mathbf{m}$ and an existing point $\mathbf{m}$ **in** $\mathbf{X}_r$ [21]. The higher value of the information entropy of a sampling point means more information can be obtained at that point. In other words, further improvement of the ANN model can be achieved. Meanwhile, we denote the information energy by

$$U(\mathbf{m}) = \hat{Q}(\mathbf{m}) - f_{\min} \tag{15}$$

where $f_{\min}$ is a constant to represent an estimated minimum value for the objective function, and $\hat{Q}(\mathbf{m})$ is the estimated function value using the ANN model. A lower information energy of a trial point $\mathbf{m}$ implies a lower objective function value estimated by the ANN model, and the trial point is, hence, worth sampling. However, the accuracy of an ANN model depends on the distribution and complexity of the contour of the objective function. Hence, there exists the need to compromise information entropy and information energy. The candidates worth evaluating through the time-consuming Monte Carlo simulation are those having the minimum information-free energy as follows:

$$\min(F = U - TS) \tag{16}$$

where T is the information temperature whose meaning is similar to the annealing temperature in a simulated annealing (SA) optimization approach. The approach adopted in this paper is a modified version of our previous work [13]. The new suggested sampling points are determined by 1) conducting random sampling on the fast computing meta-model, i.e., an ANN model in this paper, 2) deleting all unqualified points such that $F > \overline{F}$, where $\overline{F}$ is a threshold information-free energy, and 3) clustering the qualified points, the new sampling points are the cluster centers of these points. The details of the whole approach are mentioned in our previous work [13].

In the proposed interactive algorithm, time-consuming Monte Carlo simulation is only performed on the selected $\mathbf{m}$. An ANN model at the very beginning is not trustworthy because only very few "experiments" are performed. Fig. 2 shows the computation details for one "experiment." Temperature at this stage is set to be high so that the new selected point is determined more by information entropy term than by information energy term. As more "experiments" are performed, the ANN model becomes more reliable. Temperature is then set to be low so that the new points are chosen more by the prediction based on the response surface model. For the details, the reader is referred to our previous work. Our approach is summarized in the following steps as well as shown in Fig. 3.

Step 1) Uniformly select 27 points of contract capacities $\mathbf{m} = \{\text{CP, CMP, COP}\}$ from the solution space.

Step 2) Perform Monte Carlo simulation for each point in the set of $\mathbf{m}$, and get the total costs Q for each point.

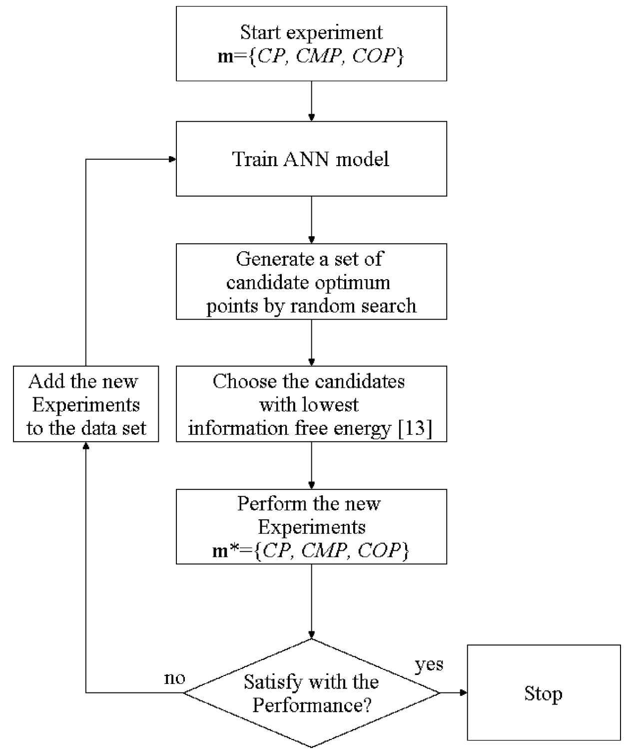

Fig. 3. Proposed algorithm.

Step 3) Construct an ANN response surface model using the obtained $\mathbf{m}$ and Q.

Step 4) Perform a random search on the ANN model, and calculate the information-free energy as (15) for each point, where the total cost is estimated by the ANN model.

Step 5) Determine the optimal number of points [13] having the lowest information-free energy.

Step 6) Perform Monte Carlo simulation for these new points, and get the new cost functions Q.

Step 7) Check if the convergence is reached. If not, update the ANN model with the addition of new experiments, and go back to step 4.

A. Illustrative Example: Modified Himmelblau Function

The following benchmark problem, two-dimensional modified Himmelblau function [13] is used to verify the proposed algorithm via comparing with the other well-known nonconvex objective function optimization solvers

$$H(h_1, h_2) = (h_1^2 + h_2 - 11)^2 + \left(h_1 + h_2^2 - 7\right)^2 + h_1 + 3h_2 + 57 \tag{17}$$

defined for $-5 \leq h_1 \leq 5$ and $-5 \leq h_2 \leq 5$. In this paper, the problem is solved by the updated algorithm, which is slightly different from the original one in our pioneering study [13]. The contour plot of the above objective function is shown in Fig. 4(a). The real optimum of this problem is located at $(-3.8, -3.32)$, and the optimum value is 43.3. This problem is solved based on the derivation of this section. In each batch, several points are suggested to be sampled as shown in Fig. 4(b), while the accumulated sampling points are shown in Fig. 4(a). The

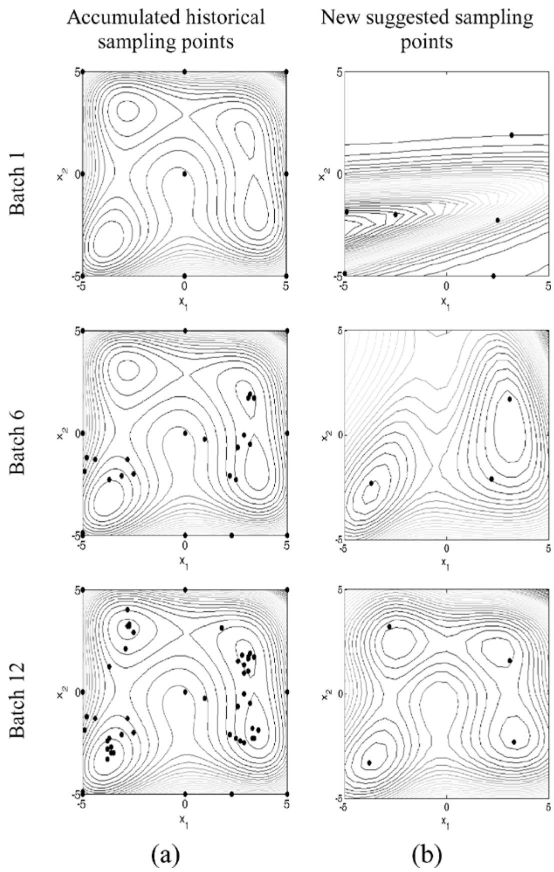

Fig. 4. History of sampling points selected from the total solution space. (a) Current and past experimental points against the contour of Himmeblau function. (b) Corresponding model contour whose solid points represent the next batch of the new experimental points.

TABLE II
PROPOSED APPROACH COMPARISON WITH THREE OPTIMIZATION APPROACHES

	Simplex method	Genetic Algorithm	Simulated Annealing	The proposed approach
Optimal Value	58.1	66.4	57.0	43.9
Standard deviation	0.573	1.466	0.949	0.173

ANN model is trained after the sampling of each batch, and the contour plots of the evolutionary ANN model are given in Fig. 4(b). Compared to Fig. 4(a), the contour plot of the ANN model is getting closer and closer to the real contour plot of the objective function, which is shown in Fig. 4(a) as the number of batches increases.

Table II lists the solution of the above modified Himmelblau function using the proposed approach and several well-known heuristic approaches, namely, Nelder-Mead simplex method [22], simulated annealing, and genetic algorithm. All are based on the same number, 50, of sampling. The gradient-based approaches are not used to solve the problem because their solution strongly depends on the initial point of the search. It can be seen from Table II that all approaches except the proposed one fail to find the global optimum. In order to obtain statistically meaningful results, all approaches are repeated ten times with various initial points, and the standard deviations are as shown in Table II. A comparison of the standard deviation shows that the solution of the proposed approach at each time nears the global optimum with the smallest variance.

TABLE III
THREE-SECTION TOU RATE STRUCTURE FOR EXTRA-HIGH-VOLTAGE POWER SERVICE

Power rates(US Dollars/kWh)		
Power sale prices(energy supplier buy-back rate)		
Peak and semi-peak period	0.0442	
Saturday Semi-peak and Off-peak period	0.0138	
Power purchase prices	Summer month	Non-summer month
Peak period	0.0967	
Semi-peak period	0.0582	0.0563
Saturday Semi-peak period	0.0318	0.0299
Off-peak period	0.0219	0.0203
Fixed Demand charge rates(US Dollars/kW month)		
contract	Summer month	Non-summer month
Peak period	6.584	4.866
Semi-peak period	4.866	4.866
Off-peak period	1.315	0.972

TABLE IV
UPPER AND LOWER LIMITS OF MAIN EQUIPMENT CAPACITY

Equipment	Max	Min
Coal boiler	130 (T/H)	82 (T/H)
Auxiliary Oil boiler	60 (T/H)	20 (T/H)
Steam turbine	34.5 (MW)	22 (MW)
Steam turbine inflow high pressure steam(120K)	100 (T/H)	
Steam turbine inflow low pressure steam(5K)	80 (T/H)	
Demand	Average demand	
Plant steam demand(87K)	43.6 (T/H)	

V. EXAMPLE—A PETROCHEMICAL PLANT WITH A COGENERATION SYSTEM

In this section, we present a real case of a petrochemical plant with a cogeneration system, which includes a coal boiler, an auxiliary oil boiler, a steam turbine, and two steam headers. The proposed algorithm is implemented to determine an optimal contracting capacity and a corresponding optimal operation under TOU rates. The plant operates in a steady state mostly with a constant steam demand. Prior to this paper, the plant purchased fixed electric power from Taiwan Power Company with three-section TOU rates, which have four different tariffs in the summer season and three in the nonsummer season. Taiwan Power Company charges a fixed monthly fee and imposes a severe penalty when power supply is beyond the contract capacity. The detailed data are shown in Table III. The operation ranges of the equipments in the cogeneration system are given in Table IV.

According to the history of the plant over the past ten years, accidental failures of the boiler occur three times in a year, and that of the grid system occurs five times. The former case needs two stages of startup, while the latter case needs a single stage. Whenever electric power failure occurs, the plant would be at least partially shut down due to the loss of power. It can tolerate sudden loss of power of 2000 kW without shutting down the whole operation. In other words, if imported electricity from the grid system does not exceed 2000 kW, the accidental failure would not interrupt the operation. When the plant is forced to shut down completely just because of the lack of enough power,

TABLE V
PROBABILITY OF BOILER TRIPS FOR MONTE CARLO SIMULATION

Summer month	probability
1.Peak−>Semi-peak	0.338
2.Peak−>Peak	0.338
3.Semi-peak−>Peak	0.095
4.Semi-peak−>Off-peak	0.095
5.Off-peak−>Semi-peak	0.028
6.Off-peak−>Peak	0.028
7. Saturday Semi-peak−>Off-peak	0.021
8.Off-peak−>Saturday Semi-peak	0.028
9.Off-peak−>Off-peak	0.028
Non-summer month	probability
10. Semi-peak−>Semi-peak	0.353
11. Semi-peak−>Off-peak	0.353
12.Off-peak−>Semi-peak	0.082
13.Saturday Semi-peak−>Off-peak	0.047
14.Off-peak−>Saturday Semi-peak	0.082
15.Off-peak−>Off-peak	0.082

TABLE VI
PROBABILITY OF GRID SYSTEM TRIPS FOR MONTE CARLO SIMULATION

Summer month	probability
1.Peak	0.678
2.Semi-peak	0.191
3.Saturday Semi-peak	0.021
4.Off-peak	0.110
Non-summer month	probability
6.Semi-peak	0.708
7.Saturday Semi-peak	0.047
8.Off-peak	0.245

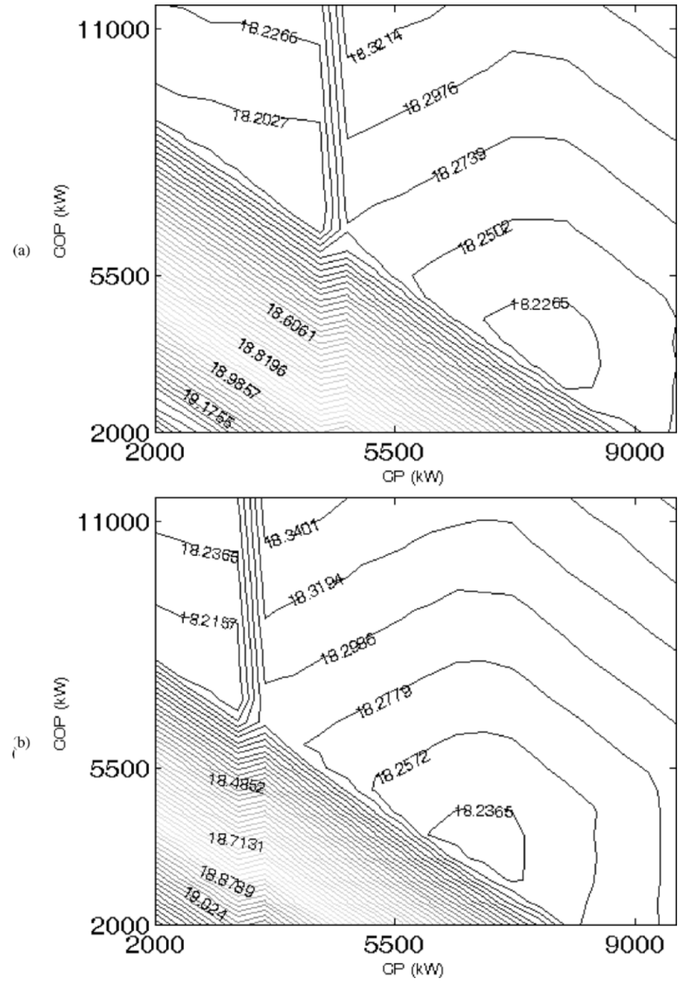

Fig. 5. Contour plots of *CP* versus *COP* based on the final ANN meta-model. (a) $CMP = 0$ kW. (b) $CMP = 1000$ kW.

it can resume the normal operation within 6 h. However, if the main boiler fails, two stages of startup are needed. The first stage is to start the operation of the boilers, while the second stage is to start the steam turbine. Each stage needs 6 h. The electric power supply during startup comes only from the grid system.

Considering the heavy penalty in the peak period in the summer season, the plant has different startup procedures to reduce the amount of imported electricity. If the first stage of restart is during the peak or semi-peak period, the plant would import 8,000 kW instead of 13 000 kW during the Saturday semi-peak or off-peak period. The plant needs to import 13 000 kW in the second stage no matter what period it is. There are four months in the summer season and eight in the nonsummer season. For the boiler's trip, two stages of startup are necessary. There are nine combinations of two stages in the summer season versus six in the nonsummer season. Assuming that the trips are uniformly distributed, we may calculate the probability of 15 situations, which are shown in Table V. Similarly, Table VI lists the probability of eight situations for power trips caused by the failure of the grid system or the steam turbine.

Considering that any one of the nine situations may occur in any one of the four summer months, then we have 36 combinations for the boiler's trip in the summer season. In addition, we have 48 combinations in the nonsummer season. On the average, the plant has three times the boiler trips in the ten-year operation history. The total combination of boiler trips in a year is $H_3^{84} = 102\,340$ and that of the grid system trips in a year is $H_5^{40} = 1\,086\,008$. These two kinds of events are independent of each other. Together, there are $1.11 * 10^{11}$ combinations. We use the Monte Carlo method to simulate them. Following the algorithm proposed in Section IV, we start with 27 experiments to construct a meta-model. The meta-model then suggests several candidates of sampling points for the next experiments. For each experiment, 15 000 runs of Monte Carlo simulations are done to mimic all the possible power failure scenarios. Estimating the annual cost at each experiment takes about 1–3 min of CPU time using a P4 2.6-G computer. The solution of optimum contracting capacity is a three-dimensional space that includes contract capacity in the peak (*CP*), semi-peak(*CMP*), and off-peak periods(*COP*). The interactive sampling process converges in the fourteenth batch, and the solution, the optimum contract capacity, and the corresponding operation conditions of the cogeneration system are obtained.

In order to look into the details of the solution space, we fix one dimension, e.g., *CMP*, and draw a contour plot of the other two dimensions. Based on the final ANN meta-model, Fig. 5 shows the contour plots of the annual energy cost Q with two fixed values of *CMP*. Both cases have two optima in the plots. In other words, this is basically a multi-local-optima system.

In Table VII, we compare the annual energy cost of the three cases: Case 1 is the original operation under the original contract, Case 2 is the optimum operation under the original con-

TABLE VII
COMPARISON OF ANNUAL COST AMONG THREE CASES

	Case1	Case2	Case3
CP	4,500 kW	4,500 kW	3,800 kW
CMP	0kW	0 kW	390 kW
COP	2,000 kW	2,000 kW	7,200 kW
FC	1.47 %	1.47 %	1.69 %
EC	97.01 %	91.66 %	87.5 %
PC&PL	1.52 %	1.66 %	1.72 %
Q	100 %	94.97 %	90.91 %

TABLE VIII
CORRESPONDING OPTIMUM OPERATION CONDITIONS AMONG THREE CASES DURING SUMMER-SEASON PEAK PERIOD

	Case 1	Case 2	Case 3
Boiler (T/hr)	124	130	130
Turbine generator (kW)	31200	31708	31708
Purchased electricity (kW)	2358	1850	`1850
Sold electricity (kW)	0	0	0
EC (US Dollars/hr)	2350	2318	2318

TABLE IX
CORRESPONDING OPTIMUM OPERATION CONDITIONS AMONG THREE CASES DURING SUMMER-SEASON OFF-PEAK PERIOD

	Case 1	Case 2	Case 3
Boiler (T/hr)	124	110	90
Turbine generator (kW)	31200	26447	22000
Purchased electricity (kW)	1747	6500	10947
Sold electricity (kW)	0	0	0
EC(US Dollars/hr)	2160	1957	1788

tract, and Case 3 is the optimum operation under the optimum contract. Taking the annual total cost of the original operation under the original contract as the basis, we itemize the total cost into three categories, i.e., fixed contract demand charge, energy cost, and penalty charge, to analyze the cost structure. Being the same for all cases, production loss is not shown in the table.

When taking optimal operation only into consideration, the plant has an annual cost saving of 5.03%. After integrating the strategic management decision making with the tactical operation, the plant has an annual cost saving of 9.09%. We then take the operation in peak and off-peak periods in the summer season to illustrate the operation difference among these three cases, as shown in Tables VIII and IX. The results in the tables indicate that the cogeneration system should operate in the near-full capacity to reduce the imported electricity during the peak period and to increase the imported electricity during the off-peak period to take advantage of the TOU rates.

However, heavy penalty charges during the peak period incurred by the power trips have made the plant maintain a certain contract capacity, not a zero contract capacity.

The Monte Carlo simulation alone gives an average picture. In order to see the consequence of the worst situation, we calculated the annual cost with the condition of all power trips occurring in the peak period. The annual energy cost in this case is still 92.28% of the basis. It demonstrates that the proposed approach to optimal energy management integration is resilient.

VI. CONCLUSION

In this paper, a general approach to solve the optimal contracting capacity for a plant with an in-house cogeneration system was derived. The problem includes the uncertainty analysis of the power system. We considered all the scenarios of accidental power failures and use the Monte Carlo method to simulate them. We developed a meta-model and information-theory-based optimization scheme to reduce the computation load. The results show that the proposed approach is effectivem and there is a dramatic cost-saving opportunity for the plant.

The other contribution of this paper is that a comprehensive analysis of TOU rates with the penalty charge is formulated into a mixed problem of the optimal contracting and optimum operation. The approach in this paper is a general algorithm that can take other uncertain factors, such as the forecast of product price and fuel cost, into the problem formulation. The final results of the study show that the best energy management should take both optimum contracting capacity and optimal operation of a cogeneration system together into consideration.

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