Efficiency and reliability joint optimization of chiller plants based on a hybrid model

Danxu Zhang, *Student Member, IEEE*, Khushboo Mittal, *Student Member*, *IEEE*, James Wilson, *Student Member*, *IEEE*, Peter B. Luh, *Life Fellow, IEEE*, Junqiang Fan, *Senior Member, IEEE* and Shalabh Gupta, *Member, IEEE*

***Abstract*—Methods for chiller plant energy savings may increase component degradation, thereby decreasing reliability. Joint optimization is thus important. The problem, however, is challenging. First, existing reliability models which are functions of time in terms of years are not suitable for operation optimization. Second, efficiency optimization are static and often runs every 10-15mins given current demand while reliability change in a short period is not obvious. In this paper, a dynamic chiller reliability model and a static hybrid plant model consisting of empirical and DNN models are developed, and a weighted sum of one hour's plant power and chiller reliability is minimized with a time interval 10mins. The formulation consisting of six independent efficiency and one dynamic reliability optimization problems, and chiller power and reliability are coupled with some common variables. To address the two-time scale issue, the long time scale reliability is approximated by reliability change as a result of operations using Taylor series. To efficiently solve the problem with dynamics, mixed-integers, nonlinearity and no explicit equations in DNN, a recently developed decomposition and coordination-based method is combined with dynamic programming with rollout and the plant is decomposed into a simplified dynamic chiller subproblem and three simple static subproblems. Gradients needed are obtained by using finite difference without requiring explicit equations. Numerical testing demonstrates the advantages of joint optimization in terms of energy savings and reliability improvement as compared with a baseline.**

***Index Terms*—Joint optimization, reliability, dynamic, deep neural network and mixed-integer nonlinear.**

I. INTRODUCTION

Chiller plants provide cooling to buildings. As shown in Fig. 1, a typical plant includes four subsystems consisting of chillers, cooling towers, primary pumps and condenser pumps. Reliability of a plant is important especially for hospitals and research facilities. Low reliability implies high risks of plants' breakdowns which may lead to significant costs. According to [1, 2], abnormal room temperature was a major cause of data centers' unplanned downtimes, and the average loss of unplanned downtime was around $5600 per minute in 2010 and $9000 per minute in 2016. Besides reliability, efficiency which implies energy consumption is another key concern of plant owners. According to [3], low efficiency plants cost billions of dollars annually in the U.S. Methods for energy savings may accelerate component degradation and increase risks of failures, thereby decreasing reliability. For example, high mass flow rates may save energy under certain conditions but cause vibration wear and erosion or corrosion of tubes and reduce reliability [4]. Efficiency and reliability joint optimization is thus important. The goal of this paper is to improve plant efficiency and reliability through their joint operation optimization by considering a commonly used primary-only plant with identical units in each subsystem. Plant reliability can be much improved by enhancing reliability of chillers' since losses caused by chillers are much more serious than others. Chiller reliability is thus studied. Empirical models are simple but may not be compatible when used for an arbitrary plant. A hybrid model consisting of Deep Neural Network (DNN) and empirical models is developed where DNN is for plants' largest energy consumer, chillers, and empirical models are for others.

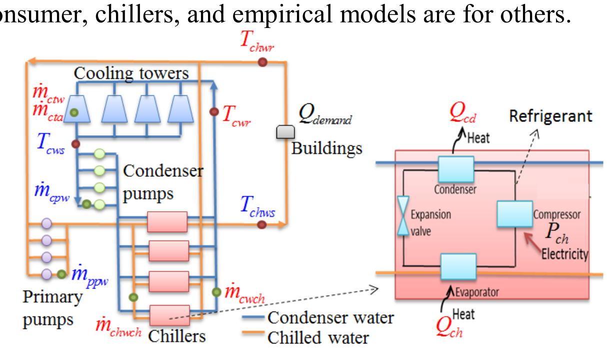

Fig. 1. Schematic of a chiller plant (Decision variables are in blue and depended variables are in red)

The problem is challenging. Generally, reliability is considered as a function of time in terms of years, and its change during a short period is small as compared to itself. Influence of operations are seldom studied for chiller plants and there is no model for plant reliability operation optimization. For efficiency optimization, static models are

Manuscript received: February, 15, 2019; Revised May, 15, 2019; Accepted June, 14, 2019. This paper was recommended for publication by Editor Dezhen Song upon evaluation of the Associate Editor and Reviewers' comments. This work was supported in part by the United Technologies Corporation Institute for Advanced Systems Engineering (UTC-IASE) at the University of Connecticut under the Supervisory Control Synthesis project. Any opinions expressed herein are those of the authors and do not represent those of the sponsor.

D. Zhang, K. Mittal, J. Wilson, P. B. Luh and S. Gupta are with the Department of Electrical and Computer Engineering, University of Connecticut, Storrs, CT 06269 USA (e-mail: danxu.zhang@uconn.edu; khushboo.mittal@uconn.edu; james.wilson@uconn.edu; Peter.Luh@uconn.edu; shalabh.gupta@uconn.edu).

J. Fan is with United Technologies Research Center, Farmington, CT 06032. USA (e-mail: Junqiang.Fan@carrier.utc.com).

Digital Object Identifier (DOI): see top of this page.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LRA.2019.2924126, IEEE Robotics and Automation Letters

commonly used considering fast heat exchange processes in plants. The static optimization often runs every 10-15 minutes independently given current cooling demand and weather [5]. Lacking of reliability models and the two-time scale issue make the problem challenging. In this paper, based on the idea of wind turbine reliability modeling in [15], chiller reliability is modelled as a function of time, the number of startups/shutdowns and water mass flow rates in Section III. Model parameters are obtained by using a plant model operated based on rules. To address the two-time scale issue, reliability is approximated by reliability at current time which is constant and reliability change as a result of future operations by using Taylor series. Based on the chiller reliability model and a static hybrid plant model consisting of empirical and DNN models, a formulation is established where a weighted sum of one hour's plant power consumption and chiller reliability is minimized with a time interval 10mins. The problem consists of six independent efficiency and one dynamic reliability optimization problems. Static models of subsystems are separable with additive coupling constraints. Chiller DNN and reliability models are coupled with some common decision variables. The problem needs to be solved by looking ahead and a moving window is used. Computational requirement of the problem $J(t)$ with t=1,…,6 increases significantly as compared with efficiency optimization $J(t)$ with t=1. Moreover, chillers are coupled across time and DNN is without explicit formulations. These increase the difficulty of solving the problem especially in view of the existence of discrete variables and nonlinearity. To the best of our knowledge, plant efficiency and reliability joint optimization has not been studied from the operation point of view. Reliability was only considered for design purpose and formulated as a function of time as shown in Section II. For efficiency optimization, both Neural Network (NN) and empirical models were used. For the former, only intelligent algorithms were adopted to solve the problem but solution quality cannot be quantified. To efficiently solve the problem for near-optimal solutions, dynamic programming (DP) with rollout, finite differences (FD), and a decomposition and coordination-based method are combined where chiller power consumption and reliability are grouped together as one subproblem and other subsystems are considered as individual subproblems in Section IV. To reduce nonlinearity and complexity of a subproblem, DP with rollout is applied where rules are used for t=2,…,6. Gradients needed are approximated by using FD without requiring explicit equations.

In Section V, three examples are tested for a plant with four components in each subsystem. In Example 1, efficiency optimization is considered and results are compared with those obtained by using empirical models and the method from [5], demonstrating accuracy and efficiency of our method for problems with hybrid models. In Example 2, joint optimization of the plant for one cooling demand is solved by looking ahead one hour to show the idea and performance of our method. In Example 3, 20 years' demands are considered. A moving window is used and for each demand, joint optimization is done by looking ahead one hour. Efficiency and reliability improvement by using our method is shown as compared with a baseline using rules, and Pareto Frontier is provided.

II. Literature Review

In this section, reliability optimization and efficiency optimization are reviewed first, followed by their joint optimization.

Reliability Optimization

Reliability is mainly considered from the design point of view or for maintenance scheduling, and is modeled as a function of time under the assumption that devices follow standard operating procedures [6, 18-20]. Relationships between operations and reliability are seldom considered. Using reliable devices and redundant configurations are two common ways to improve system reliability. For example, in [7], the number and the size of pumps are optimized by testing different combinations of pumps to reduce the life-cycle cost while maintaining reliability of a chilled water system.

Efficiency Optimization

Power consumption is commonly formulated as a function of operations considering fast heat exchanges processes in a plant and static empirical models are often used. Such models may not be compatible when used for an arbitrary plant. Artificial Neural Networks (ANN) models without the issue have been used in many applications [8]. Some papers use NN to solve simple optimization problems such as continuous linear and quadratic problems [21-24]. Chiller plant optimization, however, is complicated with mixed-integers and high nonlinearity. In existing studies [9-14], NN was only used to model component power consumption, and the problems were solved by using intelligent algorithms because NN does not have explicit equations. However, the algorithms do not exploit problem structures, and solution quality cannot be quantifies. In one of our recent works [5], a decomposition and coordination-based method overcoming the above difficulties was used, and near-optimal solutions were obtained. Different from our problem here, the problem in [5] is static and based on empirical models.

Efficiency and Reliability Joint Optimization

To the best of our knowledge, efficiency and reliability joint optimization for plants has not been studied. A possible reason might be that operations during a short period do not have obvious influence on reliability. Beyond chiller plants, problems with two-time scales have not been studied either. In [15], wind turbine joint optimization was studied by considering turbine power and the reliability of bearings that were the major cause of turbine breakdown. The reliability is modelled as a function of load, time, and so on. A long time scale, the period between fault detection and the end of device life, was used for the whole problem. The ideas for reliability optimization are adopted in our work.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LRA.2019.2924126, IEEE Robotics and Automation Letters

III. Problem Formulation

In this section, a formulation consisting of six independent efficiency and one dynamic reliability optimization problems is established based on a static hybrid plant model and a dynamic chiller reliability model. Chiller performance and reliability models are grouped together and presented in subsection A. Models of other components are briefly shown in subsections B and C, followed by coupling constraints between subsystems and the optimization problem.

A. DNN and Reliability Models of Chillers

A typical chiller is shown in Fig. 1. Chilled water is generated through heat exchange between water and refrigerant in the evaporator and the condenser, and electricity is consumed by the compressor. A Deep Neural Network (DNN) model is developed for chiller power consumption P_{ch} and the architecture is shown in Fig. 2. There are three inputs: chilled water supply temperature T_{chws}, condenser water supply temperature T_{cws} and chiller cooling load Q_{ch}, which are bounded as $4^0C \le T_{chws} \le 10^0C$, $15^0C \le T_{cws} \le 30^0C$, and $0.1Q_{capacity} \le Q_{ch} \le Q_{capacity}$, where $Q_{capacity}$ is plant capacity. Data generated from the model in [5] under 453,600 operating conditions are used where 80% of them is for training and the remaining is for testing. The model is trained using 10-fold cross validation over the training data. Hidden layers and associated neurons are determined by using grid-based parameter search. In this model, there are two hidden layers with 1100 and 100 neurons, respectively, and the ReLu activation function [25] which was found to provide the best performance is used. The model achieves an R^2 coefficient of 0.998 and root mean squared error (RMSE) of 2.04KW.

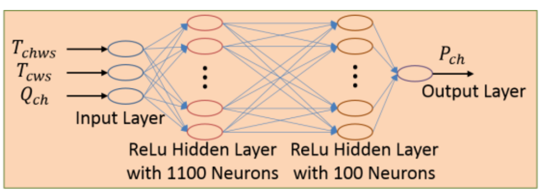

Fig. 2. DNN chiller model architecture

The reliability model which is a function of time from [20] is modified for operation optimization with key factors that affect chiller degradation considered based on the idea of [15], and shown as follows.

$$R(t) = e^{-h(t)\times t} \tag{1}$$

$$h(t) = k_0 \times e^{\frac{N_{acc}(t)-\mu_1}{c_1}+\frac{T_{acc}(t)-\mu_2}{c_2}+\frac{m_{chw}(t)-\mu_3}{c_3}+\frac{m_{cw}(t)-\mu_4}{c_4}} \tag{2}$$

where k_0 is the failure rate per year, N_{acc} is the number of startups/shutdowns, T_{acc} is running time, and m_{chw} and m_{cw} are water mass flow rates of the evaporator and the condenser, respectively. Each of the factors are normalized by subtracting their expected average number of accumulated usage per year μ_i and dividing by the expected maximum usage at the end of the chiller life c_i. The parameters are obtained by simulating a chiller plant model under ideal baseline operating procedures. When baseline operating procedures are followed, reliability matching the model in the literature. If a chiller is used prudently, the reliability will decrease faster and vice versa.

For identical chillers, they are assumed to be used alternately and have similar statuses for simplicity. Average running time, number of startups/shutdowns and mass flow rates are used. As mentioned before, reliability has a long time scale while efficiency has a short one. To address this issue, the long time scale reliability is approximated by a constant reliability and reliability change as a function of operations by using Taylor series. With small terms ignored, we have

$$\begin{aligned} R_{ch}(t) &= R_{ch,0} + \Delta R_{ch} \\ &\approx R_{ch,0} + (t-t_0)R'_t + \frac{1}{2!}(t-t_0)^2 R''_{tt} \\ &\quad + (T_{acc}-T_{acc,0})R'_{T_{acc}} + (N_{acc}-N_{acc,0})R'_{N_{acc}} \\ &\quad + (m_{chw}-m_{chw,0})R'_{m_{chw}} + (m_{cw}-m_{cw,0})R'_{m_{cw}} \\ &\quad + \frac{1}{2!}(T_{acc}-T_{acc,0})^2 R''_{T_{acc}} + \frac{1}{2!}(N_{acc}-N_{acc,0})^2 R''_{N_{acc}} \\ &\quad + \frac{1}{2!}(m_{chw}-m_{chw,0})^2 R''_{m_{chw}} + \frac{1}{2!}(m_{cw}-m_{cw,0})^2 R''_{m_{cw}}, \end{aligned} \tag{3}$$

The large constant term $R_{ch,0}$ is reliability at a certain time t_0, and can be removed in optimization. Since our goal is to improve efficiency and reliability by adjusting operations, reliability change $\hat{R}_{ch}$ caused by operations is generated.

$$\begin{aligned} \hat{R}_{ch} &= (T_{acc}-T_{acc,0})R'_{T_{acc}} + (N_{acc}-N_{acc,0})R'_{N_{acc}} \\ &\quad + (m_{chw}-m_{chw,0})R'_{m_{chw}} + (m_{cw}-m_{cw,0})R'_{m_{cw}} \\ &\quad + \frac{1}{2!}(T_{acc}-T_{acc,0})^2 R''_{T_{acc}} + \frac{1}{2!}(N_{acc}-N_{acc,0})^2 R''_{N_{acc}} \\ &\quad + \frac{1}{2!}(m_{chw}-m_{chw,0})^2 R''_{m_{chw}} + \frac{1}{2!}(m_{cw}-m_{cw,0})^2 R''_{m_{cw}}. \end{aligned} \tag{4}$$

To describe the relationship between power consumption and reliability, running time and the number of startups/shutdowns are represented by the number of active chillers N_{Ach} as follows

$$\begin{aligned} \hat{R}_{ch}(t+1) &= \Delta T_{acc}(t+1)R'_{T_{acc}} + \Delta N_{acc}(t+1)R'_{N_{acc}} \\ &\quad + \frac{1}{2}(\Delta T_{acc}(t+1))^2 R''_{T_{acc}} + \frac{1}{2}(\Delta N_{acc}(t+1))^2 R''_{N_{acc}} \\ &\quad + (m_{chw}-m_{chw,0})R'_{m_{chw}} + (m_{cw}-m_{cw,0})R'_{m_{cw}} \\ &\quad + \frac{1}{2!}(m_{chw}-m_{chw,0})^2 R''_{m_{chw}} + \frac{1}{2!}(m_{cw}-m_{cw,0})^2 R''_{m_{cw}}, \end{aligned} \tag{5}$$

where $\Delta T_{acc}(t) = T_{acc}(t) - T_{acc}(t_0)$,

$\Delta N_{acc}(t) = N_{acc}(t) - N_{acc}(t_0)$,

$$\Delta T_{acc}(t+1) = \Delta T_{acc}(t) + \frac{(N_{Ach}(t+1)\times \Delta)}{N_{ch}},$$

$$\Delta N_{acc}(t+1) = \Delta N_{acc}(t) + \frac{|N_{Ach}(t+1) - N_{Ach}(t)|}{N_{ch}}.$$

Heat exchange equations are from our previous work for chiller plant efficiency optimization [5].

$$Q_{ch}(t) = C_p\left[\dot{m}_{chchw}(t)\left(T_{chwr}(t) - T_{chws}(t)\right)\right], \tag{6}$$

$$Q_{cd}(t) = C_p\left[\dot{m}_{chcw}(t)\left(T_{cwr}(t) - T_{cws}(t)\right)\right], \tag{7}$$

$$P_{ch}(t) + Q_{ch}(t) = Q_{cd}(t), \tag{8}$$

$$N_{Ach}(t) \times Q_{ch}(t) = Q_{demand}(t), \tag{9}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LRA.2019.2924126, IEEE Robotics and Automation Letters

$$N_{Ach}(t)\times Q_{ch,\min} \le Q_{demand}(t) \le N_{Ach}(t)\times Q_{ch,\max}, \quad (10)$$

where C_p is water specific heat, T_{chwr} is chilled water return temperature, $\dot{m}_{chchw}$ is chilled water mass flow rate, Q_{cd} is heat rejected by the condenser, Q_{demand} is building cooling requirement, and $Q_{ch,min}$ and $Q_{ch,max}$ are the minimum and maximum cooling provided by a chiller, respectively.

B. Cooling Tower Model

Cooling towers are devices generating condenser water through heat exchange between water and air. The model in our previous work [5] is used.

$$P_{ct} = P_{ct,nom}\left(\frac{\dot{m}_{cta}(t)}{\dot{m}_{cta,\mathrm{nom}}}\right)^3, \quad (11)$$

where $P_{ct,nom}$ is the nominal power consumption and $\dot{m}_{cta,nom}$ is the nominal air mass flow rate.

Heat exchange is based on the approach temperature and details can be found in [5].

C. Variable-speed Pump Model

The pump model from [5] is used and details are not presented here.

D. Coupling Constraints between Subsystems

As Fig. 1 shows, chilled water of primary pumps flows into chillers, and condenser water of condenser pumps flows into chillers and then cooling towers. Based on mass balance,

$$N_{App}(t)\dot{m}_{pp}(t) = N_{Ach}(t)\dot{m}_{chchw}(t), \quad (12)$$

$$N_{Acp}(t)\dot{m}_{cp}(t) = N_{Ach}(t)\dot{m}_{chcw}(t), \quad (13)$$

$$N_{Act}(t)\dot{m}_{ct}(t) = N_{Ach}(t)\dot{m}_{chcw}(t), \quad (14)$$

where N_{App}, N_{Acp} and N_{Act} are the numbers of active primary pumps, condenser pumps and cooling towers, respectively, and $\dot{m}_{pp}$ and $\dot{m}_{cp}$ are primary and condenser pump mass flow rates, respectively.

To separate chillers and cooling towers, temperatures for individual subsystem are introduced. T_{cws_ch} and T_{cwr_ch} are for chillers, and T_{cws_ct} and T_{cwr_ct} are for cooling towers:

$$T_{cws\_ch}(t) = T_{cws\_ct}(t), \quad (15)$$

$$T_{cwr\_ch}(t) = T_{cwr\_ct}(t). \quad (16)$$

E. The Optimization Problem

The objective is to minimize one hours' plant power consumption and chiller reliability change for a plant with identical units in each subsystem. The problem is:

$$\min_{(N_{Ach},N_{Act},N_{App},N_{Acp},T_{chws},\dot{m}_{pp},\dot{m}_{cp})} J,$$

$$\text{with } J \equiv \sum_{t=1}^{T}\left[w\times\theta_1\times P_{plant}(t)\right] + (1-w)\times\theta_2\times\left(-\hat{R}_{ch}(T)\right), \quad (17)$$

where $P_{plant} = N_{Ach}P_{ch} + N_{Act}P_{ct} + N_{App}P_{pp} + N_{Acp}P_{cp}$, $0 \le w \le 1$, $\theta_1 = \frac{1}{P_{plant,base(t)}}$, $\theta_2 = \frac{1}{-\hat{R}_{ch,base(T)}}$, $T = \frac{1}{\tau}$, τ is the time interval, and subject to heat exchange constraints (6-9), lower/upper bounds such as (10), and coupling constraints (12-16). Power consumption and reliability are normalized by using costs obtained based on rules and θ_i is the normalization parameter. Weight w can be chosen by users based on their requirements. Model parameters will be updated for particular plants in the future when data are available.

According to (17), the problem is made up of T independent efficiency optimization problems and one dynamic reliability optimization problem. The static models of subsystems are separable with additive coupling constraints. Chiller DNN and reliability models share some common decision variables. The problem is a mixed-integer nonlinear problem with dynamics, and has no explicit equations for chiller power consumption. To get the optimized results for t=1, the problem is solved by looking ahead one hour and a moving window is used. τ is 10mins and T is 6 in our study. Computational requirement of the problem is much increased as compared with efficiency optimization where w=1 and T=1.

IV. Solution Methodology

To efficiently solve the problem for near-optimal solutions, a recently developed decomposition and coordination-based method, surrogate augmented Lagragian relaxation + sequential quadratic programming [5], is combined with dynamic programming with rollout and finite difference without requiring explicit gradient equations.

The Relaxed Problem

Considering that the subsystems are separable with additive coupling constraints, the relaxed problem is obtained by relaxing (12-16) and adding penalty for (12) which is difficult to be satisfied:

$$\min_{(N_{Ach},N_{Act},N_{App},N_{Acp},T_{chws},\dot{m}_{pp},\dot{m}_{cp})} L,$$

$$\begin{aligned}\text{with } L \equiv J + \sum_{t=1}^{T}\Big[&\lambda_{\mathrm{pp}}^k(t)\big(N_{App}(t)\dot{m}_{pp}(t) - N_{Ach}(t)\dot{m}_{chchw}(t)\big)\\ &+\lambda_{\mathrm{cp}}^k(t)\big(N_{Acp}(t)\dot{m}_{cp}(t) - N_{Ach}(t)\dot{m}_{chcw}(t)\big)\\ &+\lambda_{\mathrm{ct}}^k(t)\big(N_{Act}(t)\dot{m}_{ct}(t) - N_{Ach}(t)\dot{m}_{chcw}(t)\big)\\ &+\lambda_{\mathrm{T}}^k(t)\big(T_{cwr\_ch}(t) - T_{cwr\_ct}(t)\big)\\ &+0.5c^k\big(N_{App}(t)\dot{m}_{pp}(t) - N_{Ach}(t)\dot{m}_{chchw}(t)\big)^2\Big], \quad (18)\end{aligned}$$

subject to (6-9) and lower/upper bounds such as (10).

As mentioned, chiller power and reliability are coupled, they can be grouped together. The problem is then decomposed into four subproblems for each subsystem.

Chiller Subproblem

All the terms related to chillers are collected and variables of other subsystems in the quadratic terms that are not separable are replaced by their solutions of previous iterations.

$$\min_{(N_{Ach},T_{chws},T_{cws})} L_{ch},$$

$$\begin{aligned}\text{with } L_{ch} \equiv\ & (1-w)\times\left(-\hat{R}_{ch}(T)\right)\times\theta_2 + w\times N_{Ach}(1)\times P_{ch}(1)\times\theta_1\\ &+\sum_{t=2}^{T} w\times N_{Ach}(t)\times P_{ch}(t)\times\theta_1\\ &+\sum_{t=2}^{T} w\times N_{Ach}(t)\times\left[P_{ct,r}(t) + P_{pp,r}(t) + P_{cp,r}(t)\right]\times\theta_1\\ &+\lambda_{\mathrm{mb,pp}}\left(-N_{Ach}(1)\times\dot{m}_{chchw}(1)\right) + \lambda_{\mathrm{mb,cp}}\left(-N_{Ach}\times\dot{m}_{chcw}(1)\right)\\ &+\lambda_{Tcws}\left(T_{cws}(1)\right) + \lambda_{Tcwr}\left(T_{cwr}(1)\right)\end{aligned}$$

$$+0.5c^k\left(N_{App}^{k-1}(1)\dot{m}_{pp}^{k-1}(1)-N_{Ach}^{k-1}(1)\dot{m}_{chchw}(1)\right)^2\Big], \quad (19)$$

subject to (5-9) and lower/upper bounds.

With reliability considered, the subproblem is dynamic. To solve efficiently the subproblem, Dynamic Programming (DP) with rollout is used. Running time and the numbers of startups/shutdowns are the states *x(t)*. Stage-wise costs at time *t=1* are established by using sequential quadratic programming (SQP) and finite difference (FD). Gradients required are obtained by using FD and information read from DNN models as shown in Fig. 3. If no feasible solution is found, the cost is infinite. Following rules are used for t=2, …, T: T_{chws} = 6.5 ^{0}C; T_{cws} = 4 + the wet-bulb temperature; $N_{Ach} = N_{Act} = N_{App} = N_{Acp}$; A chiller is turned on when $Q_{demand} > 0.9Q_{capacity}$; $T_{chwr} = T_{chwr,max}$ and $T_{cwr} = T_{cwr,max}$. Based on rules, at t=2 ,…, 6, power consumption of cooling towers $P_{ct,r}$ and pumps $P_{pp,r}$ and $P_{cp,r}$ depends on decision variables of chillers. Thus they are collected in the chiller subproblem.

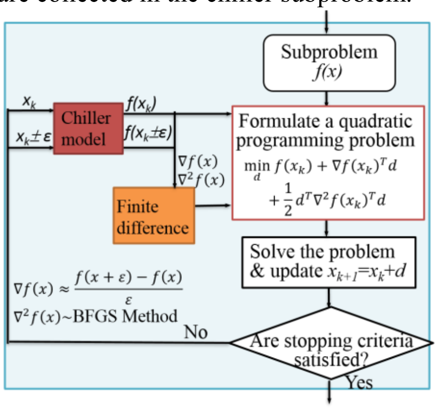

Fig. 3. The framework of SQP with finite difference

Cooling Tower Subproblem and Pump Subproblem

The cooling tower subproblem at k^{th} iteration is obtained by collecting all the terms related to cooling towers as:

$$\min_{(N_{Act})} L_{ct},$$
$$\text{with } L_{ct} \equiv N_{Act}(1)P_{ct}(1)-\lambda_{ct}^k N_{Act}(1)\dot{m}_{ct}(1)-\lambda_T^k T_{cwr\_ct}(1), \quad (20)$$

subject to heat exchange and lower/upper bound constraints. Since the subproblem is not coupled across time, SQP is used by considering all the possible cases. The final solution of the subproblem is the one with minimum cost.

Pump subproblems are obtained and solved similarly as the cooling tower subproblem. Details are not presented.

The Dual Problem and Feasible Solutions

The dual function is shown as:

$$\max_{(\lambda)} q, \text{with } q \equiv L_{ch}+L_{ct}+L_{pp}+L_{cp}. \quad (21)$$

After solving one subproblem, multipliers are updated based on (22-24) and then used for next subproblem until the dual function is maximized [16-17].

$$\lambda^{k+1}(t)=\lambda^k(t)+s^k(t)\tilde{g}\left(x^k(t)\right), \quad (22)$$

$$s^k(t)=\alpha_k s^{k-1}(t)\frac{\left\|\tilde{g}\left(x^{k-1}(t)\right)\right\|}{\left\|\tilde{g}\left(x^k(t)\right)\right\|}, \quad (23)$$

$$\alpha_k=1-\left(M\cdot k^p\right)^{-1}, 0<p<1,\ M>1,\ k=1, 2, ..., \quad (24)$$

where s is the stepsize, M and p are constants, k is the number of iterations and $\tilde{g}$ is the augmented surrogate subgradient.

With coupling constraints relaxed, solutions obtained above may not be feasible for the original problem, and a lower bound is obtained. To get feasible solutions, SQP is directly used with N_{Ach}, N_{App}, N_{Acp} and N_{Act} obtained above given.

V. Numerical Testing

Our method has been implemented in MATLAB 2018b on a Core i7 3.6 GHz desktop with 16 GB memory, and a solver *slp_sqp* [26] is used. Three examples are tested. In Example 1, efficiency optimization based on the hybrid model is considered, and the results are compared with those obtained based on empirical models for validation. In Example 2, joint optimization is considered for one cooling demand by looking one hour ahead to show the idea and performance of our method. In Example 3, 20 years' cooling demands are considered and a moving window is used to show energy savings and reliability improvement by using our methods as compared with a baseline using rules.

Example 1

Based on UTC Supervisory Control Synthesis project, a plant with four identical units in each subsystem is used for efficiency optimization based on the hybrid model. Parameters are from [15]. With cooling load requirements from 25% to 75% of $Q_{capacity}$, results for CPU times, gaps, and feasible costs are obtained and shown in Table I.

Table I. Efficiency optimization based on the hybrid model

Qp	0.25	0.35	0.45	0.55	0.65	0.75
CPU(s)	22.37	42.82	51.58	43.89	40.66	43.38
Gap(%)	0.2342	0.2013	0.2695	0.4297	0.6101	0.9387
Cost(kw)	177.56	251.54	328.48	411.33	498.16	593.24

As shown in Table I, gaps are small showing that the quality of the solutions is good. Computational times are short as compared with the requirement (within 10-15mins). For optimization validation, results based on empirical models are calculated by using the method in [15] where gradients are obtained directly from model equations. The same solver *slp_sqp* is used.

Table II. Efficiency optimization based on the empirical models

Qp	0.25	0.35	0.45	0.55	0.65	0.75
CPU(s)	21.32	16.90	19.14	17.06	19.45	23.42
Gap(%)	0.4474	0.1730	0.1389	0.1073	0.1141	0.1891
Cost(kw)	174.81	250.08	325.22	409.17	494.25	589.06

According to Table I and Table II, the differences in power consumption are within the model error (RMSE= 2.04) and CPU times by using the hybrid model are larger than those by

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LRA.2019.2924126, IEEE Robotics and Automation Letters

using empirical models, but within the requirement. The results demonstrate that our method achieves good performance for optimization based on the hybrid model.

Example 2

The plant in Example 1 is used for joint optimization. Optimized results for one cooling demand 720 KW is calculated by looking ahead one hour with demands [720 KW; 720 KW; 733.39 KW; 749.84 KW; 766.28 KW; 782.72 KW]. Initial statues are $t_0 = 1$ month, $T_{acc,0} = 0.0417$, $N_{acc,0} = 2.1250$, $N_{Ach}(0) = 2$, $m_{cw,0}$=15 and $m_{chw,0}$=10. By using our method, results for CPU times, gaps, the number of active chillers, water mass flow rates are obtained.

Table III. Joint optimization results by using our method

Weight	0	0.1	0.2	0.3	0.4	0.5
CPU(s)	-	26.28	23.42	23.98	24.73	25.69
Gap (%)	-	0.13	0.14	0.15	0.16	0.12
$T_{Acc}(min)$	5	5	5	5	5	2.5
N_{Acc}	0	0	0	0	0	0.25
$m_{chw}(kg/s)$	14.26	14.26	14.26	14.26	14.26	28.52
$m_{cw}(kg/s)$	12.5	12.5	12.5	12.5	12.5	25.0
Weight	-	0.6	0.7	0.8	0.9	1
CPU(s)	-	26.57	26.34	25.56	25.21	25.42
Gap (%)	-	0.13	0.13	0.14	0.14	0.14
$T_{Acc}(min)$		2.5	2.5	2.5	2.5	2.5
N_{Acc}	-	0.25	0.25	0.25	0.25	0.25
$m_{chw}(kg/s)$		28.52	28.52	28.52	28.52	28.52
$m_{cw}(kg/s)$		25.0	25.0	25.0	25.0	25.0

As shown in Table III, gaps of our methods are small showing that the quality of the solutions is good. Computational time is short as compared with the requirement (within 10-15mins). According to the results, the number of startups/shutdowns and water mass flow rates play an important role for reliability. Running time is not as important as them. This is reasonable since reliability has a long time scale. As *w* increases, efficiency becomes more important and the amount of average water increases.

Example 3

The plant in Example 1 and 20 years' cooling demands scaled down from UCONN's chiller plant are used to show power consumption and reliability by using our method as compared with a baseline using rules. Since the data set is large, for simplicity, considering that a plant is mainly operated at June, July and August, we select one week's demands (8 hours per day) from each of the months above to estimate the results for 20 years. A moving window is used and for each cooling requirement, the problem is solved by looking ahead one hour.

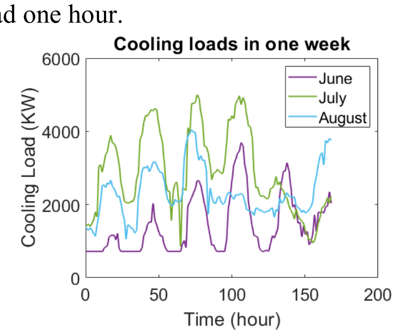

Fig. 4. Cooling loads modified from UConn's plant

Results for reliability and power consumption based on joint optimization with *w*=0.5, efficiency optimization, reliability optimization, and baseline strategies are as follows.

Table IV. Chiller reliability and power consumption

	Chiller reliability	Power consumption
Joint	0.4892	70,802,000
Efficiency	0.1863	65,716,000
Reliability	0.5323	78,762,000
Baseline	0.3401	75,050,000

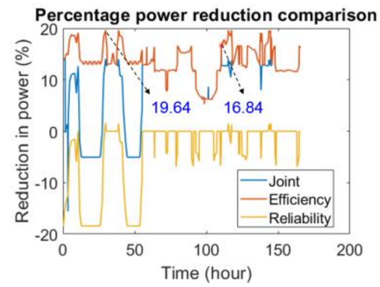

Fig. 5. Percentage power reduction as compared with the baseline

According to Table IV and Fig. 5, based on the joint optimization, total reduction is 10.59% and maximum reduction is 16.84% as compared with the baseline. The savings exceed the target set by industry partners (10%). Based on efficiency optimization, total percentage power reduction is 12.44% and the maximum one is 19.64%. Power consumption based on reliability optimization is larger than that of the baseline because energy is not considered in reliability optimization. Assume that the price of energy is \$0.05 kwh [3]. Baseline cost is \$625,420, efficiency optimization cost is \$547,630 and joint optimization cost is \$590,020. Plant capacity of our problem is small. For UConn's plant whose capacity is around 8.5 times of ours, the reduced cost based on joint optimization is around \$300,900, demonstrating significant savings.

Assume that lifespan of a chiller using baseline strategies is 20 years and the corresponding reliability 0.3401 is used as the indicator for the end of chiller life. Lifespan based on optimized strategies are estimated. According to Fig. 6, chiller lifespan based on efficiency optimization is 14.83 years, based on joint optimization is 42.75 years and based on reliability optimization is over 45 years.

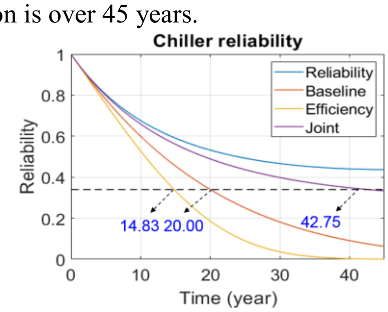

Fig. 6. Chiller reliability based on different strategies

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LRA.2019.2924126, IEEE Robotics and Automation Letters

According to results above, under certain conditions such as *w*=0.5, both energy savings and reliability are improved by using joint optimization as compared with the baseline. With *w* from 0.1 to 0.9 (increased by 0.1), Pareto Frontier is obtained and shown in Fig. 7. According to the results, the relationship between reliability and performance is almost linear. The reason is that mass flow rate has a large impact on both power consumption and reliability. As mass flow rate increases, reliability decreases while efficiency increases. As *w* increases, efficiency becomes more important than reliability and more water is used. For customers who care about energy savings, a big *w* can be used and vice versa.

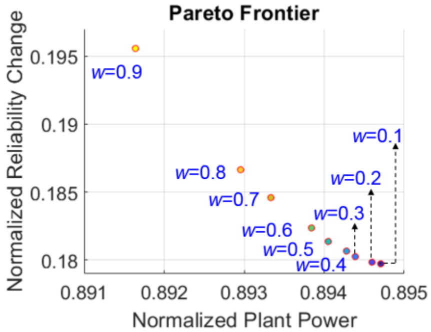

Fig. 7. Pareto Frontier

VI. Conclusion

In this paper, a decomposition and coordination-based approach is developed in combination with DP with rollout and FD for chiller plant joint optimization using a hybrid model. Results show that near-optimal solutions are obtained with short computational time by using our method and both energy savings and reliability are improved as compared with the baseline. Our method is general and can be extended to problems with multiple objectives beyond chiller plants.

Acknowledgment

The authors would like to thank Dr. Trevor Bailey and Mr. Christian Netter from United Technologies for their guidance and constructive comments on the research.

References

[1] J. Wang, Q. Zhang, S. Yoon and Y. Yu, “Reliability and availability analysis of a hybrid cooling system with water-side economizer in data center,” *Building and Environment*, vol. 148, pp. 405-416, 2019.
[2] Cost of Data Center Outages, Ponemon Institue, 2016.
[3] http://www.achrnews.com/articles/92941-maximizing-chiller-efficiency
[4] https://www.efficientplantmag.com/2005/01/maximizing-chiller-efficiency/
[5] D. Zhang, P. Luh, J. Fan and S. Gupta, “Chiller plant operation optimization: Energy-efficient primary-only and primary-secondary systems,” *IEEE Transactions on Automation Science and Engineering*, vol. 15, no. 1, pp.341-355, 2018.
[6] P. S. Hale and R. G. Arno, “Survey of reliability and availability information for power distribution, power generation, and HVAC components for commercial, industrial, and utility installations,” presented at *2000 IEEE Industrial and Commercial Power Systems Technical Conf., FL*, 2000.
[7] Q. Cheng, S. Wang, and C. Yan, “Robust optimal design of chilled water systems in buildings with quantified uncertainty and reliability for minimized life-cycle cost,” *Energy and Buildings*, vol. 126, pp. 159-169, 2016.
[8] S. A. Kalogirou “Artificial neural networks and genetic algorithms in energy applications in buildings,” *Advances in Building Energy Research*, vol. 3, no. 1, pp. 83-120, 2009.
[9] T. Chow, Z. Lin, C. Song, and G. Zhang, “Applying neural network and genetic algorithm in chiller system optimization,” *Proceedings of 7th International IBPSA Conference*, pp. 1059-1066, 2001.
[10] T. T. Chow, G. Zhang, Z. Lin and C. Song, “Global optimization of absorption chiller system by genetic algorithm and neural network,” *Energy and Building*, vol. 34, no, 1, pp. 103-109, 2002.
[11] V. Congradac and F. Kulic, “Recognition of the importance of using artificial neural networks and genetic algorithms to optimize chiller operation,” *Energy and Buildings*, vol. 47, pp. 651-658, 2012.
[12] T. Chan, Y. Chang and J. Huang, “Application of artificial neural network and genetic algorithm to the optimization of load distribution for a multiple-type-chiller plant,” *Building Simulation*, vol. 10, pp. 711-722, 2017.
[13] A. Kusiak and G. Xu, “Modeling and optimization of HVAC systems using a dynamic neural network,” *Energy*, vol. 42, no. 1, pp. 241-250, 2012.
[14] Y. Zeng, Z. Zhang, and A. Kusiak, “Predictive modeling and optimization of a multi-zone HVAC system with data mining and firefly algorithms,” *Energy*, vol. 86, pp. 393-402, 2015.
[15] S. A. Niknam, J. E. Kobza, and J. W. Hines, “Operation and maintenance decision-making using prognostic information,” *2015 Annual Reliability and Maintainability Symposium (RAMS)*, 2015.
[16] X. Sun, P. B. Luh, M. A. Bragin, Y. Chen, J. Wan, and F. Wang, “A decomposition and coordination approach for large-scale security constrained unit commitment problems with combined cycle units,” in Proc. *2017 IEEE Power and Energy Soc. General Meeting*, 2017.
[17] M. A. Bragin, P. B. Luh, J. H. Yan, N. Yu and G. A. Stern, “Convergence of the surrogate Lagrangian relaxation method,” *Journal of Optimization Theory and Applications*, vol. 164, no. 1, pp. 173–201, 2015.
[18] R. Kwak, A. Takakusagi, J. Y. Sohn, S. Fujii, B. Y. Park, “Development of an optimal preventive maintenance model based on the reliability assessment for air-conditioning facilities in office buildings,” *Building and Environment*, vol. 39, no. 10, pp. 1141-1156, 2004.
[19] D. E. Blahnik and R.F. Klein, “Aging assessment of essential HVAC chillers used in nuclear power plants,” Phase I. NUREG/CR-6043. PNL-8614, vol. 1. Pacific Northwest Laboratory, 1993.
[20] D. R. Cox, “Regression models and life-tables,” Journal of the Royal Statistical Society. Series B. vol. 34, no. 2, pp. 187-220, 1972.
[21] M. Forti and A. Tesi, “New conditions for global stability of neural networks with application to linear and quadratic programming problems,” *IEEE Transactions on Circuits and Systems-I: Fundamental Theory and Applications*, vol. 42, no. 7, 1995.
[22] X. Hu and J. Wang, “An improved dual neural network for solving a class of quadratic programming problems and its k-winners-take-all applications,” *IEEE Transaction on Neural Networks*, vol. 19, no. 12, pp. 2022-2031, 2008.
[23] P. Miao, Y. Shen and X. Xia, “Finite time dual neural networks with a tunable activation function for solving quadratic programming problems and its application,” *Neurocomputing*, vol. 143, pp. 80-89, 2014.
[24] Z. Zhang, L. Zheng, L. Li, X. Deng, L. Xiao and G. Huang, “A new finite-time varying-parameter convergent-differential neural network for solving nonlinear and nonconvex optimization problems,” *Neurocomputing*, vol. 319, pp. 74-83, 2018.
[25] X. Glorot, A. Bordes and Y. Bengio, “Deep sparse rectifier neural networks,” in *Proceedings of the fourteenth international conference on artificial intelligence and statistics*, 2017.
[26] https://www.mathworks.com/matlabcentral/fileexchange/53331-slp_sqp