Optimization and Implementation of a Load Control Scheduler Using Relaxed Dynamic Programming for Large Air Conditioner Loads

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***Abstract*—This paper presents the optimization and implementation of a relaxed dynamic programming (RDP) algorithm to generate a daily control scheduling for optimal or near-optimal air conditioner loads (ACLs). The conventional control mode for ACL includes demand control, cycling control, and timer control, to assist customers for saving electricity costs. The proposed load control scheduler (LCS) scheme supports any combination of these three control types to save costs optimally during the dispatch period. Microprocessor hardware techniques were applied to carry out the proposed strategy for realistic application. The Visual C^{++} language was adopted as the developing tool to carry out the proposed work. Field tests of controlling air conditioners located in the campus of National Kaohsiung University of Applied Sciences, Kaohsiung, Taiwan, were tested on-site to demonstrate the effectiveness of the proposed load control strategy. The results show that interruptible load scheduling can reduce the system load effectively, and the load capacity reduced by the proposed load control strategy follows closely the trajectory of the peak load.**

***Index Terms*—Implementation, load control scheduler, optimization, relaxed dynamic programming.**

I. Introduction

POWER energy is the foundation stone of industrial development. However, the demand for electrical power is growing rapidly, especially in regions where industrial and commercial activities are developing fast, so energy saving has become an important issue. The annual report on electricity load growth in Taiwan published by the Tai-Power Company (TPC), the sole provider of electricity in Taiwan, shows that approximately 65% of the total power consumption in Taiwan is used by industry and commerce. Efficient use of energy is of ongoing concern, especially for industries with high levels of power consumption, such as the iron and steel, petrochemical, cement, and paper-making industries, which need to continually consider energy-saving plans to increase their competitiveness [1], [2].

Analysis of the power consumption by commercial customers shows that the operation of air-conditioning equipment is the component with the highest power utilization. Energy-saving systems (controllers) that could aid the TPC and customers in executing various load management schemes and air conditioner loads (ACLs) dispatch strategies, such as demand control, cycling control, and timer control, to solve shortages in electricity supply and problems of energy spending during the summer season, are popular topics for studies [3], [4].

In recent years, many successful applications on direct loads control (DLC) have been reported. Bhatnager and Rahman [5] pointed out that the potency of a DLC strategy depends on the system characteristics. Lee and Wilkins [6] presented a general modeling technique to assess the benefits of loads control. England and Harrison [7] reported the controlling experiences of air conditioners and electrical water heaters in Carolina Power & Light Company. Chen [8] proposes three alternative approaches for the interruptible load control. Wei and Chen [9] proposed the multipass dynamic programming for the DLC; it can converge quickly to the near-optimal solution. To raise the customer's willingness to attend the DLC, fuzzy logic-based demand control strategy [10] is used for the periodic control of the electrical water heaters and air conditioners. Hsu and Su [11] presented a dynamic programming (DP) method to coordinate the DLC strategies and unit commitment such that the system production cost could be minimized. The interruptible load control [12]–[19] is an effective load management to reduce the peak load demand on the status of emergency.

In order to implement load management, demand contracts that require an interruptible load are offered to customers at a discount. The peak load can be reduced during periods of high demand by interrupting loads according to the load control scheduling. To keep the inconvenience for customers as small as possible, the load groups should be shed in sequence according to the schedule of the interruptible load groups (ILGs) [12], [13]. In addition to the critical issue of production quality, cost-effective electric energy management is now being considered by customers [12]–[19]. For power energy saving issue, a load control scheduler (LCS) is needed to assist customers in electricity cost saving with minimal discomfort.

The optimal scheduling policy considered here is derived using DP. The optimal sequence of current and future scheduling decisions should be determined for each initial state. Due to combinatorial expansion, an exact solution can be obtained only for very simple cases. To overcome this problem, Rantzer [20] introduced the technique of RDP, which allows suboptimal

Manuscript received January 16, 2007; revised September 25, 2007. Paper no. TPWRS-00018-2007.

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Digital Object Identifier 10.1109/TPWRS.2008.919311

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solutions with pre-specified loose bounds to be calculated for switched load control problems. We use those results to solve the optimal large ACLs scheduling problem for direct loads control tasks. This is a typical optimization under constraints problem, in which the objective function to be minimized is the total running cost over the study period subject to the constraints.

In the conventional DP method, the minimum cost-to-target is calculated at each discrete time stage for each possible state at that stage. The large number of state points, called grid points, however, demands an unreasonably large amount of computational time and memory. The RDP was introduced in order to make DP solutions feasible [20]–[22]. The optimal scheduling decision at each time stage is a function of the states of the controlled items. In order to solve the scheduling problem for online realistic examples, the factors concerned above are all taken into account and then use the RDP technique to compute optimal or suboptimal solutions with loose criteria to avoid the algorithm required for a large look-up table [20]–[23]. The proposed method could satisfy the principle of "the faster the system, the simpler the architecture needs to be."

The main contributions of this paper are

1) applying the RDP algorithm for control strategy optimization to generate a daily optimal or near-optimal ACLs control scheduling with energy payback and load uncertainty considered in an LCS;
2) saving electricity cost in incentive rate considered;
3) reducing the perturbation to customers caused by loads interrupted period;
4) considering the customers' willingness into the problem solving procedure when the parameters of the LCS are set;
5) outperforming the DP in less requirements of storage memory and computational time.

This paper is organized as follows: Section II introduces the DP background, followed by the main relaxation DP method in Section III. For further details on the theoretical basis, the reader is referred to [23] and [24]. The ACL applications are presented in the following sections. Application of a mathematical optimization approach based on an RDP algorithm to identify an optimum load control model is discussed in Section IV. By using an Intel 16-bit microprocessor to develop a load controller comprising demand control, cycling control and timer control schemes are described in Section V. The intent is to develop a multi-objective function based on RDP with an optimum load strategy to aid customers in avoiding violation of their contract, and to save electricity costs. In Section VI, a case study is presented to demonstrate the RDP performance. Finally, the conclusions are given in Section VII.

II. Dynamic Programming Algorithm Reviews

Let $x(m) \in X$ be the state of a given system at time m, while $u(m) \in U$ is the value of the control signal [23], [24]. The system evolves as

$$x(m+1) = f(x(m), u(m)), x(0) = x_0. \qquad (1)$$

For a given cost function

$$\sum_{m=0}^{\infty} l(x(m), u(m)) \qquad (2)$$

such that $l(x, m) \geq 0$with equality only if $x = 0$, we would like to find an optimal control policy $u = \mu(x)$, such that the cost is minimized from every initial state. For a fixed control policy μ, the map from initial state x_0 to the value of (1) is called a value function $R^{\mu}(x_0)$. The optimal value function is denoted

$$R^*(x_0) = \inf_{\mu} R^{\mu}(x_0) \qquad (3)$$

and is characterized by the Bellman equation

$$R^*(x) = \min_{u}\{R^*(f(x, u)) + l(x, u)\}, R(0) = 0. \qquad (4)$$

A method commonly used to find the optimal value function is value iteration, i.e., to start at some initial $R_0(x)$, for example,$R_0 \equiv 0$, and update iteratively

$$R_{k+1}(x) = \min_{u}\{R_k(f(x, u)) + l(x, u)\}. \qquad (5)$$

It is well known that value iteration converges under mild conditions. For a more extensive treatment of basic DP theory, the reader can refer to, e.g., [23] and [24]. However, in the conventional DP method, the large number of state points demands unreasonably large amount of computational time and storage memory [20]–[22].

III. Relaxing Dynamic Programming

The idea of RDP was first proposed by B. Lincoln and A. Rantzer of LTH, Lund University, Sweden, in 2003 [20]–[22]. It reduces the complexity by relaxing the demand for optimality to solve the "curse of dimensionality" problems. The distance from optimality is kept within pre-specified bounds and the size of the bounds determines the computational complexity.

We will follow the Lincoln and Rantzer's method to find a $R(x)$ which fulfills $R(0) = 0$ and

$$\begin{aligned} &\min_{u}\{R_k(f(x, u)) + \underline{l}(x, u)\} \\ &\quad \leq R_k(x) \\ &\quad \leq \min_{u}\{R_k(f(x, u)) + \overline{l}(x, u)\} \end{aligned} \qquad (6)$$

for all x and u. Iterative application of the inequalities gives

$$\min_{\{u(m)\}_{m=0}^{\infty}} \sum_{m=0}^{\infty} \underline{l}(x, u) \leq R(x) \leq \min_{\{u(m)\}_{m=0}^{\infty}} \sum_{m=0}^{\infty} \overline{l}(x, u) \qquad (7)$$

for every initial state such that the minima are finite. Moreover, the control law $u(m) = \mu(x(m))$ with

$$\mu(x) = \arg\min_{u}\{R(f(x, u)) + \underline{l}(x, u)\} \qquad (8)$$

achieves

$$\sum_{m=0}^{\infty} \underline{l}(x(m), u(x(m))) \leq R(x). \quad (9)$$

In particular, μ is a stabilizing feedback law because the lower bound in (6) implies that R is a Lyapunov function for the closed-loop system [25]. Usually, $\bar{l}$ and $\underline{l}$ are chosen to satisfy $\underline{l}(x, m) \leq l(x, m) \leq \bar{l}(x, m)$, for example

$$\bar{l}(x, m) = \bar{\alpha} l(x, m), \bar{\alpha} \geq 1 \quad (10)$$

$$\underline{l}(x, m) = \underline{\alpha} l(x, m), \underline{\alpha} \leq 1. \quad (11)$$

With this relaxation of Bellman's equation, we can search for a solution $R(x)$ which is more easily parameterized than $R^*(x)$. Readers can refer to [20]–[22] for the details of convergence.

A. Relaxed Value Iteration

Given $R_{k-1}(x)$ satisfying

$$\min_{\{u(m)\}_{m=0}^{k-1}} \sum_{m=0}^{k-1} \underline{l}(x, u) \leq R(x) \leq \min_{\{u(m)\}_{m=0}^{k-1}} \sum_{m=0}^{k-1} \bar{l}(x, u) \quad (12)$$

define $\bar{R}_k(x)$ and $\underline{R}_k(x)$ according to

$$\bar{R}_k(x) = \min_u \{R_{k-1}(f(x, u)) + \bar{l}(x, u)\} \quad (13)$$

$$\underline{R}_k(x) = \min_u \{R_{k-1}(f(x, u)) + \underline{l}(x, u)\}. \quad (14)$$

The expressions for $\bar{R}_k(x)$ and $\underline{R}_k(x)$ are generally more complicated than for $R_{k-1}(x)$. From this, a simplified $R_k(x)$ which satisfies

$$\underline{R}_k(x) \leq R_k(x) \leq \bar{R}_k(x) \quad (15)$$

is calculated. This satisfies

$$\min_{\{u(m)\}_{m=0}^{k}} \sum_{m=0}^{k} \underline{l}(x, u) \leq R_k(x) \leq \min_{\{u(m)\}_{m=0}^{k}} \sum_{m=0}^{k} \bar{l}(x, u) \quad (16)$$

and the procedure can be iterated. In particular, the lower bound shows that $R_k(x)$ grows with k at least as fast as standard value iteration with the step cost $\underline{l}(x, m)$.

The iteration of (13)–(15), which we call relaxed value iteration, can often be used to find a solution of (6). The α (and the l) values are chosen as a trade-off between complexity (time and memory) and accuracy. If $\bar{\alpha}$ and $\underline{\alpha}$ are close to 1, then the iterative condition (15) becomes close to ordinary value iteration (5), which gives high levels of accuracy and complexity. On the other hand, if the fraction $\bar{\alpha}/\underline{\alpha}$ is very large, then the accuracy drops, but (15) can be satisfied with less complex computations. Note that if l is chosen as in (10) and (11), the relative error in the value function defined by $\bar{\alpha}$ and $\underline{\alpha}$ is independent of the number of iterations [20]–[22].

The value function approximations considered will have the form

$$R_k(x) = \text{select}_{p \in I_k} p(x) \quad (17)$$

where I_k is a set of (simple, e.g., linear or quadratic) functions on x, and the "select" operator selects one of the functions according to some criterion (e.g., "maximum," "minimum," or "feasible region"). Moreover, it is essential that also $\bar{R}_k$ and $\underline{R}_k$ will have the same form. This expression will be used in the following sections.

B. Simple Algorithm to Calculate R

We have not discussed how to calculate $R_k(x)$ to satisfy (15) until now. Doing this in an optimal way with respect to complexity of the optimization may be a very hard problem. However, we can follow a simple and efficient (albeit not optimal) algorithm to obtain $R_k(x)$ for the minimum-type (and conversely maximum-type) parameterization. The algorithm is described in the following procedure (From R_{k-1} to R_k, minimum-type) [20].

1) Calculate $\bar{R}$ and $\underline{R}$ from R_{k-1}:
   $\bar{R}_k(x) = \min_u \{R_{k-1}(f(x, u)) + \bar{l}(x, u)\}$
   $\underline{R}_k(x) = \min_u \{R_{k-1}(f(x, u)) + \underline{l}(x, u)\}$
   Define $\bar{I}_k$ and $\underline{\boldsymbol{I}}_k$ such that
   $\bar{R}_k(x) = \min_{p \in \bar{\boldsymbol{I}}_k} p(x)$, and $\underline{R}_k(x) = \min_{p \in \underline{\boldsymbol{I}}_k} p(x)$.
2) Let $\boldsymbol{I}_k = \phi$ and $R_k = \infty$.
3) If possible, find $x_0 \in X$ such that $R_k(x_0) \geq \bar{R}_k(x_0)$
   If not, $R_k(x)$ satisfies (15) $\Rightarrow$ Done.
4) Define $R_k(x) = \min_{p \in \boldsymbol{I}_k} p(x)$, and go to step 3.
5) Let $\underline{p} = \arg\min_{p \in \underline{\boldsymbol{I}}_k} p(x_0)$, and add p to the set $\boldsymbol{I}_k$.

The algorithm simply adds elements from the lower bound $\underline{R}_k(x)$ until the resulting value function $R_k(x)$ satisfies the upper bound $R_k(x) \leq \bar{R}_k(x)$. The resulting value function satisfies (15) by construction. Procedure above can be iterated until the predefined stopping criterion is satisfied.

IV. STRATEGY OPTIMIZATION

A. Problem Formulation

There are two objectives to be implemented for the LCS strategy [10], [14], [15]. The first is to minimize the electricity cost and to maximize customer benefits. The second is to maintain system reliability and to minimize the perturbation of load interruption simultaneously. The proposed model can be built to achieve customer satisfaction and peak load reduction. Due to participation of the customer in the load management, the mathematical model of the problem can be formulated as follows.

1) Objective Function: The purpose of LCS is to reduce the system peak load by controlling the customers' air conditioners. For minimizing the disturbance to customers, the objective function P_t of LCS considered in this problem comprises two terms. The first term is to minimize inconvenience and disturbance to customers during the daily dispatch period, which can be expressed as follows:

$$P_t = \mathrm{Min}\left[\sum_{g=1}^{\mathrm{M}}\sum_{i=1}^{\mathrm{N}} CL_g(i) \times (1 - \mathrm{S}_g(i))\right], P_t \geq 0 \tag{18}$$

where

- M number of ACLs;
- N: number of control periods (daily);
- $CL_g(i)$ capacity of the gth ACL group in period i (kW);
- $S_g(i)$ state of the gth ACL growth in period $i = 1$ if the gth ACL group is connected to the system in period i; $= 0$ if the gth ACL group is disconnected from the system in period i.

The second term considers the willingness of customers to be charged an incentive rate for accepting interrupted control schemes [14]. The objective function of LCS (18), which contains the cost component, is revised as

$$P_w = \mathrm{MaxMin}\left[\sum_{g=1}^{\mathrm{M}}\sum_{i=1}^{\mathrm{N}} CL_g(i) \times (1 - \mathrm{S}_g(i))\right] \times \delta(\alpha_g) \tag{19}$$

$$\delta(\alpha_g) = (0.7\tanh^{-1}(\alpha_g) + 2)/2 \tag{20}$$

where

- $\delta(\alpha_g)$ incentive weighting function of the gth ACL group;
- α_g deviation of the gth ACL group from the average of all incentive rates of the ACLs;
- P_w objective weighting capacity; shed by demand control, timer control, and cycling control strategies.

The proposed LCS control mode for ACL can be fulfilled by demand control, cycling control, and timer control, to assist customers for saving electricity costs. P_w can be accomplished by using the following statement:

$$P_w = \mathrm{MaxMin}\left[\sum_{\text{daily}} IL(D) + \sum_{\text{daily}} IL(C) + \sum_{\text{daily}} IL(T)\right], P_w \geq 0 \tag{21}$$

where

- $\sum_{\text{daily}} IL(D)$ total daily saving capacity for demand control;
- $\sum_{\text{daily}} IL(C)$ total daily saving capacity for cycling control;
- $\sum_{\text{daily}} IL(T)$ total daily saving capacity for timer control.

Max-min can express as "minimal perturbation to customers caused by loads interrupted with maximal loads reduction." Since the only key issue in timer control is just time, therefore no further discussion will be made in the following contents.

Constraints considered in the first two terms of objective function P_w in each stage will be discussed in the following paragraphs.

2) Constraints: Apart from fitting the above-mentioned formulation rules, the proposed algorithm must also satisfy the following constraints. (We take into account the constraints that make the approach superior to the conventional DP method, which assumes that the predicted loads are known exactly; i.e., with no errors.) For instance, the energy payback phenomenon may thus cause a secondary peak load and variation of the load pattern. The LCS schedules the cycling on–off times and duration of the ACL groups, aiming to reduce the peak load as much as possible. The maximal disconnected duration of the ILGs should be constrained to avoiding causing inconvenience to the customer. The minimal online duration of the ILGs should be enough to cover the work that is delayed by the power interruption.

a) Load Constraints: For cycling control, during the cycling off period, only the freezing machine of air conditioners (AC) is off, the other devices such as power fans, circulating pumps, and controller are still on operation. Let $P_{\mathrm{RC}}(i)$ be the reduced capacity by LCS operation at time stage i, and$P_{\max}$, be the maximum available capacity of LCS, then

$$0 \leq P_{\mathrm{RC}}(i) \leq P_{\max}, \text{ for } 1 \leq i \leq N. \tag{22}$$

During the cycling off period, the space temperature will rise, depending on a number of factors such as the weather, the environmental conditions, the efficiency of the air conditioners, start and stop time of control, control intensities, etc. [3], [10], [17]. Therefore, in the next cycling on period, the load demand will be increased due to the energy payback phenomenon, which is expressed as follows:

$$P_{\mathrm{PB}}(i) = \sum_{i=1}^{n} R_{\mathrm{PB}}(i) \cdot P_{\mathrm{RC}}(i-j) \tag{23}$$

where

- $R_{\mathrm{PB}}(i)$ energy payback ratio appearing at the stage i;
- n energy payback period;
- $P_{\mathrm{PB}}(i)$ energy payback load in period i.

The energy payback ratio $R_{\mathrm{PB}}(i)$ represents the ac load shape impact curves. It varies with the weather, the control strategy, the end user's behavior, etc. The energy payback is a function of the device's energy demand, because the average device cycle is proportional to the difference between its thermostat setting and the surrounding temperature. Here, the energy payback pattern is considered as follows [10]:

$$P_{\mathrm{PB}}(i) = 0.6 \times P_{\mathrm{RC}}(i-1) + 0.3 \times P_{\mathrm{RC}}(i-2) + 0.1 \times P_{\mathrm{RC}}(i-3). \tag{24}$$

In the demand control operational application, to reflect the uncertainties of load forecasts and load control actions, the computing time has to be as fast as possible for an online dynamic loads scheduling problem. Once the load recovery demand increase caused by the energy payback is calculated, the load demand in period i after controlled must be modified as follows:

$$P(i) = P'(i) - P_{\mathrm{RC}}(i) + P_{\mathrm{PB}}(i) \tag{25}$$

where

$P(i)$	modified load demand in period i;
$P'(i)$	original forecasted load demand in period i;
$P_{\mathrm{RC}}(i)$	reduced capacity by interrupted control in period i.

The load demand control can be stated as follows:

$$\mathrm{MaxMin}(P(i)) = \mathrm{MaxMin}\sum_{i=1}^{N}(P'(i) - P_{\mathrm{RC}}(i) + P_{\mathrm{PB}}(i)) \tag{26}$$

subject to $0 \leq P_{\mathrm{RC}}(i) \leq P_{\max}, \mathrm{for} 1 \leq i \leq 96$.

b) ACL Online Constraints: Each ACL group can be executing the load shedding/restoring program at each time stage through the timetable given in advance. The diagnostic rules must satisfy the formulae in (27) at the bottom of the page, where

K_g	the initial time of executing control;
Tc_g	online duration of the gth ACL.

c) Operational Constraints: The time for which ACLs are disconnected should be constrained to avoid causing inconvenience to customers. Therefore, ACLs have to be reconnected to the system when the time off reaches the customer's limit. Besides, the time on for ACLs should be enough to cover the work that would be delayed by a power interruption. If cumulative time on is less than the minimum connected time, the ACL cannot be interrupted. These operational constraints can be expressed as in (28) at the bottom of the page [14], [15], where

$g = 1, 2, 3 \ldots, > 0$.

$S_g(i)$ is the on/off status of the gth ACL in period i.

If $S_g(i) = 1$, the gth ACL is connected to the system.

If $S_g(i) = 0$, the gth ACL is disconnected from the system.

$AT_g(i)$ is the cumulative time interval of the gth ACL at period i.

If $AT_g(i) > 0$, then $S_g(i) = 0$.

If $AT_g(i) < 0$, then $S_g(i) = 1$.

T_j is the time interval of the periods.

$\max T_g$ is the maximum disconnected time for the gth ACL.

$\min T_g$ is the minimum connected time of the gth ACL.

B. RDP Solution Methodology

The optimal solution can be obtained by the DP through the enumeration search structure. However, the requirements of the enormous storage memory and computational time are the drawbacks of the scheme. Thus, an RDP structure is used to overcome the complexity of DP problems and to consider the variation of the on–off control duration of the ACLs and the constraints of the expected load. The basic idea of RDP is to introduce some relaxed criteria into the solution. It is obvious from objective function (19) that, during the load control period subject to the constraints (22) to (28), there will be several different load levels at each stage as a result of scheduling different amounts of load control $P(i)$ in (25). The load level for the states at the same stage may be different, due to different amounts of load control, energy payback, and other constraints limitation which were mentioned above.

The LCS period is first divided into a number of intervals, each of which is defined as a stage in the RDP. In each stage, a number of state-sets are given. All the states contained in a state-set are faced with the same load levels, but those in a different state-set have distinct load levels, ranging from the criteria $\bar{\alpha}l$ (upper bound) to $\underline{\alpha}l$ (lower bound) around the predicted load level to account for the constrained uncertainties and to reduce the dimensional curse. Fig. 1 displays the search structure of the RDP with lower dimensions than the DP structure. As noted in the figure, each state of a state-set in the current stage represents the on–off combinations of all the ACL groups, originating from the states with the maximum objective function in the state-sets of the previous stage [17]. An efficient optimal or near-optimal program is linked with each state in Fig. 1 to obtain the corresponding schedule. To avoid the expansion of the dimension needed, a relaxed search strategy is used. Only the states with larger objective values defined in (30) are saved in

$$\begin{cases} P_{RCg}(i) > 0, \ \mathrm{for}\ K_g + 1 \leq i \leq K_g + T_{Cg}, g = 1, 2, 3 \ldots M, g \neq 0. \\ P_{RCg}(i) = 0, \mathrm{for}\ i \leq K_g, \mathrm{or}\ i \geq K_g + 1 + T_{Cg}, g = 1, 2, 3 \ldots M, g \neq 0. \end{cases} \tag{27}$$

$$AT_g(i) = \begin{cases} AT_g(i-1) + T_j, & \text{if } S_g(i-1) = 0 \text{ and } S_g(i) = 0 \\ T_j, & \text{if } S_g(i-1) = 1 \text{ and } S_g(i) = 0 \\ -T_j, & \text{if } S_g(i-1) = 0 \text{ and } S_g(i) = 1 \\ AT_g(i-1) - T_j, & \text{if } S_g(i-1) = 0 \text{ and } S_g(i) = 0 \end{cases} \tag{28}$$

$$\begin{cases} \text{maximum off} - \text{line constraints } S_g(i) = 1, \text{if } AT_g(i-1) = \max T_g, \\ \text{minimum on} - \text{line constraints } S_g(i) = 1, \text{if} - \min T_g < AT_g(i-1) < 0 \end{cases}$$

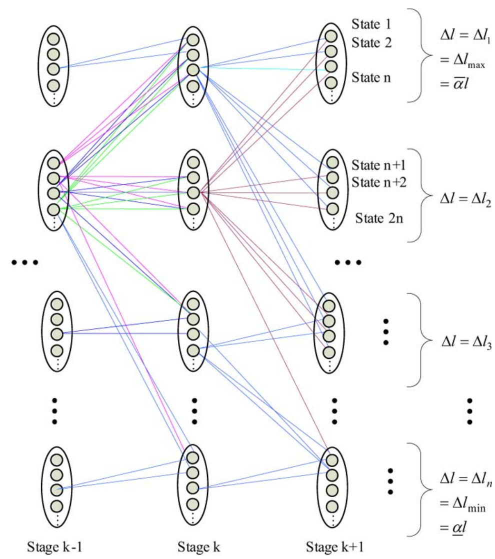

Fig. 1. RDP search structure diagram.

each stage, and then they branch out the feasible states in the next stage.

The recursive strategy to compute the minimal capacity of the interruptible load at state i which with the maximal satisfaction to the customer is expressed as follows:

$$P_{\mathrm{LTC}}(i) = \mathrm{MaxMin}(P_{\mathrm{LTC}}(i-1) + P'(i) - P_{\mathrm{RC}}(i) + P_{\mathrm{PB}}(i)) \quad (29)$$

where

$P_{\mathrm{LTC}}(i)$ least total capacity of the interruptible load at state i;

$P_{\mathrm{RC}}(i)$ reduced capacity of the interruptible load at state i.

Substitute $P_{\mathrm{LTC}}(i)$ for $R(x)$ in (30) at each state to obtain the optimization policy of RDP

$$\begin{aligned}&\min_u\{R(f(x,u)) + \underline{\alpha} l(x,u)\}\\ &\quad \le R(x)\\ &\quad \le \min_u\{R(f(x,u)) + \bar{\alpha} l(x,u)\}.\end{aligned} \quad (30)$$

According to the optimization policy of RDP, in the last stage, the optimal or near-optimal dispatch schedule of the ACLs can be obtained by backtracking the trajectory of all the states, which have the minimal reduction capacity from the last stage. (This is called value iteration [20]–[22].)

Let the function $R_k^*(x(t_k))$ denote the optimal objective from time t_k to infinity, given that the initial state is $x(t_k)$. Note that each step in the iteration involves a cumbersome minimization operation over two decision variables. This will make the function $R_k^*(x(t_k))$ more complex in every step.

We note that the complexity of computing the online scheduling decision (30) is linear in the number of elements in solution space P. Hence, as few elements as possible should be included in P. This can be adjusted by an appropriate choice of the slack variable α. If the computational burden should still be too heavy, we propose that the solution state space is girded and that the solution to (30) is stored in a look-up table. Hence, there is a trade-off between the memory consumption and the computational time consumption of the scheduler.

Here, the scalar $\alpha > 1$ is a slack parameter that can be chosen to determine the distance to optimality. By the introduction of inequalities instead of equalities, it is in principle possible to fit a simpler, approximate cost-to-target function between the upper and lower bounds. If, in each step, the upper $\bar{R}_k$ and lower $\underline{R}_k$ bounds are set as in (13) and (14) in advance, the obtained solution will satisfy

$$\underline{\alpha} R_k^*(x(t_k)) \le R_k(x(t_k)) \le \bar{\alpha} R_k^*(x(t_k)) \quad (31)$$

which gives a guarantee on how far the approximate solution is from the optimal solution. The loose parameters were chosen as $\bar{\alpha} = 1.05$ and $\underline{\alpha} = 0.9$ based separately on an average of 30 test runs in this study, which means that the approximate solution will give, at most, a 5% higher and a 10% lower boundary than the true, optimal solution, respectively. In the present study, the load levels corresponding to the objective function and loose criteria of $1.06, 1.05, 1.04, \ldots, 1.0, 0.99, 0.98, \ldots, 0.8$ are selected for each stage as a safety boundary, because we have to extend the range for considering both the constraints and complexity in the same time.

V. Implementation of the Load Controller

In order to develop the proposed algorithm into the hardware design of a load controller, the Visual C^{++} 6.0 language was adopted as the developing tool to carry out the proposed work [26]. The flowchart for the RDP-LCS program is shown in Fig. 2. When the proposed RDP-LCS scheme is executed, the program will determine the daily available capacities of ACLs controlled *via* timetable information *a priori*, and then execute the demand control, timer control, and cycling control scheme to fit the objective function. The LCS pre-scheduling of air conditioner loads obtained by the RDP can serve the system according to the forecasted load pattern. However, forecasting errors are inevitable, and the results of the peak load reduction are disturbed dynamically by the energy payback phenomenon and loads uncertainties [15]. The schedule of LCS can be adjusted adaptively by the formula of (32) to enhance the robustness of the scheduling of the load being studied. These loads are monitored by the PQ transducer which feedback the real load capacity used during the system operation. Note that the signal of P is used for real power load control to accomplish load shed/restore scheme, and the signal of Q is used for reactive power monitored for taking statistical information for the further used for the VAR compensating advisement

$$D_{\mathrm{err}}(i) = P_L(i) - T_m(i) - \left[\sum_{i=1}^{\mathrm{N}} CL_g(i) \times (1 - \mathrm{S}_g(i))\right] \times \delta(\alpha_g) \quad (32)$$

where

$D_{\mathrm{err}}(i)$ discrepancy capacity (error signal) at state i;

$P_L(i)$ practical load at state i;

$T_m(i)$ saving target margin at state i.

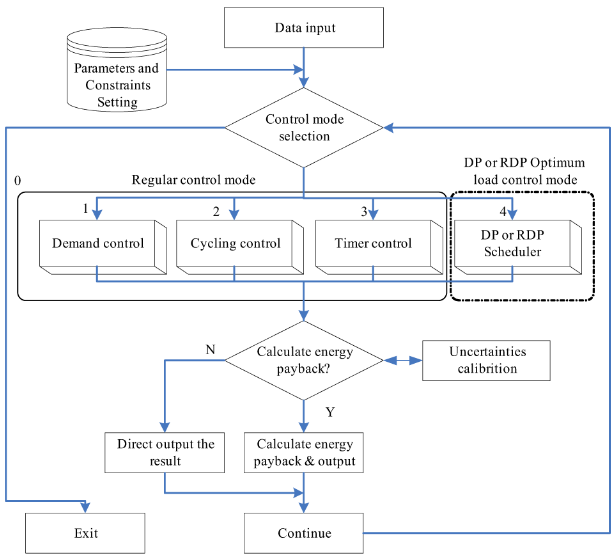

Fig. 2. Flowchart of the RDP-LCS program.

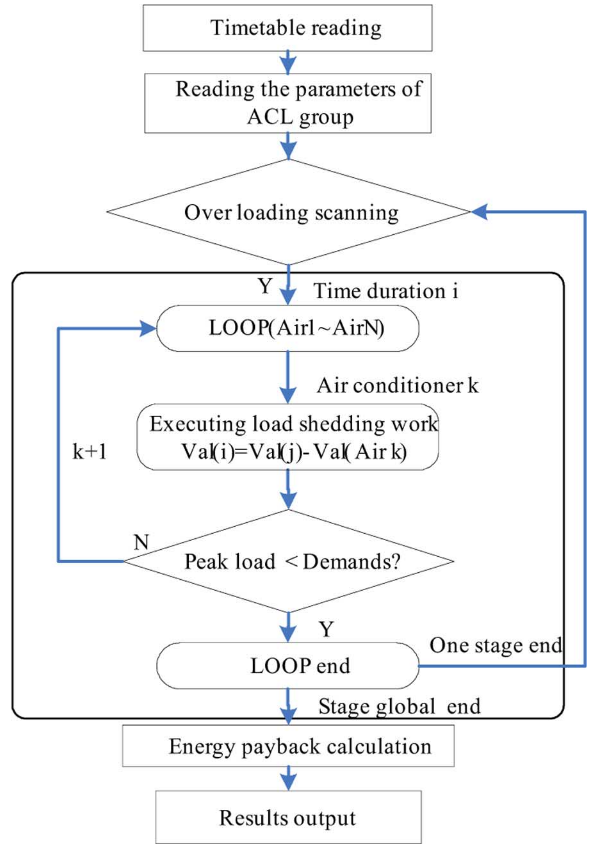

Fig. 3. Flowchart of the demand control strategy.

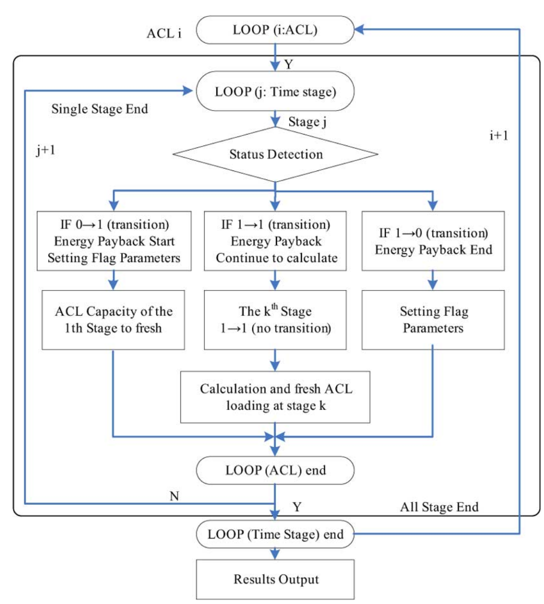

Fig. 4. Flowchart for calculating the energy payback.

The refining process of recursive work will be stopped, and the result will be output when a global optimal or near-optimal solution has been found by the RDP algorithms. With the RDP algorithm, the scheduler can perform online adjustment rapidly and requires less memory.

As seen from Fig. 3, this algorithm adopts the loop-priority method as rules to execute the demand control. When the load demand exceeds the limit set, the subroutine executes load-shedding to reduce the peak load demand; on the other hand, load restoring is enabled. This scheme uses a conventional knapsack approach based on the RDP algorithm to find a global optimal or near-optimal state-sets solution during each stage using relaxing bounds. The lower bound α value is set to 0.90 and the upper bound α value is set to 1.05 for reducing the computational complexity rather than to sacrifice too much cost. As seen from Fig. 4, when the system starts to execute load shedding/restoring, the energy payback phenomenon is considered and estimated according to (26) to revise the previous energy demand, taking the system uncertainties and constraints into account. This subroutine automatically reviews each time stage to check a suitable time for off–on transition to avoid violating the demand control constraints.

The proposed procedure includes the steps as follows.

Step 1) Data input by data acquiring and customers' settings.

Step 2) The control periods of the air conditioner loads and the interruptible loads are determined according to the customers' requirements and historical statistic data.

Step 3) Interruptible loads are grouped by statistical analysis according to the control characteristics.

Step 4) Customers' settings of the interruptible load groups are calculated by applying the demand control, timer control, and cycling control policies.

Step 5) The RDP algorithm is used to obtain a near optimal pre-scheduling in the LCS.

Step 6) The interruptible air conditioner loads control is performed according to the optimization strategy during the peak load periods of interest.

Step 7) Energy payback ratio and system uncertainties are considered to modify the control policy.

a) The pre-scheduling of interruptible load is fed for the preliminary control.

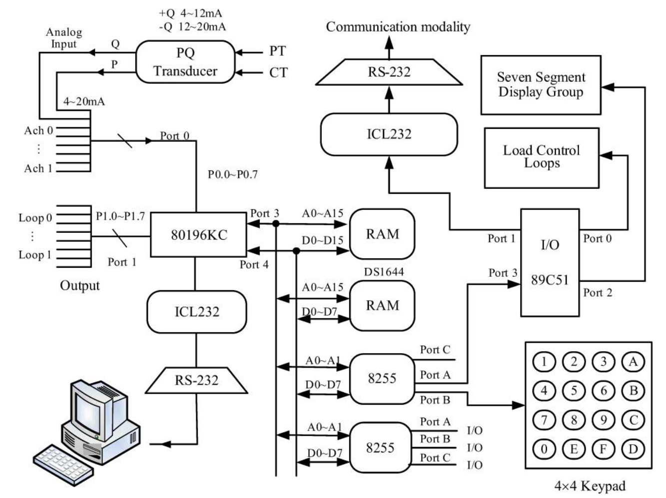

Fig. 5. Overview block diagram of the LCS.

Fig. 6. Picture of LCS under processing.

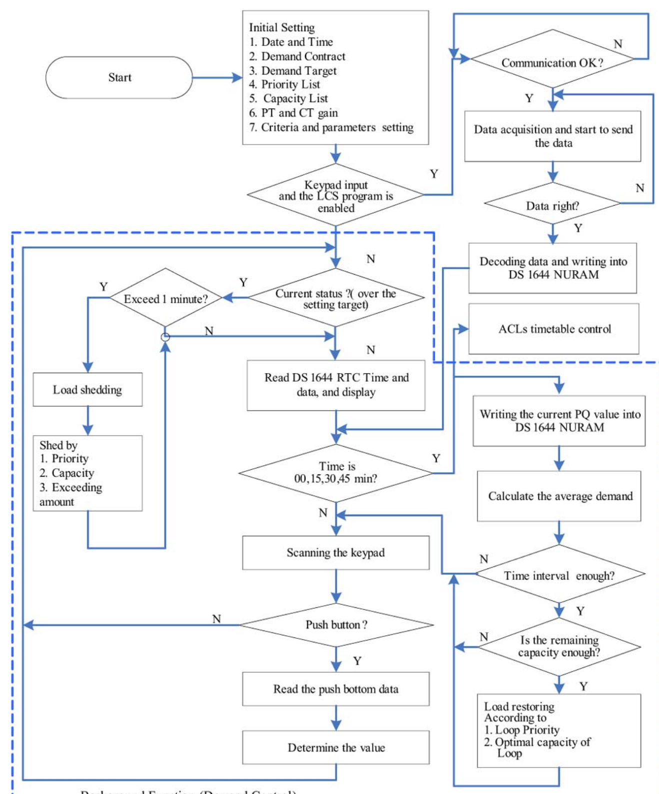

Fig. 7. Flowchart of the proposed algorithm software design.

b) The output errors between the real system and the pre-setting value of LCS are monitored through the signal P from PQ transducer.

i) If the error signal $D_{\rm err}(i)$ is positive, then the interruptible load groups be selected are interrupted in real-time according to the optimization strategy to compensate for the capacity shortages.

ii) If the error signal $D_{\rm err}(i)$ is negative, then the interruptible load groups are not interrupted to maintain the optimal results of RDP.

iii) The control results are fed back to the LCS in the next control period.

Step 8) Scheduling procedure continued until the control period is over.

A. Hardware Circuit

As seen from the overview block diagram of the load control scheduler in Fig. 5, this work was developed on a 16-bit microprocessor using the P and Q signals from the power transducer according to the requirement and function related to design the layout of the load control scheduler. We initiated the processing with forecasted load data, and we then corrected the uncertainties by the real P and Q signals to fit the real situation. Due to the limited numbers of I/O bus of a microprocessor, the decoded circuit, which consists of digital ICs, is used to expand I/O bus numbers to support peripheral interfaces (such as keypad, display, etc). The scheduler utilizes a built-in 10-bit A/D converter to convert the P and Q 4–20-mA analog signals into digital signals. The system then uses a peripheral interface *via* an interruption technique to drive an LCD monitor for synchronous display. Moreover, it provides one RS-232 serial port to connect the PC to download the LCS program setting. A picture of the LCS under case study is shown in Fig. 6.

B. Software Program

The core of the scheduler is coded by machine language for speeding system implementation. Planning of the fundamental functions involved power demand supervision, the load shedding/restoring control, computing the 15-min average of P and Q signals, and then storage of them in the corresponding memory (RAM); therefore, scanning any input actuated by the keypad and using the value for setting parameters, and then displaying the data using the LEDs, etc. Fig. 7 shows a flowchart of the main program. The background program is operated on the demand control strategy, whereas the load control scheduler is regarded as a demand controller when the external control mode is disabled. Then, the loops-priority method is adopted as the dispatch approach of ACL groups to restrain the power demand to prevent exceeding the setting target. Otherwise, according to the planning specifications, the communication between PC and the LCS is *via* an RS232 serial port.

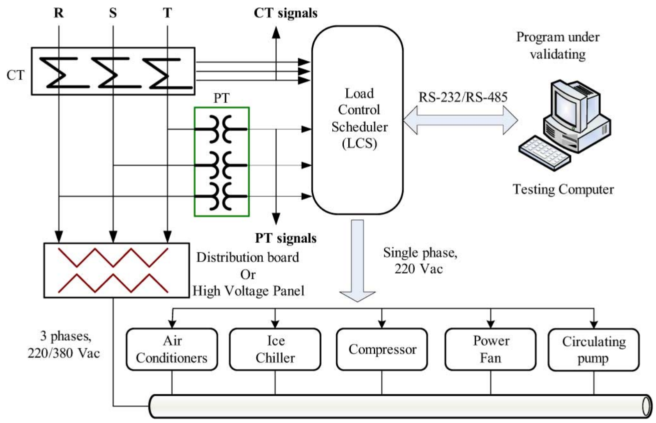

Fig. 8. Block diagram of the on-site testing model.

TABLE I
CHARACTERISTICS OF THE 16 ACL GROUPS

Load group no.	Load capacity (kW)	Total	First item	Second item	Third item	Maximum off-time	Minimum off-time	Minimum on-time
		Energy payback ratio (%)				(15min/scale)		
#1	60	97	43	35	19	3	1	5
#2	50	103	44	32	27	2	2	5
#3	40	100	43	33	24	3	2	5
#4	50	104	46	34	24	1	1	4
#5	30	101	42	32	23	2	2	4
#6	40	103	47	36	20	2	2	4
#7	20	95	45	35	15	2	1	3
#8	25	96	38	28	20	2	1	3
#9	25	99	47	33	19	2	1	2
#10	30	95	45	35	15	2	1	2
#11	20	100	44	33	23	2	1	2
#12	25	105	45	38	22	2	1	2
#13	15	98	46	32	20	1	1	2
#14	15	94	42	32	20	1	1	2
#15	27	107	47	30	30	2	1	2
#16	20	105	45	30	25	1	1	2

The MODBUS protocol format defines packages, with the control commands coming from the control PC. The communication program of the PC uses the stored results of the LCS to automatically map the ACL on–off scheduling during each 15-min stage.

VI. CASE STUDY

A. Case Example

Field tests of controlling air conditioners located in the campus of National Kaohsiung University of Applied Sciences, Kaohsiung, Taiwan, were tested on-site to demonstrate the effectiveness of the proposed load control strategy. Fig. 8 shows the model with 16 ACL groups was tested on-site practically. The case is also performed through the conventional DP for validating the usefulness of the RDP. The maximum off-time allowed and the minimum on-time required were given different values among the groups. Table I shows the characteristics of the ACL groups in which the dispatch objective target and related variables are given specific values among the groups, and the energy payback items are also included. During the controlling off period of air conditioner, the space temperature will rise to a higher level on a number of factors such as location, weather, environment conditions, surrounding temperature, efficiency of air conditioners, start and stop time of control, control intensities, etc. Therefore, in the next controlling on period of air conditioner, the load demand of air conditioner will be increased depending on the situation of those just mentioned. Consequently, it will cause a divergent requirement for the operation of the on–off duration.

In order to satisfy the customers, the best ranges for on–off duration are set at 15–90 min based on a questionnaire investigation. The historical data show that the daily load of the substation, maximum peak demand requirement, occurred between 10:00 h and 12:00 h, and between 14:00 h and 17:00 h during the summer season in the past few years. In addition, the average load forecasted errors within the peak load periods in the past years are given by the historical statistical data. The maximal positive error is 3.5% and the maximal negative error is 4% around the predicted loads, and they will be considered in the relaxed loose parameters setting and software programming for initial reference. In practice, planning of the scheduler fundamental functions involves power demand supervision, the load shedding/restoring control, computing the 15-min average of P and Q signals, and then storage in the corresponding memory (RAM). Signal P is used as the real-time control index to adjust the optimal solution on time and to ensure the accuracy of the operation. Signal Q is used for reactive power monitored for taking statistical information for the further VAR compensating advisement and to ensure the efficiency of the system.

In practice, the LCS period is first divided into a number of intervals, each of which is defined as a stage. In each stage, a number of state-sets are given. In order to improve the efficiency of the program, we set each stage of the RDP structure of the ACL scheduling at 15 min, divided into 96 stages with the same condition of DP. Each stage consists of the combination of the on–off status of ACL groups and is further divided into 21 state-sets. Each state-set consists of 100 states with the same load level. It means that the states in the same state-set have the same objective value of the load error. A quasi-membership function was established to fine-tune the load forecasting errors and energy payback phenomenon. In each stage, the values of the quasi-membership functions for the 21 state-sets vary from 1.06 to 0.86 in decrements of 0.01 to simulate the range from the upper bound $\bar{\alpha}l$ to the lower bound $\underline{\alpha}l$ around the predicted load level to suit the constraints and to reduce the dimension expense. A state in each stage (2100 states per stage in total) stands for the combinations of the on–off status of the ACL groups. There are $2^{16}(65\,536)$ status combinations in each stage for the 16 ACL scheduling problem that were used in the conventional DP processing. Simulation-executed on a Pentium-IV (2.6-GHz) computer, the programming in Visual C^{++}was linked with the software for LCS. The average execution time needed was 2.68 s. The other testing run for conventional DP was taken as 13.01 s on average.

In this case, the energy saving ratio is set at 25% of the maximum interruptible capacity (4881 kW) in the studying day, which is equal to 1220 kWh and the demand control target value is set at 2250 kW subject to the demand contracts. The system characteristics are shown in Table II. The solution, therefore, can be improved by the relaxed value iteration. Moreover, the objective of the load reduction pattern can be obtained by the load nearly in those over loading period minus the safe margin,

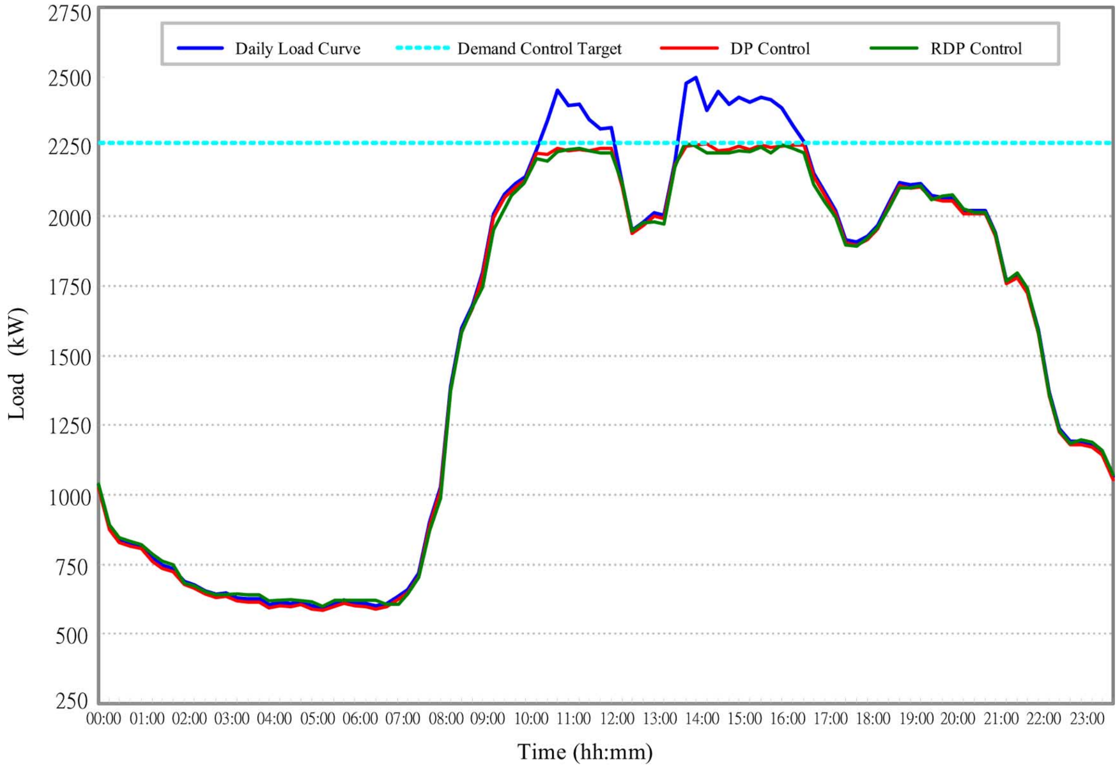

Fig. 9. Load patterns after/before control of DP and RDP schedule.

TABLE II
SYSTEM CHARACTERISTICS OF THE CASE STUDIED

Items	System characteristics
Maximum interruptible capacity of the day	4881 kWh
Energy saving ratio (of interruptible capacity)	25%
Energy saving target	1220 kWh
Demand control target	2250 kW

TABLE III
RESULTS OF THE CASE STUDIED

Algorithm	Summation of reduction load (kWh)	Execution time (sec)
RDP	1260	2.68
DP	1240	13.01

TABLE IV
TIMETABLE OF ACL GROUPS FOR TIMER CONTROL

Time	Stage no.	Load demand (kW)	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15	#16
09:00	37	1766	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	0
09:15	38	1974	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	0
09:30	39	2048	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	0
09:45	40	2084	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	0
10:00	41	2108	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	0
10:15	42	2207	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	0
10:30	43	2311	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	0
10:45	44	2421	1	1	1	1	1	1	0	1	1	0	1	1	0	1	1	0
11:00	45	2365	1	1	1	1	1	1	0	0	1	0	1	1	0	0	1	0
11:15	46	2368	1	0	1	1	1	1	0	0	1	0	1	1	0	0	1	0
11:30	47	2315	1	0	1	1	1	1	0	0	1	0	1	1	0	0	1	0
11:45	48	2281	1	0	1	1	1	1	0	0	1	0	1	1	0	0	1	0
12:00	49	2284	1	0	1	1	1	0	1	0	1	0	1	0	1	0	1	0
12:15	50	2085	1	0	0	1	1	0	1	0	0	0	1	0	1	0	1	0
12:30	51	1918	1	0	0	1	1	0	1	0	0	0	1	0	1	0	1	0
12:45	52	1984	1	0	0	1	1	0	1	1	0	0	1	0	1	0	1	0
13:00	53	1981	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0
13:15	54	1971	0	1	0	1	1	0	1	1	0	0	1	0	1	1	1	0
13:30	55	2163	0	1	1	1	1	0	1	1	0	0	1	0	1	1	1	0
13:45	56	2445	0	1	1	1	1	0	1	1	1	0	1	0	1	1	1	0
14:00	57	2466	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0
14:15	58	2349	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0
14:30	59	2416	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0
14:45	60	2370	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0
15:00	61	2392	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0

1 : on-status 0 : off-status

2250 kW. The final results are shown in Table III, the goals are achieved by two algorithms, and the demand control curves are just closely to the trajectory of the peak load. In additional, Fig. 9 exhibits the load variation of the case studied before and after controlled by the LCS during one day period.

B. Numerical Results

A timetable can be built to gather the information of the timer control scheduling, which is shown in Table IV. Table V lists the on–off status of each ACL unit at time-points throughout the day by using different colors and symbols. The results show that the optimum control scheme achieves better energy savings than each of the regular control modes under the same operating conditions. Obviously, the very peak load was reduced by the LCS that follows closely its trajectory. Resulting from the peak load reduction, the operational cost decreased by controlling the load shedding/restoring to achieve electricity cost saving for the total NT$394 090 with a cost reduction rate of 4.78%. Details of the benefits are shown in Table VI, which demonstrate that the results indeed achieve the goals of peak load reduction and cost saving with intensive rate and customer satisfaction considered.

Fig. 9 presents the results of the load controlled using DP and RDP schemes. The figure reveals that the peak load between period of 10:00 to 12:00 and period of 13:30 to 17:00 are indeed shaved by the LCS. It achieves the goal of energy saving with efficient computational time and less memory requirement. However, the energy payback phenomenon generates the second peak loads are all taken into account during the

TABLE V
RDP SCHEDULING RESULTS FOR THE CASE STUDIED

hh:mm	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15	#16
10:15	Δ	Δ	*	*	*	○		*	*		*	*		*	*	
10:30	Δ	Δ	*	*	*	○		*	*		*	*		*	*	
10:45	Δ	Δ	Δ	Δ	*	*		*	*		*	*		*	*	
11:00	Δ	Δ	Δ	*	Δ	*			*		*	*			*	
11:15	Δ		Δ	Δ	Δ	*			*		*	*			*	
11:30	Δ		Δ	*	*	*			*		*	*			*	
11:45	Δ		*	*	*				*		*	*			*	
12:00	Δ		*	*	*		*		*		*		*		*	
12:15	*			○	*		*				*		*		*	
12:30				*	○		*				*		*		*	
12:45				*	○		*				*		*		*	
13:00		*		*	*		*	*			*		*	*	*	
13:15		*		*	*		*	*			*		*	*	*	
13:30		*	*	○	*		*	*			*		*	*	*	
13:45		Δ	Δ	Δ	Δ		Δ	Δ			*		*	*	*	
14:00	Δ	Δ	Δ	Δ	Δ		*	*	*		*	*	*	*	*	
14:15	Δ	Δ	Δ	*	*	*	*	*	*		*	*	*	*	*	
14:30	Δ	Δ	Δ	Δ	Δ	*	*	*	*		*	*	*	*	*	
14:45	Δ	Δ	Δ	*	Δ	*	*	*	*		*	*	*	*	*	
15:00	Δ	Δ		Δ	*	*	*	*	*		*	*	*	*	*	
15:15	Δ	Δ		Δ	*	○	*	*	*		*	*	*	*	*	
15:30	Δ	Δ		Δ	*	○	*	*	*		*	*	*	*	*	
15:45	Δ	Δ		Δ	*	*	*	*	*		*	*	*	*	*	
16:00	Δ			Δ	Δ	*		*	*	*	*	*		*	*	
16:15	Δ			*	Δ	*		*	*	*	*	*		*	*	

* : On-status space : Off-status Δ : Demand control ○ : Cycling control

TABLE VI
BENEFICIAL RESULTS FOR RDP AND DP

Control mode	Daily peak demand	Peak load restriction	Savings in electricity costs ($/year)		
	Restriction (%)	(kW)	Basic charge	Current charge	Total
Demand control	2–5	140–230	215,100	65,500	280,600
Timer and cycling control	2–3	23–71	105,700	127,500	233,200
DP load control	3–12	32–253	231,450	161,830	393,280
RDP load control	3–12.3	32–253	231,450	162,640	394,090

system operation. Moreover, it shows the load patterns for comparison. Observing the results reveal that, in the case studied, although the performance of the proposed RDP-LCS might just a nearly optimal solution or with the same optimal solution than DP, but reflecting a trade-off between the memory requirement and computational time consumption for realistic cases. Fortunately, they are the top items considered on the real-time controlled modalities for practical applications.

VII. CONCLUSION

We have formulated the RDP online scheduling problem into an LCS to obtain the control policy. The optimal or near-optimal online scheduling policy has been tested in a case studied involving control of 16 large air conditioners. The following conclusions can be drawn.

1) The approach is compared to a preliminary DP approach in the case studied involving control of the same ACL group with almost the same results within the optimal solution searching.
2) The computational scheme aids customers in restraining peak load demand and in saving electricity costs more effectively in an online LCS.
3) ACL customers can select the optimum control mode flexibly in accordance with actual situations, which depend on the systems uncertainties.
4) RDP algorithm is also suitable for the solution of problems with other types of load control operation in the future due to its reasonable results, fast calculation speed, and less memory requirement.
5) The Tai-Power Company can use the online LCS to aid in executing various load management projects and dispatch schemes to solve shortages in electricity supply during the summer season.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for helpful comments on the original manuscript and to Mr. C.-N. Chen for his contributions on the prototype of LCS.

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