GLOBAL OPTIMISATION OF CHILLER SEQUENCING AND LOAD BALANCING USING SHUFFLED COMPLEX EVOLUTION

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ABSTRACT

A new model has been developed to optimise the sequencing and load balancing of chillers in the central plants of commercial buildings with multiple water-cooled chillers. The model uses the Shuffled Complex Evolution optmisation algorithm to minimise the total energy consumptions of chillers and pumps by maximising the whole system (central plant) coefficient of performance under a known discrete cooling load. Two commercial buildings in Melbourne’s CBD were simulated as case studies to assess the validity and effectiveness of the model. The control strategies identified by the model performed better than the existing configuration in both cases, reducing energy consumption by 12.2% and 16.6% when compared to the observed energy data for 2016.

INTRODUCTION

Chiller sequencing in commercial buildings is typically controlled as a function of return chilled water temperature using Proportional-Integral (PI) loops. This method uses return chilled water temperature from the building as a proxy for cooling load. If the temperature increases above the set point for a specified time then an additional chiller will be activated. A typical switch-on/off thresholds for return chilled water temperature-based (T-based) sequence control are listed in Table 1.

Switch-on thresholds	Switch-off thresholds
From 1 chiller to 2 chillers: $T_{rtn} > 11.94$ □C	From 2 chillers to 1 chiller: $T_{rtn} < 9.28$ □C
From 2 chillers to 3 chillers: $T_{rtn} > 11.85$ □C	From 3 chillers to 2 chillers: $T_{rtn} < 10.10$ □C
From 3 chillers to 4 chillers: $T_{rtn} > 11.81$ □C	From 4 chillers to 3 chillers: $T_{rtn} < 10.51$ □C
T_{rtn} = Temperature of return chilled water from the building	

Table 1. *Thresholds used in a typical return water temperature-based control for four identical chillers (Adapted from Liao, Sun & Huang 2015)*

While T-based chiller sequence control could provide adequate thermal comfort, it may not operate the central plant equipment at maximum energy efficiency. The return chilled water temperature is an indirect indicator of the cooling load (Huang, Zuo & Sohn 2016), which may not be proportional to the cooling load (Sun, Wang & Xiao 2013). Since the development of variable speed centrifugal compressors and magnetic bearings, the part load efficiencies of chillers have been increased significantly (Yu, Chan & Sit 2017). Central plant simulation and optimisation is becoming more widely adopted, taking advantage of the part load efficiency of this new generation of variable speed chillers (Liu et al. 2017).

There are various 'black box' central plant optimisation controls available in Australia. Many of these systems are developed by chiller manufacturers with extensive knowledge of their product (Carrier 2017). The need exists for a generalised method to model, simulate and optimise chiller sequencing and load balancing which can be applied to any types of chillers. To address this a new model has been developed to simulate the performance of the central plant and a genetic optimisation algorithm has been applied to maximise the system energy efficiency.

The Shuffled Complex Evolution (SCE) algorithm is a method for global optimisation using "a combination of probabilistic and deterministic approaches; clustering; systematic evolution of a complex of points spanning the space, in the direction of global improvement; and competitive evolution" (Duan, Sorooshian & Gupta 1992). This method is widely used in hydrological models but does not appear to have been applied to the optimisation of chillers in central plants. Using this algorithm to minimise central plant energy consumption will ensure the lowest operating cost.

1. METHOD

Two buildings in Melbourne's CBD were selected to be simulated. Both central plants have the configuration shown in Figure 1, consisting of one low load and two high load water cooled centrifugal chillers. Building One has Smardt-PowerPax chillers (1 x 286 kW_r and 2 x 988 kW_r) with Kiltech chiller optimisation software and Building Two has Carrier chillers (1 x 1100 kW_r and 2 x 2260 kW_r) with no optimisation software. Each chiller has a dedicated primary chilled water and condenser water pump. Both buildings have Alerton building management systems which record data. Six months of trend logs were used to calibrate the model. All pumps and chillers are variable speed and each chiller has a flow meter installed on the chilled water pipe. Chillers were identified as the most significant energy users in both central plants. To simplify the model, pump speed is estimated as a function of chiller loading and energy consumptions by cooling towers have been excluded.

1.1 Chillers

Trend log data that was collected from the Alerton BMS systems in each building was used to calculate the chiller cooling capacity, $\dot{Q}_r$ [kW_r] using Equation (1) (Abou-Ziyan & Alajmi 2014).

$$\dot{Q}_r = \dot{m}_{\mathrm{cw}} c_w (T_i - T_o) \tag{1}$$

where, $\dot{m}_{\mathrm{cw}}$ is the mass flow rate of the chilled water [kg s^{-1}], c_w is the specific heat of chilled water [kJ $kg^{-1}K^{-1}$] and T_i and T_o are the inlet and outlet chilled water temperatures [°C] across the chiller.

Regression analysis was conducted correlating chiller cooling capacity, $\dot{Q}_r$ [kW_r] to electrical power consumption P [kW_e]. This produced values for the coefficients *a* and *b* for each chiller which was used to simulate chiller performance in the form of Equation (2).

$$\dot{Q}_r = \mathrm{a}P + \mathrm{b}P^2 \tag{2}$$

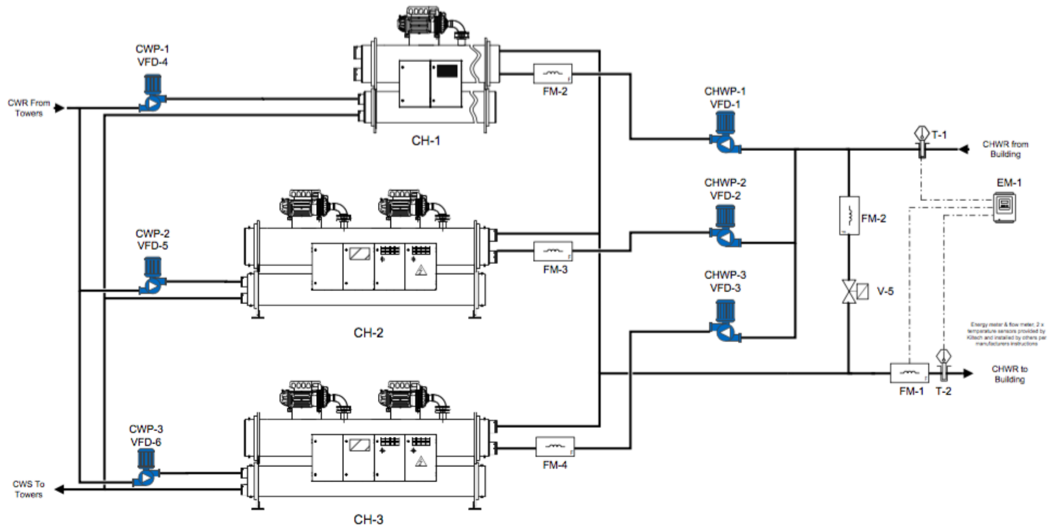

Figure 1. *Central plant chiller configuration, where CH= Chiller, CWS= Chilled Water Supply, CWR= Chilled Water Return, CWP= Condenser Water Pump, CHWP= Chilled Heating Water Pump, VFD= Variable Frequency Drive & FM= Flow Meter*

Table 2 shows the coefficients *a* and *b* of the regression analysis for each chiller model including the goodness of fit. Figure 2. shows the scatterplot and regression line for Chiller 2.

Chiller #	Input Power $[kW^e]$	Nominal Capacity $[kW^r]$	a	b	R^2
1	59	289	8.7957	-0.0699	0.9236
2	178	988	8.8461	-0.0185	0.9224
3	163	1100	7.5258	-0.0049	0.8109
4	440	2260	7.6445	-0.0057	0.8765

Table 2. *Results of chiller regression analysis*

Residual analysis was conducted (Figure 3.) indicating that the regression equation may underestimate the chiller cooling capacity [kW_r] at high loads (>75%) and overestimate at low loads (<10%). The overestimation of the chiller cooling capacity at low loads can be ignored as all chillers were assumed to operate at part load ratios greater than 10% (maximum turndown ratio of 10:1) to avoid the centrifugal compressor surging.

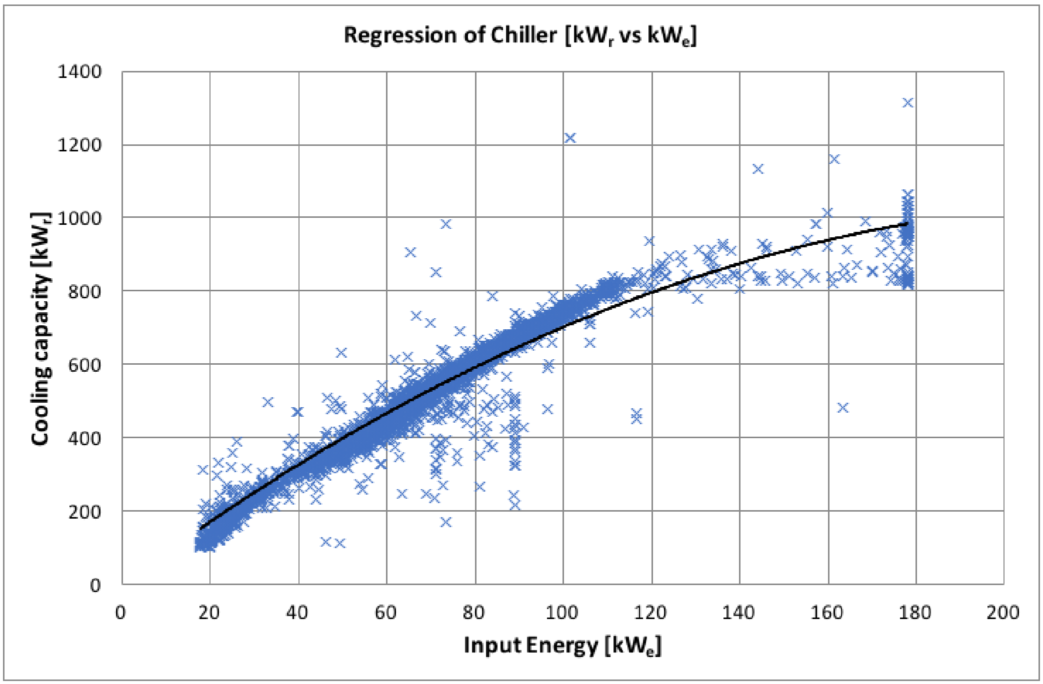

Figure 2. *Regression of chiller cooling capacity and input power*

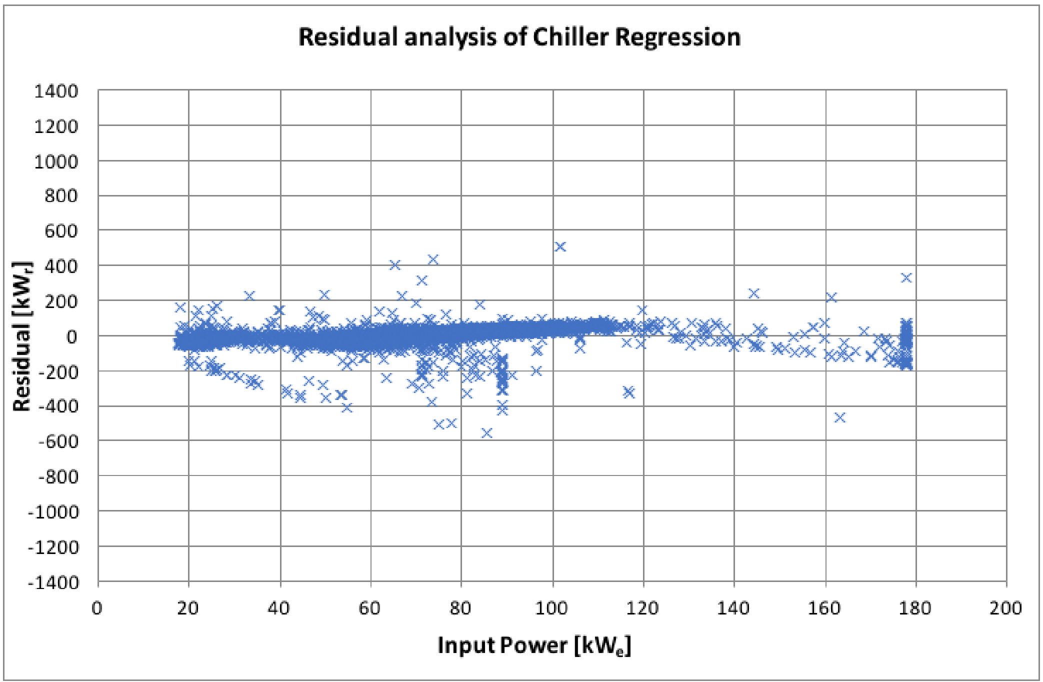

Figure 3. *Residual analysis of chiller regression*

1.2 Pumps

Building commissioning documentation provided the pump motor rating [kW$_e$], minimum flow rate [L s^{-1}], design flow rate [L s^{-1}] and maximum flow rate [L s^{-1}] for each condenser and chilled water pump. At minimum chiller loading (10%) pumps were assumed to be operating at the minimum flow rate as specified in commissioning records. For the purpose of simulation pump flow rate was assumed to increase linearly with chiller loading, reaching design flow rate when the chiller is operating at maximum capacity. Pump laws were used to calculate the power consumption of pumps operating at part loads, shown in Equation (3) (AIRAH Handbook 1995).

$$P_2 = P_1 \left(\frac{\dot{V}_2}{\dot{V}_1}\right)^3 \tag{3}$$

where, P is pump power [kW_e] and $\dot{V}$ is the volumetric flow rate of water [$L\ s^{-1}$].

1.3 Cooling load profiles

Figure 4. is an example of the daily cooling load profile of each building, showing the estimated cooling loads for January 11th, 2016. The cooling loads for each building were calculated using energy meter data and Equation (2), producing a 15-minute cooling load for each building. Building One's central plant was operational from 6:45 am to 6:30 pm and Building Two's central plant was operational from 6.30am to 7.15pm.

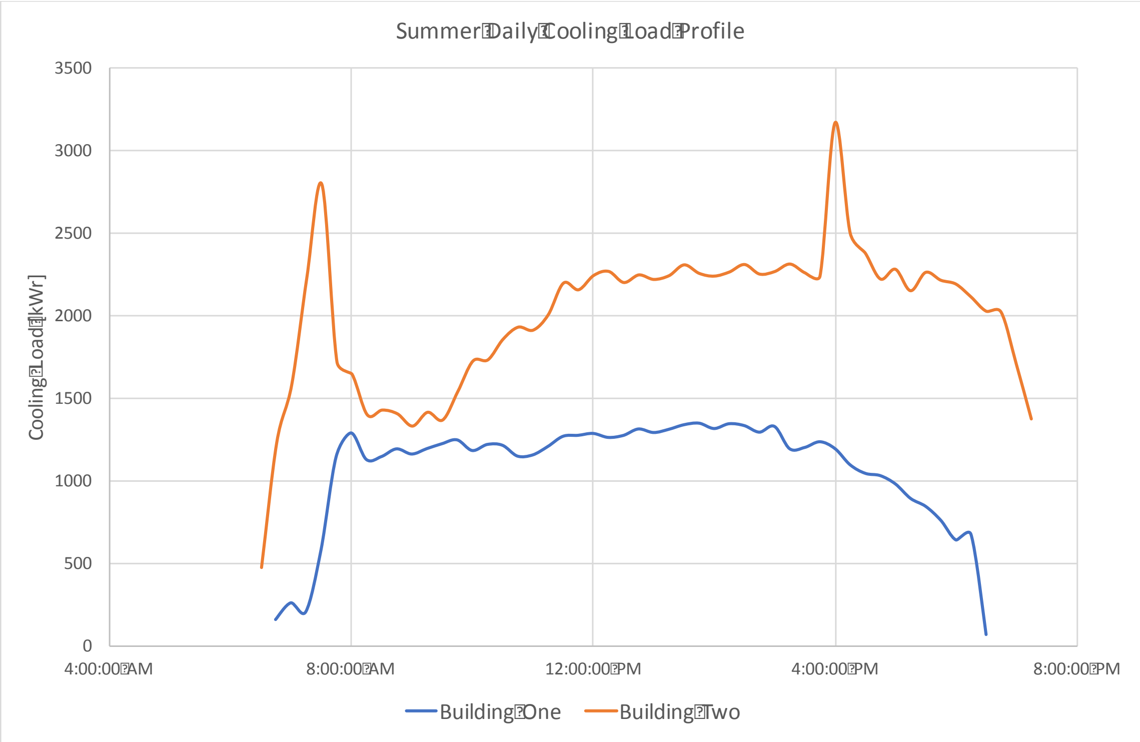

Figure 4. *Typical summer daily cooling loads*

In 2016 Building One experienced a maximum cooling load of 1806 kW_r and Building Two experienced a maximum cooling load of 3418 kW_r. The new control strategy for Building One was calculated for cooling loads up to 1825 kW_r at 25 kW_r intervals and for Building Two up to 3450 kW_r at 50 kW_r intervals. Building One has 14 floors and Building Two has 26 floors.

1.4 Shuffled Complex Evolution parameter settings

The Shuffled Complex Evolution (SCE) algorithm was used to optimise the overall efficiency of the simulated central plants. The input power, P [kW_e] for each chiller is represented as a parameter to be optimised by the algorithm, so both models had 3-degree of freedom given there are three chillers in each central plant. The objective function to be minimised was defined as the total energy consumption (chillers and pumps) that would deliver the chiller cooling capacity to meet the specified building cooling load. The chiller cooling capacity, $\dot{Q}_r$ [kW_r], for a given P [kW_e], was estimated using Equation (2) and the unique coefficient set a and b for each model of chiller.

Numerical testing was conducted to determine the appropriate settings for the SCE algorithm that produce reproducible estimates of the optimal model parameters (Peterson & Western 2014). The settings shown in Figure 5. were tested by selecting a reference cooling load for each building and repeating the optimisation 10 times. The settings were found to produce highly consistent parameter values across the ten trials. This is strong evidence that the settings reliable identify the global optima.

```
% Set shuffled complex evolution constants
maxn = 1e+10;
kstop = 30;
pcento = 1e-10;
peps = 1e-10;
ngs = 50;
```

Figure 5. *SCE parameter settings*

To test the effectiveness of the model outcome, the control strategy was applied to the cooling loads experienced by each building in 2016. To avoid overstating the energy savings of the modelled control strategy, cooling loads were rounded up to the next lowest discrete value which had been modelled and optimised. For example, in Building One for a calculated cooling load of 960 kW_r the optimised chiller input powers for a 975 kW_r were selected.

2. RESULTS

A sample of the model outputs for Building Two shown in Table 3 shows the optimised chiller loadings for a range of cooling loads. The nature of the objective function resulted in the optimal system coefficient of performance. The results of the modelled control strategy compared to the measured energy data for each building central plant are shown in Table 4. The modelled control strategy resulted in a reduction in energy consumption of 12.2% for Building One and 16.6% for Building Two. The reduction in chiller energy consumption for Building One, 4.8%, compared to Building Two, 12.7%, is likely lower due to the system having optimised control software from Kiltech. The assumption that pump speed is a linear function of chiller loading may have been an oversimplification which may cause the pump energy savings to be overestimated. Chillers require a manufacturer specified pressure drop across each compressor to function (Hartman 2001). Detailed investigation of the required pump speed to deliver an adequate pressure drop across the chiller for a range of loads would improve the simulation accuracy.

Cooling load [kW^r]	Central plant COP	Chiller 1 [kW^e]	Chiller 2 [kW^e]	Chiller 3 [kW^e]	Pumps [kW]
250	6.17	35.28	0.00	0.00	5.25
500	6.32	72.43	0.00	0.00	6.71
750	6.23	111.76	0.00	0.00	8.64
1000	6.11	53.24	87.83	0.00	22.68
1250	6.16	72.51	106.50	0.00	23.94
1500	6.16	92.39	125.76	0.00	25.36
1750	6.13	112.95	145.68	0.00	26.95
2000	6.12	72.54	106.52	106.52	41.18
2250	6.13	85.83	119.41	119.41	42.44
2500	6.12	99.43	132.59	132.59	43.79
2750	6.10	113.06	146.24	146.24	45.22

Table 3. *Model output, control strategy for Building Two*

Building One's control strategy was unknown, as Kiltech operates a 'black box' optimisation platform. Through analysis of the energy data it was found that the low load chiller was rarely used, with the modelled control strategy increasing its usage by 421%. All three chillers would also rarely function together, even at high loads. This is another significant difference in the modelled strategy, using more chillers at part load to take advantage of higher efficiencies.

The control strategy in Building Two is return chilled water temperature based, although the set points for staging were not known. The sharp increases in the cooling load shown in Figure 4. suggest that there may be integral windup in the current control mechanism (Shaunak & Thirunavukkarasu 2014). The new control strategy is based off instantaneous cooling load would negate integral windup, possibly leading to further savings.

Building One	Chillers [kWh]	Pumps [kWh]	Total [kWh]
Measured 2016	101,720	34,322	136,042
Modelled with new control strategy	96843	22,600	119,433
% Savings	4.8%	34.2%	12.2%
Building Two			
Measured 2016	169,848	30,277	200,125
Modelled with new control strategy	148,268	18,683	166,952
% Savings	12.7%	38.3%	16.6%

Table 4. *Comparison of existing control strategy and model output*

To visualise the model response to input variable changes, Figure 6. shows the response curve of central plant cooling coefficient of performance (COP) for a range of chiller loadings. The left panel shows the change in loads with one high load chiller set to 50% and the right panel at 100%.

The response surface is smooth in both cases with clear global optima, indicating a less complex numerical optimization method such as gradient decent may be sufficient to find the global optima (Vakiloroaya, Ha & Samali 2014).

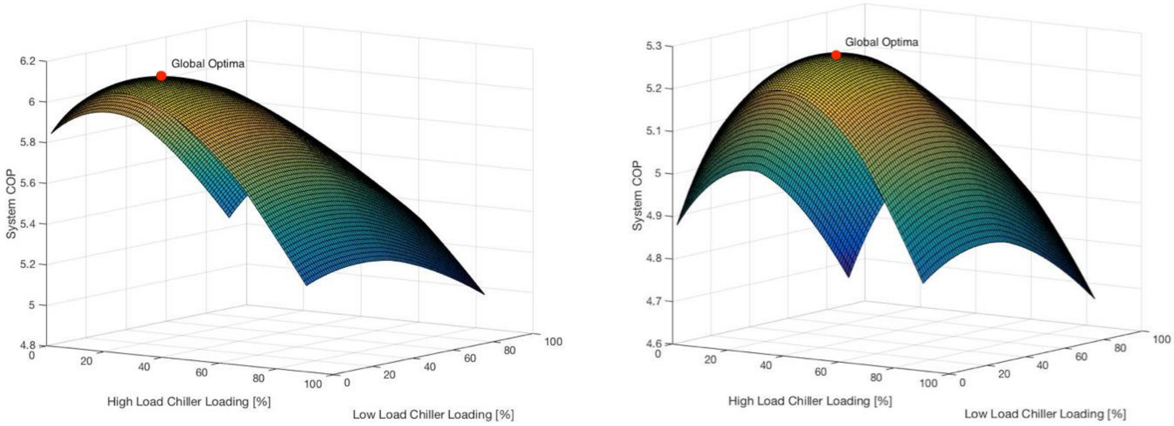

Figure 6. *Response curve, Central plant cooling COP vs Chiller loading (%)*

CONCLUSION

This paper has demonstrated that the numerical optimisation of a cooling control strategy can achieve a reduction in energy usage of 12.2 to 16.6%. The simulation of central plant equipment may have oversimplified the required pump speed, potentially leading to an overestimation of energy savings for pumps. This can be addressed by a detailed study of the relationship between pump speed and pressure drop across each chiller, improving the accuracy of the model. The SCE algorithm used for optimisation of chiller loading consistently converged to the global optima for the range of cooling loads experienced by each building in 2016. Applying the control strategies presented in the paper across the commercial sector in Australia could result in a reduction 31.1 PJ of energy consumption (Office of the Chief Economist, 2014).

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