Application of artificial intelligence (AI) control system on chiller plant at MTR station

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ABSTRACT

Chillers account for up to 40% of total station energy consumption in the Hong Kong Mass Transit Railway (MTR) system. As part of green railway initiatives, a site trial was conducted to apply a fully automated AI system to control a chiller plant in order to optimise energy performance in real time while maintaining a level of passenger comfort that suits each station's environment. Through the predictive power of the AI system, the plant power's consumption and cooling demands can be forecasted based on actual chiller, station, and weather conditions, all of which vary over time. The optimal operational settings can then be determined using an optimisation model for real-time chiller plant control, including staging, sequencing, chilled water supply temperature set-point, etc. This paper presents the formulation of an AI system using data-driven machine learning models and numerical optimisation, and the comparison of the actual energy performance of the proposed system against rule-based control optimisation in a conventional building management system (BMS) through the site trial. The results revealed the proposed AI system achieves better energy efficiency with annual energy savings of approximately 8.7%.

KEYWORDS Artificial intelligence; machine learning model; chiller plant; optimisation; railway; energy saving; smart chiller
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1. Introduction

The MTR in Hong Kong comprises 240.6 km of railway network with 97 heavy rail stations (MTR Corporation Limited, 2021). Reducing energy consumption and improving energy efficiency throughout operations is MTR's key carbon reduction measure (MTR Corporation Limited, 2020). Heating, ventilation and air conditioning (HVAC) systems often account for almost half of a building's electrical consumption (Pérez-Lombard et al., 2008). The HVAC system that contributes most to energy consumption is the chiller plant, accounting for up to 40% of total station energy use during summer. Various energy optimisation initiatives are in place, including the retrofitting of chillers plants into more energy efficient types (e.g. variable speed chillers, oil-free chillers), conversion of air-cooled chillers into water-cooled, plant operation optimisation through building management system (BMS) upgrades, etc.

BMS is an essential tool to integrate an HVAC system and manage its demand with optimised energy consumption. However, the BMS control logics most commonly adopted in the market are rule-based, and use feedback based on real-time data. The adaptability of such feedback systems against varying station environments, weather, and chiller conditions under a responsive approach might result in overcooling or overheating. Moreover, a plant's overall energy efficiency also depends on its actual operational performance at different part-load conditions and individual chiller characteristics on site that vary over time, calculations which is too complex to be handled by conventional rule-based control logics. Although manual adjustment on BMS parameters can be done during the retro-commissioning process, it is discrete, crude, and requires tremendous analysis of environmental factors and system data to customise optimal settings for each individual station at different times of day. Frequent human intervention to manually adjust the settings of chiller plants at various stations can be avoided by automating the process.

Advancement of the AI system and its ease of integration with BMS has enabled continuous data analysis and the use of self-developed software to provide optimal and real-time control parameters for operating chiller plant using machine-learning and AI algorithms (O'Grady et al., 2021). A vast amount of data is stored and continuously logged in the BMS to be analysed and translated into useful knowledge about system characteristics, potential energy savings and insights (Yu and Chan, 2012). A fully-automated AI-controlled BMS system with fast computational power can be used to predict and minimise the cooling demand and power consumption in a pre-planned manner, such that the operational pattern (e.g. staging, sequencing, temperature setpoints, etc.) of chillers can be pre-planned and implemented automatically to optimise energy consumption while maintaining the comfort level in the station.

Since 2019, a trial project has been underway to deploy an AI control system, on top of BMS with rule-based energy optimisation, to operate an air-cooled chiller plant at the Sha Tin railway station. This paper describes the methodology and application of the AI control system on the chiller plant and its performance in comparison with BMS under the project.

2. Literature review of chiller optimisation techniques

Chiller optimisation can be posed as a two-stage model (Chen et al., 2014):

- Power prediction models are built to predict chiller performance.
- An optimisation algorithm searches for the parameters with the lowest power prediction.

Power prediction models can be trained using various modelling techniques, including linear multiple regression (Yu and Chan, 2012), neural network (Chen et al., 2014) and gradient boosting trees (Touzani et al, 2018), as well as a generalised additive model (Hastie and Tibshirani, 2017), an extension of linear modelling with splines. Particle swarm optimisation (PSO) (Kennedy and Eberhart, 1995) can be applied to the problem without smoothness or convexity consumption as the numerical optimisation in the chiller optimisation problem is non-smooth and non-convex.

Single-stage end-to-end training is also possible where the control output is generated directly from the input parameters. Leurs et al. studied a small cooling system with a typical power consumption of 1 kW and the complexity of the control consisted of one binary parameter (2016). The following are the obstacles in applying the end-to-end approach to real-world scenarios (Li et al., 2020):

- Hyper-parameter tuning needs to be done on models for different cases and configurations, and thus the resulting simulation cannot be transferred directly to real-world scenarios.
- Clean data is required to make control decisions.
- Certain scenarios might not be encountered in the historical data.

Hence, this study considered the two-stage approach (Chen et al., 2014) as it is simpler to implement when compared to the end-to-end approach in a large-scale chiller plant system.

There are three main contributions in this paper. First of all, different machine learning approaches are compared: a generalised additive model, gradient boosted decision trees and neural networks. Second, the chiller plant energy problem is formulated as a numerical optimisation problem that can be solved with a PSO algorithm. Finally, the algorithm is put into operation for one year in an operating chiller plant, with the savings evaluated with a statistical t-test.

3. Proposed chiller plant optimisation approach

A chiller plant at the Sha Tin railway station was selected for the site trial. This plant serves the public and back of house areas, and represents a typical medium-scaled air-cooled chiller plant. The plant consists of four chillers (with a total cooling capacity of 600 RT) and five water pumps equipped with variable speed drives (VSD), with control and monitoring via BMS. This multiple chiller configuration was selected to allow flexibility and potential for the AI system to control the plant. The equipment specification of the chiller plant is detailed in Table 1.

Table 1. Specifications of chiller plant equipment in test site.

Attribute	Description
Type	Air-cooled
Refrigerant type	R134a
Nominal cooling capacity (Refrigerant Ton)	150
Nominal compressor power (kW)	148
Chilled water flow rate (L/s)	20.9
Design entering / Leaving temperature (°C)	7/13
Rated pump power (kW)	15
Pump Equipped with VSD	yes

The existing BMS at Sha Tin station would automatically determine the sequencing and staging of chillers based on chiller runtimes and plant part-load conditions respectively, pre-determined from the coefficient of performance (COP) characteristic curve provided by the manufacturer. In addition, the existing BMS is already equipped with the functionality to auto-adjust the chilled water supply temperature set-point (also known as CHWST reset) based on a pre-defined linear profile against real-time outdoor temperatures. Therefore, for easier comparison of the energy efficiency of the AI control system and the existing BMS, the two systems will be operated alternately, i.e. two out of seven days of the week, to establish an energy baseline for the BMS under similar variant factors, like chiller conditions, station patronage, weather, etc.

For the AI control system, it was proposed to adopt two machine-learning prediction models and one optimisation algorithm to determine the operational parameters for minimising power consumption. The optimisation solution consists of:

- A prediction model of power consumption for the chiller plant equipment
- A prediction model of the chiller plant's cooling demand
- An optimisation model using a PSO algorithm

The system architecture is shown in Figure 1.

The AI control system interfaces with the chiller plant and air side equipment via the existing BMS, with access to historical data and simultaneous direct control of the chiller plant. Real-time and forecasted weather data from the Hong Kong Observatory are uploaded to the system every hour for analysis. Historical data sampled at regular intervals are

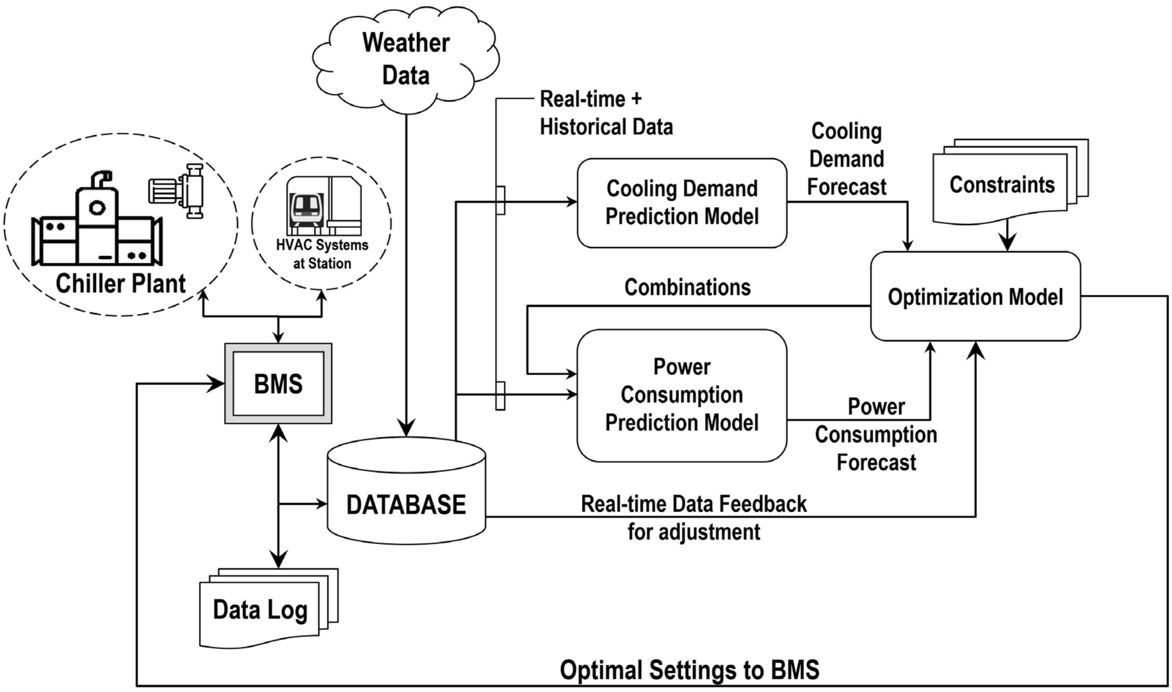

Figure 1. System architecture of the chiller plant optimisation.

used to train prediction models. Prediction models are re-trained periodically with more recent data.

To perform real-time optimisation, both real-time and historical data are fed into the predictive models where the chiller combinations are formulated, and parameters are entered to generate a suitable power consumption forecast. The optimisation solution considers the constraints, cooling demand forecast and power consumption to determine the parameter set that best minimises power consumption. The recommended parameter set is then written back to the BMS and applied to the equipment in order to operate the chillers at the optimal point under complex combinations of scenarios on site.

Operational parameters to be optimised are tabulated in Table 2 and a list of covariates for training the power prediction model are tabulated in Table 3.

Table 2. Operational parameters to be optimised.

Variable	Attribute	Description
$T_{chws(1)}$	Continuous	Chilled water temperature setpoint of chiller 1
$T_{chws(2)}$	Continuous	Chilled water temperature setpoint of chiller 2
$T_{chws(3)}$	Continuous	Chilled water temperature setpoint of chiller 3
$T_{chws(4)}$	Continuous	Chilled water temperature setpoint of chiller 4
B_1	Binary	Chiller 1 is turned on/off
B_2	Binary	Chiller 2 is turned on/off
B_3	Binary	Chiller 3 is turned on/off
B_4	Binary	Chiller 4 is turned on/off
V_{vsd}	Continuous	Chilled water pump VSD speed

Table 3. Key variables.

Variable	Attribute	Description
T_{OAT}	Continuous	Outdoor air temperature provided by on-site sensor
$T_{OAT\ (Observatory)}$	Continuous	Outdoor air temperature provided by Hong Kong Observatory (Both forecast and real-time)
$H_{(Observatory)}$	Continuous	Outdoor air humidity provided by Hong Kong Observatory
COP_i	Continuous	Coeffcient of performance of chiller *i*
$T_{chws(i)}$	Continuous	Chilled water supply temperature of chiller *i*
$T_{chwr(i)}$	Continuous	Chilled water return temperature of chiller *i*
$T_{condref(i)}$	Continuous	Saturated condenser refrigerant temperature of chiller *i*
$T_{evapref(i)}$	Continuous	Saturated evaporator refrigerant temperature of chiller *i*
F_i	Continuous	Flow rate of chiller *i*
P_i	Continuous	Power consumption of chiller *i*
$V_{vsd\ (j)}$	Continuous	Active VSD frequency of pump *j*
P_j	Continuous	Power consumption of pump *j*

4. Formulation of optimisation models

To maintain the appropriate level of comfort, it is necessary to determine the cooling demand required. Various combinations of chiller plant settings can achieve the same level of cooling demand; a power prediction for optimisation analysis is thus required. Therefore, machine learning models would need to be developed to provide estimates of:

- Power consumption P_i of the chiller *i* and P_i pump *j* given the operating parameters at time *t*

- Cooling demand at time t, D_t

Given the estimation of cooling demand $\widehat{D}_t$ and energy consumption $\hat{P}_i$ ($\boldsymbol{x}$, z) where (x) is a vector of parameters to be fine-tuned as tabulated in Table 2 and **z** is a vector of current observations as tabulated in Table 3, an optimisation algorithm can then be applied to minimise the expected power consumption.

The optimisation can be formulated as searching the parameter vector $\boldsymbol{x}$ that minimises the total of all equipment power while the total cooling load generated is not less than the predicted cooling demand.

$$\min_{\boldsymbol{x}} \sum_i \hat{P}_i\,(\boldsymbol{x}, \boldsymbol{z})\ , \tag{1}$$

while

$$\sum_i CoolingLoad_i \geq D_t, \tag{2}$$

and

$$\boldsymbol{x}_{upper}\ \geq\ \boldsymbol{x}\ \geq\ \boldsymbol{x}_{lower}, \tag{3}$$

where $\boldsymbol{x}_{upper}$ and $\boldsymbol{x}_{lower}$ are additional operational constraints.

For example, chilled water supply temperature (CHWST) setpoints should be within operating range, between 7°C (design CHWST) and 13°C (as recommended by the manufacturer per chiller characteristics).

4.1. Machine learning model of power consumption

The effciency of the chiller plant inter-correlates with cooling demand, temperature setpoints and external environmental factors, etc. All these factors shall be collected as key data for training a model to estimate the effciency under various operating conditions with a function F.

$$\hat{P}_i\ \approx\ F(\boldsymbol{x}, \boldsymbol{z}). \tag{4}$$

A predictive model will provide a power consumption estimator F based on parameters to be optimised. Variable selection is performed with the top k variables selected via a univariate linear regression score as a pre-processing step to model training. k is a hyperparameter to be fine-tuned.

Based on historical data of the variables in Table 3, three different types of machine learning models, namely neural network, gradient boosting decision tree, and generalised additive model, are trained and their performance compared below. Each model type will also have a list of relevant hyperparameters to be fine-tuned.

A 10-fold cross-validation is used to evaluate the three machine learning models on each chiller. The folds are selected by continuous block of time to evaluate the performance of the models to unseen scenarios. Mean-Absolute-Error (MAE) is used as the measurement of the cross-validation. The smaller the MAE value, the more accurate the model should be.

Neural network is a machine learning model which can learn non-linear patterns. A neural network has multiple layers of activation functions that combine and eventually generate the output value. The layered approach provides flexibility for the neural network to model non-linear patterns. A back-propagation technique is applied to train the model by tuning the weights of different layers. Theoretically, a neural network can achieve a very good performance. However, the training and modelling cost will be much higher than other approaches. In this project, the rectified linear unit (ReLU) function is used as the activation function of the neural network. A stochastic gradient-based optimiser is used because of the relatively large datasets. Random search is used to search for the optimal hyperparameters, including the number of layers and number of neurons per layer for the model of each chiller. The cross-validation results using neural network models are tabulated in Table 4.

Table 4. Accuracy of neural networks.

Equipment	Cross-Validation MAE
Chiller 1	12.595965
Chiller 2	11.811827
Chiller 3	5.613330
Chiller 4	4.4686789

Gradient boosting decision tree (GBDT) is a tree-based algorithm. It uses simple decision trees to sequentially improve prediction performance. It is highly accurate and fairly robust. For optimising the model, random search is used to find the optimal parameters for the GBDT model of the dataset of each chiller plant. The cross-validation results using GBDT is tabulated in Table 5.

Table 5. Accuracy of gradient boosting decision trees.

Equipment	Cross-Validation MAE
Chiller 1	0.895808
Chiller 2	1.082056
Chiller 3	0.946664
Chiller 4	0.714729

Generalised additive model (GAM) is a nonparametric regression model. It can be applied without the assumption of linearity, which is an assumption of all linear regression models. If linear regression is applied incorrectly, some patterns may be missing. As the pattern of the datasets cannot be confirmed to be parametric, using GAM is suitable. The cross-validation result for GAM accuracy is tabulated in Table 6.

Table 6. Accuracy of generalised additive models.

Equipment	Cross-Validation MAE
Chiller 1	2.563707
Chiller 2	2.127167
Chiller 3	2.043627
Chiller 4	1.365432

Comparison of the MAE revealed that the GBDT model delivers the most accurate result among all three methods. The MAE value achieved is between 0.71 to 1.08, while the chiller power range is between 20 to 100 kW. This is comparable to the MAE value reported (4.471) in Nisa et al (2021) while the chiller power range is between 20 to 120 kW. The ensemble of trees trained with GBDT can model more complex interactions than a GAM-based regression model. The neural network model had better training accuracy than test accuracy, indicating a decrease of prediction performance for unseen data. Further improvements can be made by hand-tuning of the neural network model's hyperparameters and regularisation level.

4.2. Cooling demand forecast

An accurate forecast of cooling demand can compensate for the time required for the heat exchange of the chiller system to come into effect with optimal cooling. The cooling demand of the railway station is highly related to time; for example, the cooling load peaks occur during chiller plant start-up, peak traffic hours and peak sunlight. The time series prediction algorithm introduced by Taylor and Letham was deployed to perform the prediction (2017). A machine learning-based time series model was used to predict the daily cooling load for every 15-minute interval, the same as the time interval of the dataset collection from the sensors. The following factors were considered in building the model:

- Temporal - time of year, hour of day
- Meteorological - outdoor dry-bulb temperature
- Real-time and forecasted weather data from the Hong Kong Observatory

To ensure the comfort of the indoor space can be maintained, operational constraints were also implemented:

- When the chilled water return temperature exceeds pre-defined upper limit; or,
- When the associated station indoor air temperature sensors exceed the designed set-point.

The algorithm would adjust the cooling demand prediction to ensure suffcient cooling is delivered while the risk of over-cooling is minimised.

4.3. Optimisation model

As the power predictors $\hat{P}$ are machine learning models, the numerical minimisation in equation (1) is not convex and non-smooth. PSO introduced by Kennedy and Eberhart (1995), is chosen as the numerical solver as the algorithm makes no assumptions of the problem convexity and smoothness. The binary selection of chillers is done by exhaustive search of all combinations of the four chillers. The number of binary parameters is four in this case study and hence exhaustive search of all $2^4 = 16$ combinations is possible. The combinations increase exponentially with the number of binary parameters. A genetic algorithm would be applicable in finding the best binary parameters in the settings.

Let B be the set of all possible values of the binary value tuple (B_1, B_2, B_3, B_4) determining whether the respective chiller should turn on. The set B of all possible chiller status combinations would depend on operational and maintenance constraints; for example, B_i would be 0 when the chiller i is under maintenance. Table 7 describes the algorithm of the full optimisation steps.

Table 7. Algorithm of chiller plant optimisation.

```
Algorithm 1: Chiller plant optimisation
    Input :     Current observational data z
    Predict     Cooling demand D
    Initialise  P_best = ∞
    Loop        All possible chiller combinations
    for (B1, B2, B3, B4) in B do
        Solve Power minimisation problem (1) with
          PSO over (T_chws(.), V_vsd) to obtain optimal value
          (T̂_chws(.), V̂_vsd)
        Obtain Expected power consumption
          p̂ = min_x Σ_{i=1}^{4} P̂((B_i, T̂_chws(.), V̂_vsd), z)
        if p̂ < P_best then
            Set P_best = p̂
            Set x_best = (B1, B2, B3, B4, T̂_chws(.), V̂_vsd)
        end
    end
    Output:     Optimal control parameters x_best
```

The optimisation algorithm generates optimal control parameters $\boldsymbol{x}_{best}$ which minimise the predicted power consumption. The optimal chiller running combinations are obtained from the binary parameters B_i where respective chiller i will be turned on if $B_i = 1$. The optimal chilled water temperature setpoints for chiller i would be $\hat{T}_{chws(i)}$. The VSD frequency setpoint of the pumps would be set at $\hat{V}_{vsd}$.

5. Result and discussion

The algorithm was deployed at the Sha Tin railway station for over one year, and the indoor air temperatures were able to be maintained at designed setpoints. As BMS and the AI control system operate on an alternating basis within the same week, this allows the data set of the two systems to be compared to each other, as the station patronage, chiller and weather conditions are similar. During the one-year trial period, the BMS captured 108 days of data, and was used to form the baseline of energy consumption for benchmarking against the performance of the AI control system.

In comparing the measured data, it was found that the chiller plant's energy consumption under the AI control system was generally lower than under BMS, as shown in Figure 2. T-test was performed to review the statistical significance of the savings analysis, and the result revealed the p-value was 0.000247, which is highly significant. The annual energy savings is around 8.7%.

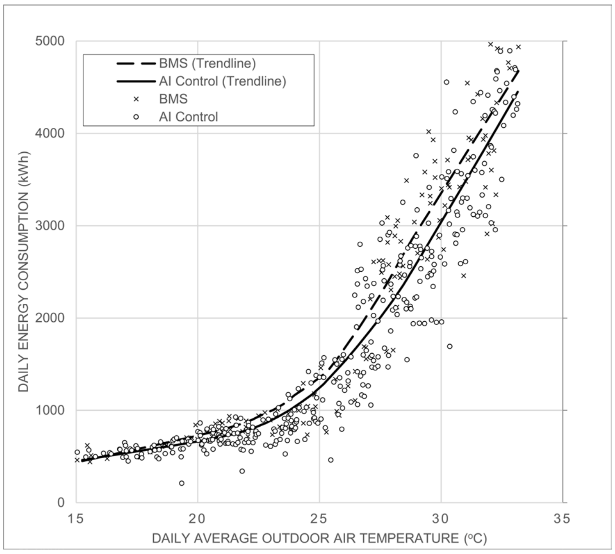

Figure 2. Energy consumption comparison.

Results from Figure 2 showed that the majority of energy savings are achievable between a daily average Outdoor Air Temperature (OAT) of 25°C and 30°C. The trendlines converge as the OAT tends cooler or hotter, i.e., a lower percentage of energy savings. Percentage ratios of daily average OAT and annual energy-saving contributions are tabulated in Table 8. These figures mean the AI control system is more effective on energy optimisation in mild seasons, approximately one-third of the year.

Table 8. Distribution of operating day by BMS/AI Control and annual energy savings at different daily average outdoor air temperature ranges.

Range of daily average Outdoor Air Temperature (OAT)	Operating day by BMS	Operating day by AI Control	Distribution of annual energy saving (8.7%)
OAT < 25°C	34%	42%	23%
25°C <= OAT < 30°C	37%	35%	52%
OAT >= 30°C	29%	23%	25%

The optimisation during cooler/hotter seasons is less significant as the flexibility for staging and adjustment on CHWST was limited by operational constraints, e.g. only one chiller required during cooler seasons, limitation on adjustment of CHWST as ambient temperature is cold, minimum designed CHWST temperature is required to perform cooling during peak summer, etc.

The optimisation is taking a non-parametric black box approach. There is no observable operating pattern of the variables by AI control system. In Figure 3, it can be observed that the variables controlled by the AI control system are more diversifying and dispersing than BMS control. This approach enables the system to attempt different combinations to achieve better energy efficiency. Upon post-result analysis, the proposed approach was able to achieve better energy efficiency than BMS via

- chilled water temperature reset that catered to individual chiller performance;
- chiller staging that utilises chillers at their best part-load to achieve better COP (e.g. two chillers under the AI system versus three chillers under BMS under similar cooling demands); and
- cooling demand prediction that helps prevent overcooling of chilled water supplied to the system.

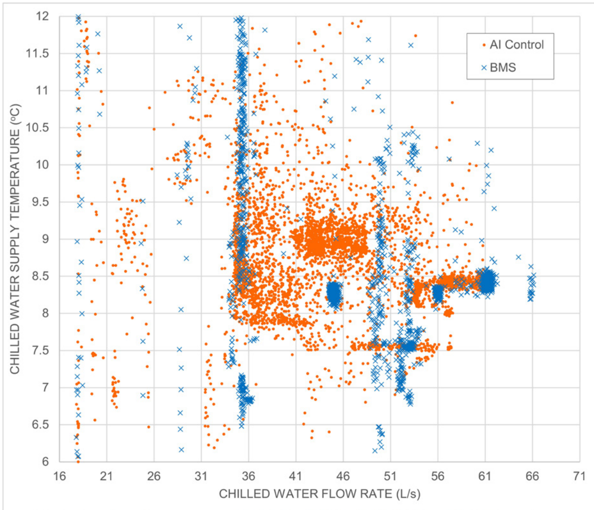

Figure 3. Chilled water supply temperature comparison.

In Figure 4, a comparison of chiller plant COP reveals the COP of a chiller plant under AI control is relatively higher than that of one under BMS control.

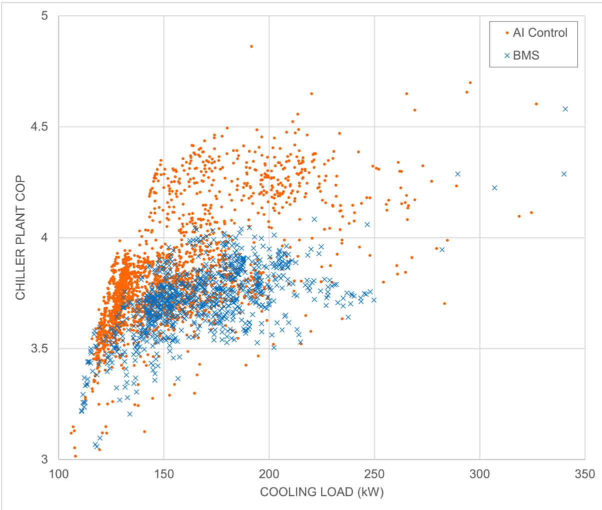

Figure 4. Chiller plant COP comparison.

The results proved that the AI control system was able to analyse vast amounts of data and adapt different external covariates to achieve a better energy performance. The dynamic and continuous adjustment of control settings to meet the optimal operation point would be too complex to be handled by manual operation; the fully automated AI control system adopted under this trial exemplifies the merits of AI application. It is considered that similar principles of AI control algorithms can be applied to water-cooled systems as it involves generic cooling demand prediction, power consumption prediction and optimisation modelling. More variables and sufficient data shall be included to train AI models for water-cooled systems in the future.

6. Conclusion

As part of building services systems, chiller plants contribute to a large proportion of total station energy consumption. With the wealth of historical data available through BMS and sensors, data-driven AI control systems can be built and trained to deliver optimal settings and results. The selection of AI algorithms depends on data characteristics of the particular system. Particle swarm optimisation can be an effective AI algorithm in generating good output for the non-convex and non-smooth optimisation with a power prediction model. Through machine learning and data analytics, the accuracy and robustness of the AI control system can also be improved along with logging of real-time data.

In this paper, the application of an AI system to the air-cooled chiller plant at the Sha Tin railway station demonstrated around 8.7% reduction of annual plant energy consumption as compared with previous BMS operation, while maintaining comfort levels in the station. As an initiative and trend, data analytics and the application of appropriate AI control systems to building services systems should be part of global efforts to reduce energy consumption in order to achieve Environmental Social Governance (ESG) goals.

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