Towards Carbon Neutrality through Smart Energy Management Solution: AI application on Energy Optimization Platform for Chiller Plant

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Abstract - To combat the adverse effect of climate change, leveraging the innovative energy-saving technologies to further enhance the energy efficiency and conservation amongst the city is one of the indispensable elements to achieve carbon neutrality before 2050. The Electrical and Mechanical Services Department (EMSD) of the HKSAR has led to implement the first-of-its-kind district cooling system (DCS) at Kai Tak Development, which is a large scale centralized air-conditioning system, serving as an energy efficient air-conditioning system as well as the environmental friendly infrastructure development. To step up efforts in promoting energy saving, energy optimization tool is a key energy management solution for chiller plant operation nowadays. Development of semantic Artificial Intelligence (AI) technology with open-source approach is also becoming a trend of smart energy control in recent years. Extending the application of AI platform to optimize the operation of DCS plant with a view to reaping greater energy saving potential at the upcoming DCS projects would be a big step towards carbon neutrality. This paper aims to present the challenges faced and the experience gained during the implementation of energy management solutions.

1. Introduction

Climate change is one of the major challenges facing the world and global warming caused by human activities had led to more frequent and intense extreme weather events. In Hong Kong, the number of hot nights is increasing while the number of cold days is decreasing. Apart from rising temperature, Hong Kong experiences more frequent heavy rainfall than before. The sea level is rising in Victoria Harbour [1]. To combat the climate change, the Government of the Hong Kong Special Administrative Region has established the Hong Kong's Climate Action Plan 2050 in October 2021 which set up the decarbonisation strategies, targets and actions. One of the long-term targets under the Hong Kong's Climate Action Plan 2050 is to reduce the electricity consumption of commercial buildings by 30% to 40%, and that of residential buildings by 20% to 30% by 2050. In accordance with the Hong Kong Energy End-use Data 2021, air conditioning was one of the major electricity consuming end-use. There were 28%, 25% and 38% of the total electricity consumption by end-use, commercial sector and residential sector respectively in 2019. To this end, incorporating energy saving design, in particular for air conditioning system, in buildings is one of the crucial actions to achieve the carbon neutrality.

The Electrical and Mechanical Services Department (EMSD) has been taking leading role to continuously improve the energy efficiency standards of buildings with implementation of green infrastructure, like District Cooling System (DCS), as one of the effective energy saving measures for new development areas so as to promote energy efficiency and mitigate the heat island effect locally. With the rapid development of innovative technologies in the world, application of the new technologies in energy-saving aspects to further optimize the energy use among air conditioning systems has been actively under development in building industry. Leveraging artificial intelligence (AI) technology, machine learning, big data analytics and the like on chiller plant system control application becomes a growing trend as the smart energy management solution in air conditioning design. This paper presents the latest development of EMSD works in this area and highlight the forward planning.

2. Application opportunity of AI in air-conditioning facilities

AI encompasses data analytics feature, both of which are interdependence and indivisible for delivery of optimum solution. Data analysis is actually not something new to Engineers. However, with the emerging new technologies and wider adoption of various electrical and mechanical (E&M) equipment sensors, data information available from E&M systems is getting highly complex in terms of its quantity and quality. Nowadays, building management system (BMS) has been commonly installed in commercial building which is not uncommon for processing over hundreds of thousands E&M operational data daily. Huge information of the E&M system being monitored and supervised is embedded therein. Good understanding of all these data in sufficient depth of underlying knowledge which are highly correlated and dynamically interactive through the use of traditional engineering skills is practically hard to be achieved without drawing support from other specialist knowledge input, like data scientists.

E&M engineering and AI data analytics are indeed two distinct professional domains that attribute to very different knowledge and experience. Integration of cross-domain knowledge for optimization control of E&M installation is one of the great challenges which require significant resources for alignment of standardization across the different knowledge domains. One of the fundamental hurdles is the lack of well-structured and consistency on identification and classification of different E&M equipment. Typically, building systems are commissioned in various naming structures that are often chaotic and unique within project-specific context defined by the project team for respective system components. Ad-hoc descriptions labels without consistency causes confusion on representation of data, exposing shortcoming of interoperability at cross domain application. In essence, efforts to resolve interoperability and reusability concerns are required on standardization of data naming and representation. Besides, capturing of entity properties, attributes of building assets and their in-situ relationships are equally significant throughout the standardization process. For example, to moderate temperature of a room, one must consider the different data points of a building's HVAC system: fan blowing speed, condenser temperature, compressor refrigerant volume, etc. Without a unified semantic representation of components in such a system, it would take significant domain knowledge and manpower to fully realize the inherent meaning of data and their interrelation in sufficient details. This creates challenges in the mass deployment of AI applications across the board under different buildings.

In order to unleash the potential of big data and AI on E&M industry, EMSD together with local and global experts co-developed the Semantic AI approach. The Semantic AI approach combines methodologies from Machine Learning, Knowledge Graph Modeling, Natural Language Processing and Text Mining. Compared with the traditional approach, Semantic AI provides a separate layer enabling creation of AI models based on the semantic relationship among different equipment. With a unified semantic model that encapsulates different subsystems in a building, programmatic exploration of various operational, structural, and functional facets of a building can be achieved and further extended for application in other buildings.

3. Semantic AI experience in EMSD

The EMSD together with experts from international institution and academia has developed a semantic data platform which consists of a graph database for storing the semantic model and a time-series database for building data (Figure 1).

The semantic model is developed as infrastructure skeleton under Semantic AI to enable data integration and sharing in machine-readable fashion. Semantic model is an ontology-based framework following the Resource Description Framework (RDF) and Web Ontology Language (OWL) from World Wide Web Consortium (W3C) [2]. Ontologies are represented in "Triples" structure composing of 3 entities, namely Subject,

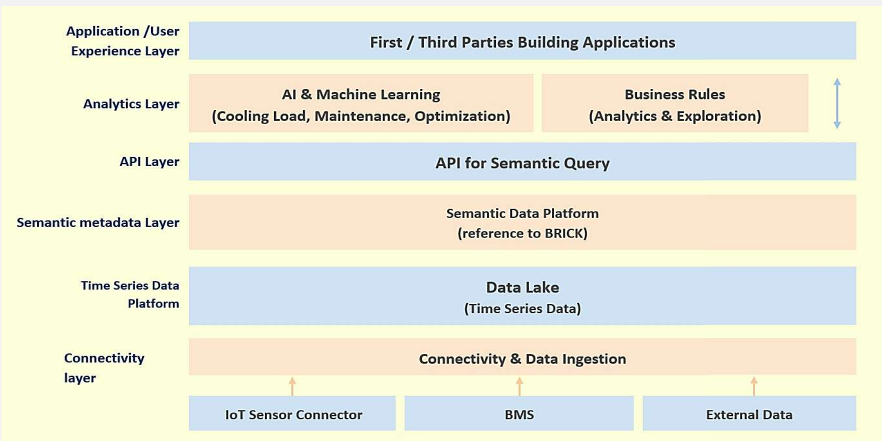


Figure 1 –
Architecture Overview of Semantic Data Platform

Predicate, Object. Some examples of Triples are illustrated in Figure 2.

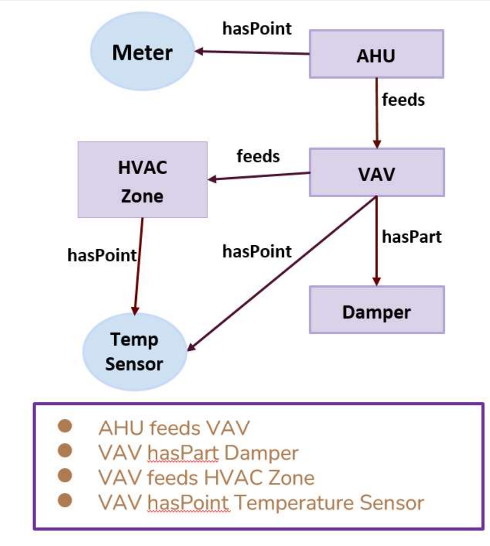


Figure 2 –
Example of ontologies of AHU (Simplified)

By creating data relationships between data entities, semantic gives identity and role to the data in the system. The building data associated with the semantic model instance is ingested into a time series database as demonstrated in Figure 3.

Entity in the instance can be reachable through an application programming interface (API) for semantic path query. Data query can be formed by the semantic data platform to retrieve the time series data that is linked to the entity. This enables different domain experts to perform analytics and diagnostics separately, thus making the programs of the AI services portable across buildings in a shorter timeframe. Other building applications such as Building Information Model (BIM) can access the building data that is open and portable using our AI semantic model approach. Application developers can directly deploy their existing solutions which are based on developed AI models for an existing building of similar profile in a new building. It can drastically save the time and cost for model development and data analytics.

Pilot of using Semantic AI

The Semantic AI is rather a new approach emerging specifically for application of E&M industry. Continuous research and development are on-going. A newly built government office complex (GOC) was identified to test out the approach. The GOC with construction floor area of about 90,000m^2 comprises of two medium rise office towers, namely South tower and North tower, and one common basement. The central water-cooled chiller plant is located at basement with fresh water cooling tower plant being situated at top roof of one of the office towers. The chiller plant comprises of 3 nos. 3,517kW (Duty) + 1 no. 3,517kW (Standby); and 1 no. duty 1,760kW chiller + 1 no. 1,760kW (Standby). The existing central chiller plant was customized with energy efficiency optimization control in a manner that the chiller plant equipment was being operated in a preset sequence according to energy optimization mapping for the plant under different scenario of cooling load demand as devised under design stage as per the equipment manufacturer's

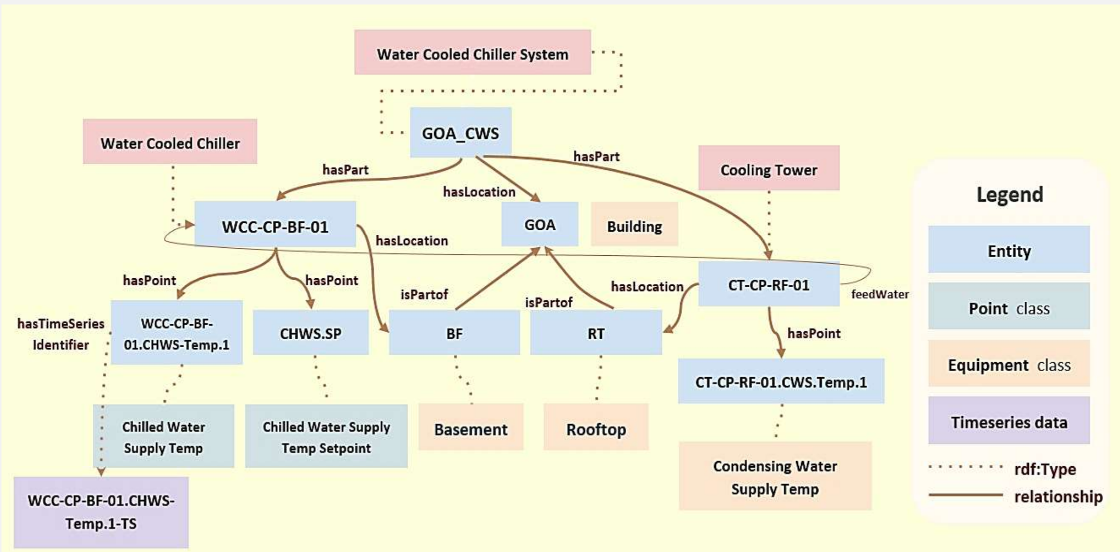


Figure 3–
Instance of a Water-Cooled Chiller System at a Government Building (Partial View)

performance datasheet. The target of this pilot project is to develop a Machine Learning (ML) model to optimize the chillers operation sequence so as to achieve an improved chillers' overall coefficient of performance (COP) by adopting Semantic AI approach. The pilot project consists of three development areas: 1. Data visualization, 2. Equipment and system modeling, and 3. Optimized COP chillers sequence selection.

Data visualization

For Chillers plant analysis, around 3200 data points from over 20 engineering features were connected the data server and trend logged in every 15-minute interval. Data integration of more than 300,000 data was then processed through extracted, transformed and loaded (ETL) to the unified analytic data lake daily at 00:00 hour. A series of data engineering processes including data checking on validity, accuracy, completeness, consistency and uniformity, removing duplicate or irrelevant data, filtering outliers and filling missing data was carried out. Over 20 engineering and ETL rules were co-developed by the engineers and data scientists. Different benchmarking can then be performed and visualized in the format of infographic or chart to facilitate analysis of the system performance, e.g. COP of a chiller as shown in Figure 4. With the help of Semantic AI, such rules are ready to be redeployed to chiller system in other buildings with semantic model.

Equipment and System modeling

Second objective of the pilot is to build up individual equipment and system COP (SCOP) models by Multivariate Polynomial Regression Model [3] for performance and cooling load predictions. ML regression technique is commonly adopted for investigation of relationship between dependent variables (i.e. outcome) and independent variable (i.e. feature) so as to perform prediction process. As the individual equipment operation data is dynamically inter-related factors subject to different scenarios with multi-combination of ever-changing parameters, such as temperature, humidity, building usage, occupants' habits and business nature, etc., traditional engineering tools can only handle scenarios with limited parameters while big data and AI can provide dynamic prediction with a wide range of variables.

By using the processed historical data, a cooling load prediction AI model was developed by using XGBoost [3] (eXtreme Gradient Boosting – Figure 5). Considering that the pilot was commissioned from September 2019 to May 2021 during which pandemic outbreak occurred and the building operation pattern would have been

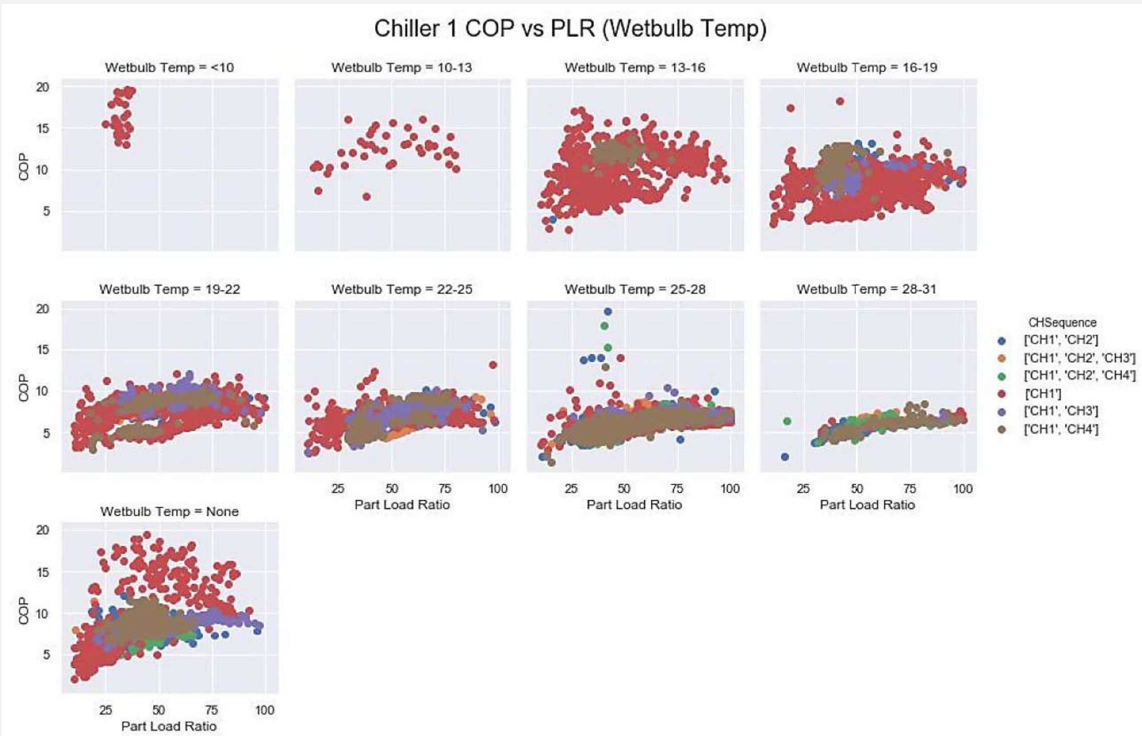


Figure 4 –
Data visualization on Chiller COP vs PLR (with different Wetbulb Temperature)]

distorted from its original state, cross-data mixing approach was adopted for one and a half years data (27/9/2019 – 31/5/2021) to minimize the bias as shown in Figure 6.

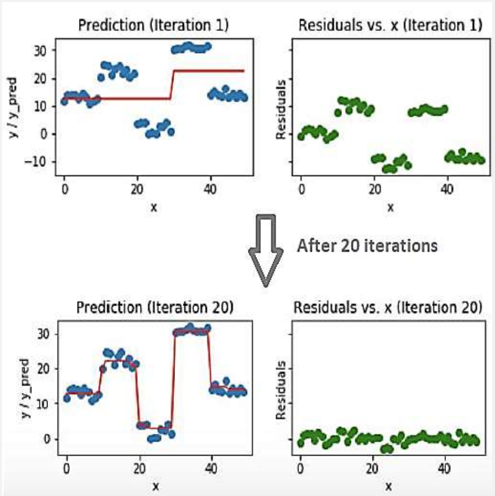


Figure 5 –
Prediction accuracy for different XGBoost (eXtreme Gradient Boosting) iterations

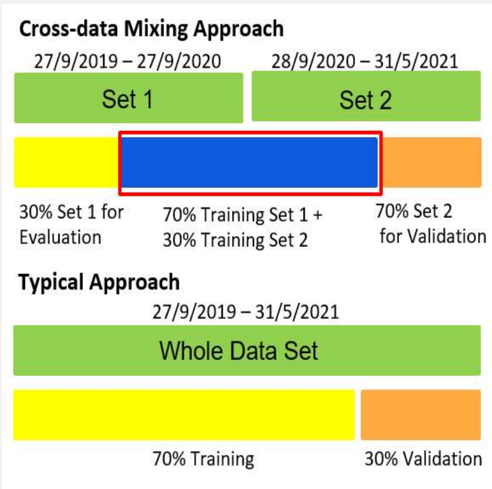


Figure 6 –
Training approach for the prediction model

In order to improve the accuracy, two cooling load prediction models were developed for the two office towers in the GOC with a view to identifying the different characteristics of the towers. Both towers are general office in nature while South tower contains 2 floors of building user's Central Command Centre where IT based equipment load was heavy. 13 number of features as described in Table 1 were identified via a series of tests.

Table 1: Model's Explanatory Variables (Cooling load)

Hour	Hour of the day e.g. 0 = 12am, 1 = 1am,... 23 = 11pm
Day of Week	The day of the week e.g. Monday=0,... Sunday=6
Month:	The month of the date
Quarter	Quarter of the date in the given year
Year	Year of the date
Day of Year	The ordinal day of the year
Day of Month	The day of the date
Week of Year	The ordinal week of the year
Holiday or Weekend	Is the date on a holiday/weekend (True/False)
Average OAT	Average outdoor temperature
Humidity	Outdoor humidity
UV Index	Daily UV Index records from 8 am to 6 pm
Average Rainfall	Average rainfall in the area

The cooling load demand of the two towers were found different magnitude of sensitivity to different features as shown in Figure 7 and Figure 8. Nonetheless, the top three high-sensitivity features are the same for both towers, namely "Average OAT", "Humidity" and "Hour". The two models were then combined to illustrate the GOC's total cooling load demand.

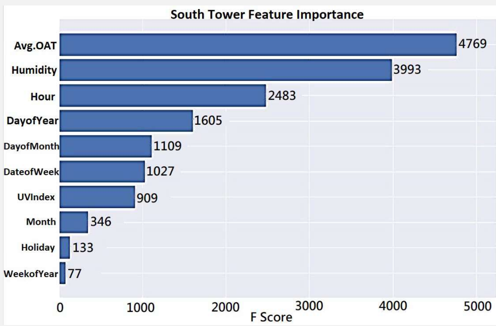


Figure 7 –
Features sensitivity for South tower cooling load prediction model

The cooling load prediction models were then tested for the same period of training data set. It predicted the hourly cooling load demand in every 7 days and continuously compared with the actual reading measured on site. The prediction results for the North tower is shown in Figure 9.

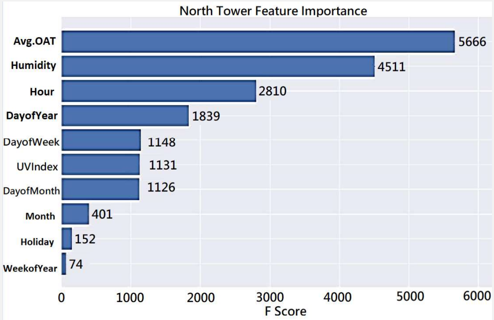


Figure 8 –
Features sensitivity for North tower cooling load prediction model

The accuracy of the cooling load prediction model was then measured by the Root Mean Square Error (RMSE) as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - a_i)^2}$$

Where n is the total number of data points, p_i is the predicted output, a_i is the actual value.

The measurement results are shown in Table 2.

Table 2: Accuracy of the model in hourly average

	RMSE	*Accuracy*
N-Tower	125.75	~ 95%
S-Tower	160.48	~ 97%

The models were designed with auto relearn feature which allows it to continuously monitor the error index and re-train itself with the latest dataset when the accuracy tended to shift.

To evaluate the system performance, an AI model for the chiller's COP was also developed. The variables associated with the AI model were identified and tabulated in Table 3 and the sensitivity of each feature is shown in Figure 10.

Table 3: Model's Explanatory Variables (Chiller's COP)

PLR	Part Load Ratio of chillers
Wet bulb	Wet bulb temperature
Month:	The month of the date
Quarter	Quarter of the date in the given year
Year	Year of the date
Day of Year	The ordinal day of the year
Day of Month	The day of the date
Week of Year	The ordinal week of the year
Holiday or Weekend	Is the date on holiday/weekend
Chiller sequence	Operation sequence of the chillers
Chiller status	On/ off/ fault status of chillers

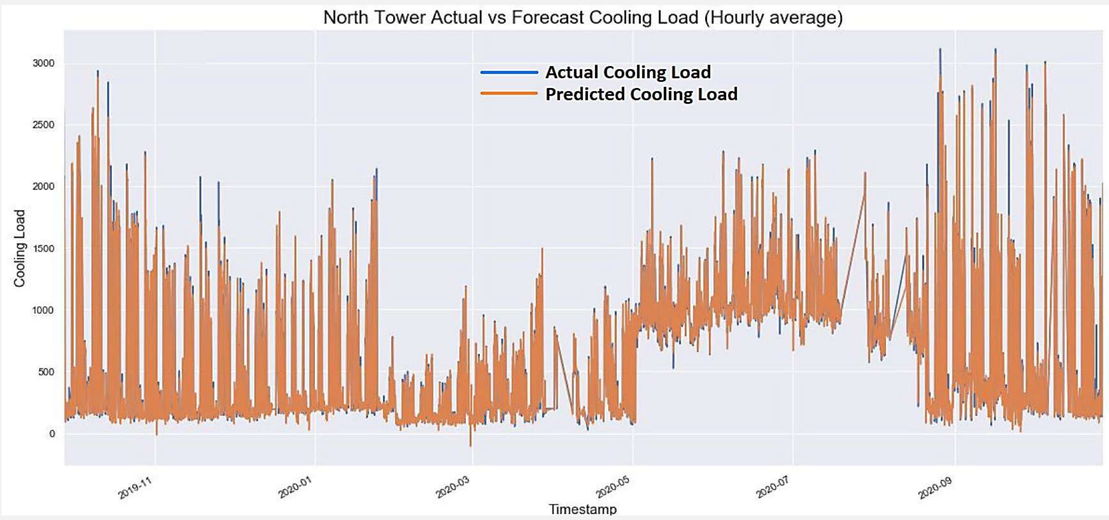


Figure 9 –
North tower cooling load – Actual vs forecast (hourly average)

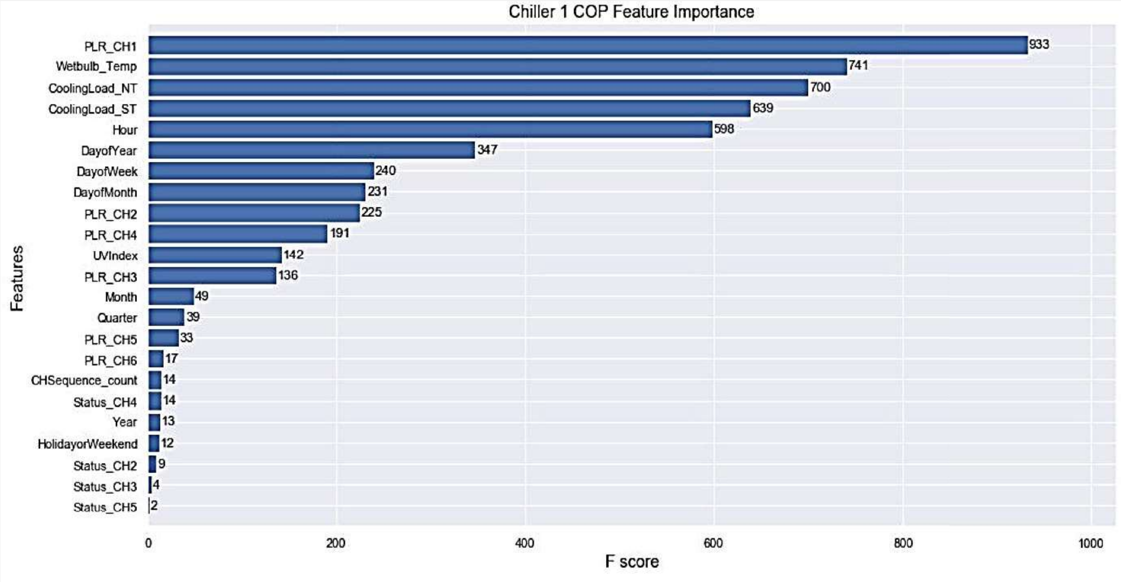


Figure 10 –
A Chiller COP prediction model features sensitivity

Optimized COP Chillers sequence selection

In order to suggest the optimized COP Chillers sequence selection, the ML models compare predicted cooling demand with chillers or chillers COP models, select appropriate chillers combination and sequence based on the particular scenario. A trial was performed to validate the models by applying them in the chiller system under the pilot. The operating mechanism of the ML models is illustrated in the Figure 11.

The ML models processed i) to firstly generate the 7-day cooling load predictions of the building on an hourly basis; ii) then to generate all possible combinations / operating sequences of the chiller(s) in the cooling plant; iii) to evaluate all combinations of the chiller(s) based on the

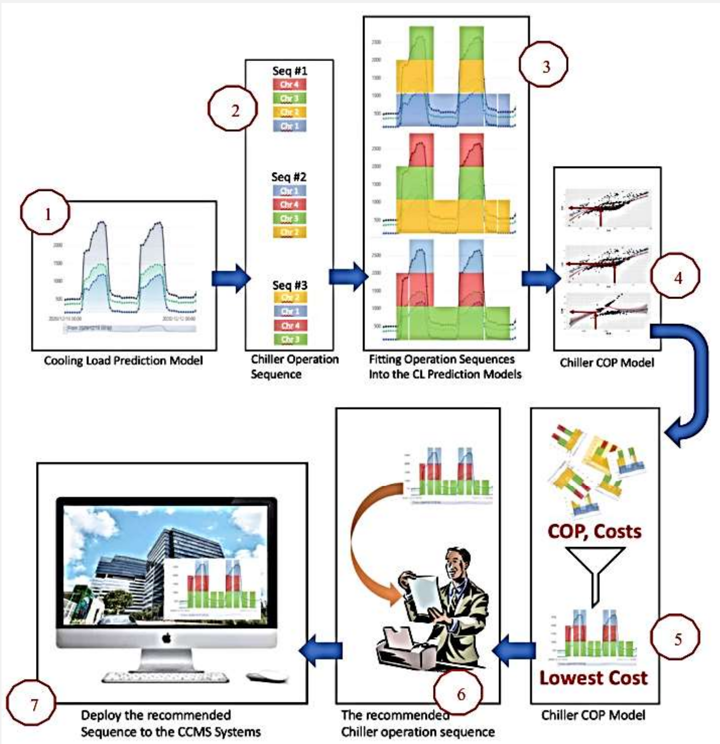


Figure 11 –
The mechanism of the ML models

forecasted cooling load profile for obtaining energy models under different chillers combination; iv) to select a set of combinations / operating sequences of chiller(s) which provide the highest averaged system coefficient of performance (SCOP) over the 7-day cooling load predictions; v) to load the determined chillers sequence with the highest SCOP into the Chillers Control System; and vi) to schedule the chillers for deployment of operation based on the optimized sequence calculated by the ML models.

The suggestions of the ML model were tested on field during June 20th to June 25th 2021. The cooling load predictions of North Tower is shown in Figure 12.

At a particular instant for example, the original system control decided the sequence chiller 2, 3, 4 according to the preset energy optimization mapping and the actual cooling load demand at that instant. However, as depicted in Figure 13, the combination of "CH1, CH2, CH3" as suggested by the AI model using live dataset can provide a better SCOP and the combination of "CH1, CH3, CH4" came after the second. The predicted average COPs of the chiller sequence are shown on Figure 14. Comparing with the sequence chiller 2, 3, 4, the average COPs of both the sequence (chiller 1, 2, 3 and chiller 1, 3, 4) were improved by more than 10%.

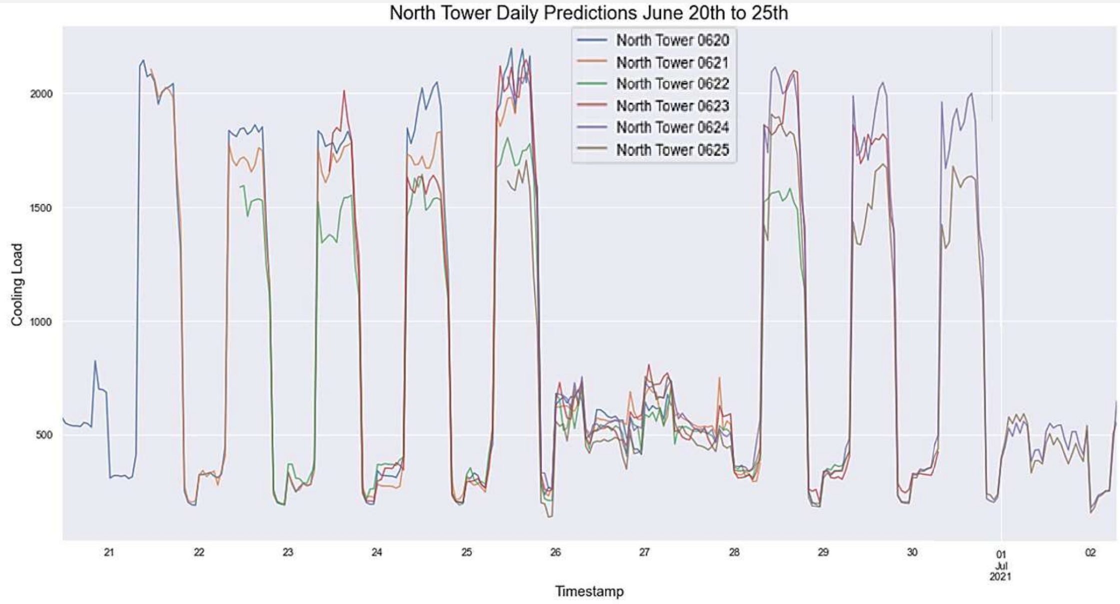


Figure 12 –
North Tower Daily Predictions from June 20th to June 25th

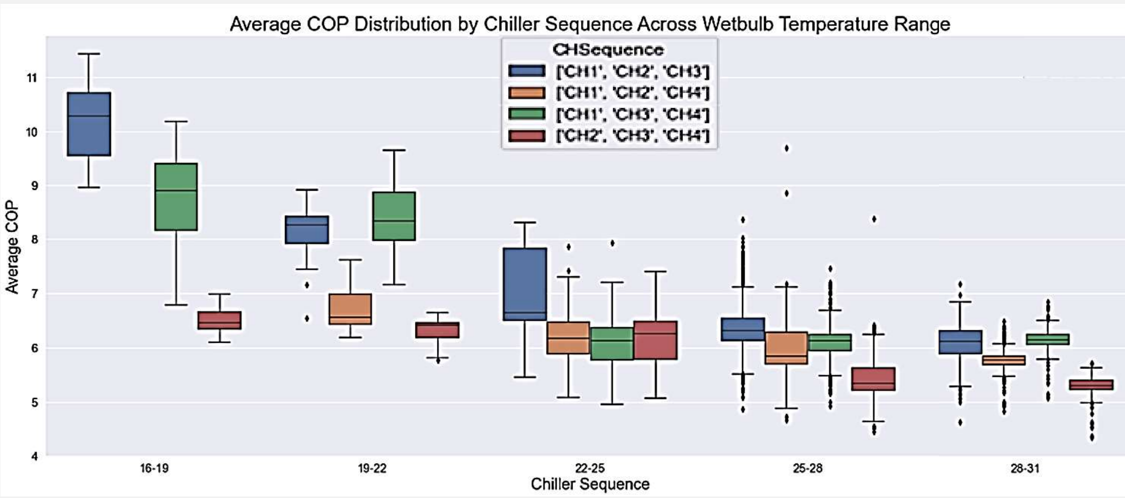


Figure 13 –
The COP distribution by chiller sequence across wet bulb temperatures
from June 20th to June 25th

Suggested Chiller Sequence	Historic Sample Size	Predicted Average COP
Chiller 1, 2, 3	**1522**	**6.47**
Chiller 1, 2, 4	858	5.91
Chiller 1, 3, 4	**930**	**6.2**
Chiller 2, 3, 4	1226	5.49

Figure 14 –
Chiller COP distribution for each chiller sequence

The field test carried out for five and a half day and the average plant COP can improve more than 10% during the testing period. While the study of energy saving is not the primary focus of the pilot, the experience gained from the trial of using Semantic AI approach was valuable and it indeed demonstrated the translatability between computing domain and E&M domain, showing the great potential for mass deployment of AI on building E&M facilities. The research and development of Semantic is still under inception stage, more related tools, platforms, data and project examples are required to allow the Semantic AI ecology to grow. To further improve the prediction accuracy, more data sets will be required to the train the ML model. Other parameters such as operation hours of the building and people flow inside the building would also be helpful to further enhance the cooling load prediction.

4. District Cooling System (DCS) experience of energy optimization control

The DCS at Kai Tak Development (KTD) is the first ever of its kind a large scale centralized air-conditioning system of infrastructure level in Hong Kong. It utilizes sea water to produce chilled water at the central plants and distributes the chilled water to consumer buildings in the KTD through underground water piping network. The DCS at KTD comprises three central chiller plants, namely the North Plant, the South Plant and the Additional Plant, underground chilled water distribution piping network, seawater supply and discharge pipes and consumer substations located in the buildings to interface with the building's own chilled water circulation systems.

DCS can save up to 35% of electricity consumption when compared with conventional central air-conditioning system in individual buildings. It is estimated that since commissioning in 2013 and up till 2019-20, the DCS at KTD has saved a total of over 20 million kWh of electricity, which is equivalent to an annual electricity consumption of about 6,000 typical three-member households. (i.e. about 0.03% of Hong Kong's total carbon emissions). Apart from energy saving, DCS allows more flexible building designs for consumer buildings; mitigates heat island effects in KTD and eliminate noise and vibration arising from the operation of heat rejection equipment and chillers of air-conditioning plants in user buildings; and allows more adaptable air-conditioning system to the varying demand as compared to individual air-conditioning systems. With the success of the DCS at KTD, it was selected by Cities 100, a C40 publication, as one of the action plans that could proactively combat climate change in 2019.

Traditionally, the operation of central air-conditioning system was highly relied on the experience of duty plant operator to determine the operating combination of the plant equipment. Nowadays, there has been increasing use of the advanced control algorithm to help operators to manage their central air conditioning system being running in a more energy efficient way. In the early operation stage of the DCS at KTD, an energy management solution, namely chilled water production optimization tool, was customized to fit the operation of the DCS plant and launched for a trial run to forecast the cooling demand and SCOP with a view to optimizing energy use of the DCS at North Plant in 2017. The tool was made use of the mathematical modelling for the formation of equipment performance characteristic curves for individual or group of district cooling equipment including the chillers, cooling towers [1] and water pumps. In the mathematical model for individual or group of equipment, regression analysis from the historical data was performed in order to find out the relationship of the equipment energy performance or characteristics against actual operating conditions. With developing an advanced control algorithm, the optimal operation conditions of the equipment was determined. The tool recommended the operator the best combination of major plant equipment including chiller and cooling tower to attain the highest energy efficiency under delivery of the prevailing cooling load supply to meet the demand.

[1] Cooling towers were adopted in the North Plant in early operation stage.

With a Structured Query Language (SQL) [2] database setup in the programme server together with the filtered historical data and equipment model characteristic curves, the optimization tool predicted the total consumers cooling demand on hourly basis taking into account the weather forecast at KTD from Hong Kong Observatory. By performing the algorithmic solving method, the optimization tool proposed the 3 options of the combination of chillers and cooling towers to match with the operational characteristic of KTDCS. The predicted COP and suggested combination of chillers, the number of cooling towers, the aggregated chilled water pump power, condensing water pump power, cooling tower power, etc and the predicted SCOP under each option of combination would be provided for the operator's consideration. During the trial, field tests were conducted to verify and evaluate the results of the suggested combination of the plant equipment in order to refine the programme code (Figure 15).

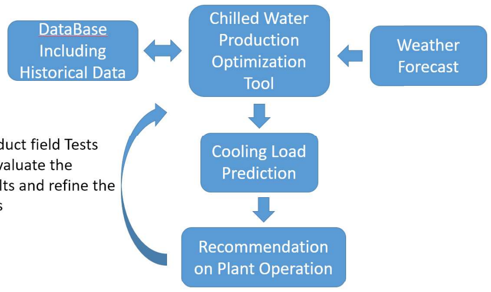
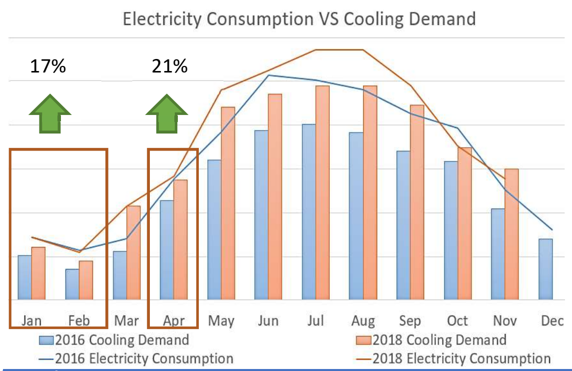


Figure 15 –
Block Diagram of Chilled Water Production Optimization Tool

The trial exercise has been conducted for a period of 20 months, the performance of the tool was evaluated based on the plant overall energy efficiency in the function of the measured SCOP of the plant. Individual equipment performance was also evaluated by comparison of the actual operation against predicted results of the tool.

To evaluate the outcome of the optimization tool, the empirical data before and after the trial was extracted for analysis which is presented in Figure 16. In general the cooling demand in 2018 was notably increased as compared with 2016 due to increasing connection of DCS consumers over time in KTD, the increase in electricity consumption had not occurred proportionally while the outdoor temperature being about the same, in particular the months of January, February and April of 2016 and 2018. After implementation of the optimization tool, the DCS plant produced 17% to 21% more cooling energy while keeping the electricity consumption about the same as that of 2016.



Year	Outdoor Temperature (°C)											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2016	16.3	15.6	17.3	22.9	26.5	29.1	29.6	28.3	28.2	27.1	22.6	20
2018	16.1	15.8	20.1	23	27.9	28.4	29	28.5	27.9	25.3	22.9	19.2

Figure 16 –
Electricity Consumption, Cooling Demand and Outdoor Temperature in 2016 and 2018

Considering the overall energy performance of the chiller plant, as shown in Figure 17, while the trend of the outdoor temperature at KTD in 2016 and 2018 did not differ much, the SCOP in 2018 was improved by over 15% in wintertime and 5% in summertime as compared with that of 2016. The annual average SCOP has been improved by 13% which is equivalent to 1.2 million kWh saving or reduction of 840 tonnes of carbon dioxide emission per annum in 2018. The above analysis demonstrated that the implementation of the optimization tool was effective on improvement of the energy efficiency in the DCS, in particular the system performance in winter.

[2] SQL is a domain-specific language used in programming and designed for managing data held in a relational database management system, or for stream processing in a relational data stream management system. It is particularly useful in handling structured data, i.e. data incorporating relations among entities and variables.

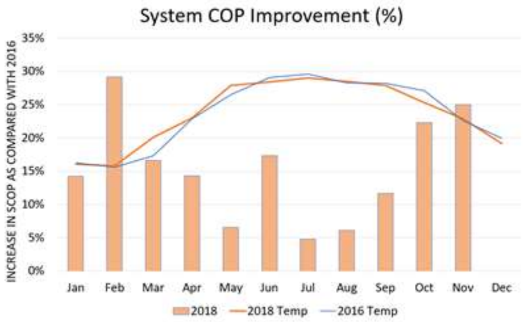


Figure17 –
Improvement of SCOP in 2018
as compared with 2016

DCS has been planned for expansion by phases to cope with the development of Kai Tak, the programme would be kept fine tuning from time to time to enrich the operation data and suit with the latest system configuration including the newly installed equipment. The field testing should be conducted for continuous trial run of programme tool to verify the constraints and defects which requires a team of highly competent control engineers. Considering vast amount of data in DCS operation, huge energy consumption and numerous combinations of equipment, there is a high energy saving potential in DCS operation. To suit the dynamic operating characteristics and of DCS with maintained optimization performance, adopting AI for DCS would be one of the promising solutions. Also, introducing the new concept of Semantic AI approach for DCS use would sustain the development of AI as a long term solution through a well-structured open source semantic platform.

5. Motivation of AI development in E&M building industry

At EMSD, an Energy Efficiency Office was established to provide the technical expertise and the drive for energy efficiency and conservation programmes. To elevate the energy savings from buildings, EMSD has been paying close watch on the new technologies development, reviewing and updating on regular basis the requirements of building energy performance through amendment of various energy efficiency publications, including Building Energy Code, the Energy Audit Code, Technical Guidelines on Retro-commissioning, and establishing energy evaluation tool including Online Building Based Electricity Utilization Index Benchmarking Tool. Besides the regulatory regime, the EMSD also implemented various energy saving projects to demonstrate our leading role in promoting energy efficiency. In order to further improve energy performance, the EMSD has implemented a series of initiatives to drive innovation and technology (I&T) development and adopted various I&T solutions in the energy management projects for trial or full implementation. The EMSD, in line with the Government policy direction, is committed to develop I&T, such as maintaining the "E&M InnoPortal" for government departments, public organizations and the electrical and mechanical (E&M) trades to set out their I&T needs, and for the I&T sector, including startups and universities, to propose matching solutions. In recent years, the EMSD signed several memorandum of co-operation (MOC) with universities and research institutions in Hong Kong and Greater Bay Area (GBA) to establish a strategic partnership to support the application of I&T in government departments so as to improve the services and enhance work efficiency. As the innovation facilitator of the Government, the EMSD supports and facilitates the application of innovative technologies by bureaus and departments to improve services and support smart city development. The EMSD will continue to adopt an accommodating and innovative mind-set to drive the industry towards innovation.

With the success of Semantic AI, the EMSD together with the Guangdong Provincial Association of Science and Technology organised the "Global AI Challenge for Building E&M Facilities" which is a global event highlighting AI development and applications in the building services industry. It aimed to promote international innovation and technology ideas through exchange and cooperation. The event is the first and largest AI event related to building electrical and mechanical services in the world.

The competition presented a unique opportunity to inspire participants, industry leaders, innovators, and researchers to exchange ideas and to progress the role of AI technology to have a positive impact on the world. The competition proved to be popular with more than 120 teams from 10 regions from all over the world. All received models were of highly sophisticated and the contestants were of superb skillful in using multiple algorithms.

6. The way forward

Following the success of DCS KTD, the EMSD has spearheaded the construction of DCS in Tung Chung New Town Extension (East) and Kwu Tung North New Development Area (NDA). It is estimated that upon utilization, the DCS in Kai Tak Tung Chung East and Kwu Tung North will achieve annual saving of 211 million kWh in electricity consumption, which is equivalent to annual electricity consumption of about 64,200 typical three-member households. Considering a significant amount of electricity consumption for plant operation, a highly sophisticated energy optimization tools should be employed to manage the energy use strategically.

In view of the success of the trial implementation of AI in chiller optimization in government buildings, it is believed that further development of the Semantic AI would facilitate the EMSD to set up a well-structured open source semantic platform for the AI application in chiller control system so that it could be redeployed to other chiller system in other government buildings and even the DCS in an effectively way. Therefore, the EMSD has planned to widely adopt AI technology in our upcoming DCS projects, such as Tung Chung New Town Extension (East) and Kwu Tung North New Development Area. Not only designing to adopt high energy efficient equipment, but also utilizing Big Data diagnosis, machine learning (ML) models and AI optimization control algorithm into the system control tools to enhance the operational efficiency as well as providing real-time, continuous, automatic optimization control strategy, for ensuring the most efficient operating combination of chiller plants year-round.

7. Conclusion

To ascertain the energy efficiency benefits of chiller plant operation, the design of the equipment configuration and control strategy and algorithm plays a crucial role. The EMSD make proactive and immediate action to implement various scales of chiller plant optimization programmes to maintain the most efficient operating mode, with the application of AI technology and big data, aiming to achieve a more aggressive energy saving target and striving towards carbon neutrality before 2050.

References:

[1]

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