Scalable application of streaming analytics for chiller plant optimisation

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ABSTRACT

This study presents the development of a scalable system named 'ChillStream', that utilizes streaming analytics for chiller plant energy optimization. Traditionally, most chiller plants have relied on rule-based control strategies. With the advent of high-efficiency chillers, there is an opportunity to leverage intelligent control strategies based on the varying Coefficient of Performance (COP) under different part-load and weather conditions. The objective of this study is to implement an Artificial Intelligence (AI)-based system that optimizes the performance of chiller plants. To achieve this, a remote connection was established between a Regional Digitalization Control Centre (RDCC) and the Building Management System (BMS) of target sites to enable real-time bi-directional communication of operational data. The core chiller plant optimization algorithm was developed using Python, a widely-used open platform language, following an object-oriented approach. The algorithm utilized a combination of Artificial Neural Networks (ANNs) and a hybrid algorithm that combines Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to search for optimized setpoints, including chilled water supply temperature, operating sequence, and chiller count. The developed control strategy was implemented in a chiller plant with a cooling capacity of 7,200 kW in a clinical laboratory building in Hong Kong. When compared to the conventional BMS rule-based control, the system achieved an approximate 8% reduction in energy consumption during the autumn/winter seasons. This scalable optimization strategy allows for real-time optimization in multiple buildings simultaneously, which can be easily replicated and adjusted for various chiller plant configurations and operating conditions.

CCS CONCEPTS

• Computing methodologies • Artificial intelligence • Control methods

KEYWORDS

Streaming analytics, Artificial Intelligence, remote real-time bi-directional communication, chiller plant optimisation, scalable optimisation strategy

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1 Introduction

Energy efficiency is of crucial priority in buildings due to its significant impact on environmental sustainability and economic effectiveness. Buildings consume a substantial amount of energy, contributing significantly to global energy consumption. In the context of Hong Kong Special Administrative Region (HKSAR), a city characterized by dense urban development and high-rise buildings, there is a pressing need for quick-win scalable strategies to capitalize on the significant energy saving potential. To address this, the HKSAR Government has set clear targets for achieving carbon neutrality by 2050, emphasizing the importance of reducing greenhouse gas emissions. The heating, ventilation, and air conditioning (HVAC) systems in buildings play a crucial role in achieving these targets. HVAC systems, essential for maintaining comfortable indoor environments in Hong Kong's hot and humid climate, are also major energy consumers. In commercial buildings, HVAC systems often account for over 50% of total energy consumption. Among these systems, chillers play a vital role in cooling buildings, presenting a significant opportunity for energy savings. This study focuses on developing scalable strategies that can deliver quick wins in energy efficiency for chillers. By integrating remote monitoring and control strategies with artificial intelligence techniques, such as streaming analytics, chillers’ energy performance could be enhanced, leading to considerable energy savings.

2 Related Work

In the context of engineering optimisation, Particle Swarm Optimisation (PSO) and Genetic Algorithms (GA) are two popular optimisation algorithms with distinct features [1]. PSO represents solutions as particles in a multidimensional search space, while GA represents solutions as individuals in an evolving population. In PSO, a swarm intelligence approach is utilized in which particles adjust their positions and velocities based on their own and the swarm's best-known positions. This allows for distributed exploration and makes PSO well- suited for exploratory search. GA on the other hand simulates genetic evolution by using selection, crossover, and mutation operations to create new individuals. This approach focuses on exploitative search, iteratively refining promising solutions. In engineering optimisation tasks such as chiller plant optimisation, there have been past trials using GA, PSO, or a combination of both to achieve better results [2-5]. In recent years, breakthroughs as well as renewed interest in Artificial Neural Networks (ANNs) gave rise to new and improved hybrid algorithms for optimisation [6-9], including prediction of cooling load and chiller COP in a dynamic manner. In addition to optimisation algorithms, robust real-time remote monitoring and control systems are also crucial for moderating and optimizing the energy performance of chiller systems, especially when such optimisation tools are to be deployed at scale. [10,11].

3 Methodology

3.1 Overview of the control strategy

To fully realise energy saving potential in chiller optimisation, this study attempts to develop a comprehensive end-to-end methodology to achieve scalable implementation of AI chiller optimisation. Specifically, this study has made use of the existing Regional Digitalization Control Centre (RDCC) located at the Electrical and Mechanical Ser-vices Department (EMSD) headquarters in the HKSAR to demonstrate the potential for the use of streaming analytics in optimising electrical and mechanical (E&M) assets in multiple venues concurrently (Fig. 1).

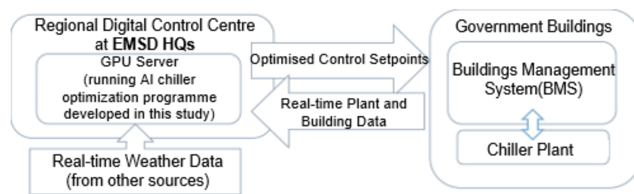

Fig. 1. Overall control strategy developed in this study.

3.2 Data collection and data cleansing

Historical data: At the core of the ‘ChillStream’, historical data were collected for the training of ANNs for prediction of chiller’s key parameters. Among these, historical weather data were obtained from an open data source provided by the local observatory in Hong Kong. In addition, the historical chiller plant data such as chiller cooling loads, chiller power consumption, and building electrical load, were collected from the BMS of the target building. These time series data were sampled at 15-minute intervals. To ensure data quality, filtering rules were applied to the plant data, eliminating transient data captured during chiller start-up or shut- down, as well as abnormal data during fault conditions. This filtering process ensured that the dataset used for analysis and optimisation was reliable and representative of normal operating conditions.

Real-time data: Real-time data, including weather and plant information, were also collected for AI inferencing. Weather data, both current and forecast, were sourced from the local observatory in Hong Kong. Plant data were obtained from the BMS and sent to the RDCC. To facilitate processing, the weather and plant data were consolidated into designated JavaScript Object Notation (JSON) format, and were then fed to the GPU server located in the RDCC for analysis.

3.3 Artificial Neural Network

Predicting total building cooling load: To predict the future total building cooling load, a fully connected artificial neural network model called ANN_TCL was developed. The model was designed to effectively capture seasonal variations in weather and activity conditions, utilizing a training dataset spanning at least 12- 18 months. During the training process, around 10% of the data were reserved for validation, while the remaining data were employed for training. The input data for the ANN_TCL (Table 1) included weather data, chiller plant data, and building electrical load data. Considering the time required for chillers to achieve target setpoints, such as on-off status and chilled water supply temperature, predictions were made for the total building cooling load at a future time frame of 15 minutes.

Table 1. Inputs to ANN_TCL

Inputs	Referenced Timestamp
Cooling load	Current
Outdoor temperature	Current and forecasted at 15 minutes later
Outdoor relative humidity	Current and forecasted at 15 minutes later
Solar Irradiation (Direct)	Current
Solar Irradiation (Diffuse)	Current
Cumulative Rainfall (past-hour)	Current
Wind direction	Current
Wind speed	Current
Building Electrical Load	Current
Hour of the day	Calculated as at 15 minutes later
Bi-week of the year	Calculated as at 15 minutes later

Predicting chiller cooling load and power consumption: To model the operational performance of each chiller, fully connected ANNs were adopted for individual chillers. These ANNs consisted of two hidden layers. For each chiller, two separate ANNs were trained: one for predicting chiller power consumption, namely ANN_CH_P, and the other for predicting chiller cooling load, namely ANN_CH_CL. Weather data and plant data (Table 2) were employed in training these ANNs. Similar to the ANN for predicting total building cooling load, predictions were made for the chiller cooling load and power consumption at a future time frame of 15 minutes.

Table 2. Inputs to ANN_CH_P and ANN_CH_CL

Inputs	Referenced Timestamp
Chilled water supply temperature setpoint	Current
Main chilled water return temperature*	Current and forecasted at 15 minutes later
Outdoor temperature	Current and forecasted at 15 minutes later
Outdoor relative humanity	Current

* A single main chilled water return temperature was adopted for all chillers.

3.4 Optimisation Algorithm

Hybrid GA-PSO Algorithm: In this study, a three-stage hybrid algorithm combining Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) has been developed (Fig.2). The hybrid algorithm consists of a PSO loop nested within a GA loop, which is further nested within another GA loop. To achieve optimal and real-time control, the control setpoints for the chillers were calculated and updated every five minutes, and this process is done based on the most recent weather data (both current and forecasted), building electrical load data, and plant data. By considering these factors, the algorithm ensures that the control setpoints respond to the dynamic nature of the environment. The first step in the algorithm involves estimating the future building cooling load through the ANN_TCL. Next, a randomized population of chilled water supply temperature setpoints and chiller on-off setpoints is initialized. This population, along with the weather and plant data, is then fed into the ANNs to calculate the chiller cooling loads (i.e. ANN_CH_CL) and power consumption (i.e. ANN_CH_P). To further improve variety of the population, at the end of the PSO loop, additional new members would be mixed with the current population to enhance exploration of the search space.

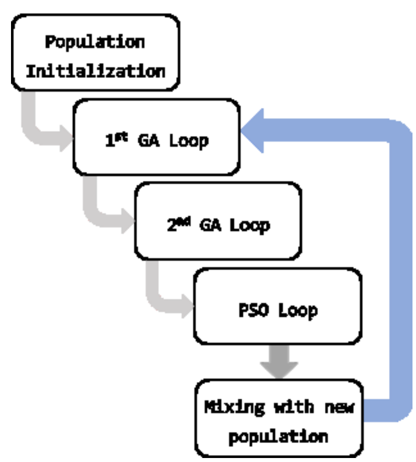

Fig. 2. Outline of the hybrid GA-PSO algorithm.

Objective function and penalty mechanism: The objective function in this study is defined as the sum of chiller power consumption as well as the total primary and secondary chiller pumps, which serves as the objective to minimize energy usage, as shown in Eq.(1) below:

$$\text{Objective function} = \sum_{i=1}^{N} P_i + P_{\text{pump}} \tag{1}$$

where P_{i} denotes the power consumption of the ith chiller, while P_{pump} denotes the total power consumption of primary and secondary pumps.

In general, the power consumption of chillers is more significant than that of chiller pumps, thus P_{pump} has been calculated by simpler empirical formulae in this study. To achieve minimisation of total power consumption, the hybrid GA-PSO algorithm is employed to minimise the objective function, while ensuring the predicted total building cooling load is met as in Eq.(2).

$$\text{Total Cooling Load} \leq \sum_{i=1}^{N} \mathrm{C}_i \tag{2}$$

where C_i denotes the cooling capacity of the i^th^ chillers.
In practice, it is essential to discourage frequent switching-on or switching-off of chillers, which leads to energy wastage and system instability. To this end, a penalty system is implemented, wherein penalties are assigned for both switching-on and switching-off of chillers.

$$\varphi_{switch} = \sum_{i=1}^{N} \varphi_{on,\ i}\ (t) + \sum_{i=1}^{N} \varphi_{off,\ i}\ (t) \tag{3}$$

$$\varphi_{on,\ i}\ (\mathrm{t}) = \begin{cases} \varphi_{on,\ i}\ (t), & chiller\ switched\ from\ off\ to\ on \\ 0, & otherwise \end{cases} \tag{4}$$

$$\varphi_{off,\ i}\ (\mathrm{t}) = \begin{cases} \varphi_{off,\ i}\ (t), & chiller\ switched\ from\ on\ to\ off \\ 0, & otherwise \end{cases} \tag{5}$$

where $\varphi_{on,\ i}$ (t) denotes the switching-on penalty of the i$^{\text{th}}$ chiller, while $\varphi_{off,\ i}$ (t) denotes the switching-off penalty of the i$^{\text{th}}$ chiller.

A time-dependent penalty scheme is introduced to further improve the effectiveness of the penalty system. For example, the switching-on penalty, φ_(on, i) (t), is immediately amplified by a constant as soon as a chiller is switched off. This intensified penalty discourages any immediate attempt to switch on the same chiller within a short period of time, and vice versa. Additionally, the increased penalty gradually dissipates over a defined time period through implementation of penalty recalculation at each prediction cycle, ensuring that the penalty diminishes gradually with time and allow flexibility of new chiller combination over time.

As a new set of chilled water supply setpoints was predicted at each optimisation cycle, it is preferable that the change in these setpoints be minimised. Accordingly, an additional penalty τ_{switch} is introduced to penalise drastic change in chilled water supply setpoints as shown in Eq.(6), and in turn the penalty function is given by Eq. (7).

$$\tau = \sum_{i=1}^{N} \alpha\left(T_{s\,new,\ i} - T_{s\,current,\ i}\right)^2 \tag{6}$$

$$\text{Penalty function} = \varphi_{switch} + \tau \tag{7}$$

where $T_{s\,new,\ i}$ and $T_{s\,current,\ i}$ respectively denote the new and current chilled water supply setpoints of the ith chiller, and α is set as an arbitrary constant representing the relative weight of this penalty term.

The fitness function for the optimisation algorithm is therefore constructed as the sum of objective function and penalties incurred, as shown in Eq.(8).

$$Fitness\ function = Objective\ function + Penalty\ function \tag{8}$$

By incorporating penalties into the fitness function, the hybrid GA-PSO algorithm could then be used to optimize chiller power consumption while promoting stable operation and minimizing energy usage. In practice, Eq.(2) is also incorporated into the optimisation as a penalty term, effectively transforming the optimisation into an unconstrained one.

Imposing part-load ratio constraints: A major characteristic of high-efficiency chillers is their optimal performance at low part-load ratios (PLRs), typically around the range of 30-50% capacity usage. However, further reduction in PLR may result in instability and potential damage under low load operation, for instance below 30%, if prolonged. Therefore, it is necessary to implement safeguarding mechanisms to discourage such low load operation. In the system, two approaches were adopted to address this issue. The first approach involves assigning a minimal baseline PLR, so that the optimisation algorithm naturally favours suitable chilled water supply temperatures to achieve basic load allocation. The second approach is to monitor the capacity of chillers at regular intervals, such as every 5 minutes. The chilled water supply temperature setpoint is decreased if the actual PLR (or full load amperage %) drops below predefined limits. Both approaches are integrated into the penalty mechanism, which enforce the desired behavior and ensure that the chiller's PLR remains within an appropriate range.

Computational efficiency: In each iteration of the hybrid GA-PSO algorithm, the fitness of the entire population was computed by evaluating a combination of set-points, weather data, and plant data using 14 ANNs, i.e. seven for chiller power con-sumption (ANN_CH_P) and seven for chiller cooling load (ANN_CH_CL). To optimize computational efficiency and promote faster convergence towards global optima, vectorisation techniques were employed instead of traditional for loops. Additionally, commercial grade GPU servers were used in the RDCC to improve inference speed.

4 Results and discussion

4.1 Test site and plant

In this study, the historical time series chiller plant data of a multi-storey clinical laboratory building in Hong Kong were acquired. The chiller plant consists of seven air-cooled chillers – two with rated cooling capacity of 600 kW and the other five with 1,200 kW. Leveraging existing communication backbones between the RDCC and the BMS of the test site, real-time plant data were also collected at 15 minutes interval for the ANN inference and optimisation purpose.

4.2 Simulation results of ANNs

The ANNs, including the ANN_TCL, seven ANN_CH_CL, and seven ANN_CH_P, were trained using historical data from the target site. The relationship between the actual and predicted values of the trained ANN_TCL demonstrates that the ANN_TCL model produces satisfactory results for practical chiller plant operation when utilized for short-term predictions of the total building cooling load (Fig. 3). The majority of the predicted values fall within the 10% scatter band.

However, when examining the scatter plots for the relationship between the actual and predicted values of the trained ANN_CH_P (Fig. 4) and ANN_CH_CL models (Fig. 5), it becomes apparent that there are instances where the predicted results may deviate beyond the 10% scatter band for certain chillers, suggesting that the accuracy of some predictions may be compromised, potentially due to specific conditions of individual chillers. To address this concern, future work may focus on developing more robust data pre-processing techniques, for instance, a continuous and automatic checking on chiller plant data to exclude data that are captured during equipment faults or abnormal conditions.

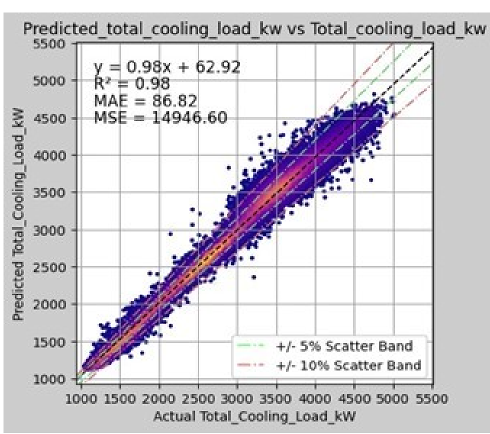

Fig. 3. Scatter plot of trained ANN_TCL for prediction of total building cooling load.

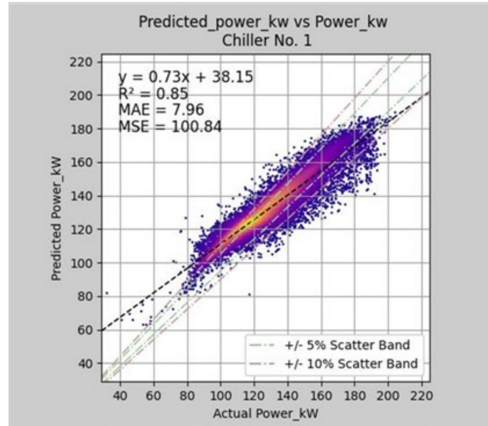

Fig. 4. Performance evaluation of ANN_CH_P for prediction of chiller power consumption (showing one of the chillers)

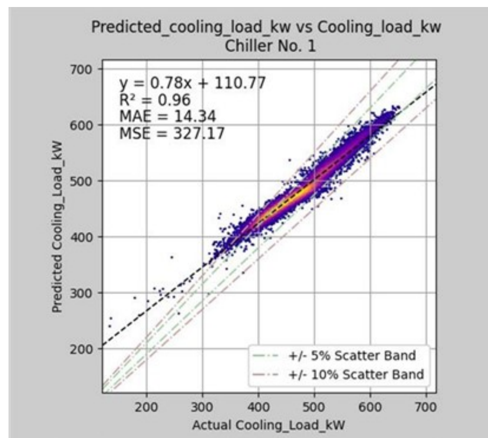

Fig. 5. Performance evaluation of ANN_CH_CL for prediction of chiller cooling load (showing one of the chillers)

4.3 Simulation results of optimisation

The hybrid GA-PSO algorithm was evaluated using various initial population sizes ranging from 100 to 4,000, with number of iterations fixed at 15. It was observed that a larger population size led to earlier convergence, at the cost of increased computational cost for each iteration. Considering the prediction cycle of five minutes in this study, it was determined that a population size of 2,000 strikes a balance between search variety and computational efficiency. Notably, the optimisation process typically completed in less than one minute, making it a suitable choice for practical application in near real-time chiller plant control.

4.4 Communication between the RDCC and BMS

Bi-directional communication was established between the RDCC and the BMS at the test site. On the BMS side, safety rules were implemented to ensure that the BMS would take control in specific scenarios, such as when there is a cessation of AI prediction, loss of communication, or when the main chilled water supply/return temperatures fall outside the acceptable range. During the testing phase, the safety rules were evaluated and confirmed to function correctly.

The implementation of safety rules established a stable foundation for the application of remote AI stream analytics for chiller optimisation, ensuring the reliability and integrity of the system. The GPU server setup was found to be stable, providing the necessary computational power for efficient AI processing, including both inference operations and routine training of neural networks. In practice, to facilitate the monitoring by site staff and the AI development team, the BMS user interface was modified to show real-time AI recommendations (Fig. 6).

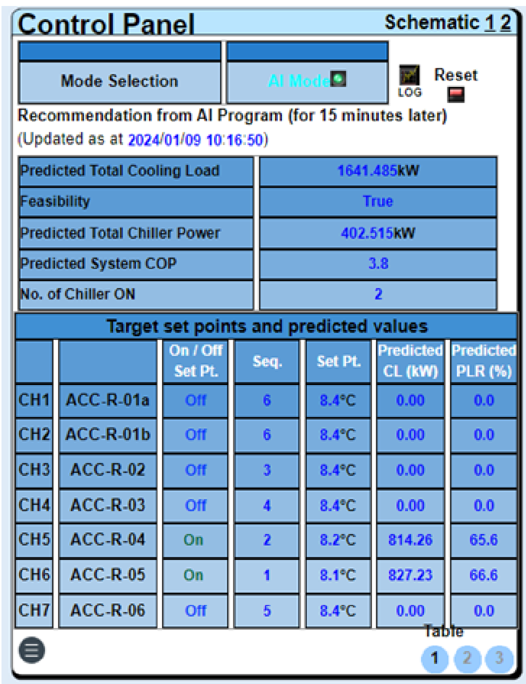

Fig. 6. Modified BMS user interface, showing real-time supply temperature setpoints and sequence order recommended by the AI system.

4.5 Site trial results

Since October 2023, a trial run of 'Chillstream' has been conducted in a multistory clinical laboratory building in Hong Kong, involving the operation of the chiller plant in an AI mode. To ensure a fair comparison of energy consumption, it was necessary to establish a method for estimating the energy that would have been consumed if the chiller plant had been operated in the conventional BMS mode under similar conditions. To facilitate this comparison, a dedicated ANN called 'ANN_Baseline' was trained using 24 months of BMS operation mode data. The ANN_Baseline model utilized key parameters as inputs, including outdoor temperature, outdoor relative humidity, and building electrical load. Throughout the trial period from October to December 2023, approximately 500 hours (around 20 days) of data were collected and analyzed while the chiller plant operated in AI mode. The analysis revealed that the chiller plant achieved an overall energy saving (including chillers and associated pumps) of approximately 8% (Table 3).

	(A) Baseline Energy Consumption under BMS mode (kWH)	(B) Actual Energy Consumption Recorded (kWH)	Difference (%) [(B)-(A)] / (A)
BMS mode	**2,331,347**	**2,383,484**	**2.24%**
2022 (Oct - Dec)	**1,177,446**	**1,221,368**	**3.73%**
October	458,354	486,492	6.14%
November	473,578	503,857	6.39%
December	245,514	231,019	-5.90%
2023 (Oct - Dec)	**1,153,900**	**1,162,116**	**0.71%**
October	594,950	615,590	3.47%
November	366,261	360,300	-1.63%
December	192,690	186,227	-3.35%
AI mode	**263,716**	**242,392**	**-8.09%**
2023 (Oct - Dec)	**263,716**	**242,392**	**-8.09%**
October	17,729	16,401	-7.49%
November	90,164	87,340	-3.13%
December	155,824	138,651	-11.02%

Table 3. Comparison of chiller plant energy consumption under AI mode and BMS mode.

To evaluate the accuracy of the ANN_Baseline model, a comparison was made between the actual energy consumption during BMS mode and the predicted values. This comparison demonstrated a small deviation of about 2%, indicating a high level of accuracy in the estimation provided by the ANN_Baseline model. It is important to note that the trial took place during the autumn/winter seasons. As a result, it is anticipated that the energy savings may be reduced if the chiller plant is operated during the spring/summer seasons where more chillers are operating at a higher cooling load. Further investigation and analysis are required to assess the system's performance under different seasonal conditions. The 'Chillstream' successfully operated 24/7, meeting stringent cooling demands in a clinical setting throughout the trial. This demonstrates the feasibility of implementing AI streaming analytics in various venues. The system's reliability and ability to handle critical applications in healthcare environments provide valuable insights for future deployments. The trial's success highlights the practicality of AI technologies for real-time monitoring, analysis, and decision-making in demanding settings.

4.6 Key means to energy saving in chiller optimisation

As demonstrated in the trial, the hybrid GA-PSO algorithm effectively identifies optimal supply temperature setpoints for each chiller. When operating the same number of chillers, the AI mode aims to optimize energy use by assigning the best combination of setpoints. In effect, the AI system has been searching for 'sweet spots' in the chillers' PLRs, and such setpoints cannot be computed manually or effectively modeled by a simple rule-based system dynamically. Another way to save energy using 'Chillstream' is by increasing the main chilled water supply temperature consistently and continuously. Since 'Chillstream' operates 24/7 and always seeks for optimal setpoints within predefined boundaries, the main chilled water supply temperature can be raised to a higher level in a safe manner, further contributing to energy savings.

4.7 Provision of GPU servers

Chiller setpoints combinations can surge significantly when more chillers are activated, typically in spring/summer. In this study, multiple GPU servers were deployed for AI training and inference. In future deployment, to achieve concurrent AI inference across various chiller plants in different venues, a powerful training server can be dedicated to ongoing AI model development, while trained AI models can be deployed to lower-grade servers for inference purposes. This approach optimizes resource utilisation, scalability, and performance, with the training server focusing on refinement and optimisation, and lower-grade servers handling real-time inference tasks.

4.8 Advantage of streaming analytics

As observed in the site trials, the use of data-driven approach and streaming analytics to optimize chiller energy performance offers several advantages. Firstly, the centralized training of ANN models can be automated as part of daily routines, saving time and effort while ensuring that the deployed models remain accurate and up-to-date. This automated training approach can account for the effect of maintenance activities and equipment derating on chiller performance, and allows the system to adapt to changes over time without requiring manual readjustment, as is necessary in rule-based approaches. Secondly, the bi-directional communication demonstrated in this study can be easily replicated in various venues. This enables the scaling up of round-the-clock optimisation for E&M assets in different locations, resulting in increased energy and cost savings. Finally, the adoption of streaming analytics in the RDCC can consolidate practical experience with different venues and plants, efficiently facilitating development of AI models and enhancing their effectiveness and applicability.

4.9 Standardised AI-BMS data-exchange interface

In the site trials, a standardised JSON data exchange interface was adopted, serving as the bridge for data exchange between the AI and BMS at regular intervals. The use of JSON files as a lightweight and expandable data format allowed for easy archiving, retrieval, and troubleshooting of all data generated by the AI and BMS. By analyzing the data exchange logs, both the AI development team and the operation & maintenance team can actively participate in project development and closely monitor the behavior of both the AI and BMS. This simple and standardised data interface also paved the way for the potential integration of other AI engines, as well as the AI application on other E&M assets, enabling future advancements without the need to rework the communication pipeline between the AI and BMS (Fig. 7).

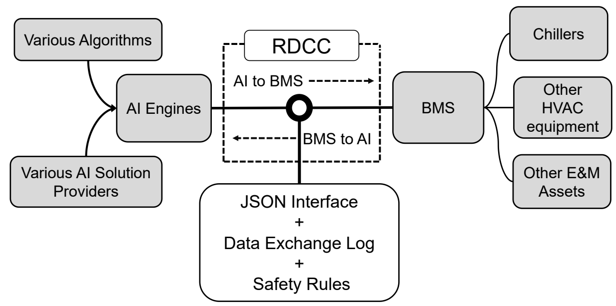

Fig. 7. Design of the interface between AI and BMS.

5 Conclusion

In this study, a hybrid GA-PSO optimisation algorithm, combined with fully connected ANNs, was developed to optimize the setpoints of chiller plants and achieve significant energy savings. The results showcased the effectiveness of employing streaming analytics from a central RDCC to remote sites, providing a viable and scalable solution for chiller plant control. By leveraging BMS in target buildings, this solution has the potential to scale up energy savings across multiple buildings. Furthermore, consolidating practical experience in control and neural network training routines within the RDCC further enhances the sustainability of this control strategy. The continuous and automated optimisation facilitated by streaming analytics not only saves manpower but also enables the identification of energy-saving opportunities. For instance, it allows for fine-tuning of cooling load baselines at different time periods, resulting in further energy efficiency improvements. Overall, this chiller plant control strategy exemplifies the practical application of artificial intelligence in promoting green building practices. By amplifying energy savings in a scalable manner, streaming analytics for chiller plant control plays a crucial role in optimizing energy consumption and reducing environmental impact.

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