Scalable AI-Based Chiller Optimisation System for Enhanced Energy Performance

Wai Leuk WL Chiu [1], Tommy KC LAM [1], Ray WH LAM [1], Safiya WK YU [1], Charlie CH LO [1], Jenny TY IP [1]

1. Electrical and Mechanical Services Department, Hong Kong

I. Introduction

Energy saving in buildings is of paramount importance due to its significant impact on both environmental sustainability and economic efficiency. Buildings consume a substantial amount of energy, with studies showing that they account for a large proportion of total energy consumption worldwide. In the context of Hong Kong Special Administrative Region (HKSAR), a city known for its dense urban environment and high-rise buildings, energy saving measures are crucial to achieve carbon neutrality. As part of global efforts to combat climate change, a comprehensive and quick-win approach is deemed to be essential to reduce carbon footprint. In this regard, the Heating, Ventilation, and Air-conditioning (HVAC) systems in buildings play a pivotal role in electrical power consumption. While HVAC systems are critical for maintaining comfortable indoor environments in a place like Hong Kong, which is characterized by hot and humid climate, they are also one of the largest consumers of energy in buildings especially commercial ones accounting for over 50% of the total energy consumption. Among the components of HVAC systems, chiller, a key equipment in Air-conditioning system responsible for generating chilled water to cool air, specifically consumes a significant fraction of energy. Therefore, automatic optimisation of chiller plant system's operation has been a hot energy saving topic in the engineering field.

II. Related Work

Particle Swarm Optimisation (PSO) and Genetic Algorithms (GA) are two popular optimisation algorithms with distinct approaches (Eberhart et al., 1998). PSO represents solutions as particles in a multidimensional search space. With a swarm intelligence approach, the particles in PSO adjust their positions and velocities based on their own and the swarm's best-known positions. In contrast, GA simulates genetic evolution and represents solutions as individuals in an evolving population, and iteratively refines optimal solution using selection, crossover, and mutation operations. PSO is better suited for exploratory search, allowing for distributed exploration, while GA tends to focus on exploitative search. PSO can converge quickly but may struggle to find globally optimal solutions, while GA maintains population diversity to avoid premature convergence and has a better chance of finding global optima. There were past trials using GA, PSO, or combination of both in achieving optimisation of engineering systems and HVAC systems (Jahanbani Ardakani et al., 2008; Beghi et al., 2012; Wei et al., 2014; Gao et al., 2022).

Traditionally, the operation of a chiller plant system is rule based or manually controlled without systematically considering the energy saving potentials and automatic optimization benefits. This results in energy inefficiency and the squander of manpower resources to operate the chiller plant system. With breakthroughs both in enabling software and hardware, and therefore renewed interest in Artificial Neural Networks (ANNs) in recent years, new and improved hybrid algorithms for optimisation were developed (Chow et al., 2002; Afram et al., 2017; Wang et al., 2019; Chen et al., 2023), including prediction of cooling load and chiller Coefficient of Performance (COP) in a dynamic manner. In addition to optimisation algorithms, robust real-time remote monitoring and control systems are also crucial for moderating and optimising the energy performance of chiller plant system, especially when such optimisation tools are to be deployed at scale (Chen et al., 2018; Suen et al., 2021).

III. Methodology

A. Overview of the chiller plant system control strategy

In this study, Artificial Neural Networks (ANNs) is adopted to understand the behaviour and interactions of the chiller plant system from historical weather, chiller plant system and building load data. An accurate and predictive model of system behaviour has been subsequently developed. Riding on the past foundation of using PSO and GA in chiller optimisation, this study further attempts to develop comprehensive end-to-end methodology to scale up the implementation of AI chiller optimisation with autonomous control. Apart from utilizing the machine learning techniques in AI for better eliciting, analysing and managing system requirements, optimal system architectures that meet simultaneously the constraints of the system and are governed by safety rules have been identified.

On the other hand, this study has specially made use of the Regional Digitalization Control Centre (RDCC) located at an anonymous building headquarter in Hong Kong to demonstrate the potential for the use of streaming analytics and real-time remote control in optimising electrical and mechanical (E&M) assets (Fig. 1). RDCC, a dedicatedly built system, performs real-time bi-directional monitoring and controlling as well as centrally collecting data for numerous applications such as facility management and operational optimization of plants. With its ability to collect significant amount of data, we can realise building informatics from the digital world. Besides, the E&M digitization also provides massive streams of data, which will open up new opportunities of collaboration for real-time and continuous optimization of energy use.

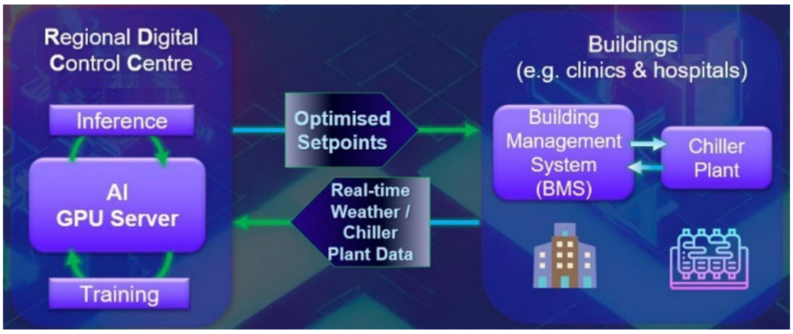

Fig. 1. Overall control strategy developed in this study

B. Data collection and data cleansing

1. Historical data

Historical data were collected for the training of ANNs. Among these, historical weather data were obtained from an open data source provided by the local observatory in Hong Kong. Additionally, historical chiller plant system data, including time series data sampled for chiller cooling loads, chiller power consumption, and building electrical load, were collected from the Building Management System (BMS), a localized rule-based control and monitoring system, of the target building. These time series data were collected at a 15-minute interval.

2. Data cleansing

To ensure data quality, automatic filtering rules were applied to the plant data, eliminating transient data captured during chiller start- up or shut-down, as well as abnormal data recorded during chiller fault conditions. This filtering process ensured that the dataset used for analysis and optimisation was reliable and representative of normal operating conditions.

3. Real-time data

Real-time data were collected and fed to the ANNs for prediction. Real-time weather data, including current and forecast data, were collected from the local observatory in Hong Kong. Additionally, plant data were collected from the BMS to the RDCC. Both the weather data and plant data were consolidated for feeding to the GPU server housed in the RDCC.

C. Artificial Neural Networks (ANNs)

1. Predicting total building cooling load

A fully connected artificial neural network model, namely ANN_TCL, was developed to predict the future total building cooling load. To ensure that the model effectively captures seasonal changes in weather and activity conditions, historical data spanning at least 12-18 months were utilized to train the ANN. Among which, around 10% of the data were reserved for validation, while the remaining data were used for training. The input data for the ANN_TCL (Table I) includes weather data, chiller plant system 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.

2. 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 individual ANNs were trained: one for predicting power consumption, namely ANN_CH_P, and the other for predicting cooling load, namely ANN_CH_CL. Weather data and plant data (Table II) were used 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 I. 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

TABLE II. INPUTS TO ANN_CH_P AND ANN_CH_CL

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

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

D. Optimisation Algorithm

1. Hybrid GA-PSO Algorithm

In this study, a three-stage hybrid algorithm combining Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) has been developed. 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 system were calculated and updated every five minutes. This was done based on the most recent weather data, building electrical load data, and chiller plant system data. By considering these factors, the algorithm ensures that the control setpoints swiftly respond to the dynamic nature of the ambient environment.

The first step in the algorithm involves estimating the future building cooling load through the ANN_TCL, followed by the initialization of a randomized population of chilled water supply temperature setpoints and chiller on-off setpoints. This population, along with the weather and chiller plant system 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. A flowchart diagram (Fig. 2) depicting the steps of the algorithm is drawn up for succinct explanation.

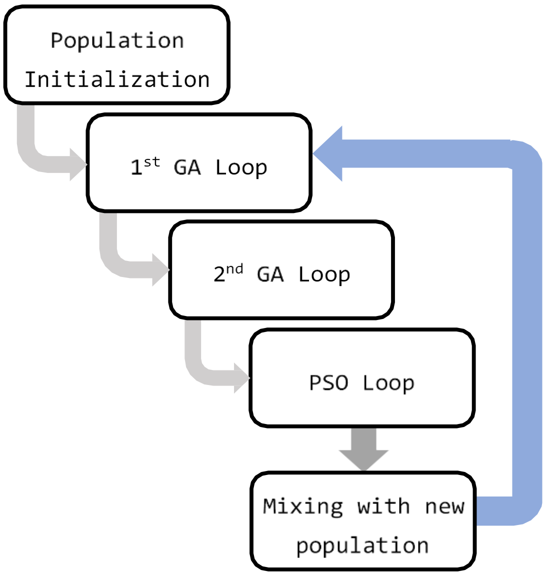

Fig. 2. Outline of the hybrid GA-PSO algorithm

2. Objective function

The objective function in this study is defined as the sum of chiller plant system power consumption, which serves as the objective to minimize energy/power usage, as shown in Eq.(1) below:

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

where P_i denotes the power consumption of the i^th chiller, while P_{pumps} denotes the total power consumption of primary and secondary chilled water pumps. In practice, the power consumption of chillers is more significant than that of chilled water pumps, and in this study P_{pumps} has been approximated by empirical formulae to simplify the optimisation process.

Chillers are often required to operate at part-load conditions, as the cooling demand can fluctuate throughout the day or seasonally. The COP of a chiller, which is a measure of its energy efficiency, varies with diverse loading conditions. Taking the advantage of the significantly high COP in part load condition of the chillers in this study, the best energy efficient combination of the servicing chillers is critical to the overall system's COP. Another important factor in the optimization of chiller plant system is the performance characteristics and the cooling capacity of the individual chillers. Each chiller has its own unique performance characteristics, which describe how the cooling capacity and power consumption vary with factors such as the chilled water supply temperature and compressor speed. This study successfully creates accurate models of the mentioned performance characteristics from the historical data, which then are used to optimize the operation of the chiller plant system. To achieve minimisation of total power consumption and meanwhile maximization of the chiller plant system's COP, 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).

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

where C_i denotes the cooling capacity of the i^th chiller.

3. Penalty mechanism for discouraging frequent chiller switching

In practice, it is essential to discourage frequent switching- on or switching-off of chillers, which leads to energy wastage, chillers detriment and system instability. To this end, a time-dependent penalty system is implemented, wherein penalties are assigned for both switching-on and switching-off of chillers.

As an indication, the switching-on penalty is immediately amplified by a certain factor 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 period through implementation of penalty recalculation at each prediction cycle, ensuring that the penalty diminishes gradually with time.

4. Penalty mechanism for discouraging drastic temperature reset

A new set of chilled water supply setpoints was predicted at each optimisation cycle. It is essential that the change in these setpoints is minimised to avoid unpredicted chiller behaviours and less accurate chilled water supply temperatures. Accordingly, an additional penalty is introduced to penalise drastic and frequent change in chilled water supply setpoints.

5. Overall fitness function

The fitness function for the optimisation algorithm is therefore constructed as the sum of objective function and penalties incurred, as shown in Eq. (3).

$$\text{Fitness function} = \text{Objective function} + \text{Penalty function} \tag{3}$$

By incorporating penalties into the fitness function, the hybrid GA-PSO algorithm could then be used to optimise chiller power consumption while promoting stable operation and minimizing energy usage.

6. Implementation of site-specific Safety Rules

Given the importance of the chiller plant system's performance, it is imperative that its operation remains within well-defined safety parameters, even when automated AI-based optimization systems are in use, to maintain system’s reliability and the conformance to building load’s requirements. Hence, this study has pursued processes for identifying, analyzing, and mitigating risks associated with the development and operation of the AI optimisation algorithm. Deliberate constraints and safety rules are designed and incorporated in the entire AI optimization to ensure the reliability, efficiency, and safety of the chiller plant system. Most importantly, safety rules were implemented to ensure that the BMS would override AI control in specific adverse circumstances.

Maintaining the chilled water supply temperature within a specific range is crucial for the proper functioning of the air-conditioning supply system. If the chilled water temperature falls outside the acceptable range, it can lead to issues such as overcooling or insufficient cooling, which can impact the comfort levels of the building's occupants. Additionally, operating the chillers at very low load level or beyond the recommended temperature range can put strain on the equipment, potentially leading to premature wear and tear or even system failures due to the damage induced to the compressors and coil pipeworks.

The safety rule regarding the loss of communication with the AI-based optimization system is in place to ensure that the chiller plant system can continue to operate safely and reliably even in the event of a failure or disruption in the AI system. By suspending AI operation and reverting to a predetermined mode of operation, that is the BMS, the chiller plant system can maintain its critical cooling function without being inevitably dependent on the AI system.

The fault signal safety rule is designed to immediately suspend AI operation and revert the chiller plant system to BMS in the event of a fault or anomaly detected in the AI system. This safeguard ensures that any issues or errors in the AI-based optimization algorithms do not jeopardize the overall performance and safety of the chiller plant system.

In brief, the safety rules outlined are vital to the chiller plant system operation, as they help to maintain the system's stability, reliability, and energy efficiency, while also protecting the equipment and ensuring the comfort and safety of the building's occupants.

7. Adoption of unconstrained optimisation approach

The hybrid GA-PSO algorithm efficiently explores ‘near-boundary’ solutions, enhancing the ability of the algorithm to thoroughly explore the search space. With GA’s inheritance approach, the algorithm can ‘remember’ and in turn differentiate among traits that would likely transgress the predefined boundaries. With the addition of more boundary conditions, an unconstrained optimisation approach becomes increasingly practical. Results will then be turned out into more realistic and refining.

8. Heuristic initialisation of the population

To enhance search efficiency and prevent drastic chiller operation changes, a fraction of the population in the optimisation program was initialized to match the current active chiller combination. Additionally, a subset of this fraction was initialized with the minimum chilled water supply temperature. This approach ensures the program covers solutions close to the existing operation conditions and increases the likelihood of meeting cooling demand. By including current chiller configurations, abrupt changes are avoided, safeguarding system stability.

9. Computational efficiency – fitness value calculation

In each iteration of the hybrid GA-PSO algorithm, the fitness of the entire population was computed by evaluating a combination of setpoints, weather data, and chiller plant system data using multiple ANNs, i.e. ANNs for chiller power consumption (ANN_CH_P) and ANNs for chiller cooling load (ANN_CH_CL). To optimise computational efficiency and promote faster convergence towards global optima, vectorization techniques were employed instead of traditional “for loops”. Vectorization is crucial for efficient computation and real-time control, especially when penalty rule complexity grows and timely solutions should be provided.

10. Computational efficiency – making good use of the idling time

In addition, because evolutionary algorithms inherently necessitate generation of multiple random numbers in iterations, a dedicated Python class was constructed to pre- generate a large pool of random numbers during the idle time between successive hybrid GA-PSO computation cycles. Accordingly, within the GA-PSO loop, the algorithm can have direct access to the pool of pre-generated random numbers, effectively saving the need of multiple calls for random number generation function.

11. Computational efficiency – GPU acceleration

To further enhance inference speed, GPU servers were deployed in the RDCC. These servers are equipped with commercial-grade GPUs. It is worth noting that the potential combinations would significantly increase as the number of chillers that need to be activated rises. Assuming that one can select r chillers out of n total chillers to operate, and each chiller has the flexibility to independently set its chilled water supply temperature among d discrete steps, the total number of combinations within the search space can be represented by Eq. (4).

$$\text{Total number of combinations} = \sum_{r=0}^{n} {}^{n}C_r \, d^r \tag{4}$$

It could be anticipated that the possible combinations in the search space grow at a staggering rate, which human being necessitates significant amount of time to provide the output results. In fact, the calculation becomes more complicated when the number of chillers required to be operated increases in spring/summer. In gist, to cope with the robust optimisation algorithm, an equivalently powerful and compatible hardware system is indispensable.

IV. Results and Discussion

1. Test site and plant

In this study, the historical time series chiller plant system data of a multi-storey clinical laboratory building in Hong Kong were acquired. The chiller plant system consists of seven air-cooled chillers – two with rated cooling capacity of 600 Kilowatt (kW) and the other five with 1,200 Kilowatt (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 ANNs inference and optimisation purpose. Due to the stringent temperature and humidity control requirement at the testing site, the operation of AI was subject to a series of simulation tests before putting to actual site trials.

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 of 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 system operation when utilized for short-term predictions of the total building cooling load (Fig. 3). The majority of the predicted values falls within the 10% scatter band. However, the scatter plots depicting the relationship of the actual and predicted values of the trained ANN_CH_CL (Fig. 4) and ANN_CH_P models (Fig. 5), reveal instances where the predicted results may deviate beyond the 10% scatter band for certain chillers. This indicates that the accuracy of these predictions may be compromised, probably due to specific conditions of individual chillers. To address this concern, future work may focus on developing more robust data pre-processing techniques.

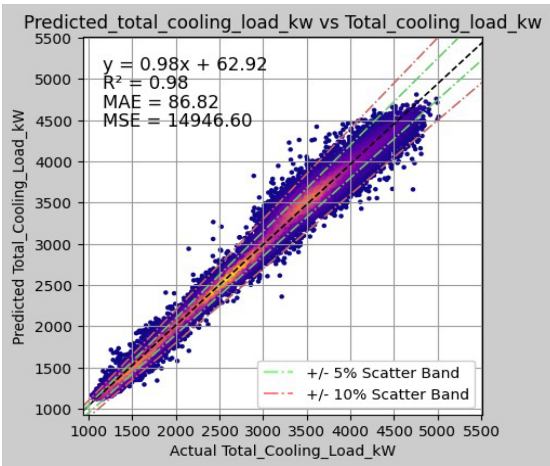

Fig. 3. Scatter plot of trained ANN_TCL for prediction of total building cooling load

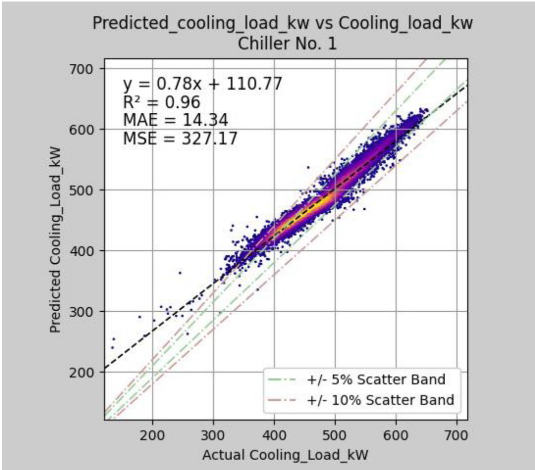

Fig. 4. Performance evaluation of ANN_CH_CL for prediction of chiller cooling load (showing one of the chillers)

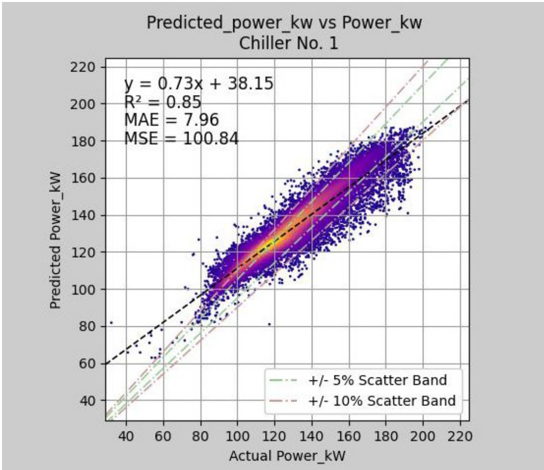

Fig. 5. Performance evaluation of ANN_CH_P for prediction of chiller power consumption (showing one of the chillers)

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 system control.

4. Communication, monitoring and feedback control between the RDCC and BMS

Bi-directional communication was established between the RDCC and the BMS at the test site. 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 streaming 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.

The AI optimization system uses advanced algorithms and sensor data to continuously evaluate the chiller plant system's operation and adjust the control parameters. This feedback control loop allows the system to respond to changes in building occupancy, weather conditions, or other factors that can impact the chiller plant system's energy efficiency and cooling capacity. By constantly monitoring and adjusting the system's operation, the AI-based optimization helps to ensure the chiller plant system remains within the established safety and efficiency parameters, maximizing the system's reliability and performance.

5. Site trial results

Since October 2023, a trial run of this AI optimisation of chillers system has been conducted in a multi-storey clinical laboratory building in Hong Kong, involving the operation of the chiller plant system in AI mode. To ensure a fair comparison of energy consumption, it was necessary to establish a method for estimating the energy consumption that would have been resulted had the chiller plant system 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 data parameters such as outdoor temperature, outdoor relative humidity, and building electrical load as inputs. 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 system operated in AI mode. The analysis revealed that the chiller plant system achieved an overall energy saving (including chillers and associated pumps) of approximately 8% (Table III). 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 system is operated during the spring/summer seasons where more chillers are operating at full load with fixed COP. Further investigation and analysis are required to assess the system's performance under different seasonal conditions.

TABLE III.
COMPARISON OF CHILLER PLANT SYSTEM ENERGY CONSUMPTION UNDER AI MODE AND BMS MODE

	Average Outdoor Temperature (°C)	Average Relative Humidity (%)	Average Building Electrical Load (kW)	Duration of Operation (Days)	(A) Baseline Chiller Plant System Energy Consumption under BMS mode (kWh)	(B) Actual Chiller Plant System Energy Consumption Recorded (kWh)	Difference (%) [(B)-(A)] / (A)
BMS mode	**22.4**	**69.9**	**1,342**	**159**	**2,331,347**	**2,383,484**	**2.24%**
2022 (Oct - Dec)	**21.7**	**68.9**	**1,255**	**86**	**1,177,446**	**1,221,368**	**3.73%**
October	25.8	62.8	1,280	26	458,354	486,492	6.14%
November	23.6	83.1	1,262	30	473,578	503,857	6.39%
December	16.2	60.3	1,227	30	245,514	231,019	-5.90%

2023 (Oct - Dec)	**23.2**	**71.0**	**1,446**	**72**	**1,153,900**	**1,162,116**	**0.71%**
October	26.1	75.5	1,466	30	594,950	615,590	3.47%
November	23.3	67.1	1,437	24	366,261	360,300	-1.63%
December	18.3	68.9	1,424	18	192,690	186,227	-3.35%
AI mode	**21.3**	**67.5**	**1,481**	**20**	**263,716**	**242,392**	**-8.09%**
2023 (Oct - Dec)	**21.3**	**67.5**	**1,481**	**20**	**263,716**	**242,392**	**-8.09%**
October	27.7	66.8	1,733	1	17,729	16,401	-7.49%
November	23.5	71.6	1,499	6	90,164	87,340	-3.13%
December	20.0	65.7	1,458	13	155,824	138,651	-11.02%

6. Practical use of the algorithm

Throughout the trial, the tested and evaluated hybrid GA-PSO optimisation algorithm efficiently and reliably executed every 5-minute cycle, ensuring near-real-time optimisation based on the latest plant and weather conditions. The adoption of key algorithmic design strategies, including vectorization of fitness value calculation, sophisticatedly trained ANNs with simulation, pre-generation of random number pools, and heuristic initialization of setpoints, played a vital role in achieving early convergence to optimised results. Additionally, the AI optimisation of chillers system, with the support of GPU acceleration using average commercial grade GPUs, successfully operated 24/7 in a setting, meeting stringent cooling demands. This successful implementation demonstrates the feasibility of applying AI streaming analytics in various venues and provides valuable insights for future deployments, particularly in electrical and mechanical systems engineering. The trial's success highlights the practicality of utilizing AI technologies for real-time monitoring, analysis, decision- making and controlling in demanding settings.

V. Conclusion

In this study, a hybrid GA-PSO optimisation algorithm, coupled with fully connected ANNs, was developed to optimise the controlled setpoints of chillers and achieve energy savings. The results demonstrated the effectiveness of amalgamating ANN, evolutionary algorithms and swarm intelligence into an AI programme that controls chiller plant system at a remote site, offering a viable and scalable solution for chiller plant system control. By leveraging existing remote control and monitoring infrastructure, as well as enhancing BMS in target buildings, this solution holds potential for scaling up energy savings across multiple buildings. In addition, consolidating practical experience in control and neural networks training routines within the RDCC further promotes the sustainability of this control strategy. The continuous and automated optimisation through streaming analytics not only leads to manpower savings, but also opens up possibilities for identifying additional energy- saving opportunities, such as fine-tuning cooling load baselines at different time periods. Overall, the success of this study attributes to the well-bonded collaboration of various disciplines, including mechanical, electrical, software, and systems engineers, as well as subject matter experts, such as chillers' operators and veteran hands-on maintenance personnel. This chiller plant system control strategy, from the initial concept and design, through development, implementation, operation, and continuous enhancement, exemplifies the practical application of artificial intelligence in pursuit of green building practices and the ultimate goal of decarbonization. In future, the AI-Based Chiller Optimisation System would be further deployed to other HKSAR Government's venues with other different kind of chiller plant system such as the water cooled chillers for comprehensive coverage.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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