Operational Management of Data Centers Energy Efficiency by dynamic optimization -Based on a Vector Autoregressive Model- Reinforcement Learning(VAR-RL) approach

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Abstract. With the increasing demands of digital computing, Data Centers (DCs) have become a leading scheme for global energy issues. Major efforts that can be observed for DC energy efficacy solutions are focusing on relatively problematic infrastructure designs. Nevertheless, we emphasised the managerial strategies of using the existing facilities to achieve energy efficiency through active intervention. It is believed that there exists a trade-off between the cooling devices and IT devices. Accordingly, the Vector Autoregressive Model- Reinforcement Learning(VAR-RL) approach will be proposed as a combination of traditional multivariate time series modeling technique and the artificial intelligence technique which allows us to predict and adjust the prediction of an error would help to explore the complex dynamic interrelationships between the two types of devices. Moreover, an optimization decision support system will also be conducted subsequently to optimize Power Usage Effectiveness (PUE) by controlling the combination of Air Conditioners (ACs). The proposed VAR-RL approach would not only increase the forecasting accuracy but also would adapt to the environment changes dynamically, this would give a better foundation for the DC energy efficiency optimization. The data we adopted is the real-time data from a DC located in Turkey. Consequently, the novel of this study would save the DC energy consumption tremendously.

Keywords: DC, Energy consumption, optimisation.

1 Introduction

DCs are energy-intensive industries and they are taking 1-1.5% of global electricity usage every year [1]. There are two main units of DCs that are supplied the energy, IT, and cooling units. Widely cited studies and conservatively evaluation demonstrated the fact that there are around 40% of energy has been taken by the cooling system in a typical air-cooling DC [2]. IT equipment, along with its respective power supply, creates heat when being in use and will raise the surrounding ambient temperature. In consequence, the equipment is likely to fail if the temperature becomes too high. Previous to 2004, IT companies were too fixated upon the performance of their equipment and adjusted the equipment's environment with only reliability in mind, with little weighting to energy costs. Nowadays the temperature range has been wider to 18 – 27℃ (ASHRAE 2016)[3]. However, there are over 90% of DCs still keeping a constant temperature which means that the DCs are over-cooled and energy inefficiency [4].

Since most of the energy consumption lies in cooling, efforts have been made on reducing the cooling energy consumption in the DCs. It has been found that configuration design predominantly affects on energy consumption. As long as there is a design revolution, the application still requires a long time. As a result, traditional air-cooling will still domain the DC cooling system in the next few decades [5]. Therefore, we are seeking DC cooling efficiency solutions from a different aspect. As we mentioned earlier, cooling devices are the biggest energy consumers in the DC however there is no guideline on how to make the optimal usage of them. The common operations in DCs are still following traditional rules by turning off some certain number of ACs to save energy in winter. But to our knowledge, there is no sophisticated analysis so far to guide the optimal use of ACs combination, which gives us ideas to fill up this gap.

According to the relationship of energy consumption units both IT and Air conditioning devices, a lower temperature will increase the energy supplied, inversely, will reduce the energy consumption of IT devices due to an increasing computing efficiency. Therefore, smart operation management on DCs to find out the optimal solution on temperature control to minimize the energy consumption without affecting the performance of IT devices and meeting the service-level agreement has been investigated. Therefore, this has become our motivation for this study. The question can be modeled as a Linear Programming (LP) problem. However, applying the LP method to the problem requires understanding the complex interactions among many variables within the DC. To solve and simplify this issue, we adopt VAR model to identify such complex interactions. It has been taken to account for common features of the industry big data

Changes rapidly in the structures. Changes in server workload, outside environment, device locations or human intervention all can be reasons that lead to structural breaks of the series. Numerous empirical studies put attention on post-event detection, which wildly used for economic or business analysis, while rarely of them are looking at this issue in a real-time. Instead, we expect the model would able to autonomous evaluate itself and correct the mistake once it notices it. In this study, we adopt RL approach for dynamic real-time adjustment of VAR model. It would take the responsibility to detect the structural break and trigger the parameter re-estimated system. With the proposed VAR-RL approach, the subsequent optimization problem can be solved with the consideration of the changes in the environment in real-time.

Our contributions to the literature including the following: (1) Give the DC energy-efficient solution without changing DC configurations. (2) A dynamic simulation system based on VAR-RL approach has been made, this will provide an efficient and accurate forecast for the complex environment with the adjustment of structural changes in the data. (3) Real-time optimization will be conducted based on the simulation result and future optimization also can be made by the forecasted data set. (4) This study will also arouse the environmental awareness of energy saving.

2 Literatures review

We have searched the empirical studies on DC effective cooling strategy of simulation-based optimization. Among the ten results, eight of them adopted the Computational Fluid Dynamic (CFD) while and the rest of them used Data-driven Models (DDM) model and other configuration design simulation tools for airflow simulation.

Most of them are from a pure configuration design and layout aspect, ie. [6] on sensors placement strategy and [8] on air aisle and racks layouts [7]. There are only [8, 9, 10] among the results that looking at the optimal temperature solutions, however [9] it doesn't take the trade-off relationships between cooling and IT into considerations and [8] is an equation-based simulation that looking at system network control. Also [10] studied the combination of water and airflow in Indirect Adiabatic Cooling (IAC) DC. Numerous studies that use the First principle (FP) in terms of DC objectives largely rely on pre-defined algorithms. However, in practical, there are a variety of unknown relationships that cannot be acquired from physical principles. Data-Driven Models (DDMs) avoid this problem by adopting experimental data to train a system. There is study compares temperature prediction performance of four different types of DDMs including Artificial Neural Networks (ANN), Support Vector Regression (SVR), Gaussian Process Regression (GPR) as well as Proper Orthogonal Decomposition (POD) in a DC, the training data is given by CFD simulation and the result demonstrated that most of them can give a relatively accurate prediction however only ANN could handle multiple output points in one model. Because of the unknown features of the system and multi-dimensional problem need to be solved in one model, so that it requires a large volume of data to feed in the model and moreover, all these types of models are facing similar difficulties which are computational expensive practical cases and relatively time-consuming [11].

We conservatively conclude that our VAR-RL approach would be the first study that further extended Linear Regression (LR) based RL to analyze complex industrial environment, then apply the simulation result to real-time optimization in industrial practical case. Due to the limited resources, we reviewed similar studies that used the similar method for different problems. RL approach has been used for an auto-select different combination of data streams to feed to the parameters-fixed LRs and practical application on typhoon rainfall prediction shows a better performance than traditional LRs [12]. More comprehensively, a Multi-Agent reinforcement learning (P-MARL) on predicting the future environment which allows the agents to adapt to the changes off-line by the combination of ANN and Autoregressive Integrated Moving Average (ARIMA) models, this joint approach also increased the prediction accuracy of the agents [13]. Moreover, efforts have been made on adapting RL to the side of the sensor to reduce the energy transmission cost in the wireless sensor networks for signal prediction [14]. These approaches provided evidences that with RL adjustment, the prediction accuracy would be largely increased and gives the model more flexibility by self-learning during prediction without any training data which would require large storage and costs for computing.

Our VAR-RL approach would take advantage of these empirical studies, moreover, we will adapt this into DC industrial practice: (1) Our model parameters will be dynamically changed according to the feedback from the learning process that would allow our model to adapt to the environment changes. (2) We will propose a time-series linear regression model that will not only consider the previous one step (MACOV) but the whole period which has an effect on the present. (3) RL tool will be plugin to determine whether the model should be reused or rebuilt. (4) We will also avoid using the technique which has a black-box property such as Artificial Neuron Network (ANN) because it hides the interrelationships into the black-box procedure which limited the interpretative of the model. (4) Also, as we expect to perform a light, fast, and efficient model to adapt to the rapid industrial practice. we will avoid the use of techniques that requires huge size of training data and local storage. (5) We will not change any DC configurations including the sensors, only managerial strategies will be applied to the DC energy-saving practice.

3 Methodology.

3.1 VAR model- A fundamental simulator

Based on the field study in TUKSAT DC target IT room, we identified the main factors that participated in the IT room computing environment. We are going to include ceiling sensors temperatures, Server rack inlet and outlet temperatures, air conditioner outflow temperatures as well as PDU values of the servers as our endogenous variables. To our knowledge, IT room objectives are mutually affected by each. As the graph shows below, we can infer that each variable can affect the others in two directions (direct or indirect), shown as a circulation (Fig.1). Statistical test (Granger causality test) results also confirmed the underlined inferences. Therefore, we briefly include all the related variables into one VAR model.

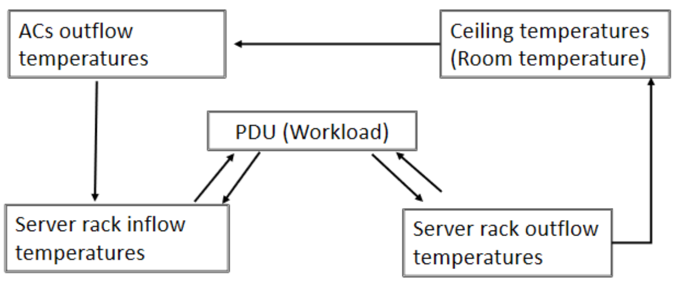

Fig. 1. The DC variables and relationships

Here we present how VAR modelling the above dynamic. VAR assumes all the variables to be endogenous and explain those endogenous variables one by one by all their past values. This allows us to use the estimated model to predict the future values of variables. A p^{th}order $VAR(p)$ can be represented as:

$$X_t = \sum_{i=1}^{k} \Pi_i X_{t-i} + C + u_t \qquad (1)$$

Assume we have N variables, then X_t is the $N \times 1$ order time series vector, C is the $N \times 1$ order constant vector, the Π_i is the $N \times N$ order parameter matrix, u_t is the $N \times 1$ order random error vector. We can extend the above equation to the matrix formula as following (The lag length will be selected by the combination of "AIC", "HQ", "SC", "FPE" criteria):

$$\begin{pmatrix} x_{1,t} \\ x_{2,t} \\ \cdots \\ x_{N,t} \end{pmatrix} = \begin{pmatrix} a_{1,1} & \cdots & a_{1,N} \\ \vdots & \ddots & \vdots \\ a_{N,1} & \cdots & a_{N,N} \end{pmatrix} \begin{pmatrix} x_{1,t-1} \\ x_{2,t-1} \\ \cdots \\ x_{N,t-1} \end{pmatrix} + \begin{pmatrix} b_{1,1} & \cdots & b_{1,N} \\ \vdots & \ddots & \vdots \\ b_{N,1} & \cdots & b_{N,N} \end{pmatrix} \begin{pmatrix} x_{1,t-2} \\ x_{2,t-2} \\ \cdots \\ x_{N,t-2} \end{pmatrix} + \ldots \begin{pmatrix} n_{1,1} & \cdots & n_{1,N} \\ \vdots & \ddots & \vdots \\ n_{N,1} & \cdots & a_{N,N} \end{pmatrix} \begin{pmatrix} x_{1,t-p} \\ x_{2,t-p} \\ \cdots \\ x_{N,t-p} \end{pmatrix} + \begin{pmatrix} q_1 \\ q_2 \\ \cdots \\ q_N \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdots \\ \varepsilon_N \end{pmatrix} \qquad (2)$$

As VAR model is a dynamic forecasting model. We can use it to simulate the DC environment as well as forecast the future values of each variable. After we get the model parameters by real-time estimation, we will feed the data that cover the lag length and forecast the future value of each variable. To make it clear, here we summarize the procedure to train a VAR model and use it as a simulator to forecast DC environment in a flowchart (See Fig.2).

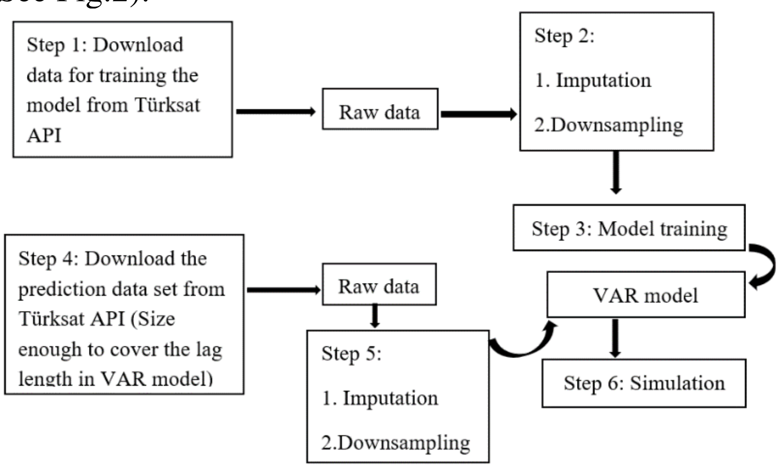

Fig. 2. The structure of the simulator

We first downloaded data from the historical Application Programming Interface (API) (Step 1). After data processing (Step 2), we use this data set to train a VAR model (Step 3). Then download historical data again (Step 4), after processing the data for another time (Step 5), we extract the most recent data which cover our lags, then input to the VAR model. The simulator will carry out iterations until reach to the requested forecasting length.

3.2 RL -A dynamic environment adaptor

As we mentioned earlier, the data estimated in DC has a rapidly changing feature, therefore our fundamental simulator VAR may not apply for some special cases: ie., suddenly changing load by holidays or online exams, temperatures changes, or other human interventions. Therefore, we need to adjust our model to ensure the prediction accuracy and be able to detect the environment changes and adapt itself to the changing world. Reinforcement learning as an environment adaptor to VAR model will be introduced in this section. The process is shown in the following graph (Fig.3).

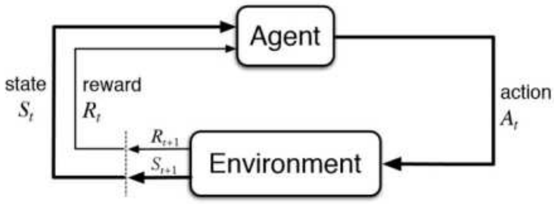

Fig. 3. The environment adaptor based on RL

With every prediction, we will have an evaluation of the accuracy. And we will give a reward (or punishment) to each prediction. The accumulated reward would be:

$$R^{cum} = \sum_{g=1}^{n} R_{t+g} \qquad (3)$$

Where R^{cum} is the total cumulated reward values, R is the reward for each forecast evaluation. With the number of time steps increasing, the difficulty level to predict would be increasing too, to make it fair enough for the judgement, we assign the weight to each reward, and the weight of the reward would be decreasing over the time.

$$R^{cum} = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}, \gamma \in [0,1) \qquad (4)$$

Where, γ is the weight.

Time windows will be plugin at every seasonality changing point. And the system will trigger RL to evaluate the prediction result. In this case, the prediction result from the fundamental simulator VAR will be evaluated by the error rate. A reward will be given to each evaluation. When the accumulated reward value reaches to a certain boundary, the environment changes will be detected. Then the RL adaptor will trigger the alarm then the VAR model parameters and features will be rebuilt.

3.3 LP approach- An energy efficiency optimizer

Empirical evidences show that increasing the AC setpoint by a single degree can result in 4-5% energy cost savings; and increasing the setpoint by 10 degrees, which is also a realistic number, can result in savings of over 40% [15]. Although this sounds straightforward and simple, considering the complex nature of DC assets, it is hardly the case. Increasing the AC setpoints blindly can jeopardize the health of servers and other hardware, as existing hot spots may become even hotter and higher hot aisle temperature

may activate server fans and offset efficiency gains. Therefore, a rigorous plan for optimizing the AC temperature setpoint is critical to increasing the energy efficiency of the DC. Particularly, we aim to optimize the energy efficiency in the DC by determining the optimal combination of the supplied temperature of AC units, while taking into consideration the dynamic nature of IT power consumption, as well as satisfying the temperature constraints.
We will use the following notations:
$S = \{S_1, S_2, \dots, S_m\}$ denotes the Server rack number 1 to m
$C = \{C_1, C_2, \dots, C_l\}$ is a set of ACs unit number 1 to l.
$T_x^{sup}(t)$: the temperature supply of the x^{th} AC unit at time t.
$T_j^{in}(t)$: the inlet temperature of the j^{th} server rack at time t.
$T_j^{out}(t)$: the outlet temperature of the j^{th} server rack at time t.
$T^{room}(t)$: the room temperature at time t.
$P_j^{Comp}(t)$: the computational power (PDU) for the j^{th} server rack at time t .
$P_x^{Cool}(t)$: the computational power for the x^{th} AC unit at time t.
$E[W_j(t)]$: the estimated workload (CPU usage) for the j^{th} server rack at time t .
CoP_x: the coefficient of performance.
CTI_{jx} is the thermal correlation index.

The IT consumption
. Assumingly, the IT power consumption would not only be influenced by the computational workload, but also will be affected by the working temperature because the temperature will affect its working performance. Hence, at any time t, the total IT computing power of server rack S_j is the function of power spent on executing IT jobs and the rack inlet temperature.

$$P_j^{Comp}(t) = \alpha_j E\left[W_j(t)\right] + \beta_j T_j^{in}(t) \qquad (5)$$

Where α_j and $\beta_j$are weight coefficients.

The cooling consumption
. Based on [16,17,18], the cooling cost of AC device $C_x \in C$ can be presented as:

$$P_x^{Cool}(t) = \frac{CTI_{xj} \sum_{j=1}^{m} P_j^{Comp}(t)}{CoP_x\left(T_x^{sup}(t)\right)} \qquad (6)$$

Where CoP_x is the performance coefficient, shown as the ratio of the amount of heat the AC device C_x needs to remove to the energy it needs to consume to perform the removal. CoP_x indicates the efficiency of the AC device, and is typically a non-linear, increasing function of the supplied cold air temperature, $T_x^{sup}(t)$. It means that operating the AC system at a higher temperature is saving energy, as providing colder air requires the AC to work harder and consume more energy to remove heat. Hence, we can minimise $P_x^{Cool}(t)$ by maximise the allowable supplied cold air temperature, $T_x^{sup}(t)$ that satisfies the constraint of redline thresholds. The simulation approach will also be used to get the function of $CoP_x\left(T_x^{sup}(t)\right)$. CTI_{jx} is the thermal correlation index, $CTI_{jx} = \frac{\Delta T_j^{in}}{\Delta T_x^{sup}}$, which represents the influence of each AC unit C_x on inlet temperature of server rack S_j. As defined in Eq. (6), it quantifies the response of the server S_j's inlet temperature T_j^{in} to a step-change in the supply temperature T_x^{sup} of C_x. CTI_{jx} is a static metric, which is stable with time but based on the physical configuration of the DC. Hence, we use the simulation approach to get the value of CTI_{jx}. The detailed explanation of this metric can be seen in [17,18].

Thermal modelling

. According to the law of energy conservation, almost all the computing power consumed by a server is transformed into heat, hence the relationship between the power consumption and inlet/outlet temperature of server rack S_j can be presented as:

$$T_j^{out}(t) = T_j^{in}(t) + K_j\, P_j^{Comp}(t) \tag{7}$$

Where $K_j = pf_jc$ is the thermal-physical term. This can be estimated by our data obtained in DC.

Typically, the server's inlet temperature (T_j^{in}) tends to be higher than the AC's supplied air temperature (T_x^{sup}) due to the phenomenon so-called heat recirculation where the hot air from the server and the supplied cool air from the AC are mixed then recirculats in the room. Based on the energy conservation as described in Eq. (8) and the assumption of the fixed airflow pattern in the computer room, prior studies (eg. [19]) characterise this phenomenon with a heat distribution matrix $A = \{a_{jo}\}$ where a_{jo} is the temperature increase at the inlet of server rack M_j due to the heat emitted at the outlet of the server rack M_o. Here we adjust this to matrix $A = \{a_j\}$ denotes the heat increased at the inlet of server rack S_j caused by the heat recirculated inside the rack due to computation. Hence, the inlet temperature of a server rack S_j comes from the combination of the supplied cold air from the AC and hot air recirculated inside the rack. This relationship can be written as:

$$T_j^{in}(t) = \sum_{x=1}^{l} c_{jx}\, CTI_{jx} T_x^{sup}(t) + d_j P_j^{Comp}(t) \tag{8}$$

Where c_{jx} is a binary variable which equals to 1 if the AC unit C_x is assigned to supply cold air to the rack slot of server rack S_j, and 0 otherwise. As the DC layout is fixed, the value of c_{jx} will be given by VAR estimation.

With equations (5) and (8), we can transfer $T_j^{in}(t)$ to the function of $T_x^{sup}(t)$.

$$T_j^{in}(t) = \frac{\sum_{x=1}^{l} c_{jx} CTI_{jx} T_x^{sup}(t) + \alpha_j E[W_j(t)]}{1-\beta_j} \tag{9}$$

Optimization solution

. PUE value is a measurement of the power utilization efficiency of DCs that is adopted internationally. It is the ratio of total power consumed by the DCs to the power consumed by the IT load.

$$PUE = \frac{P^{total}(t)}{P_j^{Comp}(t)} = 1 + \frac{P_x^{Cool}(t)}{P_j^{Comp}(t)} \quad (10)$$

The closer the PUE value is to 1, the higher the greenness of a DC.

$$\text{Let } G^* = \frac{P_x^{Cool}(t)}{P_j^{Comp}(t)} \quad (11)$$

Then to optimize PUE is equal to the question to minimize G^*.

Let denote $[t_1, t_2]$ be the interval of interest. Based on the Eq. (5, 6) above, our objective function can be written as:

$$Min\ G^* = \frac{P^{Cool}}{P^{Comp}} = \int_{t_1}^{t_2} \left(\frac{\sum_{x=1}^{l} P_x^{Cool}(t)}{\sum_{j=1}^{m} P_j^{Comp}(t)} \right) dt = \int_{t_1}^{t_2} \left(\frac{\sum_{x=1}^{l} (\sum_{j=1}^{m} (\frac{CTI_{xj} \sum_{j=1}^{m} P_j^{Comp}(t)}{CoP_x\left(T_x^{sup}(t)\right)}))}{\sum_{j=1}^{m} (\alpha_j E[W_j(t)] + \beta_j T_j^{in}(t))} \right) dt =$$

$$\int_{t_1}^{t_2} \left(\frac{\sum_{x=1}^{l} (\sum_{j=1}^{m} (\frac{CTI_{xj} (\sum_{i=1}^{m} (\alpha_j E[W_j(t)] + \beta_j T_j^{in}(t))}{CoP_x\left(T_x^{sup}(t)\right)}))}{\sum_{j=1}^{m} (\alpha_j E[W_j(t)] + \beta_j T_j^{in}(t))} \right) dt \quad (12)$$

Align Eq.(12) with Eq.(9), we can transfer the objective function to the function of the cooling temperature combinations $T_x^{sup}(t)$. Hence, to minimise G^*, we can optimise $T_x^{sup}(t)$, which is also the decision variable in this model.

Nevertheless, the adjustment of the supplied cold air temperature is subject to the constraint that the inlet temperatures of all server racks are below the redline temperature threshold specified by the device manufacturers (i.e. typically below 25oC). Hence, based on Eq. (8)(5), the constraint of redline threshold (T^{red1}) can be presented as:

$$T_j^{in}(t) = \sum_{x=1}^{l} c_{jx}\, CTI_{jx} T_x^{sup}(t) + d_j P_j^{Comp}(t) = \sum_{x=1}^{l} c_{jx}\, CTI_{jx} T_x^{sup}(t) + d_j.(\alpha_j E[W_j(t)] + \beta_j T_j^{in}(t) \leq T^{red1} (13)$$

Also, we will restrict the room temperature to be within the allowance (18~27 ºC according to AHREA 2016). As we define the room temperature as the function of ACs temperatures and the Server racks outlet temperatures, based on Eq.(7)(5), the temperature with thresholds (T^{red2}) and (T^{red3}) will be represented as:

$$T^{red2} \leq T^{room}(t) = \sum_{x=1}^{l} h_x T_x^{sup}(t) + \sum_{j=1}^{m} g_j T_j^{out}(t) = \sum_{x=1}^{l} h_x T_x^{sup}(t) + \sum_{j=1}^{m} g_j (T_j^{in}(t) + K_j P_j^{Comp}(t)) = \sum_{x=1}^{l} h_x T_x^{sup}(t) + \sum_{j=1}^{m} g_j (T_j^{in}(t) +$$

$$K_j\ (\alpha_j E[W_j(t)] + \beta_j T_j^{in}(t)) = \sum_{x=1}^{l} h_x\, T_x^{sup}(t) + \sum_{j=1}^{m}((g_j + g_j\beta_j)T_j^{in}(t) + g_j K_j \alpha_j E[W_j(t)]) \leq T^{red3} \quad (14)$$

Moreover, for each AC, there are thresholds (T^{red4}) and (T^{red5}), which will restrict the AC temperatures to be within the range ($0 - 30$°C).

$$T^{red4} \leq T_x^{sup}(t) \leq T^{red5} \quad (15)$$

Similarly, by aligning with Eq. (9), we can transfer the constraints functions Eq. (13,14) to the function of $T_x^{sup}(t)$.

In short, the operational problem that we will address at the first stage is to optimize the objective function in Eq. (12) by determining the optimal supplied cold temperature of the AC devices, given the constraints in Eq. (13, 14, 15). The optimization would start once we estimate the DC may perform inefficiently by VAR-RL forecasting, and target temperature combination will be set at $t_1 - \Delta t$ periods on the timeline (Where $\Delta t.$ is also defined by VAR-RL).

4 Future Studies

Future studies will be made on forecasting verification and model adjustment. An application UI (User Interface) will be applied for the DC managers to make sustainable DC management. Field trial studies will also be conducted subsequently, we will modify our models and further studies will be done accordingly.

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