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Cooling control of data centers using linear quadratic regulators

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***Abstract*— One of the largest contributions to a data center's power usage is its cooling system. One way to decrease the energy usage of a cooling systems by introducing an automatic control adapting the capacity of cooling units is addressed by this paper. Firstly, different configurations of linear quadratic regulators are designed and then evaluated using the nonlinear data center simulator. Design of the controllers is based on the novel idea of regulating the outlet temperature and volumetric airflow of the Computer Room Air Handler units which regulate the cooling power supplied to the servers. As controlled variables for the feedback, maximum and mean temperature of servers were used. Evaluation of controllers performance is based on their estimated energy usage as well as on analysis of the servers temperature profiles with respect to the given data centers temperature threshold value. Numerical experiments include five LQR controllers with different combination of manipulated variables and analyze their performances. Results of the experiments show that the regulator with maximum servers temperature as a feedback and Computer Room Air Handler Output temperature as manipulated variable has the best performance. Controlling the maximum server temperature minimizes hot spots occurrences and allows to operate the cooling system with minimal energy consumption.**

I. INTRODUCTION

Data centers are facility containing a lot of equipment to store, manage, process and exchange digital data and information. The need for such services has drastically increased due to new habits of the society and interconnection of the things. The energy consumption in datacenters in Europe and USA is around 3.5% of the total electricity produced. Energy use is expected to continue increasing in the near future, with a rate of 4% per year. Based on current trend estimates, USA datacenters are projected to consume approximately 73 billion kWh in 2020 [1].

The efforts of energy savings of datacenter industries are therefore estimated to be 520 billion kWh from 2015 to 2020. The overwhelming majority of these savings comes from the servers and infrastructure [1]. Since cooling accounts for nearly 40 % of the energy consumption of a data center [2], this is a suitable area to focus on when researching how to decrease the energy uses. The cooling power saving can be studied on several scales, from cooling of individual chips, to cooling of the whole room.

To support the energy intensive computing of a data center, data centers use specialized computer room air conditioning systems [3]. The room cooling system inside a typical data center can be described as follows: a computer room air handler (CRAH) cools the air inside of it by using cold water provided by an external cooler. A fan in the CRAH supplies this air to the data center, usually through a plenum. The servers racks are organized into rows dividing the data center into cold aisles and hot aisles. The chilled air is supplied to the cool aisles, passes through the server racks and exits them into the hot aisles. The hot air rises to the roof and recirculates into the CRAH where it is cooled again [4]. This is illustrated in figure 1.

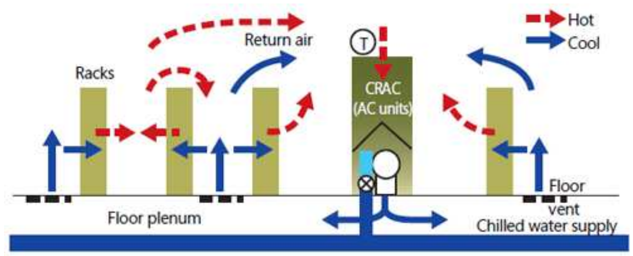

Fig. 1. A diagram showing the layout of a data center with raised floor plenum cooling.

The advantage of conventional air cooling is accessibility and maintainability, since it requires no pipes or barriers around the servers. Its disadvantage is lower efficiency because of recirculation and bypass of air. This can be remedied by isolating the cold and hot aisles, but that increases cost and decreases maintainability.

Research efforts on data centers have been led by US based organizations such as the Department of Energy, the Department of Defense, ASHRAE's Technical Committee 9.9, The Green Grid and the Uptime Institute. According to [5], the research before 2012 was mostly concerned with IT equipment characteristics and safety. On the contrary, research on energy savings in cooling of servers was limited. In 2007, the EPA published a report on data center efficiency identifying, among others, heat removal and control and management as topics in need of research [6]. Cooling control of data center has a crutial role in reducing power consumpmtion [7].

Temperature management of servers in data centers can be considered on several different scales, from the hardware in the server components, to the whole cooling architecture of a multi-room data center. Dynamic control of data center temperatures can be done on the server level, as in [8], rack level as in [9] and room level as in [10] and [11].

A study from 2006 [12] investigated the viability of using different parts of the cooling system of a data center as control variables. The conclusions were the following: The inlet temperature of the servers depends linearly on the

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CRAH supply temperature. The supply temperature would be suitable as a control variable, but it would not be enough to just change the supplied temperature if the fan speed would be too low. Increasing the fan speed would decrease the difference between inlet and outlet temperature of a server, but it would not decrease linearly. Instead, a given decrease in airflow would have a greater effect for lower initial airflows.

Cooling room control is a very interesting and challenging problem from the control point of view. It is a nonlinear system when the air flow is used as manipulated variable. It is a strongly under-actuated system, since a medium-scale data center could have thousands of server with just tens of manipulated variables. A common ratio, in practice, is 10 server racks (42 servers) per CRAH unit. Each CRAH unit has as manipulated variables for controlling cooling power, in the best case, set-points for airflow and output temperature, but frequently airflow or output temperature has a constant value. There is a limited number of temperature sensors, usually few sensors in the hot/cold aisle shared by two row of server-racks. Any server could produce a hotspot when it is working with high load and the server does not have enough cooling. This condition may produce damage on the server components. Excessive cooling power will produce waste of energy, which imply high operational costs.

II. Statement of the Problem

The goal of this paper is to design, analyze and compare performance of different kinds of LQR controllers for data centres cooling. The objective is to implement controllers with different manipulated and controlled variables and choose the one with the best performance index. As manipulated variables, CRACH outlet temperature and airflow rate are used. Concerning the control variables for the feedback, two options are considered: maximum and mean temperature of servers. Design of the controllers should be based on the test models developed earlier, see [13]. These models replicate the servers' temperatures and the cooling system power usage. Another aspect is to test and implement several performance indices to evaluated controllers. It is proposed to consider at least two main performance indices, one is the estimated total energy usage and the second is the servers temperature constraint violation.

III. LQR control for data centers

Five LQR controllers were developed: two of them using CRAH outlet temperature as the manipulated variable while keeping the airflow constant, two varying the CRAH airflow with constant outlet temperature and one using both airflow and temperature as manipulated variables.

Among the two controllers with the same controlled variables, one is a classical LQR controller and one an LQI controller. The controller using both airflow and temperature will also be an LQI controller.

LQR-controllers aim to optimally control a system defined by the linear state-space equations

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx, \end{aligned} \tag{1}$$

Where x is the vector of state-space variables, u is the controller output and y is the observed output of the system. The LQR controllers considered here are infinite horizon controllers for linear, time invariant systems, i.e. they solve the problem:

$$\begin{aligned} &\min_{u} \int_0^\infty x^T Q x + u^T R u \; dt \\ &s.t. \quad \dot{x} = Ax + Bu, \end{aligned} \tag{2}$$

where A, B, Q and R are constant matrices, R is positive definite and Q is positive semidefinite. If Q is decomposed into $C^T C$ such that (A,B,C) describes an observable and reachable system, the problem defined in (2) has a solution $u = -R^{-1}BPx$, where P is uniquely defined solution of the algebraic Riccati equation

$$A^T P + PA - PBR^{-1}B^T P + Q = 0. \tag{3}$$

If equations (1) accurately describe the controlled system, the LQR controller will drive the system towards the steady state $x = 0$. In practice, model inaccuracies may cause $x = 0$ to not be a steady state of the true controlled system. In that case, the LQR controller can still have a stabilizing effect on the system, but makes it get stuck in another state than $x = 0$. An extension to solve this problem is the LQI controller. The LQI controller extends the state space with $v(t) = \int_0^t Cx(s)ds$, yielding the new state space equations:

$$\begin{aligned} \dot{\begin{bmatrix} x \\ v \end{bmatrix}} &= \begin{bmatrix} A & 0 \\ C & 0 \end{bmatrix} \begin{bmatrix} x \\ v \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u \\ y' &= \begin{bmatrix} C & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} x \\ v \end{bmatrix} \end{aligned} \tag{4}$$

The feedback law for the LQI-controller is derived from (4) analogously to how the feedback law for the LQR controller was constructed from (1). Since the integral variables v will keep increasing or decreasing until the system reaches a state such that $Cx = 0$, the LQI extension ensures that the system does not get stuck in an undesirable state.

A. LQR formulations

The LQR model formulations will be derived from the model described in [13], describing all the details about the modelling and assumptions. To summarize, the data center model is described by the equations given below.

$$\begin{aligned} &P_{j,k}(t) = p_{idle} + (p_{peak} - p_{idle})u_{j,k}(t). \\ &\int_{t-t_{di}(t)}^{t} (1-p)a_i(\tau)d\tau = V_{airflows}. \\ &a_{i,j}(t) = \frac{s_{i,j}}{s_{influence}}(1-p)a_i(t - t_{di}(t)) \\ &A_{j,k}(t) = \frac{1}{18}\sum_{i=1}^{4} a_{i,j}(t). \\ &T_{j,k,in}(t) = \frac{\sum_{i=1}^{4} a_{i,j}(t) T_{i,out}(t - t_{di}(t))}{\sum_{i=1}^{4} a_{i,j}(t)}. \\ &\frac{dT_{j,k,out}(t)}{dt} = \frac{P_{j,k}(t)}{C_{th}} + \frac{c_p \rho A_{j,k}(t)}{C_{th}}(T_{j,k,in}(t) - \\ &\qquad T_{j,k,out}(t)). \end{aligned} \tag{5}$$

This is a nonlinear, continuous time model, although it is linear if all the control airflows $a_i(t),\ i \in \{1, 2\}$, are held constant.

Since the variables will then all depend on the same time, and the LQR models will be time-invariant, the time dependency of the variables will not be written out explicitly. From equations (5), the explicit relation between $T_{j,k,out}$, $P_{j,k}$, a_1, a_2, $u_{j,k}$, $T_{1,out}$ and $T_{2,out}$ can be written as

$$\begin{aligned}\frac{dT_{j,k,out}}{dt} &= \frac{p_{idle} + (p_{peak} - p_{idle})u_{j,k}}{C_{th}} + \\ &\frac{c_p\rho(1-p)}{18C_{th}s_{influence}} \sum_{i=1}^{2} a_i s_{i,j}(T_{i,out} - T_{j,k,out}) \\ &= f(u_{j,k}, a_1, a_2, T_{1,out}, T_{2,out}, T_{j,k,out})\end{aligned} \tag{6}$$

To obtain models for LQR controllers, the equation must be linearized around an equilibrium point. The following notation convention will be used: Let w be any variable. Then w_0 denotes the value of that variable around which the model is linearized, and $\Delta w = w - w_0$. The equilibrium point, $(u_{j,k,0}, a_{1,0}, a_{2,0}, T_{1,out,0}, T_{1,out,0}, T_{j,k,out,0})$, is found by fixing $u_{j,k,0}$, $a_{1,0}$, $a_{2,0}$, $T_{1,out,0}$ and $T_{2,out,0}$ and solving equation (7) for $T_{j,k,out,0}$.

$$\begin{aligned}f(u_{j,k,0}, a_{1,0}, a_{2,0}, T_{1,out,0}, T_{1,out,0}, T_{j,k,out,0}) &= \\ \frac{p_{idle} + (p_{peak} - p_{idle})u_{j,k,0}}{C_{th}} &+ \\ \frac{c_p\rho(1-p)}{18C_{th}s_{influence}} \sum_{i=1}^{2} a_{i,0} s_{i,j}(T_{i,out,0} - T_{j,k,out,0}) &= 0.\end{aligned} \tag{7}$$

A general linearized model around the equilibrium point can be expressed as

$$\begin{aligned}\frac{d\Delta T_{j,k,out}}{dt} &= \frac{\partial f}{\partial u_{j,k}}\Delta u_{j,k} + \frac{\partial f}{\partial a_1}\Delta a_1 + \frac{\partial f}{\partial a_2}\Delta a_2 + \\ &\frac{\partial f}{\partial T_{1,out}}\Delta T_{1,out} + \frac{\partial f}{\partial T_{2,out}}\Delta T_{2,out} + \\ &\frac{\partial f}{\partial T_{j,k,out}}\Delta T_{j,k,out},\end{aligned} \tag{8}$$

where $\frac{\partial f}{\partial v}$ denotes the partial derivative of f (defined in (6)) with respect to a variable v, evaluated at $(u_{j,k,0}, a_{1,0}, a_{2,0}, T_{1,out,0}, T_{1,out,0}, T_{j,k,out,0})$. For all LQR formulations, it is assumed that the input variables not used to control the data center are constant, so $\Delta u_{j,k}$ and for some controllers either $\Delta a_{1,out}$ and $\Delta a_{2,out}$ or $\Delta T_{1,out}$ and $\Delta T_{2,out}$ are set to 0. To ensure controllability, the number of controlled variables is reduced to 2: $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$. For simplicity, they are modeled as the average server temperature deviations from a given setpoint of racks 1 and 2, and racks 3, 4 and 5 respectively, i.e.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{36}\sum_{j=1}^{2}\sum_{k=1}^{18} \Delta T_{j,k,out} \\ \frac{1}{54}\sum_{j=3}^{5}\sum_{k=1}^{18} \Delta T_{j,k,out} \end{bmatrix}. \tag{9}$$

Considering everything above, the different LQR state space formulations, on the form described in (2), can now be stated.

For the temperature LQR controller, the state space model is

$$\dot{x} = Ax + B_{temp}\begin{bmatrix} \Delta T_{1,out} \\ \Delta T_{2,out} \end{bmatrix}, \tag{10}$$

where

$$A = \hat{A}\begin{bmatrix} -\frac{1}{2}\sum_{j=1}^{2}\sum_{i=1}^{2} a_{i,0}s_{i,j} & 0 \\ 0 & -\frac{1}{3}\sum_{j=3}^{5}\sum_{i=1}^{2} a_{i,0}s_{i,j} \end{bmatrix} \tag{11}$$

with $\hat{A} = \frac{c_p\rho(1-p)}{18C_{th}s_{influence}}$ and

$$B_{temp} = \hat{B}\begin{bmatrix} \frac{1}{2}\sum_{j=1}^{2} a_{1,0}s_{1,j} & \frac{1}{2}\sum_{j=1}^{2} a_{2,0}s_{2,j} \\ \frac{1}{3}\sum_{j=3}^{5} a_{1,0}s_{1,j} & \frac{1}{3}\sum_{j=3}^{5} a_{2,0}s_{2,j} \end{bmatrix} \tag{12}$$

with $\hat{B} = \frac{c_p\rho(1-p)}{18C_{th}s_{influence}}$

For the airflow LQR controller, the state space model is

$$\dot{x} = Ax + B_{air}\begin{bmatrix} \Delta a_1 \\ \Delta a_2 \end{bmatrix} \tag{13}$$

with

$$\begin{aligned}B_{air} &= \frac{c_p\rho(1-p)}{18C_{th}s_{influence}} \times \begin{bmatrix} B_{air}(1,1) & B_{air}(1,2) \\ B_{air}(2,1) & B_{air}(2,2) \end{bmatrix} \\ B_{air}(1,1) &= \frac{1}{36}\sum_{j=1}^{2}\sum_{k=1}^{18} s_{1,j}(T_{1,out,0} - T_{j,k,out,0}) \\ B_{air}(1,2) &= \frac{1}{36}\sum_{j=1}^{2}\sum_{k=1}^{18} s_{2,j}(T_{2,out,0} - T_{j,k,out,0}) \\ B_{air}(2,1) &\frac{1}{54}\sum_{j=3}^{5}\sum_{k=1}^{18} s_{1,j}(T_{1,out,0} - T_{j,k,out,0}) \\ B_{air}(2,2) &= \frac{1}{54}\sum_{j=3}^{5}\sum_{k=1}^{18} s_{2,j}(T_{2,out,0} - T_{j,k,out,0})\end{aligned} \tag{14}$$

For the two LQI controllers that use either airflow or temperature, the state space is extended from the above models with integrals of x_1 and x_2 as described in (4). For the LQI controller that uses both airflow and outlet temperature, the state space model is the LQI extension of the model in equation 15.

$$\dot{x} = Ax + B_{temp}\begin{bmatrix} \Delta T_{1,out} \\ \Delta T_{2,out} \end{bmatrix} + B_{air}\begin{bmatrix} \Delta a_1 \\ \Delta a_2 \end{bmatrix}. \tag{15}$$

IV. Controller tests and results

The aim of the tests was to study the behavior of the different LQR controllers described in section III to draw conclusions about the pros and cons of the different types of regulators. The LQR controllers were used in two ways in the experiments. The first way was to have them to control the average temperatures of the servers in the rack groups. The second way was to have them to control the maximum server temperatures in those racks, as that could make it easier to avoid overheating, provided that the LQR controllers could control the maxima in a stable way.

Figure 2 shows the average server utilization according to the time series that was used in the test scenario. This was obtained from a real data center [14].

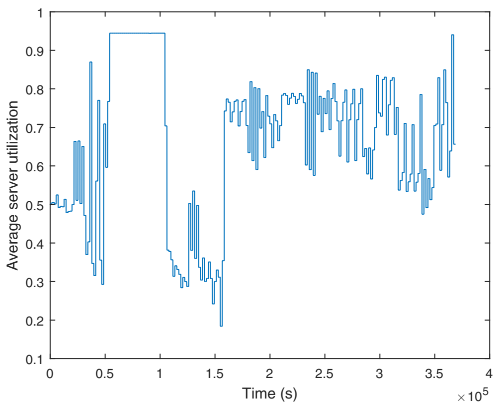

Fig. 2. A plot of the average server utilization throughout the scenario. Note the long time period between 54027 s and 104363 s where this average is essentially constant

1) Initial tests of the LQR controllers: With the data for server utilization, experiments with the different controllers could be conducted and different tests were performed. These initial tests were done with the two LQR controllers and two LQI controllers, one using the CRAH airflows and the other using the CRAH outlet temperatures as manipulated variables. The tests were done with each type of controller. In one of them, the controller received two temperature averages and in the other, the controller received two temperature maxima as feedback signal. One average or maximum was taken over the servers in racks 1 and 2, and the other over those in racks 3, 4, and 5.

A. Results

Two independent performance indices were measured: Integrated temperature constraint violation and total energy usage. Let T be the total simulation time for this test. The integrated temperature constraint violation in the tables is computed by a numerical approximation of $\sum_{j=1}^{5}\sum_{k=1}^{18}\int_0^T max(T_{j,k}(t)-35,0)dt$ using the trapezoidal method. Dividing this by $T*180$ gives the average constraint violation per server. Similarly, the average power usage is the total energy usage divided by T.

Each figure consists of 4 sub-figures. The first sub-figure shows the maximum temperature, minimum temperature and average temperature of the servers in racks 1 and 2. The second shows the same for all servers in racks 3, 4 and 5. The third shows the CRAH units' output airflows and the fourth their output temperatures.

Figures 4 to 5 show the simulations in the scenario with the LQI airflow controller controlling the maximum temperatures and the LQR and LQI temperature controllers controlling the average temperatures of the rack groups.

In the figures for the LQR controllers, their set-points are marked with a black dashed line. The upper temperature constraint of $35°C$ is marked in the figures with a red dashed line, as long as it does not coincide with the controller's set-point. Figure 3 shows why the LQI airflow controller

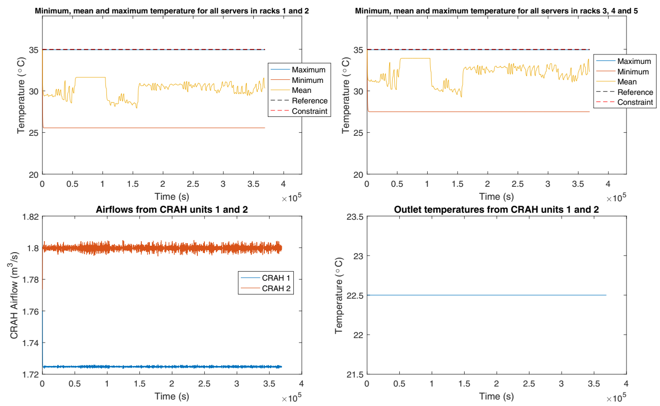

Fig. 3. Figures for the LQI airflow controller controlling the maximum temperatures of the rack groups.

that controls the maximum temperatures of the rack groups has both a low constraint violation and a low energy usage compared to other controllers. Throughout the simulation, there are almost no fluctuations in the maximum temperature of the two groups of racks. The minimum temperatures of the two groups of racks are also unchanging throughout the simulation, except for its decrease from 35 $°C$ in the beginning of the simulation. The servers that have those temperatures are the ones that are set to always run at maximum and minimum capacity respectively, and any fluctuations in the average server temperature are caused only by fluctuations in usage of the other servers, as can be seen by comparing the average server temperatures to the graph of average server utilization in figure 2.

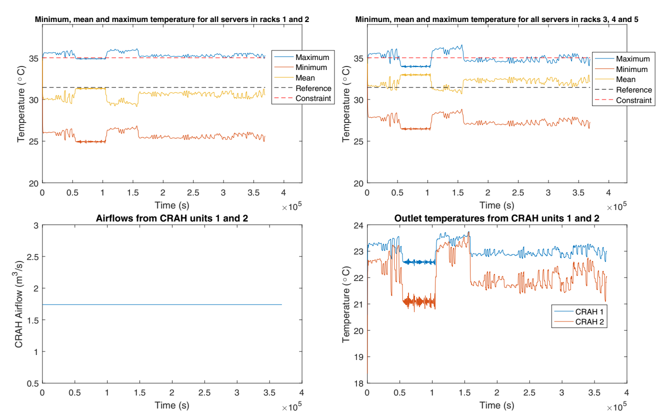

Fig. 4. Figures for the LQR temperature controller controlling the mean temperatures of the rack groups

The LQR temperature controller controlling the mean temperatures of the rack groups had an energy usage almost as low as that of the LQI controller in the previous figure, and it also had a seemingly low average temperature constraint violation per server.

Since the maximum and minimum temperatures of the rack groups will be given by those servers that constantly run at either minimum or maximum capacity, the changes in them are caused only by the CRAH units' outlet temperatures. Figure 4 shows that the server running at maximum capacity in rack 1 will be overheated, not only occasionally, but throughout whole time of the simulation.

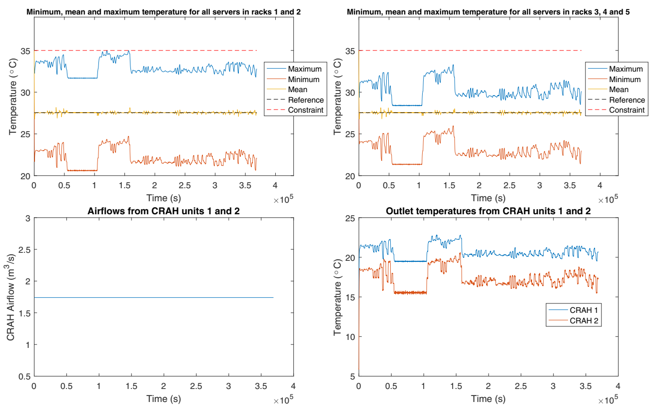

Fig. 5. Figures for the LQI temperature controller controlling the mean temperatures of the rack groups.

Figure 5 shows that with LQI control instead of LQR control. From what can be seen in Figure 5, the LQI controller manages to keep the mean temperatures at the setpoint, although with some small oscillations, and in the initial test, the LQI controller kept the mean temperatures at a similar "nearly steady state" at $35°C$.

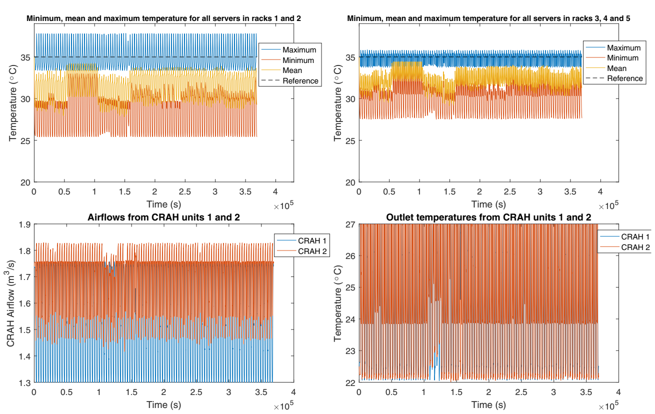

Fig. 6. Figures for the LQI controller using both airflow and temperature to control the maximum temperatures of the rack groups. The setpoint is $35°C$ in this simulation.

Figure 6 shows a simulation result for the LQI controller using both airflow and temperature when its setpoint is $35°C$. Figure 6 further below shows the first 3727.2 s of this simulation. Note how the signal saturation limits the controller outputs.

As can be seen in the figure, the maximum temperatures overshoot $35°C$ as soon as the server usage shifts. This also happens in the simulations for the LQI controllers using only one of temperature and airflow when their setpoint is $35°C$. The previous figures show that after adjusting the setpoint for those controllers, the maximum temperature in the simulations rise to a value very close to $35°C$.

V. Discussion

The aim of the controller tests was to provide results that could show which of the different control approaches that would be preferable. A comparison will be done between control of CRAH temperature and airflow, between LQR and LQI controllers and between using the rack average and maximum as controlled variables.

A. Test results discussion

1) Control of mean or maximum temperatures: One of the objectives for design of controllers was to make sure that the maximum server temperatures would not exceed the temperature threshold of $35°C$. Naturally, it would be desirable to control the temperature maximum rather than the temperature average. A potential problem with this is that the temperature maximum has discontinuous dynamics. If one server has the maximum temperature and then another server's temperature increases suddenly, so that it has a new maximum temperature, that server could be affected in a different way by the control input, making this change hard to manage by the controllers. Also, abrupt changes in the controlled variable produce more actions in the control signals which is not good for the healthy of the final control elements.

For the tests where the mean temperature was controlled, the temperature setpoint had to be decreased. The average cannot be controlled at $35°C$ because all the servers with temperatures bigger than the average will pass the threshold. The set-point selection depends on the variance of the server temperature. This control strategy require an extra system that monitors the maximum temperature for adjusting the set-point in order to avoid server temperatures consistently above the temperature threshold or a very low set-point which produces excessive overcooling, causing a large energy usage.

2) LQR vs LQI: The LQI controllers seemed to perform well when controlling the maximum temperatures. As one objective was to keep the maximum temperature below $35°C$ and the LQI controller is well suited when it is important to track a certain setpoint, this was expected.

When an LQI controller regulate the mean value, LQI would allow the maximum temperatures to be high as long as the mean temperatures would be kept at the set-point, requiring the set-point to be chosen lower for the LQI mean value controllers than their LQR counterparts, causing a large energy usage.

3) Temperature vs airflow control: The controller using both controlled variables temperature and airflow was the second best controller in terms of energy usage after the LQI airflow controller controlling the maximum temperatures. However, in this scenario, the difference in energy usage between all tested controllers with the lowest energy usage after adjusting their temperature set-points, was within 1%

of any of those controllers' energy usage. Since there were both airflow and temperature controllers among those top-performing controllers, the results in scenario do not indicate that any of these types of controllers would be more energy efficient.

Neither the results from test are very conclusive. Even though for three of the combinations of type of controller and controlled variable (i.e. LQR or LQI and maximum or mean), the controller using the CRAH airflow as manipulated variable had a higher energy usage than its counterpart using the CRAH outlet temperatures, the combination of LQI control and maximum values as controlled variables break this pattern.

From a practical point of view, it is easier to quickly adjust the airflows than the outlet temperatures of the CRAH units. However, control of airflow requires more approximations than control of temperature because of the term in the differential equations for the server temperatures depending linearly on CRAH outlet temperature when the airflow is held constant, but not linearly on airflow when the CRAH outlet temperatures are held constant.

The main differences between the both control strategies are in the transient response of step test. For example, in a step response test where the data center is loaded from 25% to 75% the controller manipulating both airflow and temperature will produce a lower settling time. But, tests conducted with real data where the system is moving around the operating point using both variables does not lead to a significant improvement.

VI. CONCLUSIONS

This paper presented and studied different control strategies applied to cooling control of data centers based on linear quadratic regulators. The study was performed in a nonlinear simulator of data center and the aim was to analyse the pros and cons of the possible structures for control design. In this paper LQRs and LQIs where compared using airflow and temperature of CRAH or both as manipulate variables. Also, It was analyzed which control variable for feedback signal to choose: maximum or mean temperature of the server. As results of this study, a LQI using the maximum server temperature as feedback signal and CRAH output temperature as manipulated variable seems to be first strategy to test in a real data center. Controlling the maximum server temperature minimizes the possibilities of hot spots, operating the cooling system with the minimum energy consumption. Selection of CRAH output temperature as manipulated variable keeping constant airflow implies that the data center has a linear behaviour, which is an appealing characteristic when linear controllers are used.

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