IOT-Based Thermal Comfort Control for Livable Environment

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Abstract. Thermal Comfort Control for indoor environment is an important issue in smart city since it is benefit to people's health and helps to maximize their working productivity and provide a livable environment. In this paper, we present an IOT (Internet of Things) based personal thermal comfort model with automatic regulation. This model employs some environment sensors such as temperature sensor, humidity sensor, etc., to continuously obtain the general environmental measurements. Specially, video cameras are also integrated into the IOT network of sensors to capture the individual's activity and dressing condition, which are important factors affecting one's thermal sensation. The individual's condition image can be mapped into different metabolic rates and different clothing insulations by machine learning classification algorithm. Then, all the captured or converted data are fed into a PMV (Predicted Mean Vote) model to learn the individual's thermal comfort level. In the prediction stage, we introduce the cuckoo search algorithm to solve the air temperature and air velocity with the learnt thermal comfort level, which is convergent rapidly. Our experiments demonstrate that the metabolic rates and clothing insulation have great effect on personal thermal comfort, and our model with video capture helps to obtain the variant values regularly, thus maintains the individual's thermal comfort balance in spite of the variation of activity or clothing.

Keywords: Thermal comfort control · IOT · PMV · Cuckoo search algorithm

1 Introduction

Nowadays, people spend most of their time in enclosed environment, especially for vulnerable senior and younger populations [1]. The indoor environment has great impact on people's health and life comfort. One of the most common requirements of human beings for indoor environment is thermal comfort, which is defined as the subjective satisfaction evaluation for the surrounding thermal environment. It has been reported that thermal comfort is of great importance to health, happiness, creative ability and working efficiency. For these reasons, indoor thermal comfort control by optimal setting has become of increasing concern in both scientific and industrial communities. However, due to the non-linear mapping between various environmental variables and personal preferences, as well as the complexity of thermodynamics of human body, the thermal comfort environment control is still a challenging task.

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Considering an optimal thermal comfort control system that predicts an individual's thermal comfort in an indoor environment automatically, compares it with the ideal value and makes calibrations in time by adjusting the set point (such as air temperature and air velocity) of an air conditioning system of a building. The key to the system is a thermal comfort model that simulates the individual's thermal sensation accurately. Fanger's PMV model [2, 3] is the dominant model, which has been adopted as an international standard in ISO 7730. It is represented by a heat balance equation describing the heat energy transfer from the body to the environment. Depending on the mean vote of thermal comfort from a group of individuals exposed to certain thermal conditions for some time, the model will consider a PMV index comfortable only when at least 95% of respondents are satisfied to this condition. Here, the thermal vote is scaled into 7 integer levels between −3 and 3 on the ASHRAE scale. Despite being widely accepted, the model appears some limitations in practice. For example, the model often need the user's feedback about his/her activity, and allocate the corresponding assumption constant for this user. This is not convenient for elder or younger people. It is often the same case to obtain user's clothing regularly.

In this work, we propose a thermal comfort control scheme for personal thermal balance adjustment with automation. It captures the capabilities of IOT network to incorporate video camera as well as normal environment sensors together. In which, the video camera is used to capture the individual's activity and clothing condition regularly, which will be converted into metabolic rate and clothing insulation by machine learning algorithm accordingly. Then all the captured or converted data are exploited to learn the PMV index, which reflecting the individual's living habit and thermal comfort preference. At last, the learnt personal PMV index value is used to predict the air temperature and air velocity of the air conditioning system for environment calibration. We derived the solution optimization process for proposed model by Cuckoo Search algorithm, which can be convergent quickly. In the experiment, we analyzed the effect of different factors such as metabolic rate, clothing insulation, and air humidity, on the predicted solution in the thermal comfort model.

The rest of this paper is organized as follows. In Sect. 2, we give a brief introduction to the PMV index equation. Then in Sect. 3, we present the framework of our thermal control system, the optimization algorithm and the procedure of solution determination. Section 4 shows the obtained results and analysis based on our optimal PMV model. Section 5 concludes the paper.

2 PMV Model

PMV is able to predict the average response about thermal sensation of a group of people exposed to certain thermal conditions for a long time. The index can be estimated as a thermal balance function considering the human body as a whole entity, which deals with the following six variables: metabolic rate (M), air temperature (t_a), mean radiant temperature (t_r), air humidity (ϕ_a), air velocity (υ_a) and clothing insulation (I_{cl}). Equations (1)–(5) show the function relations with all the variables.

$$\begin{aligned} PMV = {} & [0.303\exp(-0.036M) + 0.275] \\ & * \{M - W - 3.05[5.733 - 0.007(M - W) - P_a] \\ & - 0.42(M - W - 58.15) - 0.0173M(5.867 - P_a) \\ & - 0.0014M(34 - t_a) - f_{cl}h_c(t_{cl} - t_a) \\ & - 3.96 \times 10^{-8} f_{cl}[(t_{cl} + 273)^4 - (t_r + 273)^4]\} \end{aligned} \tag{1}$$

Where

$$Pa = \varphi_a \times EXP[16.6536 - 4030.183/(t_a + 235)] \tag{2}$$

$$\begin{aligned} t_{cl} = {} & 35.7 - 0.028(M - W) \\ & - I_{cl}\{3.96 \times 10^{-8} \times f_{cl}[(t_{cl} + 273)^4 \\ & - (t_r + 273)^4] + f_{cl}h_c(t_{cl} - t_a)\} \end{aligned} \tag{3}$$

$$h_c = \begin{cases} 2.38(t_{cl} - t_a)^{0.25}, & 2.38(t_{cl} - t_a)^{0.25} > 12.1\sqrt{\upsilon_a} \\ 12.1\sqrt{\upsilon_a}, & 2.38(t_{cl} - t_a)^{0.25} \leq 12.1\sqrt{\upsilon_a} \end{cases} \tag{4}$$

$$f_{cl} = \begin{cases} 1.00 + 1.290I_{cl}, I_{cl} \leq 0.078 \\ 1.05 + 0.645I_{cl}, I_{cl} > 0.078 \end{cases} \tag{5}$$

Most values of these variables are acquired by sensors. However, clothing insulation and human activity are variables not easily accessed since they depend on the individual's current situation at a time. Conventionally, the values related to both variables under different conditions can be found in manuals and standards [4]. Then, the resulting 7 PMV scales are: 0 neutral, ±1 slightly warm/cool, ±2 warm/cool, ±3 hot/cold. Hence, the simplest way to guarantee thermal comfort conditions in a certain environment is to keep PMV index value at 0.

3 Proposed Thermal Comfort Control System

In this section, we present the architecture of our thermal comfort control system, parameter determine approaches for PMV thermal comfort model in detail, followed by the model optimization algorithm.

Figure 1 describes the framework of our personal thermal comfort control system.

The sensors network is composed of several sensors connected together by IOT. In which, the temperature sensor, humidity sensor and air velocity sensor are used to capture the indoor environment information; video camera is used to monitor the individual's personal information, such as activity condition and clothing condition. Then, machine learning method is used to classify the individual's clothing captured and map classification result to the clothing insulation value; similarly, the activity condition is classified into 3 states (sitting, sleeping, and activity) corresponds to the of metabolic rate. Next, the PMV index is calculated by Eqs. (1)–(5) based on the

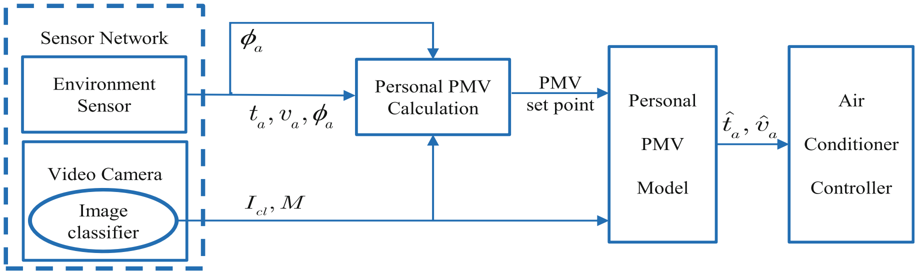

Fig. 1. Schematic illustration of the proposed thermal comfort control system.

obtained factors. The mean value of PMV recorded for a period is used for the individual's personal PMV, which reflecting the individual's living habit and preference. At last, in the prediction stage, we deduce the air temperature and air velocity through the learnt personal PMV by the PMV model. If the system finds a mismatch between predicted air temperature as well as velocity and the measured values, it will adjust the air conditioner controller automatically. The presented system tries to keep the balance between occupant's thermal sensation and expectation by minimizing the mismatch between demand and supply for thermal dynamic mechanics. Thus, it also avoids the energy wastage, and improves the energy efficiency.

3.1 Parameter Determination

PMV model depends on 6 factors actually, including the air temperature t_a, mean radiant temperature t_r, air velocity υ_a, comparative air humidity ϕ_a, metabolic rate M, and clothing surface temperature t_{cl}.

Calculation of clothing surface temperature t_{cl} and convective heat transfer coefficient h_c. From Eqs. (1)–(5), we can see PMV model deals with several complex expression. Especially for Eqs. (3) and (4), in which the calculation of two intermediate variables clothing surface temperature t_{cl} and the convective heat transfer coefficient h_c depends on each other. In this paper, we try to calculate the two variables by iteration method.

From Eq. (3), let

$$\begin{aligned} F(t_{cl}, h_c) = 35.7 - 0.028(M - W) \\ - I_{cl}\{3.96 \times 10^{-8} \times f_{cl}[(t_{cl} + 273)^4 \\ - (t_r + 273)^4] + f_{cl}h_c(t_{cl} - t_a)\} - t_{cl} \end{aligned} \tag{6}$$

Then, Eqs. (3) and (4) is expressed as follows:

$$\begin{cases} F(t_{cl}, h_c) = 0 \\ h_c = \begin{cases} 2.38(t_{cl} - t_a)^{0.25} \; when \quad 2.38(t_{cl} - t_a)^{0.25} > 12.1\sqrt{\upsilon_a} \\ 12.1\sqrt{\upsilon_a} \quad when \quad 2.38(t_{cl} - t_a)^{0.25} \le 12.1\sqrt{\upsilon_a} \end{cases} \end{cases} \tag{7}$$

Equation (7) is solved by iteration. First, set a search range for the value of t_{cl} in 20 °C–40 °C. Then, for each fixed value of t_{cl}, calculate h_c by Eq. (4); Next, calculate $F(t_{cl}, h_c)$ by Eq. (6). Repeat the above two steps until $F(t_{cl}, h_c)$ approaches to zero.

Obtain metabolic rate M and clothing insulation I_{cl} by image classification. In Fanger's study, three classes of activity condition have been given with the corresponding metabolic rate, as seen in Table 1. Thus the images we captured for activity classification are divided into 3 classes accordingly. An activity classifier is trained first to get the mapping between activity condition in the image and the metabolic rate. Then, given a new image, the classifier is used to predict the corresponding activity condition, and further, find the metabolic rate.

Table 1. Different activity conditions and their metabolic rates.

Activity condition	Metabolic rate (met)
Sitting	1
Activation	2
Sleeping	0.5

The clothing insulation is obtained in the similar method, and 4 classes of clothing have been given with the corresponding clothing insulation, as seen in Table 2.

Table 2. Different clothing and their insulations.

Clothing	Clothing insulation (clo)
Short sleeves, shorts	0.3
Long sleeves, slacks	0.5
Jacket, sweater	0.7
Padded coat	1.0

3.2 Personal PMV Training

By Fanger's model, the best thermal comfort condition is when PMV = 0. But different people have different thermal comfort sensation. The thermal sensation may differ in ages, gender, and health condition, even in physiological and psychological factors. Thus, the optimization goal of PMV = 0 does not fit all the people, especially for vulnerable seniors and youngers.

To find a personal PMV, we capture the indoor air temperature, air humidity, and air velocity by the corresponding sensors, capture the individual's clothing and activity condition, and transfer them into corresponding clothing insulation value and metabolic rate by machine leaning classification algorithm. All the data obtained for a period are feed into the PMV model to calculate the personal PMV values, which reflect the person's living habit and preference. At last, we choose the mean value as the personal PMV for the preceding model prediction, and note it as PMV_0.

3.3 Model Prediction

Among the six factors relevant to PMV index, we can see the indoor temperature t_a and the air velocity υ_a can be adjusted by air conditioner. Thus, the issue of thermal comfort control is converted into an optimization issue of t_a and υ_a simultaneously given a personal PMV value PMV_0 based on PMV model. From Eq. (1), let $fit(t_a, \upsilon_a) = PMV - PMV_0$, then the optimization problem can be formulated as:

$$\begin{cases} \underset{t_a,\upsilon_a}{\operatorname{argmin}} |fit(t_a, \upsilon_a)| \\ s.t.\, Eq.(2), Eq.(3), Eq.(4), Eq.(5) \end{cases} \tag{8}$$

Equation (8) is a continuous optimization problem. We employ the CS (Cuckoo Search) algorithm [5] to solve this problem. CS algorithm is inspired by the obligate brood parasitism of some cuckoo species laying their eggs in the nests of other host birds. It assumes that the host bird discovers the egg laid by cuckoo with a probability of $P \in [0, 1]$. In this case, the host will throw the egg or abandon the nest to build a new one. Thus, the process of finding the solution of an optimal problem is a cuckoo search process, where each cuckoo nest corresponds to a solution, and the optimal solution is evaluated by fitness function. Then we describe the process of solving Eq. (8) by CS algorithm as follows.

Denote by $\boldsymbol{X} = [\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_i, \ldots, \boldsymbol{X}_N] \in \mathbf{R}^{2\times N}$ the original research space formed by N cuckoos, where each column $\boldsymbol{X}_i = [x_{1i}, x_{2i}]^T$, $(i = 1, 2, \ldots, N)$, is the ith cukcoo of two dimension. x_{1i} and x_{2i} corresponds to t_a and υ_a in Eq. (8) respectively. Assume each cuckoo corresponds to one nest, and each nest a solution. The optimization procedure of CS algorithm is to update the nest $\boldsymbol{X}_i^t$ Iteratively, where t indexes an iteration. In each iteration, there are two steps to update the cuckoos:

① Given the current host nests $\boldsymbol{X}^t$, get new N Cuckoo nests $\boldsymbol{X}_L \in \mathbf{R}^{2\times N}$ randomly by Levy flight:

$$\boldsymbol{X}_L = \boldsymbol{X}^t + \boldsymbol{\alpha} \bullet \boldsymbol{L}(\lambda) \tag{9}$$

Where $\boldsymbol{\alpha} = [\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2] \in \mathbf{R}^{2\times N}$ is a constant parameter matrix related to the scales of the problem of interest and is often chosen such that the flight step should not be aggressive. Here, we set $\boldsymbol{\alpha}_1 = \mathbf{1}$, and $\boldsymbol{\alpha}_2 = \mathbf{0.0625}$. The product $\bullet$ means entry-wise multiplications. $\boldsymbol{L}(\lambda) \in \mathbf{R}^{2\times N}$ is the step size matrix of random walk through Levy flight.

Generally, the next location after a random walk only depends on the current location and the Levy step. The Levy step is taken from the Levy distribution, which represented as:

$$\boldsymbol{L}(\lambda) = \frac{\boldsymbol{U}}{|\boldsymbol{Z}|^{\frac{1}{(\lambda-1)}}}, (1 < \lambda < 3) \tag{10}$$

Where $\boldsymbol{U}$ and $\boldsymbol{Z}$ are obtained from a normal distribution $\boldsymbol{U} \sim N(0, \sigma_U^2), \boldsymbol{Z} \sim N(0, 1)$, and

$$\sigma_U(\lambda) = \left[\frac{\Gamma(1+\lambda)\sin\left(\frac{\pi\lambda}{2}\right)}{\lambda\Gamma\left(\frac{1+\lambda}{2}\right)2^{\left(\frac{\lambda-1}{2}\right)}}\right]^{\frac{1}{\lambda}} \tag{11}$$

Then, the original host nests $\boldsymbol{X}_i^t$ and the new generated cuckoo nests $\boldsymbol{X}_{Li}$ will be compared by fitness function $\boldsymbol{F} = fit(\cdot)$ and the better ones will be kept as $\boldsymbol{X}_i^{t+1}$.

② Next, the host throws the egg of cuckoos away or abandons the nest to build one in a new location randomly. This step commonly use the preference random walk, which make use of the other nests similarity [6]. Thus the new built nests $\boldsymbol{X}_R \in \mathbf{R}^{2\times N}$ is depicted as:

$$\boldsymbol{X}_R = \boldsymbol{X}^t + \gamma \bullet \boldsymbol{Heaviside}(P - \varepsilon) \bullet (\boldsymbol{X}^{t\prime} - \boldsymbol{X}^{t\prime\prime}) \tag{12}$$

Where, γ and ε are random obeying uniform distribution, $\boldsymbol{Heaviside}(\cdot)$ is a jump function, which is described as:

$$\boldsymbol{Heaviside}(\theta) = \begin{cases} 1, \theta > 0 \\ 0, \theta < 0 \end{cases} \tag{13}$$

$\boldsymbol{X}^{t\prime}$ and $\boldsymbol{X}^{t\prime\prime}$ are two nest arrays, each of them is the result matrix changing the column order of $\boldsymbol{X}^t$ randomly. Then the better solutions will be determined by fitness function similar to step ①. And the best solution is find by ranking. In the experiments, we set $P_a = 0.25$, number of cuckoos $N = 50$, δ is set 0.0001, maximum iteration is 30, t_a and υ_a are limited in [15, 32] and [0, 0.5]. We observed that the CS optimization converge rapidly. Figure 2 plots the changing values of the fitness function in the convergence process.

4 Experiments

In this section, we will give the result of proposed thermal control system as well as the results analysis.

4.1 Experimental Settings

In our experiment, we assume the mean radiant temperature t_r is equal to the air temperature t_a. The indoor air velocity υ_a is limited not more than 0.5 m/s. We do the experiment 20 times and get 20 solutions for each setup.

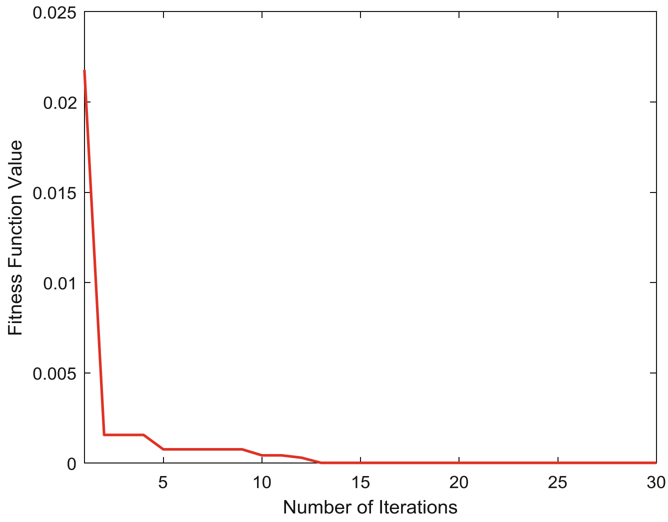

Fig. 2. The convergence of the cuckoo search optimization

4.2 Prediction Results for Thermal Comfort

The number of solutions that satisfied the given thermal comfort requirement is not limited to one. Table 3 gives some examples of predicted result when metabolic rate $M = 1$ met, and clothing insulation $I_{cl} = 0.5$ clo with humidity changing between 20% and 80%. In which, t_a and υ_a represent the solution with the air temperature nearest to the mean value. We define Δt_a as the relative variation of the predicted air temperature, which is calculated by:

$$\Delta t_a = \frac{t_{a\max} - t_{a\min}}{t_{a\min}} \times 100\% \quad (14)$$

Where $t_{a\min}$ and $v_{a\min}$ is the solution with the minimum value, $t_{a\max}$ and $v_{a\max}$ the maximum.

Table 3. Results of the thermal control system with variation of comparative humidity φ_a, keeping metabolic rate $M = 1$ met, and clothing insulation $I_{cl} = 0.5$ clo.

$\varphi_a(\%)$	$t_a(^\circ C)$	$\upsilon_a(\mathrm{m/s})$	$\Delta t_a(\%)$
20	27.69	0.24	5.4
30	27.34	0.21	6.5
40	27.00	0.19	6.7
50	26.72	0.18	6.8
60	26.09	0.12	6.9
70	26.66	0.27	7.1
80	26.04	0.18	7.3

From Table 3, we can observe:

(1) With the humidity increase from 20% to 80%, the predicted temperature for thermal comfort will decrease by 6%. While the corresponding air velocity is always changing in the whole given range. This shows that the humidity has a comparatively small effect on the predicted air temperature, and nearly has no effect on the air velocity.
(2) With the humidity increase, the relative variation of the air temperature Δt_a is increasing, which shows that the adjustable scope of air temperature for the thermal control system is enlarged with the increase of humidity.
(3) The solutions being satisfied to a given fitness requirement are more than one, which may provide the adjustment flexibility for our system and the possibility to find a common or similar thermal comfort setting for an indoor environment with more person who have different preferences.

Table 4 gives some examples of predicted result when humidity $\varphi_a = 50\%$ fixed and metabolic rate M and clothing insulation I_{cl} changing in the range of [0.5, 1, 2] met and [0.3, 0.5, 0.7, 1.0] clo respectively.

Table 4. Results of the thermal control system with variation of metabolic rate M and clothing insulation I_{cl}, keeping comparative humidity $\varphi_a = 50\%$.

M(met)	I_{cl}(clo)	$t_a(°C)$	υ_a(m/s)	Δt_a(%)
0.5	0.3	30.49	0.14	4.51
	0.5	29.95	0.19	4.36
	0.7	29.10	0.17	4.41
	1.0	27.93	0.16	4.45
1	0.3	27.90	0.20	6.64
	0.5	26.76	0.19	6.83
	0.7	25.40	0.16	6.98
	1.0	23.83	0.17	7.04
2	0.3	22.68	0.24	12.65
	0.5	20.76	0.23	13.40
	0.7	18.73	0.21	14.03
	1.0	16.11	0.23	15.40

From Table 4, we can observe:

(1) Keeping the metabolic rate M fixed as 0.5 met, increase the clothing insulation from 0.3 clo to 1.0 clo, the predicted temperature for thermal comfort will decrease by 8.4%, accordingly, the predicted temperature will decrease by 14.6% when M is set 1 met, and 28% when M is 2 met. While the corresponding air velocity is always changing in the given range. This shows that the clothing insulation has a clear effect on the predicted air temperature, and has little effect on the air velocity. Also, the effect is increasing greatly with the increase of metabolic rate.

(2) Keeping the clothing insulation I_{cl} fixed as 0.3 clo, increase the metabolic rate from 0.5 met to 2 met, the predicted temperature for thermal comfort will decrease by 25.6%. Accordingly, the predicted temperature will decrease by 30.7% when I_{cl} is set 0.5 clo; by 35.6% when I_{cl} is 0.7 clo; and by 42.2% when I_{cl} is 1.0 clo. While the corresponding air velocity is always changing in the given range. This shows that the metabolic rate has the most important effect on the predicted air temperature, and little effect on the air velocity. Also, the effect is increasing greatly with the increase of clothing insulation. Thus, the introduction of video camera in our proposed system will help to keep the thermal comfort effectively and flexibly.

(3) With the increase of metabolic rate and clothing insulation, the relative variation of the air temperature Δt_a is increasing except the case when $I_{cl} = 0.3$ clo and M = 0.5 met, which shows that the adjustable scope of air temperature for the thermal control system is enlarged with the increase of metabolic rate and clothing insulation.

(4) The multiple solutions in a certain condition also provide possibility to use the system in the environment with more persons.

5 Conclusions

In this paper, we present a personal thermal comfort control model for indoor environment, which integrates the video camera into conventional sensors into an IOT network for data acquisition. To facilitate the individuality of our model, the system combines personal information including activity and clothing condition from the video camera with environment measurements such as temperature, humidity, and air velocity. And the individual's thermal comfort is kept by continuous calibration of the air temperature and air velocity using PVM model. We deduced the solution optimization based on Cuckoo Search algorithm. Experiment result shows our model optimization process is convergent rapidly, which demonstrates the practicability of our proposed model. Furthermore, the results analysis show the humidity has smaller effect on thermal comfort compared to metabolic rate and clothing, which shows that we could pay less attention to the humidity in the future studies. Also, the multiple solutions for thermal comfort in a certain condition illustrate the potential for energy saving and the possible application of our model in environment with more than one person. For future work, we intend to make use of big data captured from more transducer, and integrate the big data driven cluster [7, 8] into the system to provide more optimal control strategy.

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