Control of an air conditioning device by recurrent neural networks

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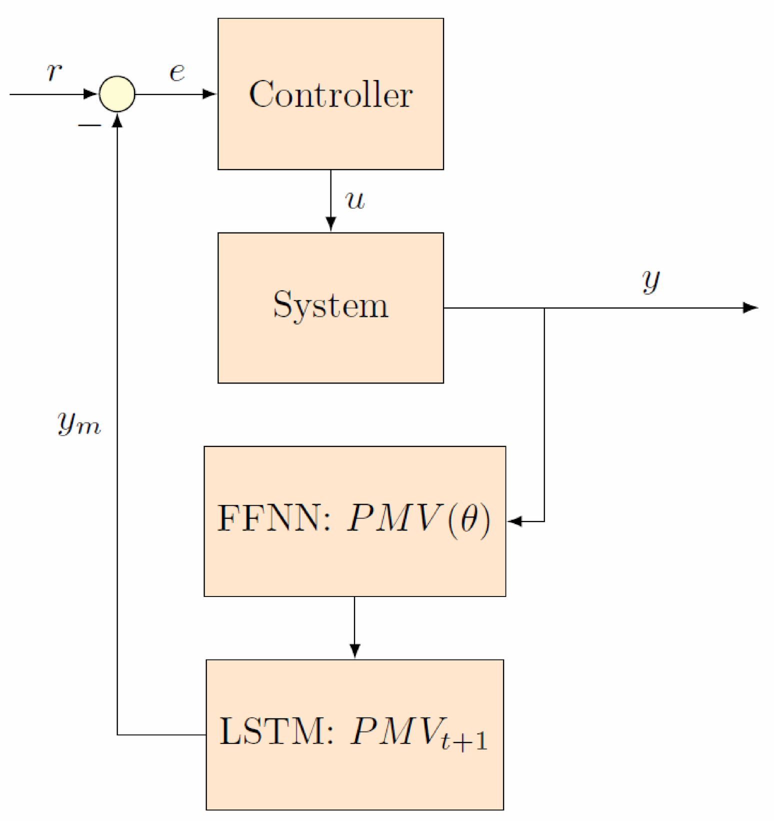
This project is about the creation of training data that is consecutively used to train a reinforcement learning (RL) model including a recurrent neural network (RNN) with the aim of controlling the climate parameters of an interior space while minimizing energy consumption.

Motivation

- Use RL to control thermal comfort of room with PMV input signal and minimum power consumption.
- Room parameters measured by sensor board [1]
- FFNN approximated PMV value for given input signals [2]
- LSTM cell predicts future PMV based on 10 previous PMV values [2]

<u>Scope of this project:</u>

Create training data for the RL algorithm



PMV & PPD

Predicted **M**ean **V**ote (**PMV**) = Empirical value of thermal comfort, based on skin temperature and sweat secretion (thermal equilibrium).

Percentage of **P**eople **D**issatisfied (**PPD**) with room climate. [3]

Defined for: $D_f = \{PMV \in \mathbb{R} | -3 \leq PMV \leq 3\}$

Optimal in: $PMV_{optimal} = [-0.5, 0.5]$

Range of PPD: $PPD = f(PMV) = [0.05, 1]$

Reinforcement learning

Agent (RNN) interacts with environment (Markov decision process (MDP) and gets feedback with state (PMV values) and reward (based on minimal energy consumption).[4]

A *policy* is an agent's strategy: $\pi(s,a) = P(a_t|s_t)$

The *cumulative reward* is the discounted sum of rewards discount:

$$G_t = \sum_{k=0}^{T} \gamma_k \cdot r_{t+k+1} \; (0 \leq \gamma \leq 1)$$

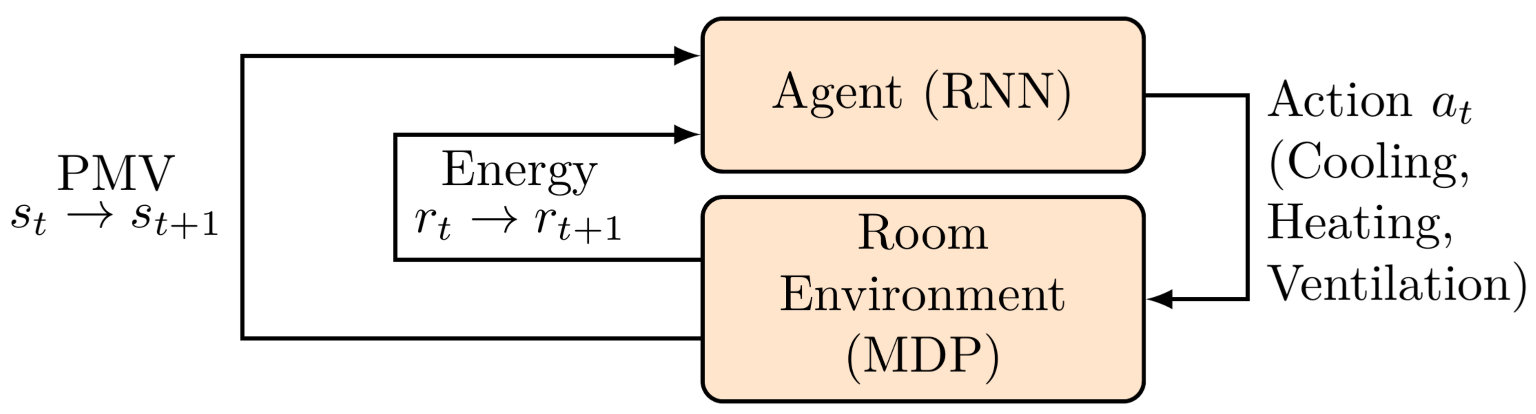
The *state-value function* yields expected return if agent starts in state s and uses the policy to choose its actions for all time steps:

$$V^{\pi}(s) = E_{a\sim\pi}[G_t | S_t = s]$$

The *action-value function* yields expected return if agent starts in state s, takes action a and then follows the policy for all future steps: $Q^{\pi}(s,a) = E_{a\sim\pi}[R_t | S_t = s, A_t = a]$

The *advantage function* determines quality of random action over policy action: $A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$

The *gradient descent* represents the fastest way towards a minimum of error function: $\nabla_x f(x) = \sum_{i=0}^{n} \left[\frac{\partial}{\partial x_i}\right] \cdot \hat{e}_i$



Controlling PMV

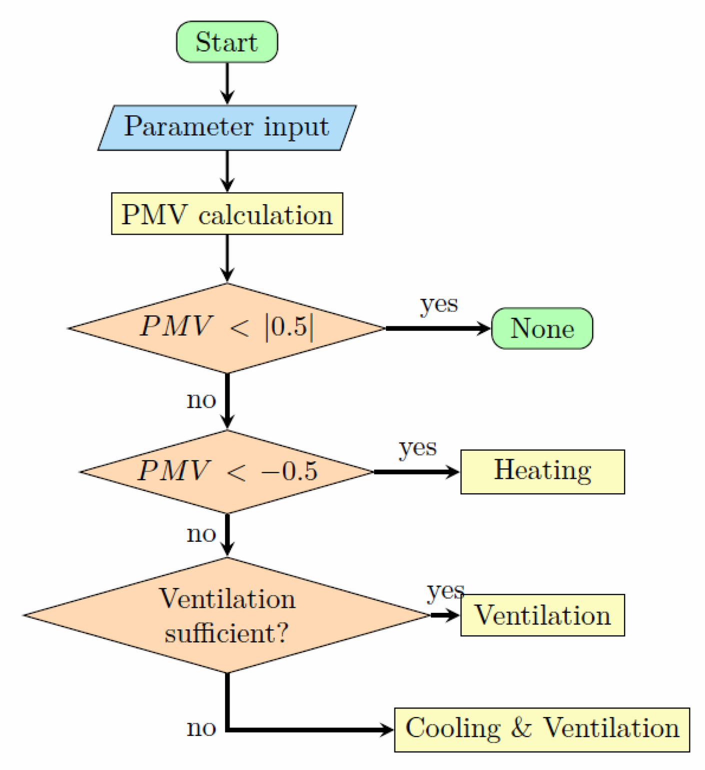
Samsung R32 Maledives is used to control the room climate. Possible actions to control the PMV: heating, cooling, ventilation.

ΔPMV AT 50% HUMIDITY

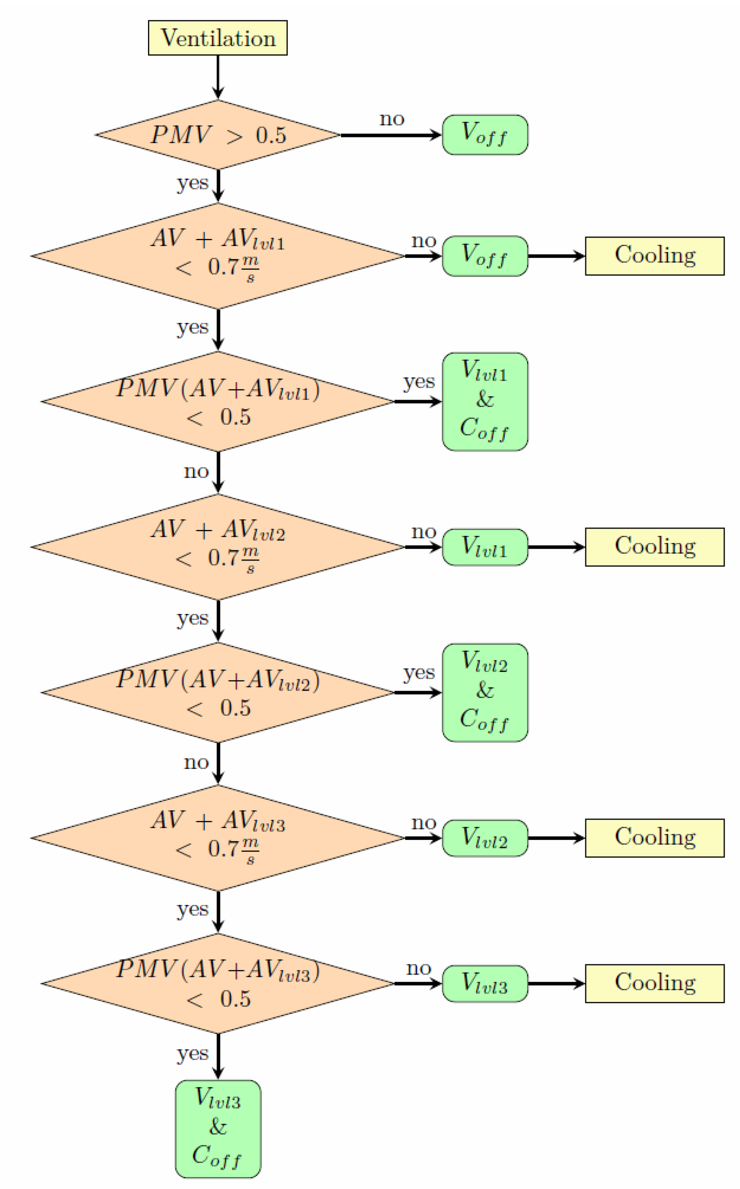
Air velocity [m/s]	16	18	20	22	24	26	28	30
0.45	-0.7	-0.7	-0.6	-0.5	-0.5	-0.4	-0.3	-0.2
0.3	-0.5	-0.5	-0.4	-0.4	-0.4	-0.3	-0.2	-0.2
0.15	-0.2	-0.2	-0.2	-0.2	-0.2	-0.1	-0.1	-0.1
0	0	0	0	0	0	0	0	0

Temperature [°C]

Program sequence



Algorithmic sequence of the training data creation and the ventilation function.



Temperature:

$T = [16°C, 30°C], T_{step} = 0.1K$

Relative humidity:

$H_{rel} = [30\%, 80\%], H_{step} = 1\%$

Air velocity:

$AV = \left[0\frac{m}{s}, 0.7\frac{m}{s}\right], AV_{step} = 0.05\frac{m}{s}$

Training data

id	$T[°C]$	$H_{rel}[\%]$	$AV[\frac{m}{s}]$	PMV_{in}	V_{lvl}	C_{lvl}	H_{lvl}	ΔPMV_{out}	PMV_{out}	PPD_{out}	$P[kW]$
4	16	30	0.15	-2.28	0	0	4	1.9	-0.38	8.01	4
6	16	30	0.25	-2.54	0	0	5	2.47	-0.07	5.1	4.9
12000	17.5	64	0.70	-2.46	0	0	4	2.35	-0.11	5.25	4
12001	17.5	65	0.00	-1.53	0	0	2	1.09	-0.44	9.04	2.2
12004	17.5	65	0.15	-1.7	0	0	3	1.55	-0.15	5.47	3.1
59127	23.7	44	0.55	-0.49	0	0	0	0	-0.49	10.02	0
59128	23.7	44	0.60	-0.52	0	0	1	0.75	0.23	6.1	1.3
59129	23.7	44	0.65	-0.54	0	0	1	0.75	0.21	5.91	1.3
59131	23.7	45	0.00	0.06	0	0	0	0	0.06	5.07	0
76467	25.9	78	0.55	0.52	1	0	0	-0.06	0.46	9.42	0.1
76480	25.9	79	0.45	0.57	1	1	0	-0.53	0.04	5.03	1
80004	26.4	59	0.40	0.59	2	0	0	-0.13	0.46	9.42	0.2
80017	26.4	60	0.30	0.66	2	1	0	-0.5	0.16	5.53	1.1
80031	26.4	61	0.25	0.71	3	0	0	-0.23	0.48	9.81	0.3
80076	26.4	64	0.25	0.73	3	1	0	-0.49	0.24	6.2	1.2
80086	26.4	65	0.00	0.99	3	2	0	-1.23	-0.24	6.2	2.75
105918	29.8	53	0.10	1.78	3	3	0	-1.98	-0.2	5.83	4.3
107859	30	80	0.40	1.99	2	3	0	-2.36	-0.37	7.85	4.2
107860	30	80	0.45	1.98	1	3	0	-2.39	-0.41	8.5	4.1
107861	30	80	0.50	1.97	1	2	0	-1.48	0.49	10.02	2.55
107863	30	80	0.60	1.95	0	2	0	-1.51	0.44	9.04	2.45
107856	30	80	0.25	2.05	3	3	0	-2.27	-0.22	6	4.3
107857	30	80	0.30	2.03	2	3	0	-2.31	-0.28	6.63	4.2
107860	30	80	0.45	1.98	1	3	0	-2.39	-0.41	8.5	4.1
107861	30	80	0.50	1.97	1	2	0	-1.48	0.49	10.02	2.55
107864	30	80	0.65	1.94	0	2	0	-1.52	0.42	8.68	2.45

- Low power consumption for scenarios with only ventilation
- Possibility of power reduction in scenarios where ventilation can substitute or lower cooling levels

Conclusion

Creation of training data successful

- 107864 records of training data created
- Nils Bitzer trained a FFNN with accuracy of 93.3% with the created training data
- Good prerequisite to train RL algorithm offline with the created training data

[1] W. Araar, T. Hofacker, K. Kohlhof, ``Developing an IoT-based control system for existing air conditioner using MEMS,'' University of Applied Sciences Cologne, 2018.
[2] M. Abdi, K. Kohlhof, ``Smart air conditioning according ISO 7730 by neural networks,'' University of Applied Sciences Cologne, 2018.
[3] DIN EN ISO 7730 2005: DIN Deutsches Institut für Normung e.V., 2005.
[4] Goodfellow, Y. Bengio, and A. Courville, ``Deep Learning,'' Massachusetts Institute of Technology, 2016.

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