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Master Degree in Automation Engineering



# Zone Temperature Control with Radiant Panels in Domestic Applications

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## Sommario

Modellazione di sistemi a pannelli radianti è un processo molto complicato in quanto coinvolge molti fattori, come: materiali utilizzati nella costruzione, l'orientamento della zona, l'invecchiamento, disturbi e così via, per cui di solito il modello non si comporta esattamente come il vero e proprio sistema, ma si comporta con certo livello di incertezza.

Lo scopo di questo lavoro è quello di realizzare analisi dell'incertezza per capire l'effetto di diversi fattori di incertezza sul comportamento del sistema sotto controllo, e poi proponendo alcuni metodi di auto-identificazione che ridurrebbe l'incertezza del sistema modellato.

## Abstract

Modeling of radiant panel systems is very complicated process as it involves many factors such as: materials used in building, orientation of zone, ageing, disturbances and etc., so usually the model doesn't behave exactly like the real system, but it behaves with some level of uncertainty.

The aim of this work is to realize uncertainty analysis to understand the effect of different uncertainty factors on the behavior of the system under control, and then proposing some methods of self-identification which would reduce the uncertainty of the modeled system.

5

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## **Table of contents**

A	Acknowledgement				
S	Sommario				
A	Abstract				
1	Ir	ntroc	luction	12	
	1.1	F	Historical background <sup>[1], [2]</sup>	12	
	1.2	τ	Underfloor heating advantages <sup>[2]</sup>	12	
	1.3	A	Aim of the work	14	
2	S	yste	m modeling	15	
	2.1	S	System description	15	
	2.2	N	Model (analytical) <sup>[3]</sup>	15	
	2	.2.1	System parameters	16	
	2	.2.2	Energy balance equations	16	
3	S	impl	lifying the analytical model and controlling the system	21	
	3.1	S	Simplifying the model	21	
	3	.1.1	Identification of model from $\Delta Te$ to $Tz$ :	22	
	3	.1.2	Identification of model from <b>Toa</b> to <b>Tz</b> :	22	
	3.2	C	Choice of controller	23	
	3.3	C	Compensating the effect of the outside temperature	25	
	3.4	S	Set point compensation	26	
	3.5	F	Robustness analysis	27	
	3	.5.1	Effect of uncertainties on PI controller	27	
	3	.5.2	Analysis in time domain	27	
	3	.5.3	Overshoot analysis	28	
	3	.5.4	Effect of uncertainties on open-loop compensator in open loop configuration.	29	

	3.5.5	Compensator in closed loop	30
	3.5.6	Effects introduced by valve limitations	. 31
	3.6 C	onclusion	32
4	Self-ic	lentification of system parameters	33
	4.1 L	east square method	34
	4.1.1	The deviation of the Rule	34
	4.1.2	The under floor heating system	35
	4.1.3	Conclusion	35
	4.2 R	ecursive least square method	36
	4.2.1	The derivation of the Rule	36
	4.2.2	The under floor heating system	37
	4.2.3	Conclusion	38
	4.3 R	LS with FF	38
	4.3.1	The under floor heating system	39
	4.3.2	Conclusion	39
	4.4 R	LS in open loop	40
	4.5 D	isturbances	41
	4.6 Id	lentification in existence of disturbances effect	42
	4.6.1	First method	42
	4.6.2	Pseudo output method	42
5	Case s	study	44
	5.1 S	implifying the model	46
	5.1.1	Identification of model from $\Delta T e$ to $\Delta T z$ :	46
	Figure	e 5-2 system identification process	46
	5.1.2	Identification of model from $\Delta Toa$ to $\Delta Tz$ :	46
	5.2 C	ontroller tuning and effect of uncertainties	48

5.	2.1	Tuning of K	49
5.	2.2	Effect of static gain uncertainty( $\alpha$ ) :	49
5.	2.3	Effect of time constant uncertainty ( $\boldsymbol{\beta}$ )	50
5.	2.4	Analysis in time domain	51
5.	2.5	Overshoot analysis	52
5.	2.6	Conclusion	53
5.	2.7	Set point compensation	54
5.3	Effe	ect of uncertainties on open-loop compensator in open loop	55
5.	3.1	Case 1 (effect of $\gamma$ (all others 1))	56
5.	3.2	Case 2 (effect of $\boldsymbol{\delta}$ (all others 1))	57
5.	3.3	Case 3 (effect of $\alpha$ (all others 1))	57
5.	3.4	Case 4 (effect of $\boldsymbol{\beta}$ (all others 1))	58
5.	3.5	Other cases	59
5.	3.6	Conclusion	59
5.4	Cor	npensator in closed loop	60
5.	4.1	Case 1 (effect of $\gamma$ (all others 1))	60
5.	4.2	Case 2 (effect of $\boldsymbol{\phi}$ (all others 1))	61
5.	4.3	Case 3 (effect of $\alpha$ (all others 1))	61
5.	4.4	Case 4 (effect of $\boldsymbol{\delta}$ (all others 1))	62
5.	4.5	Case 5 (effect of $\boldsymbol{\beta}$ (all others 1))	62
5.	4.6	Conclusion	63
5.5	Effe	ects introduced by valve limitations	64
5.	5.1	Effect of saturation	64
5.	5.2	Effect of delay	65
5.6	Lea	st square method	66

5.6.1	Testing the system	66
5.6.2	Conclusion	67
5.1 Re	cursive least square method	68
5.1.1	Step input (from 21 °C to 22 °C)	69
5.1.2	Square wave amplitude of 1 °C & period of 24 hrs	71
5.1.3	RLS with saturation	73
5.1.4	Step input (from 21 °C to 22 °C)	74
5.1.5	Step input (21 °C to 31 °C)	76
5.1.6	Square wave of amplitude 1 °C . of 24 hrs	78
5.2 RL	S with FF	80
5.2.1	Step input (from 21°C to 22 °C)	81
5.2.2	Square wave of amplitude 1 °C and period 24+step of 1 °C	83
5.2.3	Square wave of amplitude 1 °C and period 12 +step of 1 °C	85
5.2.4	Conclusion	87
5.3 RL	S in open loop	88
5.3.1	Step input on T <sub>e</sub> (1 °C)	89
5.3.2	Square wave of amplitude 1 oC and period on Te	91
5.4 Dis	sturbances of outside temperature	93
5.4.1	Step input (1 °C, 10 °C &15 °C)	94
5.4.2	Step of 1 °C+ square wave of 12 hrs period& diff amps (in closed loop)	96
5.4.3	Step input (in open loop)	98
5.4.4	Step of 1 $^{\circ}$ C + square wave of 12 hrs and diff. amps. (in open loop) 1	.00
5.5 Dis	sturbances outside temperature + solar radiation1	.02
5.5.1	Step of $^{\circ}C$ + square wave of 12 hrs and diff amps (in open loop) 1	.02
5.5.2	Suggested procedure of identification1	.04
References		.05

# Table of figures

Figure 2-1 Zone model
Figure 3-1 System in open loop
Figure 3-2 Identified model + PI controller
Figure 3-3 Open loop compensator
Figure 3-4 System in closed loop + PI + open loop compensator
Figure 3-5 Set point compensator
Figure 3-6 Open loop compensator in open loop
Figure 3-7 open loop compensator in closed loop
Figure 3-8 valve limitations
Figure 4-1 RLS in closed loop
Figure 4-2 RLS in closed loop with saturation
Figure 4-3 RLS (FF) with saturation
Figure 4-4 RLS in open loop 40
Figure 5-1 System in open loop 45
Figure 5-2 system identification process
Figure 5-3 identification of outside temperature effect
Figure 5-4 scheme of the simplified model in closed loop (considering only one input( $\Delta Te$ )48
Figure 5-5 Tuning of K 49
Figure 5-6 Effect of $\boldsymbol{\alpha}$
Figure 5-7 effect of $\boldsymbol{\beta}$
Figure 5-8 zero effect from time domain
Figure 5-9 over shoot analysis
Figure 5-10 Set-point compensation

Figure 5-11 set-point compensation results
Figure 5-12 compensator in open loop
Figure 5-13 effect of $\gamma$
Figure 5-14 effect of $\boldsymbol{\delta}$
Figure 5-15 effect of $\alpha$
Figure 5-16 effect of $\beta$
Figure 5-17 special case
Figure 5-18 PI + compensator
Figure 5-19 effect of $\gamma$
Figure 5-20 effect of φ
Figure 5-21 effect of α
Figure 5-22effect of $\boldsymbol{\delta}$
Figure 5-23 effect of <b>β</b>
Figure 5-24 limitations of valve
Figure 5-25 effect of saturation
Figure 5-26 effect of delay
Figure 5-27 4-states model step response
Figure 5-28 Transfer function step response
Figure 5-29 RLS in closed loop
Figure 5-30 RLS with saturation73
Figure 5-31 RLS in open loop

## **1** Introduction

#### **1.1** Historical background <sup>[1], [2]</sup>

Underfloor heating and cooling is a form of central heating and cooling that achieves indoor climate control for thermal comfort using conduction, radiation and convection.

Although underfloor heating is seen as a modern technological advancement that provides luxury and comfort, it actually has a history spanning 7,000 years. The origins of the concept of heated flooring are first noted in Korea as far back as 5,000 BC. There is evidence to suggest that they had heated floors which would later become known as 'ondol', meaning 'warm stone'. The Greeks and Romans had adopted the idea of underfloor heating and they were both using hypocausts, a primitive system that involved the floor being raised up on pillars while hot air passed through the space beneath.

By the twentieth century advancements were made in heating that brought together the principles from the past and transformed them into the underfloor heating systems that we recognize and use today.

In England, 1907, Professor Arthur H. Barker invented a system to warm panels using small pipes. Then a major development in domestic heating systems occurred in 1945 when William Levitt, an American developer, used water based radiant heating in thousands of homes that he built in a huge development intended for GIs returning from WWII and this was the first time this type of heating was used on such a large scale, and it proved that it could be incorporated into almost any design project.

By 1970s, Architecture in Korea at that time involved the construction of many multi-storey houses. The 1980s were a period when using underfloor heating systems became more widespread in every corner of the globe.

By the turn of the millennium, the HVAC system was introduced in many areas of Europe. This used high temperatures for cooling and low temperatures for heating. Underfloor cooling and heating systems are now used for integrated climate control globally and are fully integrated with many building management systems.

## **1.2 Underfloor heating advantages**<sup>[2]</sup>

Though being more expensive to install, underfloor heating offers advantages over the traditional heating, some of these advantages could be:

**Less maintenance:** It rarely requires any form of maintenance (Especially if the systems installed are certified to standards).

**Far more efficient than old-fashioned** regarding the utility bills: Because the floor itself is heated it retains heat far better than traditional radiators which cool down very quickly when turned off.

**More comfortable:** Quite simply this is because the temperature will be consistent around the room.

**More hygienic:** The results of switching to in-floor heating can be astounding. Studies show that installing radiant heating in your home can reduce the amount of dust mites present by up to 80%.

**Easier to control**: Thanks to each room having its own dedicated thermostat there's no obligation for one room to be kept as warm as others. With a good UFH control system, it's easy to save energy by keeping temperatures low (or even off) in rooms that are rarely used, while key living areas are kept as warm as liked.

Can now work under almost any kind of floor.

## 1.3 Aim of the work

Modeling of such systems is very complicated process as it involves many factors such as: materials used in building, orientation of zone, ageing, disturbances and etc., so usually the model doesn't behave exactly like the real system, but it behaves with some level of uncertainty.

Based on that controllers that are designed to control the system should show some robustness in existence of such constraints.

The aim of this work is to test the robustness of the controller designed and its ability to overcome the model uncertainty as well as disturbances introduced by different factors.

In the second chapter the development of the analytical model would be described briefly and then the analytical model would be simplified and a suitable **PI** controller would be adapted and disturbances compensation method for the outside temperature would be introduced.

In the third chapter a robustness analysis would be held where the effects of uncertainty is going to be discussed.

In the fourth chapter self-identification method would be proposed in order to overcome the modeling process limitations where a generic system (zone subjected to underfloor heating) parameters would be identified and suitable controller would be adapted based on the identified parameters.

In the fifth chapter a case study would be adapted where all the previous work is going to be tested.

By the end of the work a strategy to adapt the self-identification would be proposed as well as the conclusion of the work.

## 2 System modeling

## 2.1 System description

The system in question is a room whose orientation is facing south (fig 2.1). The zone is composed of the opaque surfaces (walls and ceiling) in dark grey color, the transparent surface (windows) in blue color and the pavement in light grey color. **Underfloor radiant panels** are installed in order to heat the zone.



#### Figure 2-1 Zone model

#### **2.2** Model (analytical) <sup>[3]</sup>

Several heat exchanges are taking place in the system previously described, those heat exchanges would be considered in order to generate a dynamic linear model.

The heat exchanges which are taking place in the previously described system could be presented as:

- The heat exchange between the zone air and outdoor air through the walls.
- The heat exchange between the zone air and the ground through the walls.
- The heat exchange between the zone air and the pavement.
- The heat exchange between the pavement and the ground.
- The radiation energy received by both pavement and zone air through transparent surface.
- The radiation energy received by opaque surface increase the temperature of walls resulting in zone temperature variation.

- The heat exchange between fresh air from Air Handling Unit and zone space;
- The heat brought by internal gains.
- The heat brought by terminals (i.e. the **underfloor radiant panels**).

## 2.2.1 System parameters

The dynamic linear model can be generated considering 4- state variables which are:

- Zone temperature: T<sub>z</sub> [°C]
- Walls (includes ceiling) temperature: T<sub>w</sub> [°C]
- Pavement (includes furniture) temperature: T<sub>p</sub> [°C]
- Pipe (including both water and pipe) temperature: T<sub>pi</sub> [°C]

While the inputs to the system would be:

- Temperature of outside air: T<sub>oa</sub> [°C]
- Solar radiation (divided by facade, opaque and transparent surfaces):  $W_{sol,i}[W/m^2]$
- Internal gains: P<sub>int gains</sub> [W/m<sup>2</sup>]
- Temperature of ground: T<sub>G</sub> [oC]
- m<sub>sa</sub> : supply air mass flow (AHU) [kg/s]

And the variables which could be manipulated would be:

- Heat flux from air handling unit: P<sub>AHU</sub> [W]
- Inlet temperature of the radiant panel: T<sub>e</sub> [°C]

## 2.2.2 Energy balance equations

By considering the heat exchanges which took place in the described system, now the system would be mathematically modeled using energy balance concept.

Four energy balances would be considered in building the model, each one would consider one of the state variables of the model.

The first considered energy balance relation would take in account that the rate of the change of heat energy of the wall (including ceiling) would be equivalent to the sum of the rate of heat exchange taking place between the open air and the walls (including ceiling); rate of heat exchange taking place between zone air and wall (including ceiling) and effect of solar radiation on each wall, as it would be shown in the next relation.

$$C_{wc}\dot{T}_{w} = U_{wceo}(T_{oa} - T_{w}) + U_{wci}(T_{Z} - T_{W}) + \frac{\alpha_{w}R_{e_{wall}}}{\frac{R_{e_{wall}} + R_{wall}}{k_{wall}}}{\sum_{i=N,S,W,E,Ciel}} W_{sol,i}S_{op,i}$$
$$+ \frac{1}{2}Ksol, tr. \sum_{i=N,S,W,E,ceil} W_{sol,i}S_{tr,i} + U_{weG}(T_{G} - T_{W})$$

Where:

- C<sub>wc</sub> : walls(include ceiling) average thermal capacity [J/K];
- *R<sub>e\_wall</sub>* : external wall convective resistance [K/W];
- *R<sub>wall</sub>* : wall convective resistance [K/W];
- *U<sub>wce0</sub>*: average external convective conductance of walls (ceiling) with open; air [W/K];
- *U<sub>wci</sub>*: average internal convective conductance of walls (ceiling) [W/K];
- *U<sub>weG</sub>*: external convective conductance of walls (ceiling) with ground [W/K];
- $S_{op,i}$ : opaque area of façade i [m<sup>2</sup>];
- $S_{tr,i}$ : transparent area of façade  $i [m^2]$ ;
- $\alpha_w$ : walls solar radiation absorbance coefficient [#];
- **Kwall**: Coefficient of solar radiation effect on opaque area [#];
- Ksol,tr: Coefficient of solar radiation effect on transparent area [#];

The second relation would consider that rate of change of heat energy in the zone would be equivalent to the sum of: the rate heat exchange between walls and zone air; rate of heat exchange between outside air and zone air; the rate of heat exchange taking place between the pavement and zone air; internal gains and AHU, as it would be shown in the next relation.

$$C_{Z}\dot{T}_{Z} = U_{wci}(T_{W} - T_{Z}) + U_{win}(T_{oa} - T_{Z}) + U_{pav}(T_{P} - T_{Z}) + \underbrace{\underbrace{ic_{pa}}_{P_{AHU}}(T_{oa} - T_{Z})}_{P_{AHU}} + P_{intgains}$$

Where

- $C_z$ : zone air mass thermal capacity [J/K]
- $U_{wci}$ : average internal convective conductance of walls (ceiling) [W/K]
- $U_{win}$ : convective conductance of transparent surface [W/K]
- $U_{pavi}$ : air-pavement convective transmittance [W/K]

- *C<sub>pa</sub>* : air specific heat [J/KgK]
- $U_{sa}$ : convection conductance of supply air [W/K]

The third relation would consider that rate of change of heat energy in the pavement would be equivalent to the sum of: the rate heat exchange between zone air and pavement; the rate heat exchange between pavement and ground; solar radiation effect; internal gains and the power from terminals, as it would be shown in the next equation, as it would be shown in the next relation.

$$C_P \dot{T}_P = U_{pavi}(T_Z - T_P) + P_{int \ gains} + \underbrace{\frac{1}{2}(1 - FF). \ ggl. F_{sm}}_{K_{sol,tr}} \sum_{i=N,S,W,E,Ceil} W_{sol,i}S_{tr,i} + U_{pavG}(T_G - T_P) + P_{TERM}$$

Where

- $C_p$ : pavement thermal capacity
- *U<sub>pavi</sub>*: air-pavement convective transmittance [W/K]
- U<sub>pavG</sub>: pavement- ground convective transmittance [W/K]
- $S_{tr,i}$ : transparent area of façade  $i \text{ [m}^2\text{]}$
- $F_{sm}$ : windows solar protection shading factor [#]
- *ggl* : windows solar factor [#]
- *FF* : windows frame factor [#]

The fourth relation would consider that rate of change of heat energy in the pipe would be affected by: rate of change of water indie the pipe; the rate of change of heat energy in the pavement and the rate of change of heat energy in the as it would be shown in the next relation

$$C_{aq}.\vec{T}_{pi} = -wC_{p-aq}T_{pi} + (wC_{p-aq}\left(e^{-\alpha} - \frac{1 - e^{-\alpha}}{\alpha}\right) + U_1A_pL\left(\frac{1 - e^{-\alpha}}{\alpha}\right))T_p + \left(wC_{p-aq} - wC_{p-aq}\left(e^{-\alpha} - \frac{1 - e^{-\alpha}}{\alpha}\right) - U_1A_pL\left(\frac{1 - e^{-\alpha}}{\alpha}\right)\right)T_e$$

- *C<sub>p-aq</sub>* : Specific heat of water [J/kgK]
- *C<sub>aq</sub>* : Water heat capacity [J/K]
- *w* : Water mass flow in the panel [kg/s]
- *L* : length of the pipe [meter]
- *U*<sub>1</sub> : A constant heat transfer coefficient []
- *A<sub>p</sub>* : outside girth of the pipe [meter]

• 
$$\boldsymbol{\alpha}: \frac{U_1.A_p.L}{\rho.Ar. C_p.\vartheta}$$

- **9** : flow speed [meter/s]
- Ar: cross sectional inner area of the pipe [m2]
- **ρ**: water density

From the previously shown energy balance equation a state-space continuous would be derived. The state representation of the system can be shown as:

$$\begin{cases} \dot{x} = A. x + B. u\\ y = C. x + D. u \end{cases}$$

Such that

$$\dot{x} = \begin{bmatrix} \dot{T}_w \\ \dot{T}_z \\ \dot{T}_p \\ \dot{T}_{pi} \end{bmatrix}; \qquad x = \begin{bmatrix} T_w \\ T_z \\ T_p \\ T_{pi} \end{bmatrix}; \qquad u = \begin{bmatrix} T_{oa} \\ W_{sol,N} \\ W_{sol,S} \\ W_{sol,W} \\ W_{sol,Eil} \\ T_G \\ P_{int \ gain} \\ Te \end{bmatrix};$$

And

$$A_{o} = \begin{bmatrix} -\frac{1}{C_{WC}} (U_{wee} + U_{wei} + U_{wei}) & \frac{1}{C_{W}} U_{wei} & 0 & 0 \\ \frac{1}{C_{Z}} U_{wei} & -\frac{1}{C_{Z}} (U_{wei} + U_{win} + U_{pari} + U_{sa}) & \frac{1}{C_{Z}} U_{pari} & 0 \\ 0 & \frac{1}{C_{p}} U_{pari} & -\frac{1}{C_{p}} (U_{pari} + U_{pari} + U_{nar} - \frac{1}{C_{p}} (U_{pari} + U_{pari} - \frac{1}{C_{p}} (U_{pari} + U_{pari} - \frac{1}{C_{p}} (U_{pari} + U_{pari} - \frac{1}{C_{q}} - \frac{1 - e^{-\alpha}}{\alpha})) & 0 \\ 0 & 0 & \frac{1}{C_{aq}} (wC_{p-aq} \cdot (e^{-\alpha} - \frac{1 - e^{-\alpha}}{\alpha}) + U_{1} \cdot A_{p} \cdot L(\frac{1 - e^{-\alpha}}{\alpha})) & -\frac{1}{C_{aq}} wC_{p-aq} \end{bmatrix}_{4\times4} \\ B_{o} = \begin{bmatrix} b11 & b12 & b13 & b14 & b15 & b16 & b17 & b18 & b19 \\ b21 & b22 & b23 & b24 & b25 & b26 & b27 & b28 & b29 \\ b31 & b32 & b33 & b34 & b35 & b36 & b37 & b38 & b39 \\ b41 & b42 & b43 & b44 & b45 & b46 & b47 & b48 & b49 \end{bmatrix}_{4\times9} \end{cases}$$

Where

$$b11 = \frac{1}{C_{wc}} U_{wc0}$$

$$b21 = \frac{1}{C_z} (U_{win} + U_{sa})$$

$$b31 = 0$$

$$b12 = \frac{1}{C_{wc}} (k_{wall} S_{op,N} + \frac{1}{2} K_{sol,r} S_{tr,N})$$

$$b22 = 0$$

$$b32 = \frac{1}{2C_p} K_{sol,r} S_{tr,N}$$

$$b24 = 0$$

$$b33 = \frac{1}{2C_p} K_{sol,r} S_{tr,N}$$

$$b26 = 0$$

$$b14 = \frac{1}{C_{wc}} (k_{wall} S_{op,N} + \frac{1}{2} K_{sol,r} S_{tr,N})$$

$$b27 = 0$$

$$b34 = \frac{1}{2C_p} K_{sol,r} S_{tr,N}$$

$$b15 = \frac{1}{C_{wc}} (k_{wall} S_{op,E} + \frac{1}{2} K_{sol,r} S_{tr,E})$$

$$b28 = \frac{1}{C_z} S_{pavi}$$

$$b35 = \frac{1}{2C_p} K_{sol,r} S_{tr,E}$$

$$b16 = \frac{1}{C_{wc}} k_{wall} S_{op,ceil}$$

$$b41 = 0$$

$$b41 = 0$$

$$b42 = 0$$

$$b36 = \frac{1}{2C_p} K_{sol,r} S_{tr,ceil}$$

$$b17 = \frac{1}{C_{wc}} U_{weG}$$

$$b43 = 0$$

$$b44 = 0$$

$$b37 = \frac{1}{C_p} U_{pavG}$$

$$b18 = 0$$

$$b46 = 0$$

$$b46 = 0$$

$$b46 = 0$$

$$b47 = 0$$

$$b48 = 0$$

$$1 = a^{-\alpha}$$

$$1 = a^{-\alpha}$$

$$1 = a^{-\alpha}$$

$$b49 = w.C_{p-aq} - w.C_{p-aq}.(e^{-\alpha} - \frac{1 - e^{-\alpha}}{\alpha}) - U_1.A_p.L(\frac{1 - e^{-\alpha}}{\alpha})$$

## **3** Simplifying the analytical model and controlling the system

As it was shown earlier, the system (the zone) was modeled considering the heat transfer occurring inside the zone, using energy balance equations a dynamic linear 4-states model was produced which can be represented by the following state space representation:

$$\dot{x} = A_{4\times4} \, \bar{x}_{4\times1} + B_{4\times9} \bar{u}_{9\times1}$$
$$y = C \bar{x}_{4\times1} + D_{4\times9} \bar{u}_{9\times1}$$

The 4-states model-though being very precise- is very complicated to analyze, and in fact it is required to find out a relation between the inlet temperature (manipulated input) and the zone temperature (state variable), so that a suitable controller would regulate the inlet temperature by regulating the opening and closing of the valve.

Also another relation between the outside temperature (input) and the zone temperature (state variable), would be studied, as it is possible to measure the outside temperature and therefore it can be dealt with (i.e. compensated).

In order to simplify the model, the following assumptions were considered:

- Solar radiation effect on the system wouldn't be considered.
- Internal gain of the zone would be considered constant.
- The ground temperature would be considered constant.

#### **3.1** Simplifying the model

As it could be seen from the system configuration shown in figure 3-1, the system inputs now are limited into two inputs: Inlet temperature  $(T_e)$  and outside temperature  $(T_{oa})$  and one output: Zone temperature  $(T_z)$ .

Two transfer functions (G, H) would be identified modeling the behavior of the system  $output(T_z)$  for each of the system  $inputs(T_e, T_{oa})$ 

The equilibrium points which would be considered for the next work are:

- $T_{oa\_eq}$ : The outside temperature that would put the system in equilibrium (usually chosen to be the average temperature over a period of time (i.e. winter).
- $T_{z eq}$ : The equilibrium temperature of zone temperature.

•  $T_{e_eq}$ : Which is the inlet temperature which would put the zone temperature in equilibrium and it was calculated by inverting the system equations



Figure 3-1 System in open loop

## **3.1.1** Identification of model from $\Delta T_e$ to $T_z$ :

Using the 4-states dynamic model now the first transfer function (G) can be identified by applying a step input on the  $\Delta T_e$  while keeping all other inputs at equilibrium.

A simplified model (Transfer function) is identified by simulating the analytical model for 10 days and identifying *1-pole* system by minimizing the least square error.

The identified transfer function was chosen to be *1- pole* system as it was found out the system behavior is very similar to be one-pole system and it would be shown by experiments in the following sections .

The identified transfer function from  $T_e$  to  $T_z$  can be presented in the following way:

$$G = \frac{\mu}{1 + s.\tau}$$

#### 3.1.2 Identification of model from $T_{oa}$ to $T_z$ :

Similarly the identification of the H transfer function was done, a step input was applied on the  $T_{oa}$  while the other input  $\Delta T_e$  kept at zero, by simulating the analytical model for 20 days and identifying 2- *poles one zero* system by minimizing the least square error.

The identified transfer function was chosen to be 2- *poles one zero* system as it was found out that the system behavior is very similar to that and it would be shown by experiments in the following sections .

Transfer function from  $T_{oa}$  to  $T_z$  (2<sup>nd</sup> order)

$$H = \mu_e \frac{1 + T_e s}{(1 + \tau_{e1} s)(1 + \tau_{e2} s)}$$

#### **3.2** Choice of controller

Based on the *1- pole* transfer function – identified earlier – A model based PI controller was designed in order to regulate the average inlet temperature( $\Delta T_e$ ).

$$G = \frac{\mu}{1+s.\tau}$$

The PI is expected to accelerate the system and provide better set point tracking, where the proportional action is required to accelerate the system and the Integral action is required to decrease the steady state error.

The PI parameters would be tuned in the following way:

P (Proportional action) = 
$$\frac{K}{\mu}$$
 & I (Integral action) =  $\frac{K}{\tau\mu}$ .

Where

- $\tau$ : Time constant of the system.
- $\mu$ : The static gain of the system.
- K: The velocity factor of the controller.

Therefore the controller transfer function would be in following form:

$$PI = \frac{K(1+\tau s)}{\tau \mu \ s}$$

Ideally the controlled system would be represented by the following equation:

$$F_{ol}(s) = PI \times G = \frac{K(1+\tau s)}{\tau \, \mu \, s} * \frac{\mu}{1+\tau s} = \frac{K}{\tau \, s}$$

Therefore the response of the system in closed loop can be shown as:

$$F_{cl}(s) = \frac{K}{\tau s + K}$$



Figure 3-2 Identified model + PI controller

#### **3.3** Compensating the effect of the outside temperature

The other input of the system is considered to be the change of the outside temperature, the effect of the outside temperature would be considered as undesired effect for the system, therefore a compensator would be designed in order to eliminate the effect of this undesired effect.

Considering the system T.F is:

$$G = \frac{\mu}{1+s.\tau}$$

And the T.F from  $T_{oa}$  to  $T_z$  is:

$$H = \mu_e \frac{1 + T_e s}{(1 + \tau_{e1} s)(1 + \tau_{e2} s)}$$

Then an open loop compensator would be adapted with the form shown in the figure 3-3



Figure 3-3 Open loop compensator

So the  $\Delta T_z$  would tend to be

$$\Delta T_z = G\left(\Delta T_e - \frac{H}{G}T_{oa}\right) + H T_{toa}$$

So ideally the effect of the H should be totally eliminated using the open loop compensator

$$\Delta T_z = G \Delta T_e$$



Figure 3-4 System in closed loop + PI + open loop compensator

The system under control scheme is shown in the figure 3-4, ideally when a suitable input is applied on the system input it is compared with the measured data, and then the error is treated with the PI controller who is producing a suitable inlet temperature. In the meantime the effect of the outside temperature of the system would be compensated by the open-loop compensator discussed earlier.

#### 3.4 Set point compensation

A possible modification for the system control is addition of set-point compensator, a set point compensator was added to the control scheme (figure 3-5).

A set point compensator would use the inverse of the system (i.e.  $\frac{1}{G}$ )



Figure 3-5 Set point compensator

#### **3.5 Robustness analysis**

Modeling of such systems is very complicated process as it involves many factors such as: materials used in building, orientation of zone, ageing, disturbances and etc., so usually the model doesn't behave exactly like the real system, but it behaves with some level of uncertainty.

Based on that controllers that are designed to control the system should show some robustness in existence of such constraints.

#### 3.5.1 Effect of uncertainties on PI controller

As it was shown before the PI controller (ideally) is expected to be in following form:

$$PI = \frac{K(1 + \tau s)}{\tau \mu s}$$

Thus producing a closed loop system in the following form:

$$F_{cl}(s) = \frac{K}{\tau s + K}.$$

In fact the system model is expected to have some uncertainties. In order to understand the behavior of the system in case of uncertainties two main uncertainties factors would be considered in the next section: uncertainty of the time constant ( $\tau$ ) and it would be called  $\beta$  and uncertaity on the system's static gain and it would be called  $\alpha$ .

So the system equation in closed loop would tend to be:

$$F_{cl}(S) = \frac{\alpha k(\tau s + 1)}{\beta \tau^2 s^2 + \tau (1 + \alpha k) s + k\alpha}$$

#### 3.5.2 Analysis in time domain

Closed loop transfer function (with step response):

$$F(S) = \frac{\alpha k(\tau s + 1)}{s(\beta \tau^2 s^2 + \tau(1 + \alpha k)s + k\alpha)}$$

Which is equivalent to the second order system general model multiplied by one zero

$$F(S) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n + \omega_n^2} (\tau s + 1)$$

Where:

• 
$$\omega_n = \sqrt{\frac{k\alpha}{\beta\tau^2}} (natural freq)$$
  
•  $\zeta = \frac{(1+\alpha k)}{2\sqrt{\beta k\alpha}} (damping ratio)$ 

Applying the inverse Laplace transformation to the transfer function it would be found out that:

$$y(t) = 1 - \frac{e^{-\zeta\omega_n t}}{\sqrt{1-\zeta^2}} \sin\left(\omega_d t + \phi\right) + \frac{\zeta\omega_n \tau e^{-\zeta\omega_n t}}{\sqrt{1-\zeta^2}} \sin\left(\omega_d t + \phi\right) - \frac{\omega_d \tau e^{-\zeta\omega_n t}}{\sqrt{1-\zeta^2}} \cos(\omega_d t + \phi)$$

Where the effect of zero is

$$y(t)_{zero} = \frac{\zeta \omega_n \tau e^{-\zeta \omega_n t}}{\sqrt{1-\zeta^2}} \sin(\omega_d t + \phi) - \frac{\omega_d \tau e^{-\zeta \omega_n t}}{\sqrt{1-\zeta^2}} \cos(\omega_d t + \phi)$$

## 3.5.3 Overshoot analysis

Based on the experiments, it was found out that overshoot was the main problem that can be introduced by uncertainties on the system controlled by the PI controller discussed earlier.

The analysis would take in account only any overshoot which would happen in first 10 hrs of simulation.

The aim of such analysis is to find out for which combinations of the three factors (K, $\beta \& \alpha$ ) the overshoot happens.

#### 3.5.4 Effect of uncertainties on open-loop compensator in open loop configuration

As it was shown before the open-loop compensator is supposed to eliminate all the effect of the change of outside temperature but practically the uncertainty could exist also here for the same reasons discussed before.

Considering the scheme shown in figure 3-6, it is required now to understand the effect of the uncertainty on the open-loop compensator behavior where :

Considering the system T.F is:

$$G = \frac{\mu}{1 + s.\tau}$$

Considering the uncertainty:

$$\tilde{G} = \frac{\alpha \, \mu}{1 + s. \tau. \beta}$$

And the T.F from T<sub>oa</sub> to T<sub>z</sub> is:

$$H = \mu_e \frac{1 + T_e s}{(1 + \tau_{e1} s)(1 + \tau_{e2} s)}$$

Considering the uncertainty:

$$\widetilde{H} = \mu_e \gamma \frac{1 + T_e \phi s}{(1 + \tau_{e1} \delta s)(1 + \tau_{e2} s)}$$

Where  $\gamma$ ,  $\delta$ ,  $\phi$  are uncertainty factors

Then the equation of compensator would tend to:

$$\Delta T_{z} = \tilde{G} \left( \Delta T_{e} - \frac{H}{G} T_{oa} \right) + \tilde{H} T_{toa}$$



Figure 3-6 Open loop compensator in open loop

Then:

$$\Delta T_z = \frac{\alpha \mu}{1 + s.\tau.\beta} \left( \Delta T_e - \frac{\mu_e \frac{1 + T_e s}{(1 + \tau_{e1} s)(1 + \tau_{e2} s)}}{\frac{\mu}{1 + s.\tau}} \Delta T_{oa} \right) + \mu_e \gamma \frac{1 + T_e \phi s}{(1 + \tau_{e1} \delta s)(1 + \tau_{e2} s)} \Delta T_{oa}$$

At high frequencies:

$$\Delta T_z = \alpha \left( -\mu_e \Delta T_{oa} \right) + \mu_e \gamma \Delta T_{oa}$$

From the previous expression it can be deduced that at high frequencies the behavior of the average zone temperature would vary depending on the type of uncertainty, the gain uncertainties ( $\gamma$  and  $\alpha$ ) would affect the steady state while in case of uncertainties of time constants( $\beta$ ,  $\gamma$  and  $\phi$ ) only the transient period would be affected.

#### 3.5.5 Compensator in closed loop

After studying the behavior of the compensator in open-loop, it is predicted that that the system would behave differently in case of closed loop as a result of the permitive property of the closed loop which is disturbances rejection.

Closing the loop would reduce the effect the system's sensitivity to the uncertainties, also having the PI in action would help the system having better tracking of set-point and therefore better steady-state performance, while it might dieteriorate the traniseint behavior.



Figure 3-7 open loop compensator in closed loop

$$\Delta T_{z} = HT_{oa} + \Delta T_{e}G$$
$$\Delta T_{z} = HT_{oa} + \left(-\frac{H}{G}\Delta T_{oa} + PI(\Delta T_{ref} - \Delta T_{z})\right)G$$

Considering only  $\Delta T_{oa}$  as an only input:

$$\Delta T_z = HT_{oa} + \left(-\frac{H}{G}\Delta T_{oa} + PI(-\Delta T_z)\right)G$$

In case of uncertainty:

$$\Delta T_z = \frac{\left(\widetilde{H} - \frac{H\widetilde{G}}{G}\right)}{1 + PI.\,\widetilde{G}} \Delta T_{oa}$$

From the previous expression it can be deduced that at high frequencies, the behavior of the average zone temperature would always be zero, while uncertainty would cause problems only in the transient period.

#### 3.5.6 Effects introduced by valve limitations

The model of the system used so far is not practical and does not consider some limitations on the real system. For instance the model is not considering the limits of the inlet temperature, which practically has upper and lower limits, because the valve is mixing the water returned from the panels with percentage of water produced by heat pumps.

Also delay of the valve of the inlet temperature is not considered, as in practice it's not opening and closing instantly.



Figure 3-8 valve limitations

## 3.6 Conclusion

- Modelling of the system is so complicated procedure and uncertainties can exist.
- The system performance shows high sensitivity to combination of uncertainties.
- Also it should be clear that the saturation is very important to the system even if it doesn't affect the system much.
- A self-identification method can be used in order to reduce the uncertainty and facilitate the modeling.

## 4 Self-identification of system parameters

Based on the previous work, it was found out that the modelling of the system is so complicated procedure and uncertainties can exist, and it was also found out that the system is showing high sensitivity to combinations of uncertainties.

Also it was found out that system in most of the cases is acting like *1-pole* system (i.e.  $G = \frac{\mu}{1+\tau s}$ ) and that the system reacted very well to the PI controller by the following TF:  $PI = \frac{k(\tau s+1)}{\mu \tau s}$ (where  $\tau$  is the time constant of the system, and  $\mu$  is its static gain).

One way to get over modeling uncertainty and the complications of the modeling procedure is to apply self-identification methods.

For the next work some self-identification methods would be considered:

First the LS method would be considered where it would be used to identify the system in the open-loop, (ie  $\mu$  and  $\tau$ ) and then the controller would be updated by the values.

Second method would be RLS method in closed loop where a controller would be self-tuned using our previous control rule and with reasonable initial values of the parameters of the system.

Also it would be used in open loop, in order to identify the system parameters and then the controller parameters would be updated later.

In fact the aim of this methods is to reduce the uncertainty and facilitate the modeling process.

## 4.1 Least square method

#### 4.1.1 The deviation of the Rule

The method of Least Squares is a procedure to determine the best fit line to data, minimizing the square of the error between the estimated data and real data as an objective function (J).

Considering a generic system, it can be assumed that the system is represented by the following relation:

$$y(t) = a_o y(t-1) + a_1 y(t-2) + \dots a_n y(t-n-1) + b_o u(t) + b_1 u(t-1) \dots b_n u(t-m)$$

then:

$$y(t) = \theta \phi^{T}$$
Where:  $\theta = \begin{bmatrix} a_{0} \\ \vdots \\ a_{n} \\ b_{0} \\ \vdots \\ b_{m} \end{bmatrix}$ 
And  $\phi = \begin{bmatrix} y(t-1) & y(t-2) & \cdots & \cdots & y(t-n-1) & y(t-n) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y(t-N) & y(t-N-1) & \cdots & \cdots & y(t-N-n-1) & y(t-N-n) \\ u(t) & u(t-1) & \cdots & \cdots & u(t-m-2) & u(t-m-1) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ u(t-N) & u(t-N-1) & \cdots & \cdots & u(t-m-N-1) & u(t-m-N) \end{bmatrix}$ 

objective function : 
$$J = \frac{1}{N} \Sigma \left( y(t) - \hat{y}(t) \right)^2 = 0$$

By minimizing the function we can find out that:

$$\theta = \left(\phi \, \phi^T \,\right)^{-1} \phi \, y(t)$$

#### 4.1.2 The under floor heating system

Considering the underfloor system, as it was said before, the system itself (from  $T_e \text{ till } T_z$ ) acts like *1- pole* system.

The system can be represented in the following way (discrete):

$$\hat{y}(t) = a_o y(t-1) + b_o u(t)$$
$$\hat{y}(t) = \theta \phi^T$$

$$\theta = \begin{bmatrix} a_o \\ b_o \end{bmatrix} \qquad \& \qquad \phi = \begin{bmatrix} y(t-1) & y(t-2) & \cdots & y(t-n-1) & y(t-n) \\ u(t) & u(t-1) & \cdots & u(t-1) & u(t-n-1) \end{bmatrix}$$

Where:

- *y*(*t*): Zone temperature (T<sub>z</sub>) at instant(*t*).
- u(t): Inlet temperature (T<sub>e</sub>) at instant(t).
- *n* is the number of the samples

#### 4.1.3 Conclusion

- As it was seen the method is very easy to apply and provides very precise results in case of absence of disturbances.
- The application of the method doesn't require initialization.
- The application of the method requires very high memory.
## 4.2 Recursive least square method

In order to overcome the limitations concluded in the LS, RLS would be adapted. RLS would not require much information(less memory) as it would be shown briefly in the formulation.

Knowing the input and output of the system (relation between Te (u(t)) and Tz (y(t)), the method is able to identify the parameters of the system recursively. Using this relation a suitable controller would be updated online optimizing a specific objective function.

RLS can be adapted in online configuration as it is shown in figure 4-1.



Figure 4-1 RLS in closed loop

#### 4.2.1 The derivation of the Rule

Considering a generic system, it can be assumed that the system is represented by the following relation:

$$y(t) = a_o y(t-1) + a_1 y(t-2) + \dots a_n y(t-n-1) + b_o u(t) + b_1 u(t-1) \dots b_n u(t-m)$$

Then

Where: 
$$\theta = \begin{bmatrix} a_0 \\ \vdots \\ a_n \\ u_0 \\ \vdots \\ u_m \end{bmatrix} \& \phi = \begin{bmatrix} y(t-1) \\ \vdots \\ y(t-n-1) \\ u(t-1) \\ \vdots \\ u(t-m) \end{bmatrix}$$

 $y(t) = \theta \, \phi^T$ 

Where  $\phi$ : regression vector

Then the parameters are identified recursively using the next relation, ensuring the minimization of the objective function (least square error).

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(y(t) - \phi^T \hat{\theta}(t-1))$$

where  $\hat{\theta}$  is the vector of identified parameters

where 
$$K = p(t) \phi$$

$$p(t) = s(t)^{-1}$$

where p(t): Is the filter coefficient

$$\& s(t) = s(t-1) - \phi^T \phi$$

For easiness the p(t) can be represented by the following representation

$$p(t) = p(t-1) - \frac{p(t-1)\phi^T \phi p((t-1))}{1+\phi^T \phi p(t-1)}$$
(matrix inversion lemma)

## 4.2.2 The under floor heating system

Considering the underfloor system, as it was said before, the system itself (from  $T_e$  till  $T_z$ ) without the consideration of any disturbances acts like *1- pole* system.

The system can be represented in the following way (discrete):

Figure 4-2 RLS in closed loop with saturation

#### 4.2.3 Conclusion

- The algorithm is showing less dependency on the memory.
- The algorithm depends on the persistent excitation of the system as well as the initial values.

#### 4.3 RLS with FF

As it would be seen in simulations, some problems aroused as a result of very fast convergence of the filter coefficient p(t), a solution for such problems can be by making the filter coefficient more oscillating (less stable) which can be realized either by persistent excitation, or -as it would be seen in formulation- by adding forgetting factor to the filter coefficient.

Same as it was done for the RLS, a system was considered to be represented by the following representation:

$$y(t) = a_o y(t-1) + a_1 y(t-2) + \dots a_n y(t-n-1) + b_o u(t) + b_1 u(t-1) \dots b_n u(t-m)$$

Then 
$$y(t) = \theta \phi^T$$
  

$$\begin{bmatrix} a_o \end{bmatrix} \begin{bmatrix} y(t-1) \end{bmatrix}$$

Where: 
$$\theta = \begin{bmatrix} \vdots \\ a_n \\ u_o \\ \vdots \\ u_m \end{bmatrix} \& \phi = \begin{bmatrix} y(t-n-1) \\ y(t-n-1) \\ u(t-1) \\ \vdots \\ u(t-m) \end{bmatrix}$$

Then the system parameters can be identified recursively by the following formula:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(y(t) - \phi^T \hat{\theta}(t-1))$$

$$K = p(t) \phi$$
 Where  $p(t) = s(t)^{-1}$ 

And 
$$s(t) = \lambda s(t-1) - \phi^T \phi$$
 where  $0 < \lambda \le 1$ 

The smaller  $\lambda$  is, the smaller contribution of previous samples. This makes the filter more sensitive to recent samples, which means more fluctuations in the filter coefficient p (t). In practice is usually chosen between 0.98 and 1

## 4.3.1 The under floor heating system

Considering the underfloor system, as it was said before, the system itself (from  $T_e$  till  $T_z$ ) without the consideration of any disturbances acts like *1- pole* system.

The system can be represented in the following way:

$$\hat{y}(t) = a_o y(t-1) + b_o u(t)$$

$$\hat{y}(t) = \theta \phi^T$$

$$\theta = \begin{bmatrix} a_o \\ b_o \end{bmatrix} \qquad \& \qquad \phi = \begin{bmatrix} y(t-1) \\ u(t) \end{bmatrix}$$

$$\hat{\theta}(t) = \hat{\theta} (t-1) + K \left( y(t) - \phi^T \hat{\theta}(t-1) \right)$$

$$K = p(t) \phi$$
Where  $p(t) = s(t)^{-1}$ 
And  $s(t) = \lambda s(t-1) - \phi^T \phi$  where  $0 < \lambda \le 1$ 



Figure 4-3 RLS (FF) with saturation

### 4.3.2 Conclusion

- By adding the forgetting factor, the algorithm is converging to the real parameters though more dynamics are introduced.
- The algorithm is less dependent on the persistent excitation of the system.

## 4.4 RLS in open loop

RLS – with or without forgetting factor- also allows identification in open loop configuration as it can be seen from figure 4-4.

Same as before knowing the input and output of the system (relation between  $T_e(u(t))$  and  $T_z(y(t))$  as shown in figure 4-4, the method is able to identify the parameters of the system recursively .

The parameters would be used to update the PI controller after the identification period.

By applying the identification in open loop it can be guaranteed that the zone temperature wouldn't behave in strange manner as a result of continuous change in the controller parameters.

Also as it would be seen later that the system would be able to identify the static gain of the system without much excitation, while to identify the system time constant a persistent excitation would be necessary.



Figure 4-4 RLS in open loop

#### 4.5 Disturbances

Up to now the system is considered with only one input which is  $T_e$  (inlet temperature) as shown in the next equation:

$$y(t) = a_o y(t-1) + b_o u(t)$$

In fact the system would be subjected to more than one input, as the system would be affected by the outside temperature and the solar radiation which would act like disturbances on the system in question.

Those disturbances would affect the process of identification and could lead to wrong and misleading parameters of the system and as consequence the PI parameters.

It should be remembered that the identification is expected to reduce the parameters uncertainty, so a small uncertainty is still expected.

The system with disturbances can be shown as:

$$y(t) = a_o y(t-1) + b_o u(t) + c_o u_2(t) + S_{rad}$$

Where  $u_2(t)$ : is the outside temperature  $T_{oa}$ 

And  $S_{rad}$ : the solar raditation effect

$$y(t) = a_o y(t-1) + c_o u_2(t) + S_{rad}$$

As it can be seen in the equation: if the solar radiation won't be measured, it wouldn't be possible to distinguish the effect of solar radiation from the effect of the outside temperature on the zone temperature.

Also it wouldn't be possible to construct an outside temperature compensator as the one constructed in previous sections.

#### 4.6 Identification in existence of disturbances effect

It was found out in previous work that the effect of disturbances is much less than the effect of the inlet temperature  $T_e$  (i.e. u(t)).

#### 4.6.1 First method

One solution to reduce the effect of the disturbances on the identified parameters is to increase the effect of  $T_e$  (for instance: 100 % opened valve for the identification period).

As it was discussed before, the system model would tend to:

$$y(t) = a_o y(t-1) + b_o u(t) + \underbrace{c_o u_2(t) + S_{rad}}_{Dist}$$

So when u(t) is high in comparison to  $\underbrace{c_o u_2(t) + S_{rad}}_{Dist}$ 

The system tend to be:

$$y(t) \approx a_o y(t-1) + b_o u(t)$$

#### 4.6.2 Pseudo output method

Other solution to the problem could be recording the effect of outside temperature and solar radiation for a period and register it on memory, by the registered data a pseudo output could be constructed, by which the identification process can be realized.

For the first period (1 day) of identification the system could be represented as:

$$y_{dis}(t) = \underbrace{a_o \ y_{dis}(t-1) + c_o u_2(t) + S_{rad}}_{\text{effect of } T_{oa}} S_{rad}$$

For the second period the system would be considered:

$$\hat{y}(t) = y(t) - y_{dis}(t)$$

Where:

- $\hat{y}(t)$ : Pseudo output.
- y(t): Actual output.
- $y_{dis}(t)$ : Disturbances registered from past day.

$$\hat{y}(t) = a_o y(t-1) + b_o u(t) + c_o u_2(t) + S_{rad} - (a_o y_{dis}(t-1) + c_o u_2(t) + S_{rad})$$

$$\hat{y}(t) = a_o \, \hat{y}(t-1) + b_o u(t)$$

By constructing these data, the system can be identified by either LS or RLS methods.

Drawbacks of such a method would be the need for high memory, also it is not guaranteed that the two periods would have the same outside temperature and same intensity of the solar radiation.

# 5 Case study

A specific zone would be considered for the next analysis, the zone in question would have the physical parameters listed in the next table:

Туре	Parameters	Values[Unit]	Description
Pipe	L	90.05 [m]	Length of pipe
	R <sub>1</sub>	0.0065 [m]	Inside parameter of pipe
	<b>R</b> <sub>2</sub>	0.0085 [m]	Outside diameter of pipe
Pavement	S <sub>pave</sub>	18.1 [m <sup>2</sup> ]	Pavement area
Zone	V	48.9208 [m <sup>3</sup> ]	Volume of the zone
Wall, Ceiling	$\mathbf{S}_{wall}$	18.94 [ m <sup>2</sup> ]	Wall area
	Sceil	18.01 [ m <sup>2</sup> ]	Ceiling area
	S <sub>transparent,N</sub>	0 [ m <sup>2</sup> ]	Transparent surface on North
	S <sub>transparent,S</sub>	2.08 [ m <sup>2</sup> ]	Transparent surface on South
	S <sub>transparent,W</sub>	2.5 [ m <sup>2</sup> ]	Transparent surface on West
	$S_{transparent,E}$	0 [ m <sup>2</sup> ]	Transparent surface on East
	S <sub>transparent,Ceil</sub>	0 [ m <sup>2</sup> ]	Transparent surface on ceiling facades

Then the following system configuration parameters would update the model:

Parameters	Values[Unit]	Description
TG	13 [°C ]	Ground temperature
Msa	0.6 [m <sup>3</sup> /hr ]	Supply air mass flow
Pint	5.1 [W]	Internal gain
W <sub>sol,N</sub>	0 [W/m <sup>2</sup> ]	Solar radiation on façade North
Wsol,S	0 [W/m <sup>2</sup> ]	Solar radiation on façade South
W <sub>sol,W</sub>	0 [W/m <sup>2</sup> ]	Solar radiation on façade West
Wsol,E	0 [W/m <sup>2</sup> ]	Solar radiation on façade East

The simplified model would consider the following assumptions:

- Two inputs  $\Delta T_{oa}$  (outside temperature)  $\Delta T_e$ (inlet temperature)
- One output  $\Delta T_z$
- Solar radiation effect on the system wouldn't be considered.
- Internal gain of the zone would be considered constant.
- The ground temperature would be considered constant.

The equilibrium points which would be considered for the next work would be:

- $T_{oa_eq} = 1.5 \,^{\circ}\text{C}$
- $T_{z_eq} = 21 \, {}^{\circ}\mathrm{C}$
- $T_{e_eq} = 27.2456 \,^{\circ}\text{C}$



Figure 5-1 System in open loop

#### 5.1 Simplifying the model

## **5.1.1** Identification of model from $\Delta T_e$ to $\Delta T_z$ :

By simulating the analytical model for 10 days and inserting the results into the Matlab identification tool (reducing the least square between the real data and identified data), two transfer functions were identified where:

• The identified transfer function from  $T_e$  to  $T_z$  (1<sup>st</sup> order)

$$G = \frac{\mu}{1+s.\tau} = \frac{0.6925}{1+17161}$$

Which gives a fit of **89**.1% to the real data.

• The identified transfer function from  $T_e$  to  $T_z$  (2<sup>nd</sup> order)

$$G = 0.7144 \frac{1 + 614137 \, s}{(1 + 15990s)(1 + 651688s)}$$

Which gives a fit of **99.5**% to the real data.

Then it is evident that it would be feasible to use  $1^{st}$  order transfer function to present the relation from  $T_e$  to  $T_z$ 



Figure 5-2 system identification process

## 5.1.2 Identification of model from $\Delta T_{oa}$ to $\Delta T_z$ :

Similarly the identification of the H transfer function was done, a step input was applied on the  $T_{oa}$  (from 1.5 to 2.5) while the other input  $\Delta T_e$  kept at zero, by simulating the analytical model

for 20 days and inserting the results into the Matlab identification tool (which applies LS concept), two transfer functions were identified where:

Transfer function from  $\Delta T_e$  to  $\Delta T_z$  (1<sup>st</sup> order)

$$H = \frac{\mu_e}{1 + s.\,\tau_e} = \frac{0.268}{1 + 45392s}$$

Which gives a fit of **36.5** % to the real data.

Transfer function from  $\Delta T_{oa}$  to  $\Delta T_z$  (2<sup>nd</sup> order)

$$H = 0.287 \frac{1 + 396385s}{(1 + 9296.7s)(1 + 531147s)}$$

Which gives a fit of 92.3% to the real data.

As it was evident from the identification procedure that  $2^{nd}$  order transfer function to present the relation from  $T_{oa}$  to  $T_{z}$ .



Figure 5-3 identification of outside temperature effect

## **5.2** Controller tuning and effect of uncertainties

By adapting a PI controller by the following form:

$$PI = \frac{K(1+\tau s)}{\tau \mu \ s}$$

Now it can be updated by the system's time constant & static gain to be:

$$PI = \frac{K(1+17161s)}{0.6925 \times 17161s}$$





In case of uncertainty the system with the controller in closed loop would have the following representation:

$$F(S) = \frac{\alpha k(\tau s + 1)}{s(\beta \tau^2 s^2 + \tau (1 + \alpha k)s + k\alpha)}$$

Now it is required to find out:

- The optimum value of K (velocity factor);
- Effect of static gain uncertainty  $(\alpha)$  on the response of the system to step input;
- Effect of time constant uncertainty  $(\beta)$  on the response of the system to step input.

#### 5.2.1 **Tuning of K**

In order to choose appropriate value of K a simulation was realized modulating the variable K from 0.5 till 10, and applying a step input on the set point (from 21 to 22).

Based on the results (figure 5-5) it was possible to claim that K affects much the settling time: increasing K the system takes less time to reach the steady state condition.

As a conclusion it was found out that (K=10) shows good performance regarding the settling time.



Figure 5-5 Tuning of K

#### Effect of static gain uncertainty( $\alpha$ ) : 5.2.2

In order to understand the effect of the uncertainty of the static gain ( $\alpha$ ) a simulation was realized modulating  $\alpha$  from 0.5 to 2 and keeping constant K and  $\beta$  (K at 10,  $\beta$  at 1).

A step with value of 1 was applied on the set-point (from 21 to 22).



The results of the simulation can be seen from the figure 5-6 and it be concluded that the system is not changing much in terms of overshoot or settling time (if compared to the effect of K), although the system is getting faster as the alpha is getting higher .

#### 5.2.3 Effect of time constant uncertainty ( $\beta$ )

In order to understand the effect of the uncertainty of the time constant ( $\beta$ ) a simulation was realized modulating  $\alpha$  from 0.5 to 2 and keeping constant K and  $\alpha$  (K at 10,  $\alpha$  at 1).

A step with value of 1 was applied on the set-point (from 21 to 22).

The results of the simulation can be seen from the figure 5-7 and it can be concluded from this simulation it is possible to understand that  $\beta$  is effecting slightly the speed of the system (reduced speed for high value of  $\beta$ ) as well as increasing the overshoot percentage significantly.



Figure 5-7 effect of  $\beta$ 

## 5.2.4 Analysis in time domain

As it was discussed before the system is 2-poles 1-zero system and it can be presented as:

$$F(S) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n + \omega_n^2} (\tau s + 1)$$

Where:

• 
$$\omega_n = \sqrt{\frac{k\alpha}{\beta\tau^2}} (natural freq)$$

• 
$$\zeta = \frac{(1+\alpha k)}{2\sqrt{\beta k \alpha}}$$
 (damping ratio)

Applying the inverse Laplace transformation to the transfer function it would be found out that the system response to step input would be:

## **Effect of poles only:**

$$y(t) = 1 - \frac{e^{-\zeta\omega_n t}}{\sqrt{1-\zeta^2}} \sin\left(\omega_d t + \phi\right) + \frac{\zeta\omega_n \tau e^{-\zeta\omega_n t}}{\sqrt{1-\zeta^2}} \sin\left(\omega_d t + \phi\right) - \frac{\omega_d \tau e^{-\zeta\omega_n t}}{\sqrt{1-\zeta^2}} \cos(\omega_d t + \phi)$$

### And the effect of zero:

$$\mathbf{y}(t)_{zero} = \frac{\zeta \omega_n \tau \, e^{-\zeta \omega_n t}}{\sqrt{1-\zeta^2}} \sin(\omega_d t + \phi) - \frac{\omega_d \, \tau e^{-\zeta \omega_n t}}{\sqrt{1-\zeta^2}} \cos(\omega_d t + \phi)$$

It can be seen that the zero of the system is accelerating the system as a result an overshoot might happen, as it was found out for higher values of  $\beta$ .



Figure 5-8 zero effect from time domain

#### 5.2.5 Overshoot analysis

The model is tested by changing the  $\beta$  (from 0.3 till 3) and  $\alpha$  (from 0.3 till 3) and k (from 0.5 till 100), while overshoot is detected only if it would happen in the first 10 hrs.

In the end of the simulation the points of overshoot are collected and plotted on a 3D-graph.

A Matlab code was constructed in which values of alpha and beta are inserted and the range of values of k where overshoot happens is returned.





From the plot (shown in figure 5-9) it can be seen that the uncertainty of  $\alpha$  has a role in having overshoot: as the smaller the  $\alpha$  the more points of overshot are returned, and that  $\beta$  has also big

role in determining the occurrence of overshoot as it can be seen in the plot the overshoot possibility when the value of the  $\beta$  is more than 1.75 is minimal.

It can be also realized from the figure that the highest value of K where overshoot happens is about 85.

## 5.2.6 Conclusion

- K has very significant role concerning settling time and rise time.
- $\beta$  has the most significant role in determining the overshoot of the system.
- The overshoot for high values of  $\beta$  is due to the LHP ZERO.
- The overshoot existence can be determined by:
- $\beta < 1.75$  : no overshoot at all.
- For  $\beta \ge 1.75$ :
  - no overshoot if  $k > (52 \times \beta 71)$ ;
  - overshoot if k≤ (52 × β − 71) but for special values of alpha;
  - $\circ$  with K=10, overshoot for every alpha (0.3-3);
  - overshoot for "every"  $\alpha$  and "every" K.

## 5.2.7 Set point compensation

Now a set-point compensator would be added to the control scheme as it would be shown in figure 5-10.



**Figure 5-10 Set-point compensation** 

The results of the test are shown in the figure 5-11 where can be seen: the system is faster using the set point compensator but slight overshoot appears, which could introduce more problems later on.

Generally the effect of the set-point compensator is very small, also the static performance of the system in case of PI and PI + set-point compensator is same.



Figure 5-11 set-point compensation results

## 5.3 Effect of uncertainties on open-loop compensator in open loop

As it was shown before the open-loop compensator is supposed to eliminate all the effect of the change of outside temperature but practically the uncertainty could exist also here for the same reasons discussed before.

Considering the scheme shown in figure 5-12, it is required now to understand the effect of the uncertainty on the open-loop compensator behavior where:

Considering the system T.F is:

$$G = \frac{\mu}{1+s.\tau} = \frac{0.6925}{1+17161}$$

Considering the uncertainty:

$$\tilde{G} = \frac{\alpha \,\mu}{1 + s.\,\tau.\,\beta} = \frac{0.6925\alpha}{1 + 17161\beta}$$

And the T.F from  $T_{oa}$  to  $T_z$  is:

$$H = \mu_e \frac{1 + T_e s}{(1 + \tau_{e1} s)(1 + \tau_{e2} s)} = 0.287 \frac{1 + 396385s}{(1 + 9296.7s)(1 + 531147s)}$$

Considering the uncertainty:

$$\widetilde{H} = \mu_e \gamma \frac{1 + T_e \phi s}{(1 + \tau_{e1} \delta s)(1 + \tau_{e2} s)} = 0.287 \gamma \frac{1 + 396385 \phi s}{(1 + 9296.7 \delta s)(1 + 531147s)}$$

Where  $\gamma$ ,  $\delta$ ,  $\phi$  are uncertainty factors.

Then the equation of the system with the compensator would tend to:

$$\Delta T_z = \tilde{G} \left( \Delta T_e - \frac{H}{G} T_{oa} \right) + \tilde{H} T_{toa}$$

Then:

$$\Delta T_{z} = \frac{\alpha \,\mu}{1 + s.\,\tau.\,\beta} \left( \Delta T_{e} - \frac{\mu_{e} \frac{1 + T_{e}s}{(1 + \tau_{e1}s)(1 + \tau_{e2}s)}}{\frac{\mu}{1 + s.\,\tau}} T_{oa} \right) + \mu_{e} \gamma \frac{1 + T_{e}\phi \,s}{(1 + \tau_{e1}\delta \,s)(1 + \tau_{e2}s)} \,T_{toa}$$

To test the robustness of the open-loop behavior, various tests were held by adding a step input to the outside temperature and no input on the inlet temperature, ideally the system should keep at equilibrium.



Figure 5-12 compensator in open loop

#### **5.3.1** Case 1 (effect of $\gamma$ (all others 1))

By modulating  $\gamma$  (uncertainty on state gain of H) from 0.5 to 2 while keeping all other uncertainty factors fixed at 1, it was found out that in case of uncertainty (*i.e.*:  $\gamma \neq 1$ ) the T<sub>z</sub> is always deviating from the equilibrium generating a steady state error (figure 5-13 left).

In most cases the error is less while using the compensator while in some cases its same with or without using the compensator (i.e.  $\gamma = \frac{1}{2}$  the performance with compensator is same without it).



Figure 5-13 effect of  $\gamma$ 

#### **5.3.2** Case 2 (effect of $\delta$ (all others 1))

Similarly by modulating  $\delta$  (uncertainty on time constant (of the dominant pole of H)) from 0.5 to 2 while keeping all other uncertainty factors fixed at 1, it was found out that in case of uncertainty (*i.e.*:  $\delta \neq 1$ ) the T<sub>z</sub> is always deviating only for a transient period and then returning to the equilibrium point (figure 5-14 left).

By comparing the results the performance is always better using the compensator.





#### **5.3.3** Case 3 (effect of $\alpha$ (all others 1))

Similarly by modulating  $\alpha$  (uncertainty static gain of G) from 0.5 to 2 while keeping all other uncertainty factors fixed at 1, it was found out that in case of uncertainty (*i.e.*:  $\alpha \neq 1$ ) the T<sub>z</sub> is always deviating from the equilibrium generating a steady state error (figure 5-15 left) which is very similar to the effect of  $\gamma$ .

In most cases the error is less while using the compensator while in some cases its same with or without using the compensator (i.e.  $\alpha = 2$  the performance with compensator is same without it).





## **5.3.4** Case 4 (effect of $\beta$ (all others 1))

With Compensator

Similarly by modulating  $\beta$  (uncertainty on time constant of G) from 0.5 to 2 while keeping all other uncertainty factors fixed at 1, it was found out that in case of uncertainty (*i.e.*:  $\beta \neq 1$ ) the T<sub>z</sub> is always deviating only for a transient period and then returning to the equilibrium point (figure 5-16 left). By comparing the results the performance is always better using the compensator.

Without Compensator





#### 5.3.5 Other cases

Based on the results presented earlier, it was evident that for some cases of uncertainty, using the compensator might give worse performance than without it. Such as the case when: ( $\alpha = 2$  $\gamma = \frac{1}{2}\beta = \delta = 2$ ).



Figure 5-17 special case

#### 5.3.6 Conclusion

- The uncertainty factors  $\alpha$  and  $\gamma$  (uncertainty of gains) provide the most significant deviation of the response.
- The uncertainty factors  $\delta$  and  $\beta$  (uncertainty of time constants) are small and they don't affect the steady state values.
- When all the 4 factors are equal the deviation from steady state temperature is zero.
- The performance of the compensator can be evaluated by the following formula:  $\left|1 - \frac{\alpha}{\nu}\right| \le 1$  then :
  - If  $\frac{\alpha}{\gamma} < 2$ , then results with compensator is better;
  - If  $\frac{\alpha}{\nu} > 2$ , then results with compensator is worse;
  - If  $\frac{\alpha}{\gamma} = 2$  then it is same with or without compensator (note $\gamma = 0.5$ ).

### 5.4 Compensator in closed loop

As it was shown before, the behavior of the outside temperature compensator would differ when it would be applied in closed loop.

The following tests would be held by the following scheme, adding a step of 1 on the T<sub>oa</sub>.



Figure 5-18 PI + compensator

#### **5.4.1** Case 1 (effect of $\gamma$ (all others 1))

By modulating  $\gamma$  (uncertainty on state gain of H) from 0.5 to 2 while keeping all other uncertainty factors fixed at 1, it was found out that in case of uncertainty (*i.e.*:  $\gamma \neq 1$ ) a deviation of T<sub>z</sub> for a transient time. It can be seen from the figure 5-19 that for  $\gamma > 1$  positive deviation and  $\gamma < 1$  negative deviation happens.



Figure 5-19 effect of  $\gamma$ 

#### **5.4.2** Case 2 (effect of $\phi$ (all others 1))

Very similar results were obtained by testing the system while modulating the uncertainty of time constant of the zero of H.

It can be seen from the figure 5-20 that for  $\phi > 1$  positive deviation and  $\phi < 1$  negative deviation happens.



Figure 5-20 effect of

## **5.4.3** Case 3 (effect of $\alpha$ (all others 1))

Similar results were obtained by testing the system while modulating the uncertainty of time constant of the static gain of G ( $\alpha$ ). It can be seen from the figure 5-21 that for  $\alpha < 1$  positive deviation and  $\alpha > 1$  negative deviation happens.



Figure 5-21 effect of a

### **5.4.4** Case 4 (effect of $\delta$ (all others 1))

Again very similar results were obtained by testing the system while modulating the uncertainty of time constant of the dominant pole of H ( $\delta$ ).

It can be seen from the figure 5-22 that for  $\delta < 1$  positive deviation and  $\delta > 1$  negative deviation happens.



Figure 5-22 effect of  $\delta$ 

## 5.4.5 Case 5 (effect of $\beta$ (all others 1))

Similar results were obtained by testing the system while modulating the uncertainty of time constant of the pole of G ( $\beta$ ). It can be seen from the figure 5-23 that for  $\beta > 1$  positive deviation and  $\beta < 1$  negative deviation happens.



62

### 5.4.6 Conclusion

From the previous tests, it was found out that:

- The system in closed loop would have no effect in steady state.
- Taking in account all the five uncertainty factors it can be said that the behavior can be represented by the this formula :  $\frac{\gamma \phi \beta}{\alpha \delta}$  such that :
- $\frac{\gamma \phi \beta}{\alpha \delta} > 0.5$  performance worse without compensator;
- $\frac{\gamma \phi \beta}{\alpha \delta} < 0.5$  performance worse with compensator;
- $\frac{\gamma \phi \beta}{\alpha \delta} = 0.5$  same performance with or without compensator;
- $\frac{\gamma \phi \beta}{\alpha \delta} = 1$  for perfect performance;
- $\frac{\gamma \phi \beta}{\alpha \delta} > 1$  performance not good in general but better than without.

#### 5.5 Effects introduced by valve limitations

Now the limitations on the control action would be considered in order to study their effect on the system performance. Saturation would be added to the output of the system whose upper limit would be assumed to be 35 °C and lower limit would be assumed to be 23 °C.

Concerning the delay: a 5 minutes delay of valve response would be considered.



Figure 5-24 limitations of valve

#### 5.5.1 Effect of saturation

A test was held where the system initially starts from equilibrium points (Toa =1.5, Te = 27.548, T<sub>z</sub> =21°C). A unit step would be applied for the set point (21 to 22) and 5 degrees step will be applied on the ambiance temperature ( $T_{oa}$ ).

It is aimed to see the effect of the saturation performance of the system and compensator in comparison with idealized system.

The results can be shown in the figure 5-25, it can be seen that performance of the compensator is worse than the case when saturation was applied, while the set-point following properties and speed of system is almost same like before.



Figure 5-25 effect of saturation

#### 5.5.2 Effect of delay

Similarly the system was tested with the application of the delay only (no saturation).

The results shown in the figure shows that the delay has very tiny effect on the system performance.





Overall the system response is very acceptable after adding the saturation and delay while the saturation is introducing more effect than that of delay especially in terms of compensator performance.

## 5.6 Least square method

#### 5.6.1 Testing the system

The algorithm would be now tested by the following steps:

- Analytical model would be used (4- states model).
- A step of inlet temperature will be added on the input of the system in open loop.
- NO disturbances would be considered.
- The data would be registered for 24 hrs then constructing the  $\phi$  matrix.
- And then the next formula would be applied  $\theta = (\phi \phi^T)^{-1} \phi y(t)$ .
- $\tau \& \mu$  would be extracted from the previous equation.
- Then  $G = \frac{\mu}{\tau s+1}$  would be realized.
- Finally a step input would be applied to the transfer function G and the response would be compared with the response of the (4-states model response).



Figure 5-27 4-states model step response

By fitting the data it was found out that the system can be represented by the following transfer function:

$$G_{ident} = \frac{0.6856}{16589s + 1}$$

A step input response of the system can be seen in the figure 5-28.



Figure 5-28 Transfer function step response

## 5.6.2 Conclusion

As it was seen the method is very easy to apply and provides very precise results in case of absence of disturbances.

- The application of the method doesn't require initialization.
- The application of the method requires very high memory.
- Also it is expected that the identification process would be very sensitive to any disturbances.

#### 5.1 Recursive least square method

RLS can be adapted in online configuration as it is shown in the following figure.





#### **Test conditions**:

In order to test the algorithm the 4-states model was updated with new values, which leaded to have a new time constant and new gain.  $\tau = 10984$ ,  $\mu = 0,89$ .

The system would be tested first without adding any limitation on the control action (neither delay nor saturation) with controller that is given by  $PI = \frac{k(\tau s+1)}{\mu \tau s}$ , then if the results would be satisfactory, a saturation would be applied on the control action.

The algorithm would be tested with different initial points ( $\tau$ ,  $\mu$ ) and would be tested with different uncertainties (uncertainty =  $[\frac{1}{32} \ \mathbf{123}]$ ) (ie: first test  $\tau(\mathbf{0}) = \frac{\tau}{3} \& \mu(\mathbf{0}) = \frac{\mu}{3}$  and etc), finally p (0) would be chosen heuristically to be  $\frac{1}{225}$ .

First set of tests would be held with step of 1 °C (21 to 22) would be applied and the system will be excited for 3 days. Then input would be changed in other tests as it would be shown later.

Finally 5 figures should be considered: the zone temperature (y (t)), the control action (u (t)), the filter coefficient (p (t)) & the most important the identified parameters  $\mu(t), \tau(t)$ .

# 5.1.1 Step input (from 21 °C to 22 °C)



69



## Test results analysis:

From test results it can be seen that the filter coefficient is converging to small value which is a satisfactory result, it can be also seen that when the system goes to steady state the identification process almost stop. That's why it can be seen that when the system parameters are underestimated the parameters are not identified well.

So the next test: a square wave would be applied and results would be analyzed.

# 5.1.2 Square wave amplitude of 1 °C & period of 24 hrs



71


From test results it can be seen that also here the filter coefficient is converging well, it can be also seen that a square wave showed better estimates for system parameters as the estimated values are approaching more the real values of the system. It is also evident the one step was not enough to identify the system parameters.

From the two tests done so far it is also evident that the RLS algorithm is highly dependent on the initial conditions of the system as well as the excitation to the system.

#### 5.1.3 RLS with saturation

In the next work a suitable saturation (minimum  $\Delta T_e$  would be -5 and maximum value of  $\Delta T_e$  would be 15) can be applied to make the system more realistic (figure 5-30), and filter coefficient initial value can be estimated as  $p(0) = [\phi(0)\phi(0)^T]^{-1}$ .



Figure 5-30 RLS with saturation

# 5.1.4 Step input (from 21 °C to 22 °C)





By applying the saturation, it can be seen that the results are not much different than without saturation, also when the system goes to steady state, the identification process stops.

It is also here seen that the static gain is estimated better than before.

Again it is evident that only one step is not enough to estimate system parameters.

# 5.1.5 Step input (21 °C to 31 °C)





Test results analysis:

By adding a big step, it can be seen clearly that the filter coefficient is converging also well, and estimation of the static gain is precise, while the step input is not enough to estimate the time-constant, as the approaching to real values is almost stopped when the system goes for the steady state.

# 5.1.6 Square wave of amplitude 1 °C &period of 24 hrs





By applying a square wave, the results are somehow better concerning the estimation of time constant, though by applying a square wave, the results are somehow better concerning the estimation of time constant, though estimation of static gain isn't so satisfactory.

It can be also seen that p(t) is showing very good convergence properties though it converges without guaranteeing that the system parameters converges for the real values which delays the process of estimation. To get better results, composition of different excitation can be subjected to the system.

Other solution for such problem is using the RLS with forgetting factor (as mentioned earlier).

#### 5.2 RLS with FF

#### **Test conditions:**

Similarly, the system would be tested again with same conditions which were:

- The algorithm would be tested on the analytical model with  $\tau = 10984$ ,  $\mu = 0.89$ ;
- The saturation introduced by the valve would be considered;
- The control action would be limited by [-5 15];
- NO disturbances would be considered (i.e. just the system);
- The controller would be given by  $PI = \frac{k(\tau s+1)}{\mu \tau s}$ ;
- Different inputs would be considered;
- The system would be excited for 3 days;
- Different initial points ( $\tau$ ,  $\mu$ ) would be tested (unc =  $\left[\frac{1}{32} \ 1 \ 2 \ 3\right]$ );
- $P(0) = \frac{1}{15^2} = \frac{1}{225}$ ;
- Finally 5 figures should be considered: the zone temperature (y (t)), the control action (u (t)), the filter coefficient (p (t)) & the most important the identified parameters μ(t), τ(t).

# 5.2.1 Step input (from 21°C to 22 °C)





From the test results, it can be found out that the estimation of the gain is perfect. The time constant estimation though is not good.

The filter coefficient is converging and getting higher, which means faster convergence.

Again it is evident that one step isn't enough to estimate the time constant of the system, while it could be enough to find out the static gain of the system.

# 5.2.2 Square wave of amplitude 1 $^{o}\mathrm{C}$ and period 24+step of 1 $^{o}\mathrm{C}$





By exciting the system with a step and square wave, it is evident that the estimation of the parameters is much better.

Higher frequency wave can be tested to reduce the time of estimation of time constant.



# 5.2.3 Square wave of amplitude 1 $^{\circ}$ C and period 12 +step of 1 $^{\circ}$ C



Here it was found out that higher frequency enhances the estimation of the parameters, although higher frequency would add more oscillations and as consequence would not produce steady estimation.

It is recommended to have the wave close to the time constant of the system which ranges usually between 2 to 6 hrs.

### 5.2.4 Conclusion

LS

• The algorithm is able to find out real parameters precisely, but it needs much memory to register all data.

#### RLS

- The algorithm is showing less dependency on the memory.
- The algorithm depends on the persistent excitation of the system as well as the initial values.
- The algorithm is showing acceptable results.

#### RLS with FF

- By adding the forgetting factor, the algorithm is converging to the real parameters though more dynamics are introduced.
- The algorithm is less dependent on the persistent excitation of the system.
- Generally the RLS with FF method is showing good results.

#### 5.3 RLS in open loop

### **Test conditions**:

Now the system would be tested in open loop, where an input would be applied directly on the system (inlet temperature T<sub>e</sub>), and the test conditions are somehow similar such that:

- The algorithm would be tested on the analytical model with  $\tau = 10984$ ,  $\mu = 0.89$ ;
- The saturation introduced by the valve would be considered;
- The control action would be limited by [-5 15];
- NO disturbances would be considered (i.e. just the system);
- Different inputs would be different;
- The system would be excited for 3 days;
- Different initial points ( $\tau$ ,  $\mu$ ) would be tested (unc =[ $\frac{1}{32}$  123]);
- $P(0) = \frac{1}{15^2} = \frac{1}{225}$ ;
- Finally 5 figures should be considered: the zone temperature (y (t)), the control action (u (t)), the filter coefficient (p (t)) & the most important the identified parameters μ(t), τ(t).



# 5.3.1 Step input on T<sub>e</sub> (1 °C)





Again the system gives very good and precise results concerning the identification of the static gain while this is not the case for time constant, it seems like more persistent excitation should be applied.







It can be seen by applying a square wave with period of 6 hrs, the estimation of both parameters is very good.

Finally a square wave ranging with period of 12 hrs or 3 hrs would show good results but not less and not more.

### 5.4 Disturbances of outside temperature

#### **Test conditions:**

Concerning the disturbances, first the outside temperature effect would be considered alone, and the system would be tested in open loop and closed loop.

The test conditions would be:

- The algorithm would be tested on the analytical model with  $\tau = 10984$ ,  $\mu = 0.89$ ;
- The saturation introduced by the valve would be considered;
- The control action would be limited by [-5 15];
- NO disturbances would be considered (i.e. just the system);
- The controller would be given by  $PI = \frac{k(\tau s+1)}{\mu \tau s}$ ;
- Different inputs would be different;
- The system will be excited for 3 days;
- Same initial points ( $\tau$ ,  $\mu$ ) would be tested (unc =  $\begin{bmatrix} 1 \\ 3 \end{bmatrix}$ );
- The system would be tested for different amplitudes of the input ;

• 
$$P(0) = \frac{1}{15^2} = \frac{1}{225}$$
;

Finally 5 figures should be considered: the zone temperature (y (t)), the control action (u (t)), the filter coefficient (p (t)) & the most important the identified parameters μ(t), τ(t).

# 5.4.1 Step input (1 °C, 10 °C &15 °C)





Test results analysis:

As it can be seen here, the more the effect of the  $T_{e}$ , the better the estimation, taking in consideration that one step is not enough to estimate the time constant.



# 5.4.2 Step of 1 °C+ square wave of 12 hrs period& diff amps (in closed loop)



Test results analysis:

For the time constant, it can be seen that the estimation is slightly better in case of higher input (wide opened valve), although it can be seen that if the reading is taken at the last point of the day (24:00) the uncertainty is the least for any kind of inputs, as the effect of the outside temperature is almost the average of the day.

# 5.4.3 Step input (in open loop)





From here it can be seen that the best results for the static gain is achieved while the time constant still needs some excitation.



### 5.4.4 Step of 1 ° C + square wave of 12 hrs and diff. amps. (in open loop)



Test results analysis:

Finally the time constant is estimated very well, reducing the uncertainty to minimum, applying a square wave with big amplitude.

It is still noticed that the estimation is much better at the end of the day.

#### **5.5** Disturbances outside temperature + solar radiation

Finally the solar radiation effect would be considered keeping the test conditions same as it was in the previous simulations.

As a result of the previous simulations it can be deduced that the best way to estimate the parameters is the open loop.

Again the system would be tested in open loop, different amplitudes of the square wave would be applied as an input and results would be compared.

#### **5.5.1** Step of °C + square wave of 12 hrs and diff amps (in open loop)





It is obvious that the identification process is so good by this method, and the uncertainty is reduced.

### 5.5.2 Suggested procedure of identification

- Avoid any kind of internal gain inside the zone.
- Minimize the solar radiation entering the zone.
- As much as possible the zone should be isolated
- The valve should be opened by 60% for the first day for the whole day.
- Only the static gain should be registered after first day.
- From second day till the end of the fourth day the valve should be opened and closed in a sequence (square wave).
- By the end of the fourth day (at 23:59) the time constant should be registered.

# References

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