Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

DYNASTEE

Application to exercise using PSA data series 16, 17. An overview will be given of applied data and analysis with CTSM-R.

Irati Uriarte

(University of the Basque Country (UPV/EHU))

1

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

WEBINARS 2021

6 October 11:00 – 12:00

Dynamic Calculation Methods for Building Energy Performance Assessment

Technical University of Denmark DTU GCU Glasgow Caledonian University Universidad del País Vasco Euskal Herriko Unibertsitatea University of Salford MANCHESTER Gobierno de España Ministerio de Ciencia e Innovación Ciemat

presented by DYNASTEE-INIVE, CIEMAT, DTU, UPV/EHU, GCU, University of Salford

DYNASTEE

2

0.0 – Aim and Background

The application of the Grey Box modelling method CTSM-R is described in order to obtain the Heat Loss Coefficient (HLC) results for the provided data.

Other methods such as the average method and LORD has also been applied to the data in order to compare the results between the methods. However, only the CTSM-R results are shown.

0.0 – Aim and Background

- There can be seen a considerable **“performance gap”** between the real and the designed energy consumption in buildings.
- In order to carry out a correct building envelope energetic characterization it is indispensable to analyse its:

Heat Loss Coefficient (HLC) [W/°C]

=

Transmission heat loss (UA [W/°C]) + Infiltration and ventilation heat loss (C_v [W/°C])

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

1.0 – Introduction

- Round Robin Experiment is proposed as first step before start analysing real building cases.
- Then, it will be easier to investigate the issues in current buildings.

1.1- Test box

- The characterization of the Round Robin Test Box in order to analyse how it behaves.
- The investigated test box has a cubic form with exterior dimensions of 120x120x120 cm^3.
- The window glazing area dimensions are 52x52 cm^2.
- The box is not in contact with the floor, so is considered that it is floating in free air.

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

1.0 – Introduction

1.2- Test location and period

- The experiment has been carried out at Plataforma Solar de Almeria (PSA), Spain.
- The testing period started the 6th of December of 2013 and ended the 7th of January of 2014.
- The test has been developed under real weather conditions.

1.3- Data acquisition:

- Several sensors were installed in order to measure the data affecting the box.
- The measured parameters are shown in the following table:

Temperature	Solar radiation	Humidity	Wind characteristics	Heating
4 air temperature sensors	1 vertical south, 1 vertical north and 1 horizontal global solar radiation sensor	1 relative humidity sensor	1 wind speed sensor	1 heat power sensor
14 surface temperatura sensors	1 beam solar radiation and 1 diffuse solar radiation sensor		1 wind direction sensor	6 heat flux sensors
8 average surface temperatura sensors	1 horizontal and 1 vertical long wave radiation sensor			

- The data has been read and recorded every minute in the GMT timeframe in three datasets.

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

2.0 – Pre-processing:

2.1- Input data

Only the following parameters have been necessary in order to estimate the HLC of the box:

- **Ambient temperature** (Ta, °C): The ambient air temperature has been measured by several sensors:
  - Two **air temperature sensors** located in the lower side and the middle side of the box.

- **Internal temperature** (Ti, °C): The internal temperature has also been measured by several sensors:
  - Two **air temperature sensors** located in the lower side (1/3 height of the box) and the upper side (2/3 height of the box) of the box.

- **Heating power** (Ph, W): The heating device used in order to provide heating power into the box has been a 100W incandescent lamp.

- **Solar radiation** (Gv, vertical south global solar radiation (W/m^2)): The exercise has provided data for every type of radiation affecting the box. However, since the window of the box is orientated to the south, the vertical south global solar radiation will be the main solar radiation signal affecting the HLC estimation.

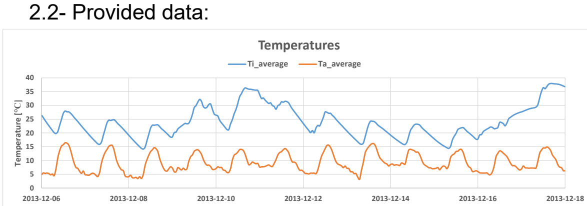
All data was provided in minutes. However, due to some difficulties found when working with the methods, the data has been converted into hourly data.

Universidad del País Vasco Euskal Herriko Unibertsitatea

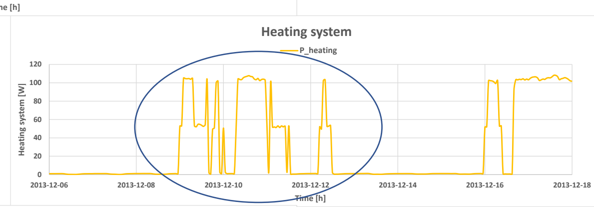
DYNASTEE

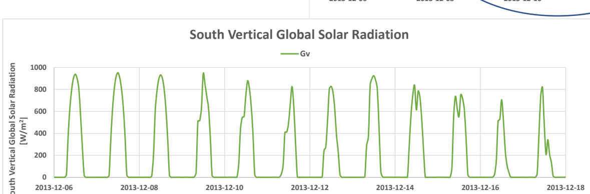
2.0 – Pre-processing:

2.2- Provided data:



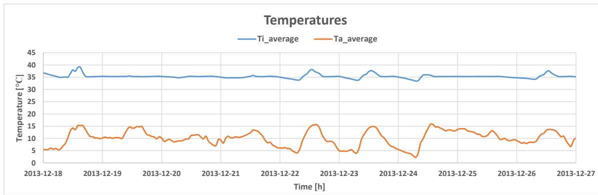
PSA_data_Series16



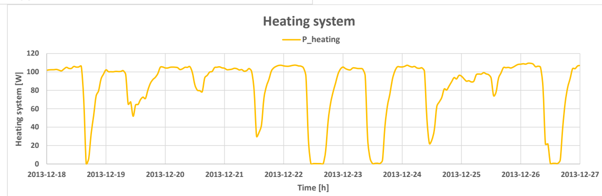


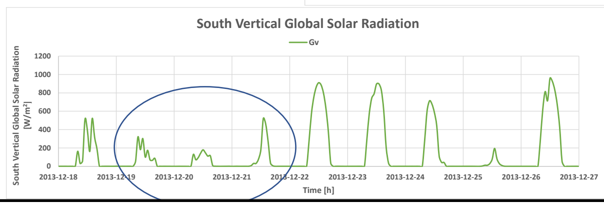
2.0 – Pre-processing:

2.2- Provided data:



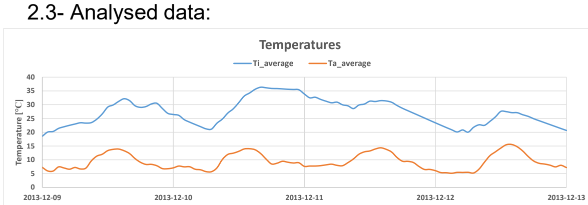
PSA_data_Series17



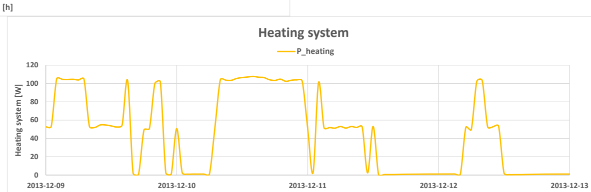


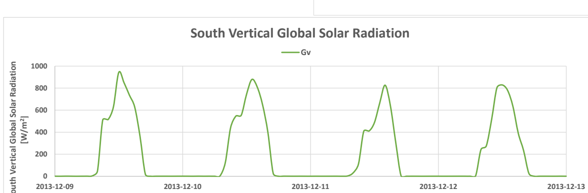
2.0 – Pre-processing:

2.3- Analysed data:



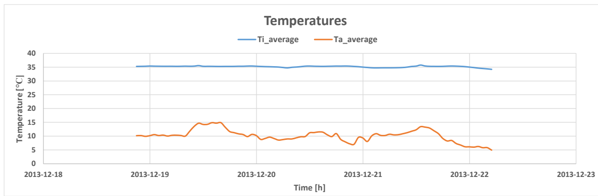
PSA_data_Series16



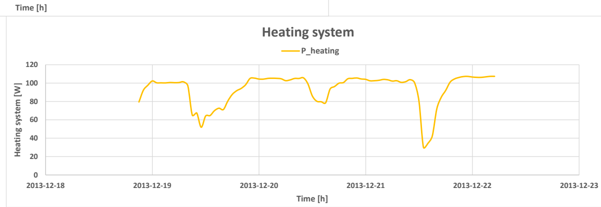


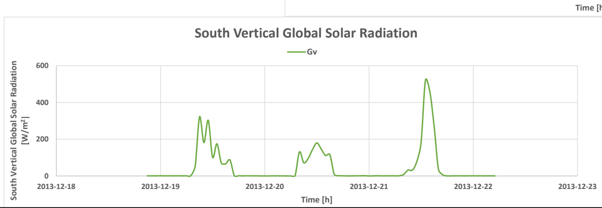
2.0 – Pre-processing:

2.3- Analysed data:



PSA_data_Series17





3.0 – Modelling:

3.1- Grey Box Models:

- The grey box models are also useful in order to identify **the internal dynamics** of a building or a **box** in this case.
- This method works with a **model case**, where each model includes the internal parametrization of the model. In order words, the models need to have some **previous physical knowledge** in order to make proper estimations.

Thus, during the grey box models analysis, the simplest one will be the first model been studied and then, the model will be becoming more complex. Thus, a set from the simplest to the most complex model will be fitted and the results will be described.

There, the physical part is stochastic linear state-space model and the dynamics of the states are written as;

$$dT = ATdt + BUdt + d\omega$$

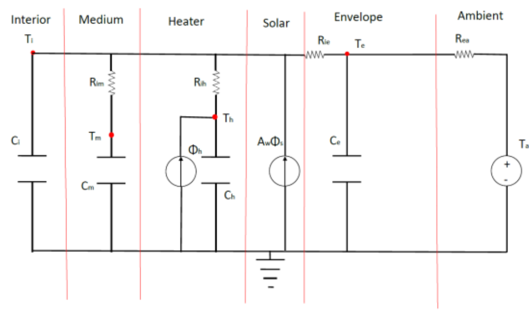
where T is the state vector (depending on the model this varies) and U is the input vector, and A and B are the estimated parameters. All the considered models have an input vector with three inputs:

$$U = [Ta, Ph\,, Gv\,]$$

where Ta is the ambient temperatura, Ph the internal heat and Gv the solar gains.

3.0 – Modelling:

The figure shows the most complex model that could be find when working with grey box models:

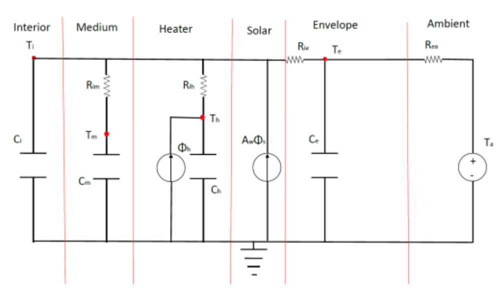


This model have six parts that will be combined in order to estimate the rest of the models. The parts are the interior, the medium, the heater, the solar radiation, the envelope and the ambient.

As seen, this model includes four state variables that represent the temperature in each part of the building; the interior temperature (T_i), the medium temperature (T_m), the heater temperature (T_h) and the building envelope temperature (T_e).

3.0 – Modelling:

The thermal resistances and heat capacities are also parameters of the model. Between the resistances $\mathbf{R_{im}}$ (thermal resistance between the interior part and the medium part), $\mathbf{R_{ih}}$ (thermal resistance between the interior part and the heater part), $\mathbf{R_{ie}}$ (thermal resistance between the interior temperature and the envelope part) and $\mathbf{R_{ea}}$ (thermal resistance between the envelope and the ambient).



Also the heat capacities of each of the parts are presented as $\mathbf{C_i}$ (for the interior), $\mathbf{C_m}$ (for the medium part or interior wall), $\mathbf{C_h}$ (for the heater) and $\mathbf{C_e}$ (for the building envelope). Moreover, also the effective window area ($\mathbf{A_w}$) is estimated.

Finally, $\boldsymbol{\omega_{i,t}}$, $\boldsymbol{\omega_{m,t}}$, $\boldsymbol{\omega_{h,t}}$ and $\boldsymbol{\omega_{e,t}}$ are standard Wiener processes, and $\sigma_i^2, \sigma_m^2, \sigma_h^2$ and σ_e^2 are the incremental variances of the Wiener processes.

Once all the models are plotted, the **maximum likelihood estimates** of the parameters can be achieved. Thus, it will be possible to compare them and select the most reliable model for the selected data.

3.0 – Modelling:

3.2- Data introduction:

3.2.1- Call the packages and set the directory:

library(gtools) → Charges some R tools
library(lubridate) → Allows to work with data times
library(ctsmr) → Activates the CTSM-R

setwd("/Users/iuriarte036/Desktop/doctorado/03CURSOS/06Almeria curso/Exercise")

3.2.2- Call the data (CSV files):

December16_1 <- read.csv("Data/Almeria16_1.csv",header=TRUE,sep=",",dec=".", skip=0,stringsAsFactors = FALSE)

3.2.3- Identify the data and modify:

db.december16_1=data.frame(date=December16_1$Time..DD.MM.AAAA.h.mm.,Ti1=December16_1$Ti_up,Ti2=December16_1$Ti_down,Te1=December16_1$Te_down,Te2=December16_1$Te_middle,Gv=December16_1$Gv, Q=December16_1$P_heating)

In order to obtain the required data, the provided data is modified. Therefore, the internal heat is converted from W into kW, the external and internal average temperatures are calculated…

3.2.4- Join the data in the same file and save it:

db.december_1= rbind(db.december16_1, db.december17_1)

saveRDS(db.december_1, file = paste0("Data1/db.december_1.RData"))

3.0 – Modelling:

3.3- Model selection process:

3.3.1- Call the packages and set the directory:

library(gtools) → Charges some R tools
library(lubridate) → Allows to work with data times
library(ctsmr) → Activates the CTSM-R

setwd("/Users/iuriarte036/Desktop/doctorado/03CURSOS/06Almeria curso/Exercise")

3.3.2- Call the source with the scripts where the models are saved:

files <- dir("functions2", full.names=TRUE)
for(i in 1:length(files)) source(files[i])

3.3.3- Set the latitud and the longitud:

prm <- list()
prm$latitude <- 37.09
prm$longitude <- -2.36

3.3.4- Call the file:

data= readRDS("Data1/db.december_1.RData")

3.0 – Modelling:

3.3.5- Set the best period:

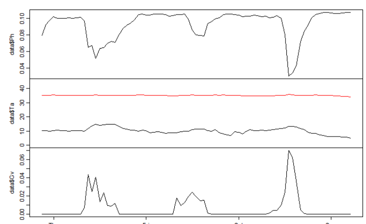
The provided data is too long in order to obtain good results with the model. Then, analysis has been carried out using two different period; the series 16 period between the **9th of December 2013 and the 13th of December 2013** and the period of series 17 between the **18th of December 2013 to the 22nd of December 2013**.Therefore, the data is converted into a readable code and is limited using the following code:

```
data$timedate=as.POSIXct(data$timedate, tz="UTC")
data= data[order(data$timedate, decreasing = FALSE),]
t.start = strptime("2013-12-18 20:59:00", format = "%Y-%m-%d %H:%M:%S")
t.end = strptime("2013-12-22 04:59:00", format = "%Y-%m-%d %H:%M:%S")
t0 = which(data$timedate == t.start)
tN = which(data$timedate == t.end)
data = data[(t0+1):(tN+1),]
```

3.3.6- Plot the selected period:

In order to see the selected period data it will be plotted using the following code:

```
data$timedate <- asP(data$timedate)
data$t <- asHours(data$timedate-data$timedate[1])
plotTSBeg(3,cex=0.7)
plot(data$timedate,data$Ph,type="l")
plot(data$timedate,data$Ta,type="n",ylim=c(0,45))
lines(data$timedate,data$Ta)
lines(data$timedate,data$yTi,col=2)
plot(data$timedate,data$Gv,type="l")
plotTSXAxis(data$timedate)
```

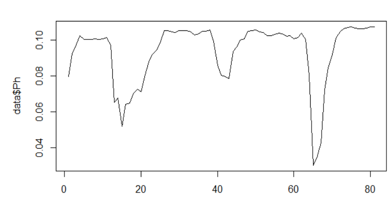


3.0 – Modelling:

3.3.7- Generate the weight vectors:

Since the residuals obtained when plotting the models were not good, weight vectors are applied in order to obtain better residuals. Thus, the model will behave differently when the heater is switched on or off:

```
i <- which(abs(diff(data$Ph))>2)
data$weights = 0
weightsAfterSwitch =1 # how long do you want to consider it
L <- unique(c(sapply(i,function(x){(x-1):(x+weightsAfterSwitch)})))
if(length(L)>0)
{
 data$weights[L] <- 1
data$weights[1:min(which(data$weights==1))] <- 1
}
par(mfrow= c(1,1))
plot(data$Ph,type="l", col=1)
lines(data$weights,type="l", col=5)
points(data$weights)
```



These weights will be after introduced as input in the diffusion term of the state formula, which will make the models provide better residuals. Therefore, it also means that it will be easier for the model to estimate the real value of the parameters.

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

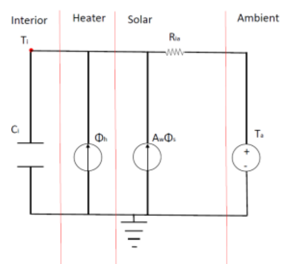
functions2

3.0 – Modelling:

3.3.8- Models:

Since there are several models to be tested, the structure of the most simple model (Ti model) will be shown first:

Ti




```
sdeTi <- function(data, weighting)
{
  ##Fit a SDE model for the room
  ## Be a bit smart and do the same in a function, see functions/Ti.R
  if(weighting){
  model <- ctsm()
  ## Add a system equation and thereby also a state
  model$addSystem(dTi ~ ( 1/(Ci*Ria)*(Ta-Ti) + 1/Ci*Ph + Aw/Ci*Gv)*dt
+(1+(weights*Wlev))*exp(p11)*dw1)
  ## Set the names of the inputs
  model$addInput(Ta,Ph,Gv,weights)
  ## Set the observation equation: Ti is the state, yTi is the measured
output
  model$addObs(yTi ~ Ti)
  ## Set the variance of the measurement error
  model$setVariance(yTi ~ exp(e11))
```

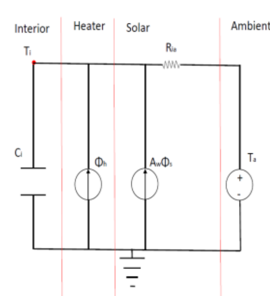

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:

3.3.8- Models:

```
## Set the initial value (for the optimization) of the value of the state at the starting time point
model$setParameter(  Ti0 = c(init=15 ,lb=0 ,ub=60 ) )

 ## Set the initial value for the optimization
 model$setParameter(  Ci = c(init=1 ,lb=1E-4 ,ub=1E7 ) )
 model$setParameter( Ria = c(init=20 ,lb=1E-3 ,ub=1E5) )
 model$setParameter( p11 = c(init=1  ,lb=-30 ,ub=10 ) )
 model$setParameter( e11 = c(init=-1 ,lb=-100 ,ub=100 ) )
 model$setParameter( Aw = c(init=8 ,lb=1E-6 ,ub=50 ) )
 model$setParameter( Wlev= c(init=10  ,lb=0   ,ub=100) )

}
 ## Run the parameter optimization
 fit <- model$estimate(data, firstorder=prm$firstorder)
 fit$Rnames <- c("Ria")
 #For HTC
  return(fit)
}
```

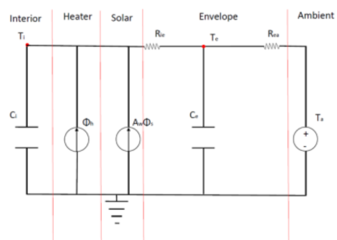


3.0 – Modelling:

3.3.9- Other models:

```
sdeTiTe <- function(data, weighting)
if(weighting){
  model <- ctsm()
  ## Add a system equation and thereby also a state
  model$addSystem(dTi ~ ( 1/(Ci*Rie)*(Te-Ti) + 1/Ci*Ph + Aw/Ci*Gv )*dt +(1+(weights*Wlev))*exp(p11)*dw1)
  model$addSystem(dTe ~ ( 1/(Ce*Rie)*(Ti-Te) + 1/(Ce*Rea)*(Ta-Te))*dt +(1+(weights*Wlev))*exp(p22)*dw2)
  ## Set the names of the inputs
  model$addInput(Ta,Ph,Gv,weights)
  ## Set the observation equation: Ti is the state, yTi is the measured output
  model$addObs(yTi ~ Ti)
  ## Set the variance of the measurement error
  model$setVariance(yTi ~ exp(e11))
```

TiTe



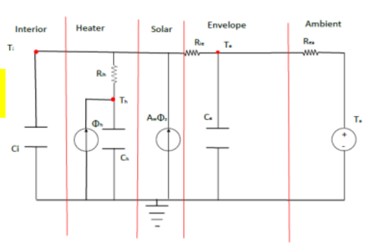

```
## Set the initial value (for the optimization) of the value of the state at the starting time point
  model$setParameter(  Ti0 = c(init=15 ,lb=0 ,ub=100 ) )
  model$setParameter(  Te0 = c(init=15 ,lb=0 ,ub=200 ) )

  ## Set the initial value for the optimization
  model$setParameter(  Ci = c(init=3 ,lb=1E-5 ,ub=60 ) )
  model$setParameter(  Ce = c(init=3 ,lb=1E-5 ,ub=2E5) )
  model$setParameter( Rie = c(init=20 ,lb=1E-4 ,ub=2E2) )
  model$setParameter( Rea = c(init=20 ,lb=1E-4 ,ub=1E5) )
  model$setParameter( p11 = c(init=1  ,lb=-30 ,ub=20 ) )
  model$setParameter( p22 = c(init=1  ,lb=-30 ,ub=20 ) )
  model$setParameter( e11 = c(init=-1 ,lb=-50 ,ub=10 ) )
  model$setParameter( Aw = c(init=6 ,lb=1E-2 ,ub=200 ) )
  model$setParameter( Wlev= c(init=10  ,lb=0    ,ub=100) )

}

  ## Run the parameter optimization
  model$options$maxNumberOfEval =2000
  fit <- model$estimate(data, firstorder=prm$firstorder)
  fit$Rnames <- c("Rie","Rea")
  return(fit)
}
```


3.0 – Modelling:

3.3.9- Other models:

```
sdeTiTeTh <- function(data, weighting)
if(weighting){
  model <- ctsm()
  ## Add a system equation and thereby also a state
  model$addSystem(dTi ~ ( 1/(Ci*Rih)*(Th-Ti) + Aw/Ci*Gv+ 1/(Ci*Rie)*(Te-Ti) )*dt +(1+(weights*Wlev))*exp(p11)*dw1)
  model$addSystem(dTe ~ ( 1/(Ce*Rea)*(Ta-Te)+ 1/(Ce*Rie)*(Ti-Te))*dt +(1+(weights*Wlev))*exp(p22)*dw2)
  model$addSystem(dTh ~ ( 1/(Ch*Rih)*(Ti-Th)+ 1/Ch*Ph)*dt +(1+(weights*Wlev))*exp(p33)*dw3)
  ## Set the names of the inputs
  model$addInput(Ta,Ph,Gv,weights)
  ## Set the observation equation: Ti is the state, yTi is the measured output
  model$addObs(yTi ~ Ti)
  ## Set the variance of the measurement error
  model$setVariance(yTi ~ exp(e11))
```

TiTeTh



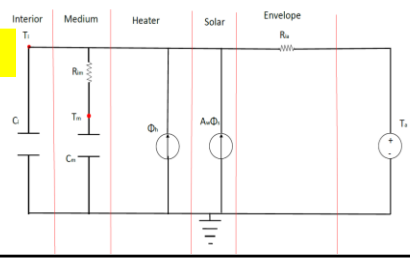

```
## Set the initial value (for the optimization) of the value of the state at the starting time point
  model$setParameter(  Ti0 = c(init=25 ,lb=0 ,ub=70 ) )
  model$setParameter(  Te0 = c(init=25 ,lb=0 ,ub=70 ) )
  model$setParameter(  Th0 = c(init=25 ,lb=0 ,ub=150 ) )

  ## Set the initial value for the optimization
  model$setParameter(  Ci = c(init=10 ,lb=1E-2 ,ub=1E6 ) )
  model$setParameter(  Ce = c(init=10 ,lb=1 ,ub=1E7) )
  model$setParameter(  Ch = c(init=10 ,lb=1E-2 ,ub=1E6 ) )
  model$setParameter( Rie = c(init=1,lb=1E-6 ,ub=100) )
  model$setParameter( Rea = c(init=1 ,lb=1E-6 ,ub=1000) )
  model$setParameter( Rih = c(init=1 ,lb=1E-6 ,ub=100) )
  model$setParameter( p11 = c(init=1  ,lb=-30 ,ub=30 ) )
  model$setParameter( p22 = c(init=1  ,lb=-30 ,ub=30 ) )
  model$setParameter( p33 = c(init=1  ,lb=-25 ,ub=30 ) )
  model$setParameter( e11 = c(init=-1 ,lb=-30 ,ub=50 ) )
  model$setParameter( Aw = c(init=2 ,lb=1E-3 ,ub=300) )
  model$setParameter( Wlev= c(init=10  ,lb=0    ,ub=100) )

}

## Run the parameter optimization
  model$options$maxNumberOfEval =2000
  fit <- model$estimate(data, firstorder=prm$firstorder)
  fit$Rnames <- c("Rie","Rea")
  return(fit)
}
```

3.0 – Modelling:

3.3.9- Other models:

```
sdeTiTm <- function(data, weighting)
if(weighting){
  model <- ctsm()
  ## Add a system equation and thereby also a state
  model$addSystem(dTi ~ ( 1/(Ci*Rim)*(Tm-Ti) + 1/Ci*Ph + Aw/Ci*Gv+
1/(Ci*Ria)*(Ta-Ti) )*dt +(1+(weights*Wlev))*exp(p11)*dw1)
  model$addSystem(dTm ~ ( 1/(Cm*Rim)*(Ti-Tm))*dt
+(1+(weights*Wlev))*exp(p22)*dw2)
  ## Set the names of the inputs
  model$addInput(Ta,Ph,Gv,weights)
  ## Set the observation equation: Ti is the state, yTi is the measured
output
  model$addObs(yTi ~ Ti)
  ## Set the variance of the measurement error
  model$setVariance(yTi ~ exp(e11))
```

TiTm

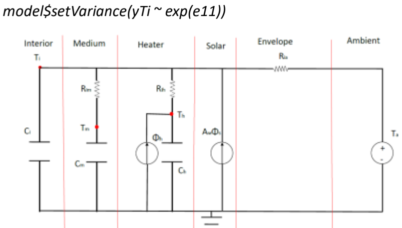



```
## Set the initial value (for the optimization) of the value of the state
at the starting time point
  model$setParameter(  Ti0 = c(init=15 ,lb=0 ,ub=50 ) )
  model$setParameter(  Tm0 = c(init=15 ,lb=0 ,ub=100000) )

  ## Set the initial value for the optimization
  model$setParameter(  Ci = c(init=1 ,lb=1E-3 ,ub=50 ) )
  model$setParameter(  Cm = c(init=1 ,lb=1E-2 ,ub=500 ) )
  model$setParameter( Ria = c(init=20 ,lb=1E-3 ,ub=1E3) )
  model$setParameter( Rim = c(init=20 ,lb=1E-3 ,ub=1E6) )
  model$setParameter( p11 = c(init=1  ,lb=-30 ,ub=10 ) )
  model$setParameter( p22 = c(init=1  ,lb=-30 ,ub=10 ) )
  model$setParameter( e11 = c(init=-1 ,lb=-50 ,ub=10 ) )
  model$setParameter( Aw = c(init=6 ,lb=1E-2 ,ub=100 ) )
  model$setParameter( Wlev= c(init=10  ,lb=0    ,ub=200) )
  }

  ## Run the parameter optimization
  model$options$maxNumberOfEval =2000
  fit <- model$estimate(data, firstorder=prm$firstorder)
  fit$Rnames <- c("Ria")

  return(fit)
}
```


3.0 – Modelling:

3.3.9- Other models:

```
sdeTiTmTh <- function(data, weighting)
if(weighting){
  model <- ctsm()
  ## Add a system equation and thereby also a state
  model$addSystem(dTi ~ ( 1/(Ci*Rim)*(Tm-Ti) + 1/(Ci*Rih)*(Th-Ti)+
Aw/(Ci)*Gv+ 1/(Ci*Ria)*(Ta-Ti) )*dt
+(1+(weights*Wlev))*exp(p11)*dw1)
  model$addSystem(dTm ~ ( 1/(Cm*Rim)*(Ti-Tm))*dt
+(1+(weights*Wlev))*exp(p22)*dw2)
  model$addSystem(dTh ~ ( 1/(Ch*Rih)*(Ti-Th)+ 1/(Ch)*Ph)*dt
+(1+(weights*Wlev))*exp(p33)*dw3)
  ## Set the names of the inputs
  model$addInput(Ta,Ph,Gv,weights)
  ## Set the observation equation: Ti is the state, yTi is the measured
output
  model$addObs(yTi ~ Ti)
  ## Set the variance of the measurement error
  model$setVariance(yTi ~ exp(e11))
```




```
## Set the initial value (for the optimization) of the value of the state at
the starting time point
  model$setParameter(  Ti0 = c(init=15 ,lb=0 ,ub=60 ) )
  model$setParameter(  Tm0 = c(init=15 ,lb=0 ,ub=500 ) )
  model$setParameter(  Th0 = c(init=15 ,lb=0 ,ub=50 ) )
  ## Set the initial value for the optimization
  model$setParameter(  Ci = c(init=3 ,lb=1E-3 ,ub=1E2 ) )
  model$setParameter(  Ch = c(init=3 ,lb=1E-3 ,ub=1E7 ) )
  model$setParameter(  Cm = c(init=3 ,lb=1E-3 ,ub=1E2 ) )
  model$setParameter( Ria = c(init=3 ,lb=1E-2 ,ub=1E3) )
  model$setParameter( Rih = c(init=3 ,lb=1E-2 ,ub=1E4) )
  model$setParameter( Rim = c(init=3 ,lb=1E-2 ,ub=1E4) )
  model$setParameter( p11 = c(init=1  ,lb=-30 ,ub=10 ) )
  model$setParameter( p22 = c(init=1  ,lb=-30 ,ub=20 ) )
  model$setParameter( p33 = c(init=1  ,lb=-30 ,ub=10 ) )
  model$setParameter( e11 = c(init=-1 ,lb=-50 ,ub=10 ) )
  model$setParameter( Aw = c(init=6 ,lb=1E-4 ,ub=3000 ) )
  model$setParameter( Wlev= c(init=10  ,lb=0    ,ub=1000) )

  }

  ## Run the parameter optimization
  model$options$maxNumberOfEval =2000
  fit <- model$estimate(data,  firstorder=prm$firstorder)
  fit$Rnames <- c("Ria")

  return(fit)
}
```

TiTmTh

3.0 – Modelling:

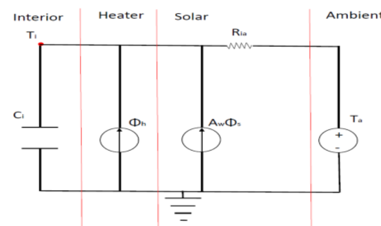
3.3.9- Testing the models:

Fit.sdeTi = sdeTi(data, weighting =T)

analyzeFit(Fit.sdeTi)

Once all the previous procedures are completed, the models will be tested and selected depending on their results. Therefore, all the convergent models will be analysed one by one.

Ti model



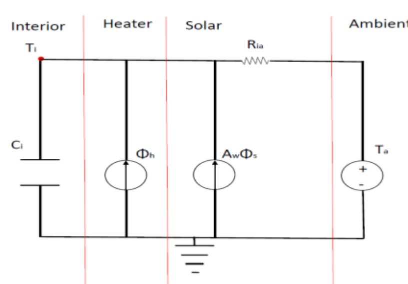
Insignificant

```
Coefficients:
       Estimate    Std. Error    t value      Pr(>|t|)     dF/dPar     dPen/dPar
Ti0    3.5260e+01  1.1568e-01  3.0481e+02  0.0000e+00  2.4679e-06    8e-04
Aw     1.3179e-01  1.7219e-02  7.6541e+00  1.0760e-10  2.5238e-08    0e+00
Ci     1.0665e+02  1.7330e+01  6.1541e+00  4.4388e-08  1.5042e-07    0e+00
e11   -2.2591e+01  2.2796e+02 -9.9103e-02  9.2132e-01  4.9309e-07    0e+00
p11   -2.9047e+00  1.4912e-01 -1.9479e+01  0.0000e+00  1.1952e-07    0e+00
Ria    2.3969e-01  3.0284e-03  7.9148e+01  0.0000e+00 -1.1419e-06   -1e-04
Wlev   1.1641e+00  4.3816e-01  2.6567e+00  9.6877e-03  1.4286e-08    0e+00
```

In case these values were significant, the limits given to the parameters in the model should be changed.

25/45

3.0 – Modelling:




```
Correlation of coefficients:
      Ti0   Aw    Ci    e11   p11   Ria
Aw   -0.01
Ci    0.00  0.28
e11   0.00  0.00 -0.01
p11   0.01 -0.20  0.21  0.00
Ria   0.02 -0.45 -0.54  0.01  0.25
Wlev -0.01  0.14 -0.30  0.00 -0.84 -0.26
```

```
[1] "loglikelihood = 82.7031439067979"
```

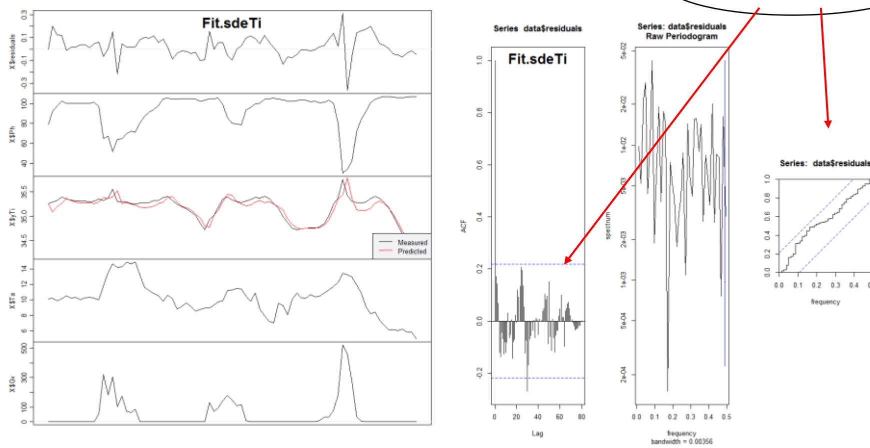
26/45

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:

Residuals



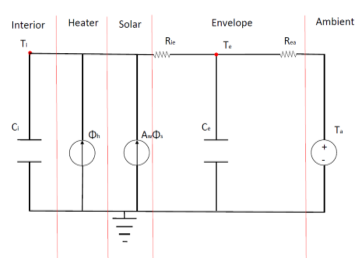
The ACF shows that the residuals are not white noise since there are still some peaks. However, the periodogram is able to describe quite well the dynamics of the building since it is inside the bandwidth. The reason for having bad result in the ACF can be related with the correlation between inputs values.

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:

TiTe model



Insignificant

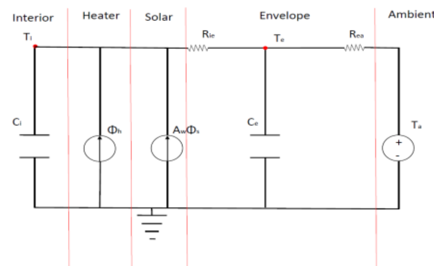
Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	dF/dPar	dPen/dPar
Ti0	3.5262e+01	7.5523e-02	4.6691e+02	0.0000e+00	7.8677e+00	8e-04
Te0	3.4275e+01	1.8257e-01	1.8773e+02	0.0000e+00	1.4594e+00	7e-04
Aw	1.5467e-01	1.2680e-02	1.2198e+01	0.0000e+00	1.2040e-01	0e+00
Ce	8.4925e+01	1.3008e+01	6.5285e+00	1.2323e-08	2.2753e-02	0e+00
Ci	1.8436e+01	5.3480e+00	3.4472e+00	9.7461e-04	-1.0109e-01	0e+00
e11	-2.2477e+01	7.3172e+00	-3.0718e+00	3.0506e-03	7.6041e-05	1e-04
p11	-5.6848e+00	3.1326e+00	-1.8147e+00	7.3885e-02	-1.8879e-01	0e+00
p22	-2.9311e+00	1.7085e-01	-1.7156e+01	0.0000e+00	-1.2669e-01	0e+00
Rea	2.2424e-01	2.4874e-03	9.0149e+01	0.0000e+00	-2.3862e+00	0e+00
Rie	1.3619e-02	6.5928e-04	2.0658e+01	0.0000e+00	-4.9033e-01	-1e-03
Wlev	1.5564e+00	4.8869e-01	3.1849e+00	2.1806e-03	-4.4863e-02	0e+00

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:



Correlation of coefficients:

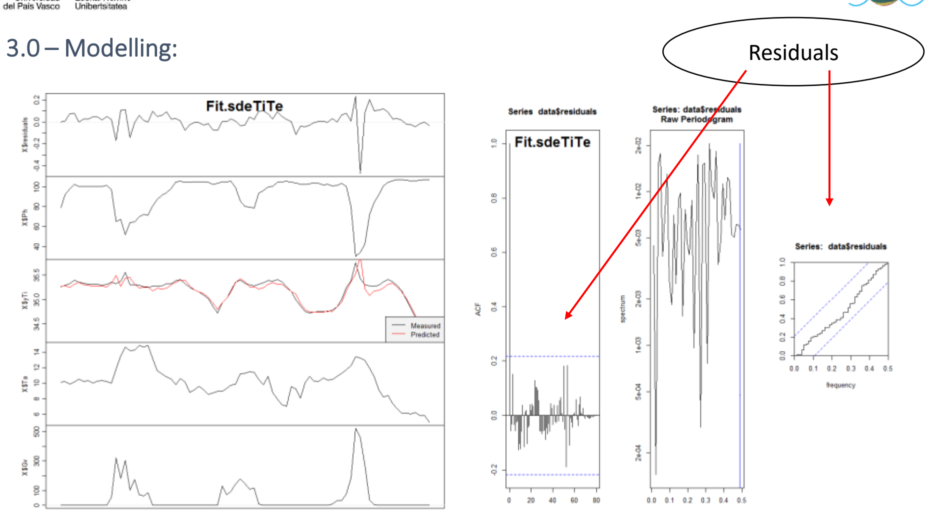
	Ti0	Te0	Aw	Ce	Ci	e11	p11	p22	Rea	Rie
Te0	0.55									
Aw	0.06	-0.14								
Ce	-0.04	-0.33	0.40							
Ci	0.16	0.02	0.44	0.04						
e11	-0.23	-0.25	-0.06	-0.04	0.07					
p11	-0.22	-0.27	-0.01	-0.02	0.18	0.97				
p22	0.01	-0.11	0.04	-0.17	0.52	-0.03	0.04			
Rea	0.00	0.31	-0.45	-0.68	-0.35	-0.03	-0.08	-0.01		
Rie	-0.14	-0.50	0.12	0.47	0.20	0.35	0.41	0.53	-0.47	
Wlev	0.07	0.15	0.02	0.00	-0.15	0.11	0.07	-0.72	-0.20	-0.36

[1] "loglikelihood = 101.846497808796"

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

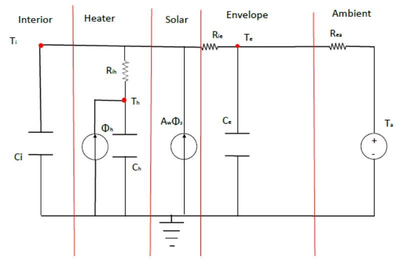
3.0 – Modelling:



The ACF shows that the residuals are close to be white noise since all the peak are inside the limits. The periodogram is also able to describe quite well the dynamics of the building since it is inside the bandwidth. There is not any observable correlation between the input data.

3.0 – Modelling:

TiTeTh model

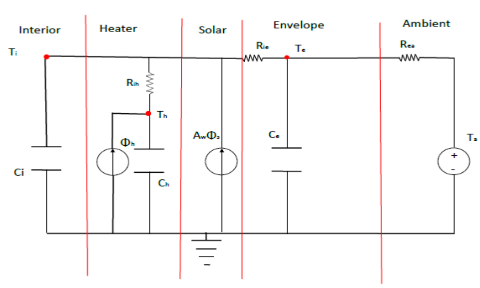


Insignificant

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	dF/dPar	dPen/dPar
Ti0	3.5260e+01	7.2331e-02	4.8748e+02	0.0000e+00	3.6820e-02	8e-04
Te0	3.7443e+01	7.9430e+00	4.7139e+00	1.3963e-05	-1.8965e-02	2e-04
Th0	3.1956e-02	3.2344e+00	9.8802e-03	9.9215e-01	-5.0585e-06	0e+00
Aw	1.9802e-03	4.5562e-02	4.3463e-02	9.6546e-01	-2.1543e-04	0e+00
Ce	5.3317e+02	1.3256e+04	4.0220e-02	9.6804e-01	5.1460e-05	2e-04
Ch	1.6902e+08	2.5593e+10	6.6042e-03	9.9475e-01	2.4360e-05	0e+00
Ci	1.0934e+01	2.5105e+02	4.3552e-02	9.6539e-01	3.5184e-04	0e+00
e11	-4.8379e+01	4.4121e+02	-1.0965e-01	9.1302e-01	-1.9651e-05	0e+00
p11	-3.0748e+00	2.1089e-01	-1.4581e+01	0.0000e+00	-1.8052e-04	0e+00
p22	-1.6041e+00	4.3231e-01	-3.7104e+00	4.3571e-04	7.1915e-04	0e+00
p33	-1.5175e+01	1.3730e+02	-1.1052e-01	9.1233e-01	7.3950e-05	1e-04
Rea	-1.1949e+03	2.1712e+04	-5.5033e-02	9.5628e-01	-2.2972e-04	0e+00
Rie	3.1820e-01	7.3062e+00	4.3553e-02	9.6539e-01	9.4003e-04	0e+00
Rih	5.5056e+00	1.3296e+02	4.1408e-02	9.6710e-01	-9.2140e-04	0e+00
Wlev	4.9682e-01	3.1439e-01	1.5803e+00	1.1886e-01	-5.1222e-05	0e+00

3.0 – Modelling:



Correlation of coefficients:

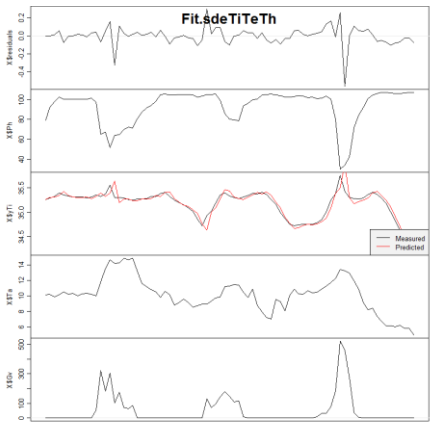
	Ti0	Te0	Th0	Aw	Ce	Ch	Ci	e11	p11	p22	p33	Rea	Rie	Rih
Te0	0.02													
Th0	0.00	-0.89												
Aw	0.03	0.31	-0.55											
Ce	0.03	0.44	-0.64	0.98										
Ch	0.00	0.90	-0.99	0.40	0.51									
Ci	0.03	0.31	-0.54	1.00	0.99	0.40								
e11	0.02	-0.72	0.67	0.26	0.15	-0.78	0.26							
p11	0.05	0.01	0.00	-0.07	-0.06	0.01	-0.07	-0.06						
p22	0.05	0.26	-0.25	0.01	0.07	0.27	0.05	-0.27	0.02					
p33	0.00	-0.91	0.98	-0.36	-0.47	-1.00	-0.36	0.80	-0.02	-0.28				
Rea	0.00	-0.89	1.00	-0.53	-0.63	-0.99	-0.53	0.68	-0.01	-0.30	0.98			
Rie	-0.03	-0.31	0.54	-1.00	-0.99	-0.40	-1.00	-0.26	0.06	-0.03	0.36	0.52		
Rih	-0.03	-0.45	0.65	-0.99	-1.00	-0.52	-0.99	-0.14	0.06	-0.06	0.48	0.63	0.99	
Wlev	-0.04	-0.01	0.01	0.05	0.04	-0.02	0.06	0.05	-0.74	0.07	0.02	0.01	-0.05	-0.04

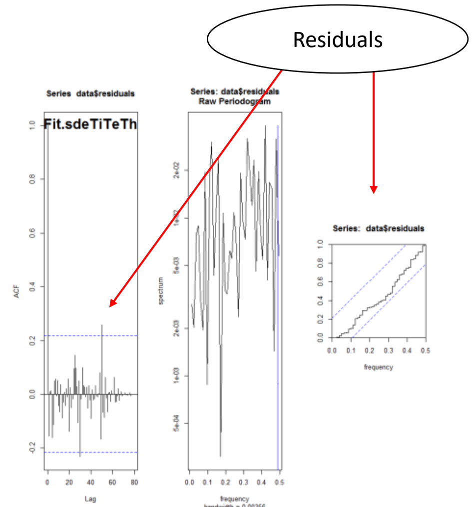
[1] "loglikelihood = 76.5247091478197"

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:





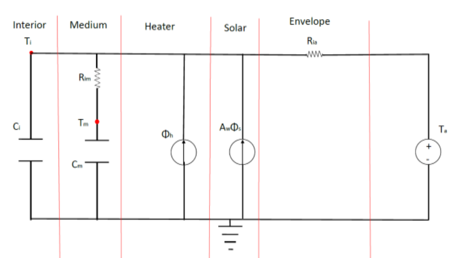
The ACF shows that the residuals are not white noise since there are some peak outside the limits. The periodogram is describing quite well the dynamics of the building but not as well as in previous cases since it is close to cross the bandwidth lines. This residual results are probably related to the input data correlation.

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:

TiTm model



Insignificant

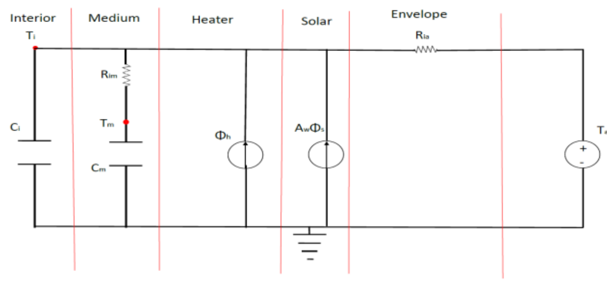
Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	dF/dPar	dPen/dPar
Ti0	3.5260e+01	9.2128e-02	3.8273e+02	0.0000e+00	-1.0957e-04	3e-04
Tm0	3.5683e+01	2.8510e-01	1.2516e+02	0.0000e+00	1.7427e-05	4e-04
Aw	1.5969e-01	1.9136e-02	8.3449e+00	1.0885e-11	2.5554e-06	0e+00
Ci	3.3927e+01	1.5733e+01	2.1565e+00	3.4520e-02	7.7047e-07	7e-04
Cm	9.1547e+01	3.8905e+00	2.3531e+01	0.0000e+00	-1.9010e-04	2e-04
e11	-1.9500e+01	4.4893e+00	-4.3436e+00	4.8475e-05	-1.4712e-07	5e-04
p11	-9.5177e+00	2.6744e+00	-3.5588e+00	6.8431e-04	1.4313e-06	1e-04
p22	-2.5819e+00	2.9129e-01	-8.8636e+00	1.5761e-12	-2.6797e-06	0e+00
Ria	2.3542e-01	3.4365e-03	6.8505e+01	0.0000e+00	2.0106e-05	0e+00
Rim	1.2396e-02	3.2643e-03	3.7976e+00	3.1464e-04	2.2678e-06	0e+00
Wlev	1.3220e+00	4.0267e-01	3.2830e+00	1.6205e-03	6.3277e-06	0e+00

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:



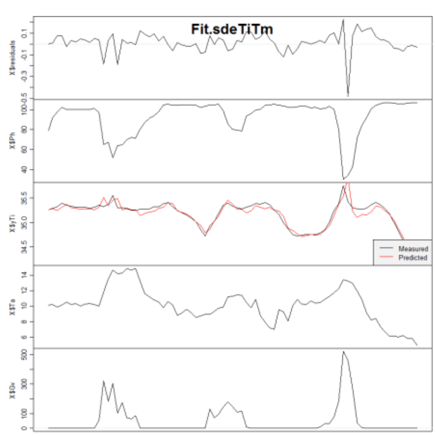

```
Correlation of coefficients:
      Ti0   Tm0   Aw    Ci    Cm    e11   p11   p22   Ria   Rim
Tm0   0.65
Aw    0.19  0.36
Ci    0.31  0.65  0.55
Cm   -0.20 -0.41 -0.13 -0.36
e11  -0.01 -0.09 -0.14 -0.11 -0.54
p11  -0.19 -0.40 -0.20 -0.44  0.63 -0.23
p22   0.30  0.67  0.41  0.90 -0.44 -0.10 -0.49
Ria  -0.23 -0.52 -0.54 -0.64  0.13  0.15  0.22 -0.54
Rim   0.13  0.46  0.13  0.49 -0.20 -0.10 -0.23  0.62 -0.32
Wlev -0.30 -0.60 -0.27 -0.59  0.51  0.10  0.52 -0.76  0.27 -0.34

[1] "loglikelihood = 93.3483979154611"
```

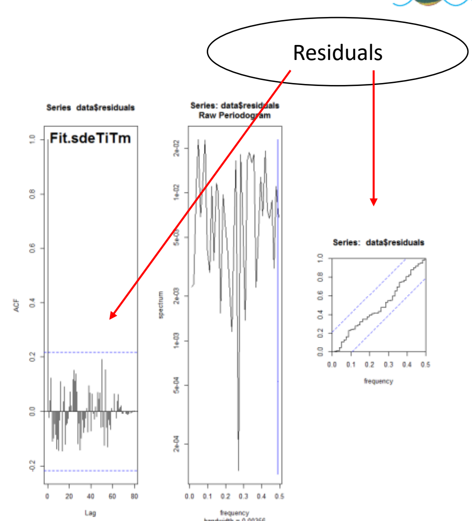
35/45

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:



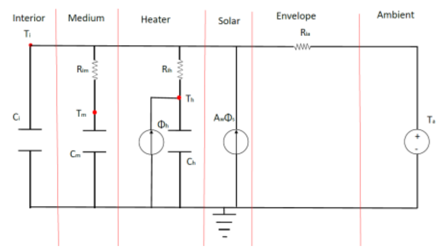


The ACF shows that the residuals are close to be white noise since all the peak are inside the limits. The periodogram is also able to describe quite well the dynamics of the building since it is inside the bandwidth. There is not any observable correlation between the input data.

36/45

3.0 – Modelling:

TiTmTh model

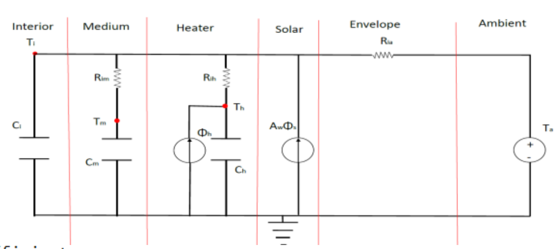


Insignificant

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	dF/dPar	dPen/dPar
Ti0	3.5321e+01	2.5243e-01	1.3992e+02	0.0000e+00	1.1039e+01	8e-04
Tm0	2.5174e+00	4.0628e+00	6.1962e-01	5.3765e-01	-6.9043e-03	0e+00
Th0	6.3100e+00	8.0052e+00	7.8824e-01	4.3339e-01	3.3708e-05	0e+00
Aw	3.9056e+00	4.2679e+00	9.1511e-01	3.6347e-01	1.6810e-01	1e-04
Ch	3.9275e-02	7.5852e-02	5.1779e-01	6.0634e-01	4.8761e-01	0e+00
Ci	1.1242e+04	1.4885e+04	7.5528e-01	4.5277e-01	9.6637e-02	0e+00
Cm	8.2556e+01	2.5264e+02	3.2677e-01	7.4488e-01	-2.9544e-01	0e+00
e11	1.9715e-06	3.8235e-05	5.1562e-02	9.5903e-01	7.0628e-05	0e+00
p11	-6.0928e+00	4.1177e+00	-1.4797e+00	1.4375e-01	-1.1527e-01	0e+00
p22	-3.6713e+00	1.9566e+01	-1.8763e-01	8.5174e-01	-4.7494e-03	0e+00
p33	3.4119e+00	1.9849e+01	1.7189e-01	8.6405e-01	1.9731e-03	0e+00
Ria	8.3852e-02	6.0412e-02	1.3880e+00	1.6983e-01	3.5357e-01	0e+00
Rih	-7.1714e+02	1.4243e+03	-5.0352e-01	6.1628e-01	4.8700e-01	0e+00
Rim	-3.6586e-01	4.3759e-01	-8.3608e-01	4.0613e-01	-5.0459e-01	0e+00
Wlev	1.3695e-01	5.8802e-01	2.3290e-01	8.1656e-01	1.8303e-03	0e+00

3.0 – Modelling:

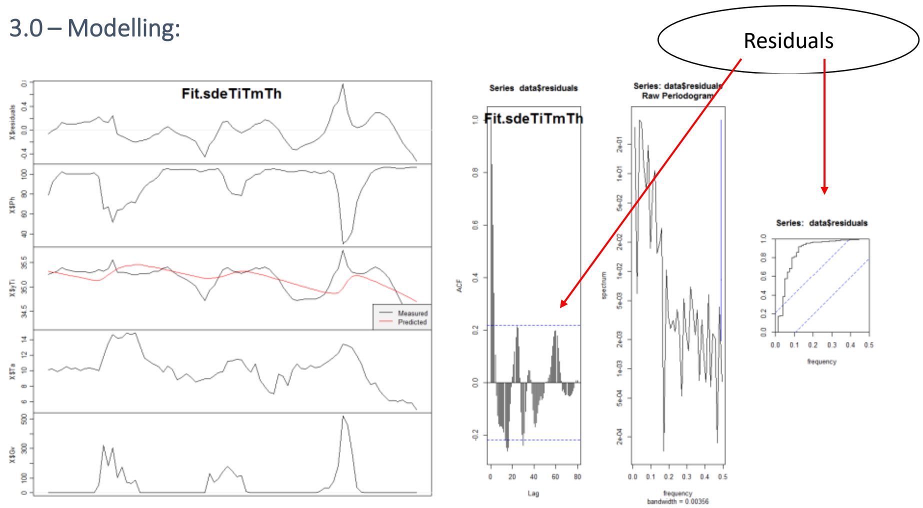


Correlation of coefficients:

	Ti0	Tm0	Th0	Aw	Ch	Ci	Cm	e11	p11	p22	p33	Ria	Rih	Rim
Tm0	-0.35													
Th0	-0.04	-0.04												
Aw	-0.05	0.39	0.24											
Ch	-0.01	0.18	0.36	0.87										
Ci	-0.11	0.38	0.16	0.65	0.45									
Cm	0.35	-0.98	0.21	-0.26	-0.04	-0.29								
e11	-0.18	0.52	0.54	0.86	0.86	0.54	-0.36							
p11	-0.05	-0.27	-0.05	-0.86	-0.71	-0.78	0.19	-0.59						
p22	0.07	0.10	0.15	0.13	0.18	0.04	-0.07	0.07	-0.40					
p33	-0.04	0.33	-0.87	0.21	0.11	0.11	-0.43	-0.06	-0.30	-0.09				
Ria	-0.60	0.39	-0.29	-0.57	-0.65	-0.34	-0.50	-0.37	0.59	-0.11	0.09			
Rih	-0.23	0.72	0.15	0.82	0.79	0.55	-0.62	0.89	-0.67	0.19	0.34	-0.19		
Rim	0.34	-0.96	0.08	-0.54	-0.35	-0.42	0.93	-0.59	0.42	-0.10	-0.42	-0.24	-0.79	
Wlev	-0.09	0.56	-0.03	0.90	0.83	0.57	-0.47	0.78	-0.83	0.25	0.51	-0.38	0.93	-0.69

[1] "loglikelihood = -76.2547057019933"

3.0 – Modelling:



The ACF shows that the residuals are not white noise since there are several peak outside the limits. The periodogram is not showing good the dynamics of the building since the line is going out of the bandwidth. This residual results are probably related to the input data correlation.

3.0 – Modelling:

3.3.10- Evaluating and selecting the models:

Once all the models have been tested and the residuals analysed, it is indispensable to make a comparison between the obtained results. Therefore, the Likelihood Ratio Test is used:

DATASET 16	Log-likelihood	p-value (LRT)
Ti	-71.0	
TiTe	**-1.5**	**0 (Ti ->TiTe)**
TiTeTh	-48.9	1 (TiTe ->TiTeTh)
TiTm	-9.2	0 (Ti ->Tm)
TiTmTh	-	- (TiTm ->TiTmTh)

DATASET 17	Log-likelihood	p-value (LRT)
Ti	82.7	
TiTe	**101.9**	**9.7* 10^{-8} (Ti ->TiTe)**
TiTeTh	76.5	1 (TiTe ->TiTeTh)
TiTm	93.4	2.8* 10^{-4} (Ti ->Tm)
TiTmTh	-76.3	1 (TiTm ->TiTmTh)

The Likelihood Ratio Test value is achieved as D = 2 (log LA - log LB), where log LA is the logarithm of the likelihood function for model A. Given that the model can be reduced to model B the quantity D is χ^2 (k - m) distributed, where k and m are the number of parameters in model A and B, respectively.

```
D <- 2*(log LA - log LB)
c <- 4 (k-m)
p-value <- 1- pchisq (D, c)
```

3.0 – Modelling:

3.3.11- Heat Loss Coefficient calculation:

Then, it is necessary to estimate the HLC of the models in order to see the result for each of the models:

```
analyzeHTC <- function(fit, tPer=NA, plotACF=FALSE, plotSeries=FALSE, plotMore=FALSE, newdev=FALSE, acfRmNA=FALSE, acftext="",
printSummary=TRUE,...)
{
## Calculate the loglikelihood value
  if(printSummary) print(paste("Loglikelihood", format(fit$loglik,digits=2)))
  ##---------------------------------------------------------------
  ## The estimated HTC-value
  i <- which(names(fit$xm)%in%fit$Rnames)
  HTC <- 1/sum(fit$xm[i])
  if(printSummary) print(paste("HTC:",format(HTC,digits=4))) ## W/C
  ## The covariance for the two estimated R values
  ii <- which(colnames(fit$corr)%in%fit$Rnames)
  if(length(i)==1) cov <- fit$sd[i] * fit$corr[ii,ii] * fit$sd[i]
  else cov <- diag(fit$sd[i]) %*% fit$corr[ii,ii] %*% diag(fit$sd[i])
#if(printSummary) print(paste("Cov = ",cov))

  ## Calculate the uncertainty of the HTC value with a linear approximation to the covariance
  ## The Jacobian, the derived of the HTC-value with respect to each estimate in fit$xm[i]
  J <- t( sapply(1:length(i), function(ii,x){ -1/sum(x)^2 }, x=fit$xm[i]) )
  ## The estimated variance of HTC
  varHTC <- J %*% cov %*% t(J)
  ## and standard deviance
  sdHTC <- sqrt(varHTC)
  ## Return the confidence interval
  if(printSummary) print(paste("HTC 95% confidence band:",paste(format(c(HTC-1.96*sdHTC,HTC+1.96*sdHTC),digits=4),collapse=" to ")))
  #if(printSummary) print(paste("HTC 95% values:",paste(format(c(1-((HTC-1.96*sdHTC)/HTC),((HTC+1.96*sdHTC)/HTC)-
1),digits=4),collapse=" and ")))
}
```


3.0 – Modelling:

3.3.12- Solar aperture calculation:

Then, it is necessary to estimate the S_a of the models in order to see the result for each of the models:

```
## The gA value
  gA <- fit$xm["Aw"]
  #names(gA) <- NULL
  sdgA <- fit$sd["Aw"]
  #names(sdgA) <- NULL
  if(printSummary) print(paste("gA:",paste(format(gA,digits=2)))) ## W/C
  if(printSummary) print(paste("gA 95% confidence band:",paste(format(c(gA-1.96*sdgA, gA+1.96*sdgA),digits=2),collapse=" to ")))
```

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

3.0 – Modelling:

If the HLC is estimated for all the models, the following results will be achieved:

DATASET 16	HLC [W/°C]	Error [W/°C] (HTC 95% Confidence Interval of the estimation method)	Aperture (A2) [m²]	Error [m²]	Log-likelihood	P value
Ti	3.80	±0.48	0.11	±0.04	-71.0	
TiTe	**4.10**	**±0.11**	**0.15**	**±0.01**	**-1.5**	**0 (Ti ->TiTe)**
TiTeTh	13.70	±27.90	3.40	±1.00	-48.9	1 (TiTe ->TiTeTh)
TiTm	4.20	±0.15	0.16	±0.02	-9.2	0 (Ti ->Tm)
TiTmTh	-	-	-	-	-	- (TiTm ->TiTmTh)

DATASET 17	HLC [W/°C]	Error [W/°C] (HTC 95% Confidence Interval of the estimation method)	Aperture (A2) [m²]	Error [m²]	Log-likelihood	P value
Ti	4.20	±0.10	0.13	±0.03	82.7	
TiTe	**4.20**	**±0.09**	**0.15**	**±0.03**	**101.9**	**$9.7 * 10^{-8}$ (Ti ->TiTe)**
TiTeTh	-0.01	±0.03	0.01	±0.08	76.5	1 (TiTe ->TiTeTh)
TiTm	4.30	±0.12	0.16	±0.04	93.4	$2.8 * 10^{-4}$ (Ti ->Tm)
TiTmTh	11.90	±16.90	3.90	±8.40	-76.3	1 (TiTm ->TiTmTh)

After the Likelihood Ratio Test we assumed that the obtained best model is the **TiTe** model for both cases. Therefore, it will be estimated as the best one for the provided data two datasets. In this case, the obtained HLC values for dataset 16 is **4.1W/°C** and for dataset 17, **4.2W/°C**. Moreover, the same solar apertura value has been estimated for both dataset with a value of **0.15m²**.

Universidad del País Vasco Euskal Herriko Unibertsitatea

DYNASTEE

4.0 – Conclusions

- The models are able to provide quite accurate responses although sometimes they can be affected by the correlation of the input data.
- After the Likelihood Ratio Test it is assumed that **TiTe** is the best model for both datasets. In this case, the obtained HLC for this model is **4.1 ± 0.11W/°C** for dataset 16 and **4.2 ± 0.09 W/°C** for dataset 17.
- The TiTe model is showing good residuals. The ACF shows residuals close to white noise without any periodical behaviour or considerable peak. Moreover, the periodogram is defining quite accurately the dynamics of the box.
- If the aperture results are checked can be concluded that the results are exactly the same for both datasets, **0.15m²**.

Thank you for your attention!

Irati Uriarte (irati.uriarte@ehu.eus)

(University of the Basque Country (UPV/EHU))

Further questions can be sent to Hans Bloem at: hans.bloem@inive.org