

UNIVERSITY OF PADUA  
INFORMATION ENGINEERING DEPARTMENT

Master in Automation Engineering

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# Development of a dryer model for fabric care applications

Graduate student: **Davide Sambo**



Relator: **Alessandro Beghi**  
Correlator: **Gian Antonio Susto**  
Correlator: **Mirco Rampazzo**  
Electrolux Tutor: **Terenzio Giroto**

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# Abstract

In this thesis is dealt the evaluation of a dryer Simulink model; it is the top Electrolux dryer and adopts the heat pump technology. In the model the components and interactions of the refrigerant circuit of the heat pump are not simulated but they are represented by only exchanges of powers that modify the air conditions passing through the exchangers (evaporator and condenser). The aim of the model is to allow performance evaluation and software debug of the dryer without use of the real machine. This means a considerable time and cost saving, allowing to Electrolux to use these resources in other useful ways.



“The universe is full of magical things patiently  
waiting for our wits to grow sharper.”  
- **Eden Phillpotts**



I dedicate this work to my parents Anastasia  
and Vanni and my sister Martina.  
Thank you for being there for me.





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# Thesis activity

The thesis activity aims to analyze a Matlab/Simulink model of an old dryer model with heat pump technology to obtain a complete and exhaustive analysis, allowing to understand what to modify in the old model to make it more adherent to the top heat pump dryer model subject of this thesis. This will allow to the company to earn money since, having better simulations, there will need less real tests (saving of current, water, ...) and less working hours, obtaining the "same" results in little minutes instead to wait a machine cycle (2/3 hours).





# Introduction

This work is the result of my stage in Porcia (Pordenone) near Electrolux, Swedish multinational home appliance manufacturer, one of the largest appliance maker. In particular I worked in R & D, in which can be developed a new product or improved an existing one.

In the last six months I followed the following working plan:

- **Phase 0:** it was analyzed old Simulink model evaluating its performance with a dataset of machine of interest. It was chosen to use RMSE and normalized RMSE as key performance indicators (KPIs) to compare dataset signals and simulation ones.

Two different comparisons were implemented to understand performance of pre-existing model:

- Real test (I/O acquired in laboratory) vs Output of the timeseries<sup>1</sup> model
  - Real tests (I/O acquired in laboratory) vs Snake<sup>2</sup> model
- **Phase 1:** after the first evaluation it was necessary to understand better the model and those parameters and blocks are important to tune/modify; for this reason there was a in-depth study of the model and a sensitivity

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<sup>1</sup>A timeseries is a series of data points indexed (or listed or graphed) in time order. It is a sequence taken at successive equally spaced points in time (thus it allows to evaluate a sequence of discrete-time data).

The timeseries-model is a Matlab/Simulink model that simulates the behavior of the dryer, generating output signals. Whose inputs are fed by the signals of a real test in the form of timeseries

<sup>2</sup>Snake is an interface available in Electrolux that allows to set some conditions (lab conditions, laundry conditions, laundry type, ...) in which you can simulate the machine. After that you put in them, Snake use automatically the model that we implemented.

Snake model is a free evolution model with initial conditions (room temperature, linen quantity, etc.) equal to those of the real test with which the comparison is made

analysis, so evaluating how to operate and obtain the best result for this work. Based on this general model view, it will be able to start to modify the model to reach our objective

- **Plus phase:** in this last phase it will explained possible model modifications and will make a least square estimation to improve a particular signal

# Chapter 1

## Theoretical part

### 1.1 A dryer

A dryer is a powered household appliance that is used to remove moisture from a load of laundry. Many dryers consist of a rotating drum, called "tumbler", through which heated air is circulated to subtract water from the laundry, while the tumbler is rotated to maintain air space between laundry.



**Figure 1.1:** Dryer

It is important to note that the incoming air has to have a low relative humidity (percentage of the humidity in an element), thus the air is not suited for an other cycle as it is; for this reason it is necessary to find a way to separate humidity and dry air.

### 1.1.1 Heat-pump dryer

One of most common way to avoid humidity by laundry is heat-pump. A closed-cycle heat pump clothes dryer uses this technology to dehumidify the processing air. Such dryers typically use under half the energy per load of a condenser one.

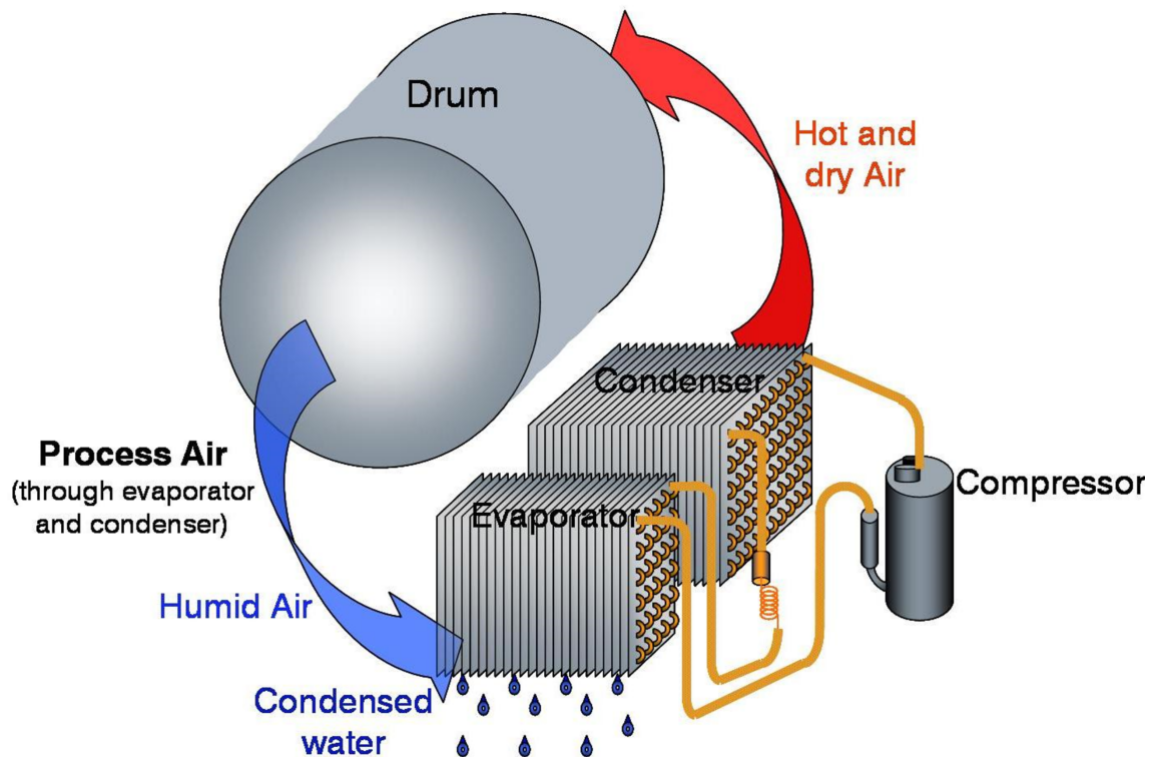


Figure 1.2: Dryer with heat-pump circuit

Whereas condensation dryers use a passive heat exchanger cooled by ambient air, these dryers use a heat pump. The hot, humid air from the tumbler is passed through a heat pump where the cold side condenses the water vapor into either a

drain pipe or a collection tank and the hot side reheats the air afterward for re-use. In this way the dryer also conserves much of its heat within the dryer instead of exhausting it into the surroundings.

Domestic heat pump dryers are designed to work in typical ambient temperatures from 5 to 35°C that will be extreme temperatures. Below 5°C, drying times significantly increase, while over 35°C the environment temperature is too much high to allow a right working of the machine.

## 1.2 The heat-pump [5]

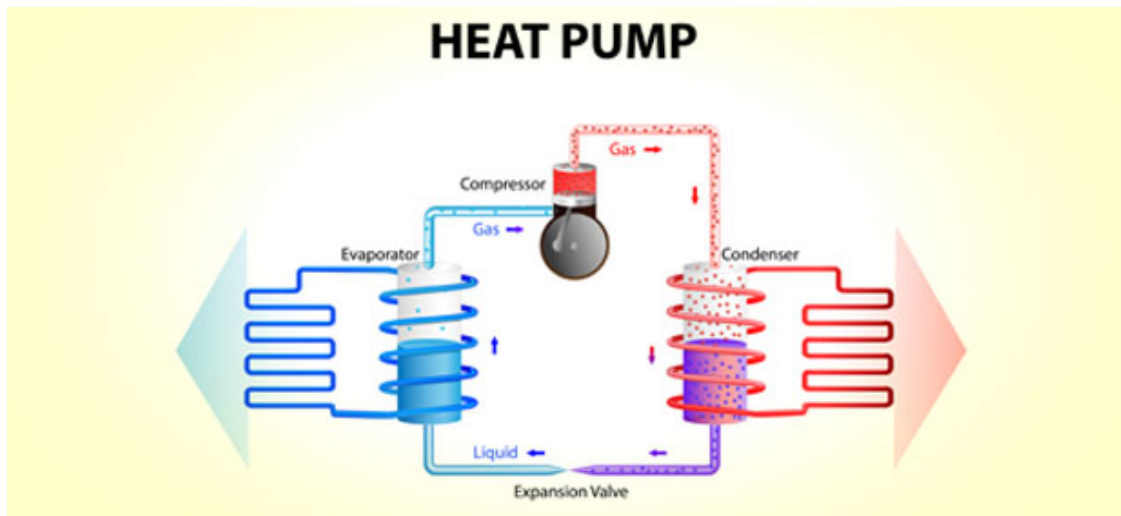
Heat pumps move thermal energy in the opposite direction of spontaneous heat transfer, by absorbing heat from a cold space and releasing it to a warmer one. The most common design of a heat pump involves four main components: a condenser, a capillary, an evaporator and a compressor (see Figure 1.2). The heat transfer medium circulated through these components is called refrigerant.

Heat pumps are significantly more energy efficient than simple electrical resistance heaters (but the typical cost of installing a heat pump is higher than that of a resistance heater). Heat pumps are more efficient than resistance heaters because less high-grade energy is required than is released as heat (most of the energy for heating comes from the external environment). In electrically-powered heat pumps, the heat transferred can be three or four times larger than the electrical power consumed, giving the system a coefficient of performance (COP) of 3 or 4, as opposed to a COP of 1 for a conventional electrical resistance heater, in which all heat is produced from input electrical energy.

Heat pumps use refrigerant (in our case it used R134a refrigerant) as an intermediate fluid to absorb heat where it vaporizes, in the evaporator, and then to release heat where the refrigerant condenses, in the condenser.

There are several factors that will affect the efficiency of a heat pump such as climate, temperature, auxiliary equipment, technology, size and control system. The cooling gas in the form of steam is heated in the compressor, which performs a work included in the gas, increasing its temperature and pressure, moving the refrigerant inside the circuit.

On the discharge side of the compressor, the now hot and highly pressurized vapor passes through a heat exchanger, called condenser where it transfers heat to the air by cooling and changing state (condensing). The liquid refrigerant then passes through a pressure-lowering device called capillary. The low-pressure liquid refrigerant then enters another heat exchanger, the evaporator, in which the fluid absorbs heat and change state (gas). The refrigerant then returns to the



**Figure 1.3:** Heat-pump circuit

compressor and the cycle is repeated.

The pressure difference must be great enough for the fluid to condense at the hot side and still evaporate in the lower pressure region at the cold side. The greater of temperature difference, the greater of required pressure difference, and consequently the more energy needed to compress the gas (the coefficient of performance decreases with increasing temperature difference).

# Chapter 2

## Phase 0

### 2.1 First view of the old model

For the first thing it was evaluated the structure of the old model, that it was used as base model. As from Figure 2.1 the model is characterized by inputs (green ports), outputs (red ports) and the logical blocks. The logic of the model consists of three blocks:

- **Motor subsystem:** this block calculates the motor speed signal and motor feature one
- **TDHP:** it simulates the whole air circuit of dryer
- **Humidity Sensor:** output block signals are variables that depend by this sensor

Into the block TDHP (see Figure 2.2), that will be that of most interest, there are four main MATLAB functions that correspond to four main components of the dryer (air side):

- **Fan** (blue)
- **Drum** (light green)
- **Evaporator** (orange)
- **Condenser** (red)

In practice, each MATLAB function calculates the specific variables that occur during that part of cycle; the cycle iteration is allowed by feedback block. As we will see more deeply later, the model was made with a black-box approach. It uses many look up tables, deriving by experimental data, to calculate various model physical variables (temperatures, enthalpies, specific and relative humidity, ...).

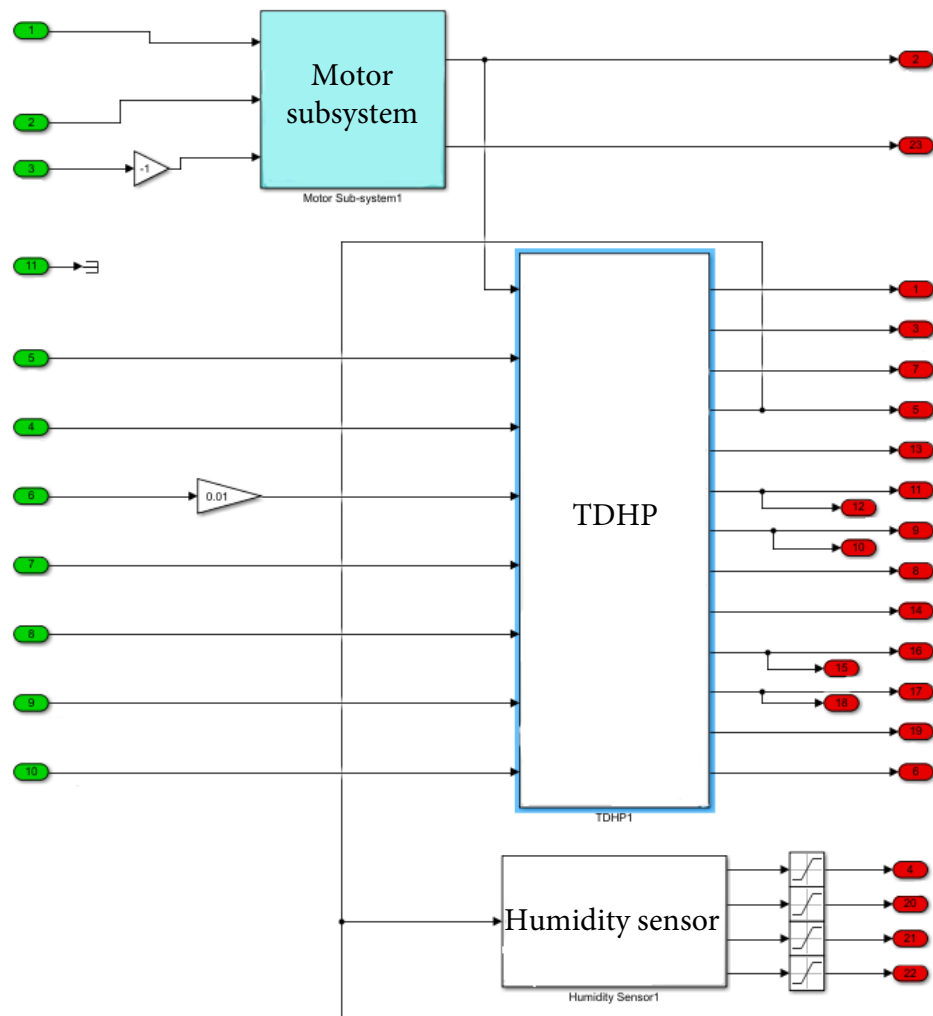


Figure 2.1: Structure of the base model



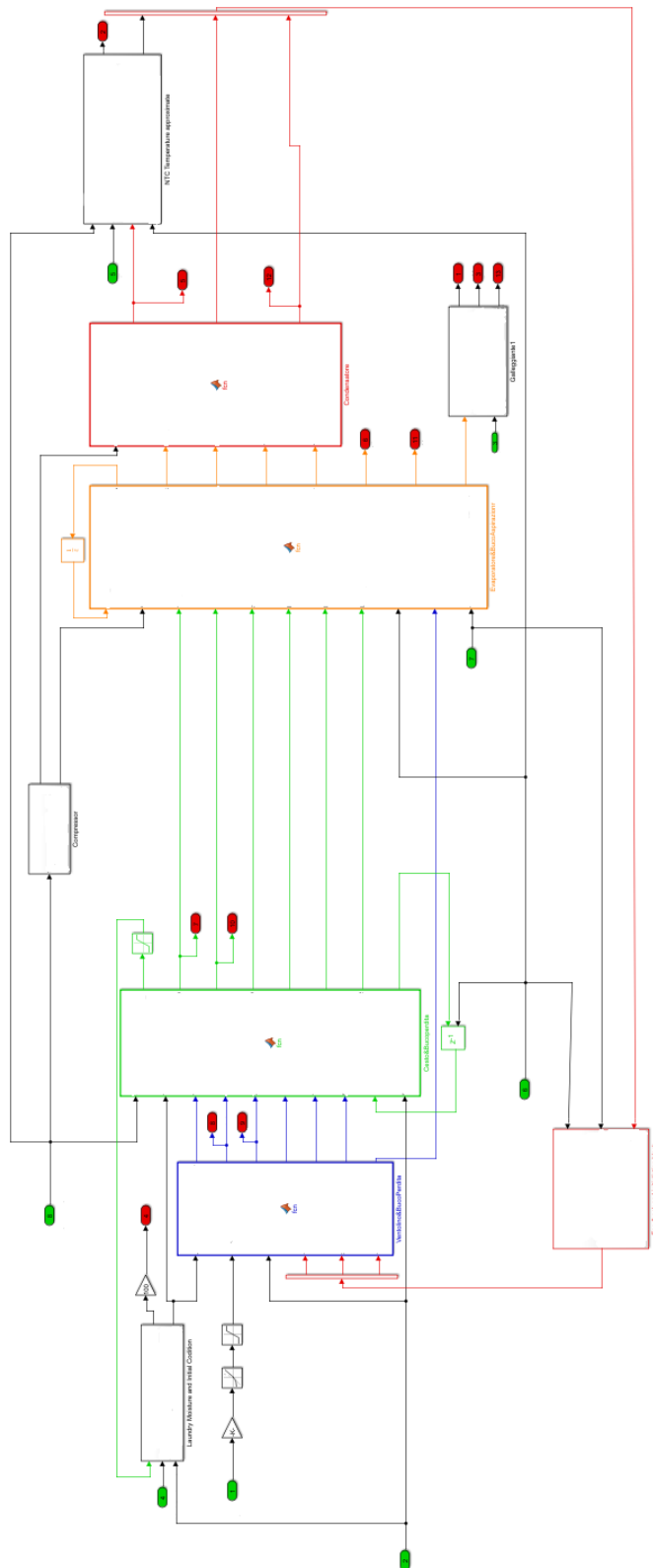


Figure 2.2: Structure of block TDHP

## 2.2 Model signal outputs

In this section model signal outputs are listed with a brief description:

- **Motor speed:** it is the speed of dryer motor. This signal allows to evaluate RPM at every moment
- **Laundry moisture:** it is the moisture in the laundry. This output signal is important. From it, it is observable to drying efficiency, final laundry moisture (thus if we dry laundry correctly) and if drying performance is about constant
- **Temperature of condenser exit (air side):** it is the temperature of condenser exit (air side), that give an idea of air temperature at the drum inlet
- **Temperature of condenser exit (refrigerant side):** in truth it is the refrigerant temperature to the inlet of condenser
- **Temperature of drum exit:** it is the air temperature of drum exit. It allows to understand how much temperature surge we have in the dryer drum
- **Motor feature signal:** it is a signal feature of dryer motor
- **Condensed water:** it is the condensed water of the process. From it, it is observable to condensation efficiency and so how much water vapour is released in the environment
- **Humidity sensor 1:** it is the humidity sensor signal. It is a sum of various effect of this sensor
- **Humidity sensor 2:** it is the humidity sensor 1 signal after some rework

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## 2.3 Timeseries model scripts

When the Matlab/Simulink model was created, was calibrated with acquisitions of a different machine; moreover it was modified more times during years. In order to evaluate the performance of the model respect to the tumble dryer object of the thesis we wanted to compare the model outputs with the signals acquired from real tests.

Powering the inputs of the model with signals acquired from real tests, the input data are in the form of a timeseries series. In this subphase some scripts were implemented, in particular (in order of use):

- **avoid\_disturbances\_tests:** it allows to avoid all disturbances/noises by acquired signals (for example peaks, acquisition error, loss of part of signal during acquisition) using an interpolation technique. This script was necessary to allows us a simulated-acquired comparison without errors
- **snake\_create\_timeseries\_tests:** it creates all timeseries model input/output signals
- **timeseries\_starter\_multitests:** this script allows to simulate the entire Simulink model; furthermore, put in output a report with graphical comparison between simulated and acquired signals

### 2.3.1 Correction of real test dataset

Before to analyze key performance indicators and model performance it is important to explain better how were avoided the disturbances of the acquisition.

The main problems were due to a unexpected falling/peak, in turn caused by various motivation:

- errors of laboratory technicians as touching dryer, wrong condition data, ...
- errors due to acquisition sensor types and their accuracy
- errors due to malfunction or break of sensors

Another problem was the absence of some signals in some real tests used for performance evaluation. These signals have been reconstructed but this has led to the introduction of possible errors. Some signal reconstruction example are the motor feature signal and the condensed water one. This work is made in "snake\_create\_timeseries\_tests" script.

## 2.4 Correction of some initial errors

Running the model, some compilation errors were found. The main motivation of these errors is the presence of new critical cases. A case of particular importance is due to compressor on/off switch; with the activation/deactivation of compressor the model did not work, probably due to a different compressor switch rule respect to the past. For this problem was necessary to modify exchange powers curves (in particular their tracks, not their target values), that how we will see later, are some of model knobs and represent our link between refrigerant machine side and air one.

Moreover, we also removed unused parameters from *Model\_Parameters.m* (it is a script where are defined some of main model parameters). In particular we removed the parameter *Vdot* (volumetric flow of the fan) since in our dryer the fan is directly powered with dryer motor and not with a dedicated one (so in the Simulink model there is a parameter controlled by motor speed).

## 2.5 Key performance indicators

In this section it is explained what are the model key performance indicators (KPIs). To choose them it was done a KPI search and a comparison between different possibilities (for all possibilities it was calculated the relative mean, min, max value for each signal):

- **RMSE:** It represents the square root of the second sample moment of the differences between simulated signals and acquired signals and is scale-dependent
- **NRMSE:** It facilitates model comparison with different scales and is RMSE divided by standard deviation of the acquired signal
- **Variance-explained:** It measures the proportion to which a model accounts for the variation (variance) of a given data set
- **Coefficient of determination under square root (R coefficient):** It is the square of the proportion of the variance in the dependent variable that is predictable from the independent variable(s).

In the following table there are the corresponding formula.

	<i>Formula per all other signals</i>	<i>Formula per motor feature signal</i>
<b>RMSE</b>	$\sqrt{\frac{\sum(x_i - \hat{x}_i)^2}{N}}$	$abs[x_i - \hat{x}_i]$
<b>Variance explained</b>	$\left(1 - \frac{Var(x - \hat{x})}{Var(x)}\right) * 100$	$\left(1 - \frac{Var(x - \hat{x})}{Var(x)}\right) * 100$
<b>NRMSE with standard deviation</b>	$\frac{RMSE}{\sqrt{\frac{\sum(x - mean(x))^2}{N}}}$	$\frac{abs[\max(x) - \max(\hat{x})]}{\sqrt{\frac{\sum(x - mean(x))^2}{N}}}$
<b>sqrt(Coefficient of determination)</b>	$\sqrt{1 - \frac{\sum[x - \hat{x}]^2}{\sum[mean(x(i)) - x]^2}}$	$\sqrt{1 - \frac{\sum[x - \hat{x}]^2}{\sum[mean(x(i)) - x]^2}}$

Figure 2.3: KPI table for comparison between signals

After some considerations it was chosen to use two KPIs: one to evaluate the behaviour for single signal and the other one to analyze performances regarding various signals. The single signal KPI will be RMSE, while the "general" behaviour KPI will be NRMSE. The second decision was derived from a in-depth analysis due to a behaviour comparison, an evaluation best-worst case sort (the used key sort is RMSE), a boxplotevaluation.

### 2.5.1 Root mean square error (RMSE)

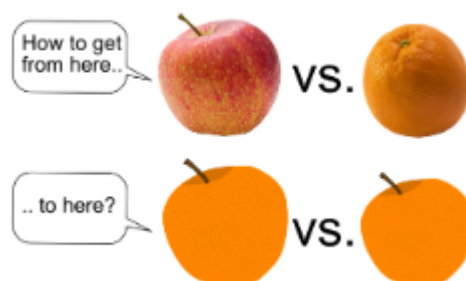
The RMSE serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. It is a measure of accuracy, to compare forecasting errors of different models for a particular dataset and not between datasets (as said before it is scale-dependent). RMSE is always non-negative, and a value of 0 (almost never achieved in practice) would indicate a perfect fit to the data, while greater is the value and greater is the signal error. The effect of each error on RMSE is proportional to the size of the squared error; thus larger errors have a disproportionately large effect on RMSE (RMSE value also depends by outliers).

Root mean square error is the standard deviation of the prediction errors (called residuals), commonly used to evaluate fit quality of a model. Residuals are a measure of how far from the acquired signal. In other words, RMSE tells how concentrated simulated data respect to acquired data. The formula is

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}} \quad (2.1)$$

where  $x_i$  are the acquired data,  $\hat{x}_i$  are the simulated data,  $n$  is the length of the considered signal,  $i$  states test indices (it is useful to remember that for the analysis of the model were considered 91 acquired tests).

## 2.5.2 Normalized root mean square error (NRMSE)



There is a saying that apples should not be compared with oranges or in other words, don't compare two items or group of items that are practically incomparable. But the lack of comparability can be overcome if the two items or groups are somehow standardized or brought on the same scale. This is the idea behind NRMSE. In particular for this work RMSE is normalized with standard deviation, thus the formula is

$$NRMSE = \frac{RMSE}{\sqrt{\frac{\sum_{i=1}^N (x - \text{mean}(x))^2}{N}}} \quad (2.2)$$

where N is the number of considered tests (therefore it is 91). In doing so it is possible to compare, with same benchmark, different signals.

## 2.5.3 The special case of motor feature signal

As regards the motor feature signal, for kind of the signal, it is useful to assess a punctual error to replace RMSE. The motivation of this choice is the punctual usage of the value as feature of the weight estimation. So, the formula for this signal is the following

$$\text{punctual error} = \text{abs}(x_i - \hat{x}_i) \quad (2.3)$$

The same consideration can be used as regards NRMSE. It was used the same standard deviation formula of other signals, with only difference that in this case it was considered a punctual value for each test.

## 2.6 Comparison: Real tests vs Timeseries

The first comparison was implemented between real test dataset and timeseries model output.

The timeseries model is the old model, fed by timeseries of the signals, less than small modifications to run the model.

As all comparisons in this thesis, we will analyze results with KPIs, using some evaluation table and boxplots.

### 2.6.1 Evaluation table

For this first comparison we chose to put in the evaluation table (from left to right) *RMSE mean*, *mean NRMSE*, *NRMSE min*, *NRMSE max*, *mean value of signal* (the acquired one), *Standard deviation*, *Range of signal* and *Performance*.

Acquired signal name	Unit of measurement	RMSE Mean	NRMSE Mean	NRMSE Min	NRMSE Max	Mean value of signal	Standard deviation global	Range of signal	Performance
Motor speed	[rpm]	157.76	0.65	0.53	1.11	2776.08	242.75	[0 3000]	●
Laundry moisture	[%]	3.16	0.18	0.09	0.52	28.23	17.70	[0 60]	●
Temperature of condenser exit (air side)	[°C]	9.12	0.55	0.34	1.14	62.30	16.72	[20 90]	●
Temperature of condenser exit (refrigerant side)	[°C]	12.95	0.77	0.55	1.44	62.30	16.72	[20 90]	●
Temperature of drum exit	[°C]	8.08	0.91	0.48	2.05	36.41	8.90	[20 60]	●
Motor feature signal	[ / ]	80.66	1.00	0.01	4.51	179.78	80.62	[0 500]	●
Condensed water	[liters]	0.25	0.20	0.03	0.50	1.34	1.23	[0 5]	●
Humidity sensor 1	[dimensionless]	914.50	0.45	0.10	1.37	4562.86	2046.00	[0 20000]	●
Humidity sensor 2	[dimensionless]	731.04	0.29	0.06	0.58	8176.73	2548.91	[0 10000]	●

Figure 2.4: Evaluation table (phase 0 - Timeseries)

A particular look has to be carried out for Performance item. The legend of "traffic lights" is the following

- NRMSE mean: 0 – 0.1
- NRMSE mean: 0.11 – 0.4
- NRMSE mean: 0.41 – 0.8
- NRMSE mean: > 0.8

Figure 2.5: Evaluation table legend

This legend divides (with mean NRMSE as KPI) good and bad simulated signals



for us, making it clear a performance without an analysis of numerical results. To conclude, we can divide output signals into four groups:

- **Bad performance:** *drum exit temperature* and *motor feature signal*
- **Medium performance:** *motor speed, condenser exit temperature (refrigerant side and air one)* and *delta hat*
- **Good performance:** *laundry moisture, condensed water* and *normalized delta hat*
- **Excellent performance:** no signals

## 2.6.2 Boxplot evaluation

### What is a boxplot?

A boxplot is a method for graphically depicting groups of numerical data through their quartiles<sup>1</sup>. Box plots may also have lines extending vertically from the boxes, called whiskers, indicating variability outside the upper and lower quartiles. The distance between the different parts of the box indicate the degree of dispersion and skewness in the data, showing outliers.

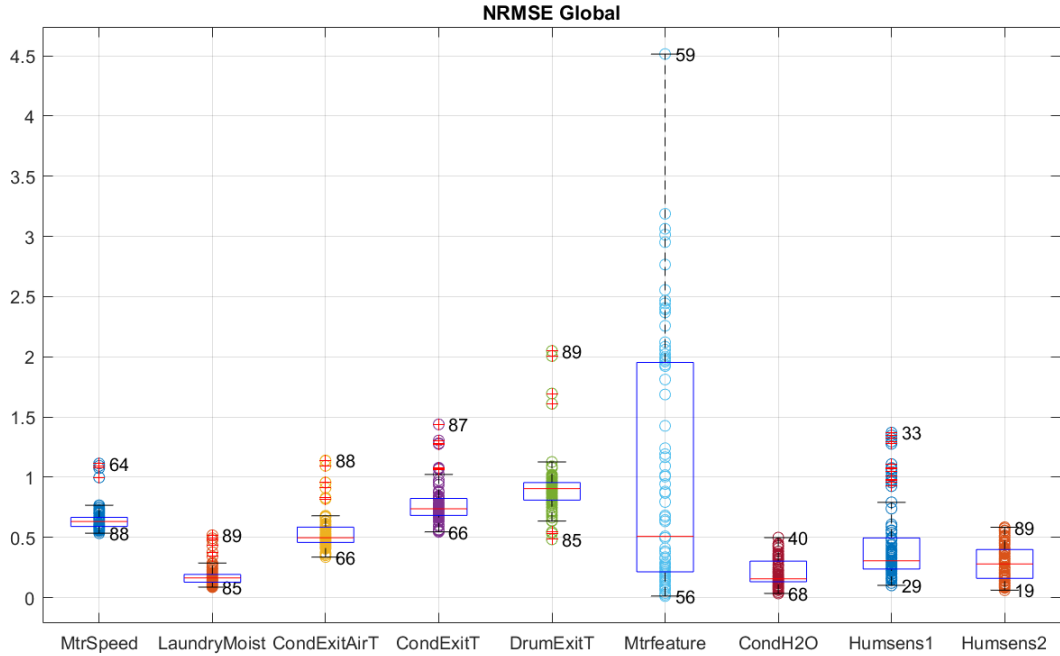
The boxplot allows quick graphical examination of one or more data sets and does have some advantages, as take up little space and intuitively give a general idea of many data features.

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<sup>1</sup>There are three quartiles:

- The first quartile (Q1) is defined as the middle number between the smallest number and the median of the data set
- The second quartile (Q2) is the median of the data
- The third quartile (Q3) is the middle value between the median and the highest value of the data set

## Boxplot analysis



**Figure 2.6:** Boxplot analysis (phase 0 - Timeseries)

To conclude first comparison, it is useful to make a boxplot NRMSE analysis. This analysis gives a better view of whole situation, makes clear distribution of the error for each signal and for each test, also highlighting the best and worst tests. The worst simulated signal is motor feature one, for both outliers and mean NRMSE.

## 2.7 Comparison: Real tests vs Snake

The second comparison was implemented between real tests dataset and Snake dataset; in other words, lab acquired data and Snake simulated data with the same initial conditions.

### 2.7.1 Test software recipes

The aim of this section is to bring to the attention the "problem" of the different recipes. A recipe is a set of various features (for example thresholds, on/off components, drum inversions that have an impact on signal evolution) that are used to simulate the outputs of the model. In our case, for the tests there are 9 recipes (see the following table).

	SOFTWARE SIGNATURE	4 Kg Load1	8 Kg Load1	4 Kg Load2	8 Kg Load2	5.6 Kg Load3	3.5 Kg Load4	6 Kg Load5	4 Kg Cold load	4 Kg Hot load	8 Kg Cold load	8 Kg Hot Load
1	C48CE858-D001-8640-ACA6-C4936B52CC20	15	19	8/20	9	9	4/7	0	0	0	0	0
2	8168D505-9237-AD47-9469-A076FD2EE0D2	0	0	6/20	0	0	0	0	0	0	0	0
3	D06BDC65-70D9-3748-AFA6-9C7882A70E2B	0	0	6/20	0	0	0	0	0	0	0	0
4	D741910A-C26D-E24A-98A7-C04D464FB4F7	0	0	0	0	0	0	2/4	0	0	0	0
5	B51D55A6-7657-1744-B2E7-21E122D23497	0	0	0	0	0	0	2/4	0	0	0	0
6	875AA5D1-E0B2-9242-B405-74CC24912398	0	0	0	0	0	2/7	0	0	0	0	0
7	FD568CFD-05C2-2443-8A80-6813AEB89C12	0	0	0	0	0	1/7	0	0	0	0	0
8	AA8814B7-C2ED-8749-89E8-CAD36CD30AA5	0	0	0	0	0	0	0	0	2	0	2
9	1AFB2A41-64EF-9747-A220-4E9D7BB9773B	0	0	0	0	0	0	0	2	0	2	0

Figure 2.7: Test software recipes

It is very important to make this differentiation since in this way simulated test signals and acquired ones "live" in the same conditions.

### 2.7.2 Comparison analysis

#### Signal cut

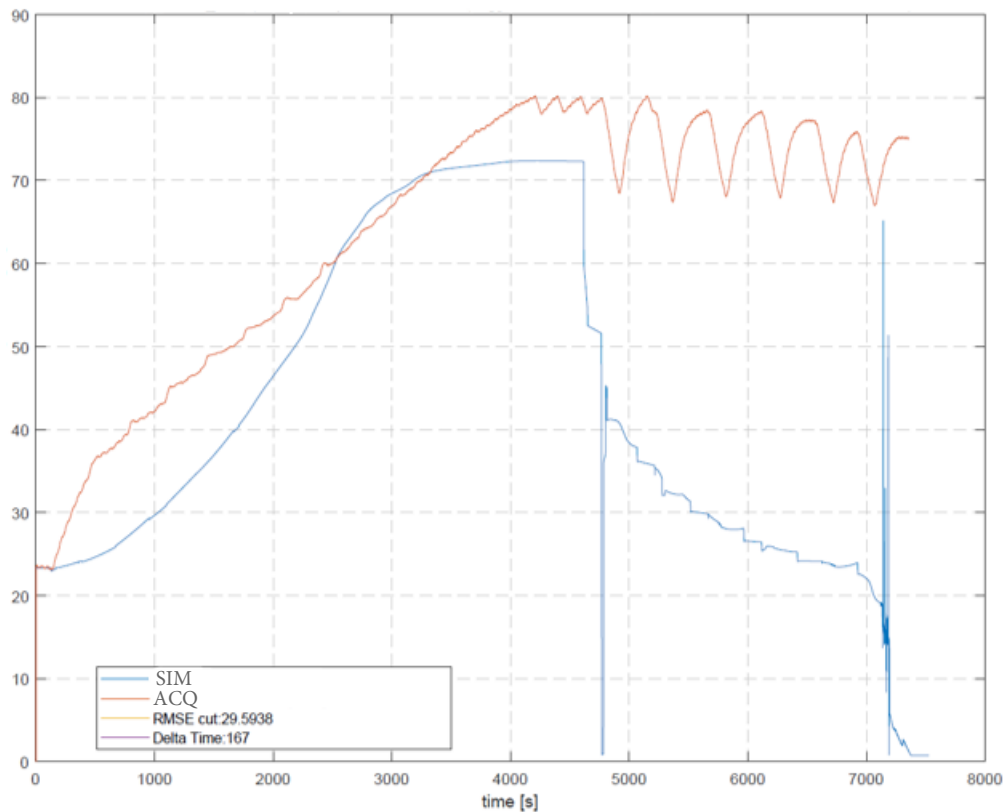
In general, the acquired signal and the Snake one have not same length time. Therefore, to make possible the comparison, it is necessary to cut longer signal, also avoiding anti-crease phase<sup>2</sup>. To not lose this information, in this comparison

<sup>2</sup>anti-crease phase is a period, after the end of the process, in which dryer applies drum inversions to not make folds to laundry

it was also evaluated difference of cycle duration between acquisitions and Snake simulated signals.

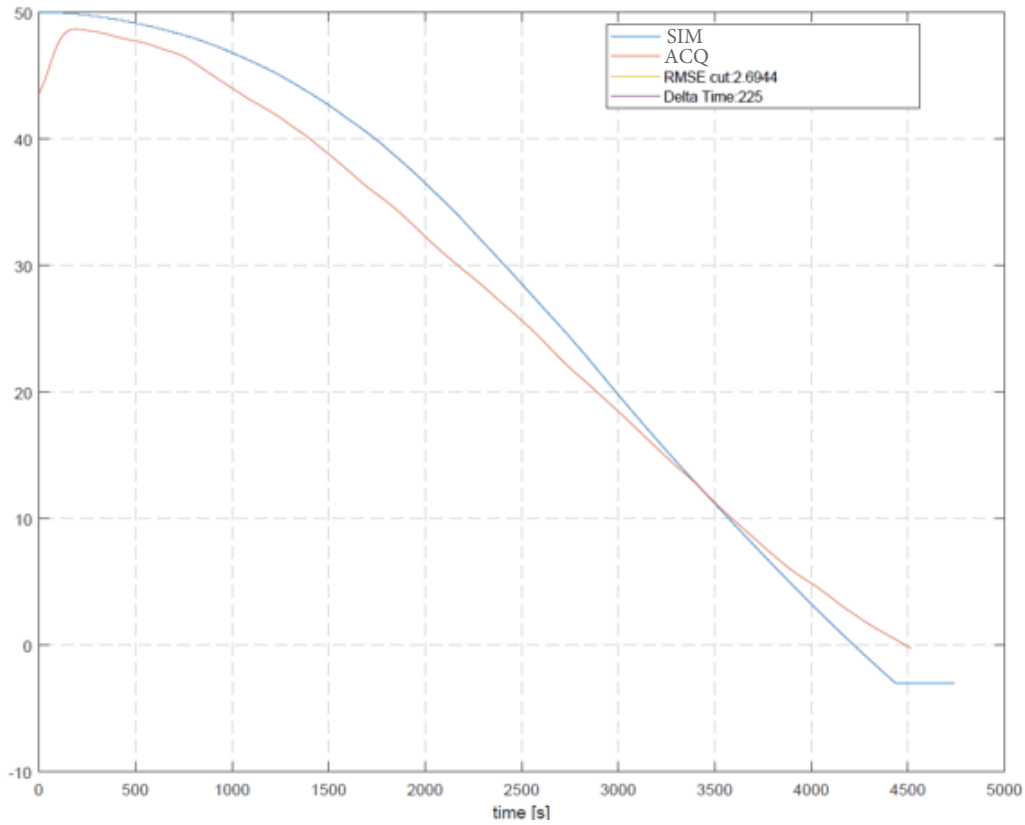
### Signal critical cases

The most critical problem, shared by *laundry moisture*, *temperature of condenser exit (air side)*, *temperature of condenser exit (refrigerant side)*, *temperature of drum exit (air side)*, *condensed water*, is due to not optimal simulation of on/off compressor. In particular, with compressor switch, the simulated signal stops to work, do not track the acquired signal. By way of example, it is kept a comparison regarding temperature of condenser exit (air side) for an Universal test. In the Fig. 2.8, it is easy to note the wrong nature of the simulated signal.



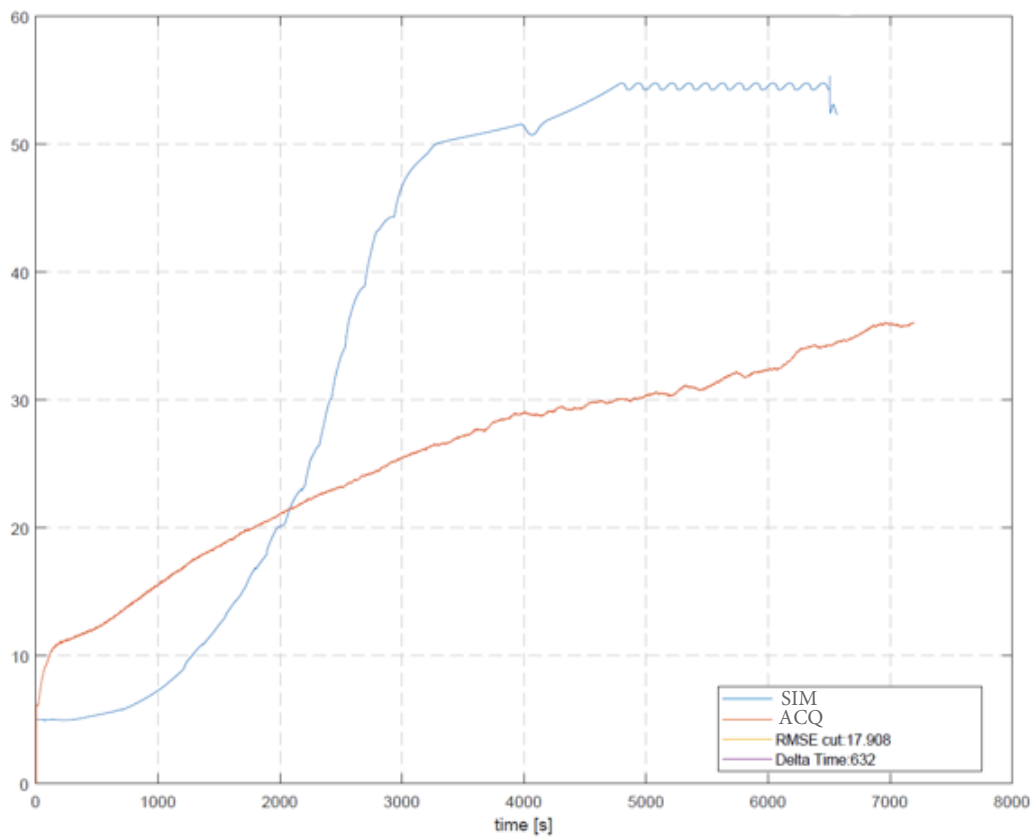
**Figure 2.8:** Temperature of condenser exit (air side) for a Load5 test, on/off compressor problem

- *Laundry moisture*: for some tests, it is possible to note a differential initial point, due to a not perfect moisture signal reconstruction



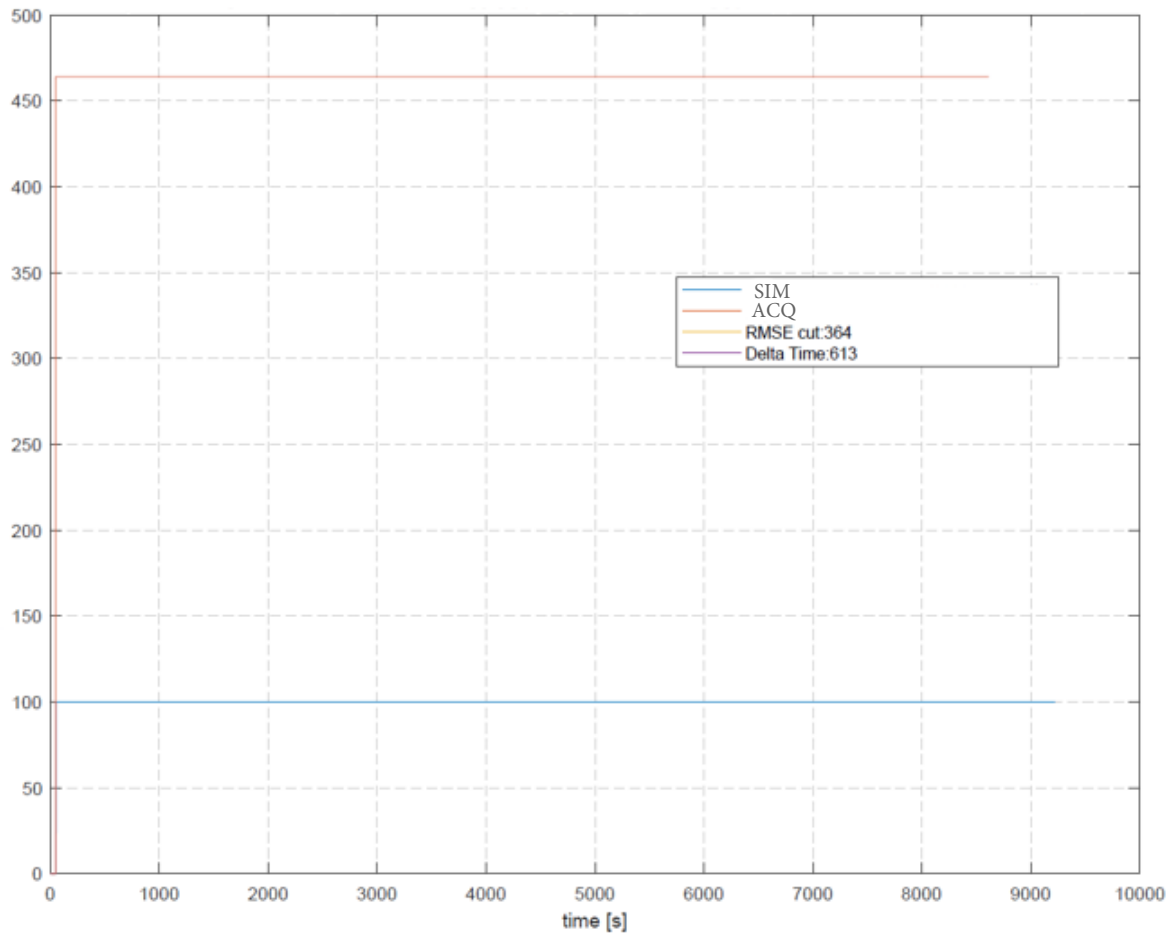
**Figure 2.9:** Laundry moisture for a Load2 4 Kg test, different initial point problem

- *Temperatures:* for climatic chamber test (laboratory temperature equal to  $5^{\circ}\text{C}$ ), the Snake model does not take into account different machine behaviour respect to a standard condition (with laboratory temperature equal to  $23^{\circ}\text{C}$ ). In Fig. 2.10, it is considered the signal regarding temperature of drum exit (since it is the signal in which the problem is clearer). It is easy to note that the simulated signal overestimates the acquired one, almost by twice of the real value.



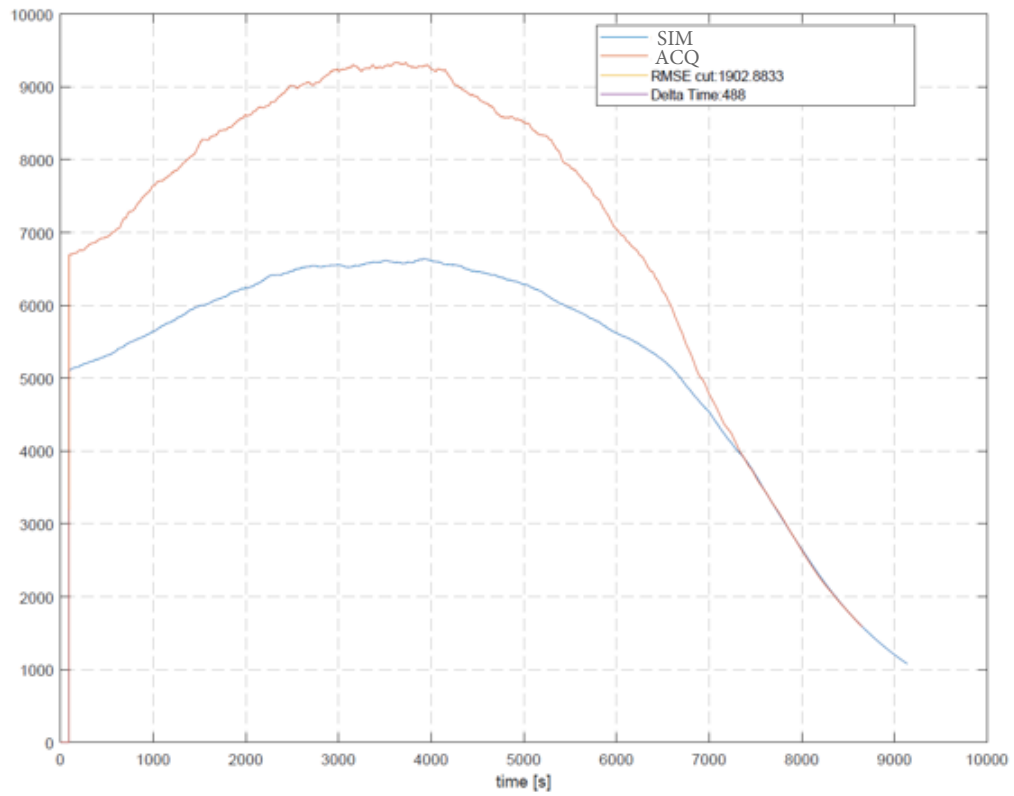
**Figure 2.10:** Temperature of drum exit for a Cold climatic chamber load 4 Kg test, cold temperature problem

- *Motor feature signal:* for this signal, the model always simulated a value equals to 100, that is a good tracking with half-load, but when full load tests are implemented, acquired signal and simulated one are completely different (as can be seen from Fig. 2.11)



**Figure 2.11:** Motor feature signal for a Load1 8 Kg test

- *Humidity sensor signal 1*: there is an underestimation problem for all full-load tests (in particular Load1 full-load)



**Figure 2.12:** Humidity sensor 1 for a Load1 8 Kg test



### 2.7.3 Evaluation table

In this subsection results of the comparison will be told; in particular we will comment KPIs and performance evaluation.

Acquired signal name	Unit of measurement	Range of signal	Mean value of signal	Standard deviation global	RMSE Mean	NRMSE Mean	Performance
Motor speed	[rpm]	[0 3000]	2776.03	242.75	259.28	1.07	●
Laundry moisture	[%]	[0 60]	28.23	17.70	2.80	0.16	●
Temperature of condenser exit (air side)	[°C]	[20 90]	62.30	16.72	10.32	0.62	●
Temperature of condenser exit (refrigerant side)	[°C]	[20 90]	62.30	16.72	13.44	0.80	●
Temperature of drum exit	[°C]	[20 60]	36.41	8.90	8.81	0.99	●
Motor feature signal	[ / ]	[0 500]	179.78	80.62	80.66	1.00	●
Condensed water	[liters]	[0 5]	1.34	1.23	0.30	0.25	●
Humidity sensor 1	[dimensionless]	[0 20000]	4562.83	2046.00	786.62	0.38	●
Humidity sensor 2	[dimensionless]	[0 10000]	8176.69	2548.91	683.67	0.27	●
Cycle Duration	[s]	[0 14000]	6191.33	1775.50	346.84	0.20	●

**Figure 2.13:** Evaluation table (phase 0 - Snake)

In this table we chose to put in the evaluation table (from left to right) *RMSE mean*, *NRMSE mean*, *mean value of signal* (the acquired one), *Standard deviation*, *Range of signal* and *Performance*.

A particular look has to be carried out for Performance item. The legend of "traffic lights" is the following

- NRMSE mean: 0 – 0.1
- NRMSE mean: 0.11 – 0.4
- NRMSE mean: 0.41 – 0.8
- NRMSE mean: > 0.8

**Figure 2.14:** Evaluation table legend

As for previous comparison, legend divides (with mean NRMSE as KPI) good and bad simulated signals, making it clear a performance without an analysis of numerical results.

We can divide output signals into four groups:

- **Bad performance:** *drum exit temperature, motor speed and motor feature signal*
- **Medium performance:** *condenser exit temperature (refrigerant side and air one)*
- **Good performance:** *laundry moisture, condensed water, delta hat and normalized delta hat, cycle duration*
- **Excellent performance:** no signals

It is important to highlight cycle duration evaluation, since is a not considered variable in the first comparison (for the explanation of its presence in evaluation, see section "Signal cut").

#### 2.7.4 Mean NRMSE evaluation for load condition

A load condition is a laundry feature and consists in a wording to identify the typology of laundry in a specific test (laundry material, ...).

For Snake comparison, respect to the first one, it was decided to also make a load condition evaluation, in particular using mean NRMSE as KPI. This decision is due to different importance between two comparison; Snake comparison is more important because gives a performance picture in the environment in which company models are used.

A load condition analysis allows to highlight if model problems are present in all tests or if they are limited at one specific case.

	4 Kg Load1	8 Kg Load1	4 Kg Load2	8 Kg Load2	5.6 Kg Load3	3.5 Kg Load4	6 Kg Load5	4 Kg Cold load	4 Kg Hot load	8 Kg Cold load	8 Kg Hot Load
Motor speed	0.99	0.85	0.74	0.9	1.03	2.10	2.70	1.14	0.82	1.07	0.95
Laundry moisture	0.16	0.11	0.15	0.12	0.14	0.14	0.12	0.50	0.34	0.46	0.15
Temperature of condenser exit (air side)	0.55	0.44	0.57	0.48	0.58	0.61	1.71	0.72	0.59	0.73	0.38
Temperature of condenser exit (refrigerant side)	0.77	0.72	0.75	0.74	0.81	0.72	1.77	0.40	0.51	0.37	0.40
Temperature of drum exit	0.91	1.03	0.89	0.98	0.84	0.78	1.40	0.80	0.25	0.78	0.29
Motor feature signal	0.28	2.35	0.29	2.35	1.07	0.23	0.56	0.11	0.03	0.67	0.67
Condensed water	0.19	0.46	0.16	0.39	0.18	0.10	0.12	0.05	0.08	0.07	0.12
Humidity sensor 1	0.17	0.72	0.39	0.34	0.27	0.22	0.17	0.10	0.11	0.05	0.06
Humidity sensor 2	0.13	0.37	0.17	0.37	0.25	0.18	0.06	0.07	0.09	0.06	0.09
Cycle Duration	0.07	0.26	0.10	0.23	0.10	0.19	0.04	0.06	0.08	0.11	0.07

Figure 2.15: Load condition evaluation table (phase 0 - Snake)

It is easy to note that, in general, four load conditions that enclose the use of climatic chamber are (surprisingly) the best. This is probably due to a lucky circumstance, since these four load condition should be the most difficult to simulate; so their good results are not synonymous with good model.

The worst load condition is Universal; we expected this result since it is a critical case on a par with test in climatic chamber.

## 2.7.5 Boxplot analysis

It is possible to note that (obviously) this analysis is similar to first one; this fact is important since allows to verify good implementation of timeseries. As regards Fig. 2.16, boxplots are similar but not equal (Snake model is that effectively used in Electrolux, while Timeseries model is only to evaluate easier the performances). As first comparison, for outliers, the worst simulated signal is motor feature one, but as regards mean NRMSE the worst one is motor speed signal.

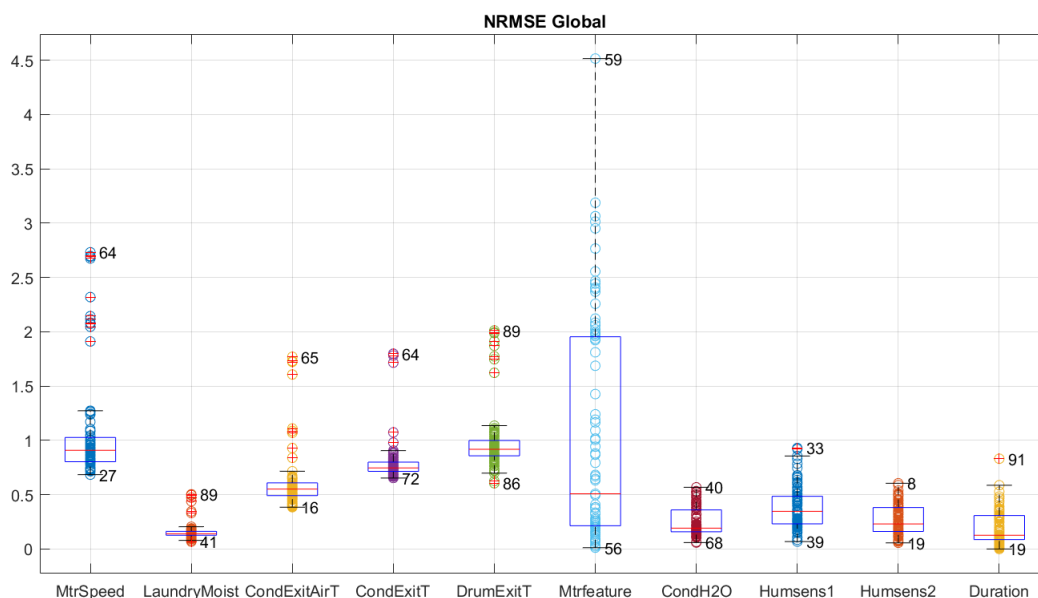


Figure 2.16: Boxplot analysis (phase 0 - Snake)



# Chapter 3

## Phase 1

### 3.1 What is sensitivity analysis?

Sensitivity analysis [3] is the study of how the uncertainty in the outputs of a mathematical model or system can be divided and allocated to different sources of uncertainty (in our case sources are model parameters). The sensitivity analysis is useful for:

- testing the robustness of the results of a model
- increased understanding of the relationships between model parameters and model output
- uncertainty reduction
- model simplification, searching model parameters that have no effect on outputs, or identifying and removing redundant parts of the model
- calibrate a model with large number of parameters, a sensitivity analysis can ease the parameters tuning by focusing on the most important parameters, not spending time on non-sensitive ones.

All these features lead to develop a better model.

Quite often, some parts of the model are subject to sources of uncertainty, including errors of measurement, absence of information and poor or partial understanding of the driving forces and mechanisms. This uncertainty imposes a limit on our confidence with model outputs.

Good modeling practice requires that the modeler provide an evaluation of the

confidence in the model. Sensitivity analysis addresses the issues, performing the role of ordering by importance parameters and the part of the model in which are "lived".

Typical constraints of a sensitivity analysis are:

- **Computational time:** sensitivity analysis is almost always performed by running the model a (possibly large) number of times, thus with a sampling-based approach. This can be a significant problem if a single run of the model takes a significant amount of time; also little minutes to run the model, if multiplies with a large number of simulations, imply many computational time. This problem is known as the curse of dimensionality<sup>1</sup>. To limit this constraints are often used some methods of reducing computational expense include the use of screening methods (for reducing the dimensionality of the problem)
- **Precision of model analysis:** this constraint is the opposite of computational time. To obtain a good precision it must use more computational time, and vice versa. An optimal range of precision is very important to give value to sensitivity analysis results; without precision is not possible be sure and this may involve future wrong modifications of the model

On these items we will build our sensitivity analysis and in particular we will use Morris method (Campolongo version) to implement it. This method is based on OAT approach and elementary effects method (that it is a screening method). We will use following subsections to explain this approach/method.

### 3.1.1 OAT approach

The logic of one-at-a-time (OAT) approach is to move one parameter, keeping others at their baseline (nominal) values, then, returning the parameter to its nominal value, then repeating for each of the other parameters in the same way. Sensitivity may be measured by monitoring changes in the outputs.

This appears a logical approach so that any change observed in the outputs will unambiguously be due to the single variable changed. Furthermore, by changing one parameter at a time, one can keep all other parameters fixed to their central or baseline values. This minimizes the chances that MATLAB crashes, more likely when several factors are changed simultaneously.

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<sup>1</sup>The expression "the curse of dimensionality" was coined by Richard E. Bellman when considering problems in dynamic programming. It denotes the problem that evaluating an extra model feature, computational time increases exponentially

Despite its simplicity however, this approach does not fully explore the input space, since it does not take into account the simultaneous variation of input variables. This means that the OAT approach cannot detect the presence of interactions between input variables.

### 3.1.2 Screening

Screening is a particular instance of a sampling-based method. The objective here is rather to identify which parameters are contributing significantly to the outputs uncertainty, rather than exactly quantifying sensitivity.

Screening tends to have a relatively low computational cost when compared to other approaches. One of the most common screening method is the elementary effect method.

#### Elementary effects method

The elementary effects (EEs) method is the most used screening method in sensitivity analysis. Like all screening, the EEs method provides qualitative sensitivity analysis measures (so it allows to rank parameters in order of importance respect to the outputs), but do not quantify exactly the relative importance of the parameters. A elementary effect is defined as

$$d_i(X) = \frac{Y(X_1, \dots, X_{i-1}, X_i + \Delta, X_{i+1}, \dots, X_k) - Y(X)}{\Delta} = \frac{Y(X_\Delta) - Y(X)}{\Delta} \quad (3.1)$$

where  $i$  is the current simulation number,  $Y(X)$  and  $Y(X_\Delta)$  are respectively the calculated outputs with nominal parameter values and vector with one modified parameter value,  $\Delta$  is the difference between nominal value and new parameter value.

The original EEs method of Morris provides two sensitivity measures for each input factor:

- 

$$\mu_i = \frac{1}{r} \sum_{j=1}^r d_i(X^{(j)}) \quad (3.2)$$

where  $r$  is the number of considered points and  $d_i(X)$  is the specific elementary effect. This measure, that is the mean of EEs, allows to understand how much important is the parameter for the outputs

•

$$\sigma_i = \sqrt{\frac{1}{r-1} \sum_{j=1}^r (d_i(X^{(j)}) - \mu_i)^2} \quad (3.3)$$

This measure, that is the standard deviation of EEs, allows to evaluate parameter interactions and non-linear effects

In this sensitivity analysis it was used the Campolongo version of this method that allows a greater robustness of the analysis. The difference respect the classic Morris method is the use of abs in the  $\mu$  calculation. The new formula is the following

$$\mu_i = \frac{1}{r} \sum_{j=1}^r |d_i(X^{(j)})| \quad (3.4)$$

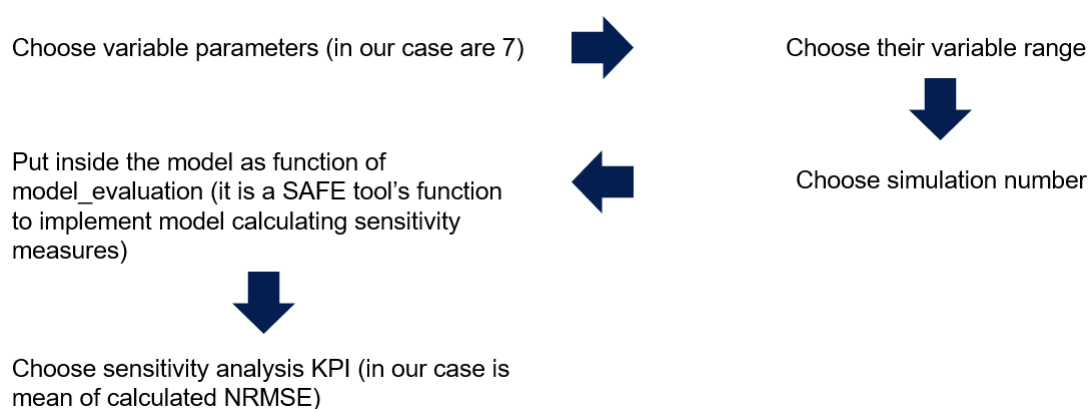


## 3.2 SAFE Tool

To implement sensitivity analysis with Morris method it was used SAFE Tool [7] in which some tools for this type of sensitivity analysis are already present.

### 3.2.1 Sensitivity analysis steps

There are a large number of approaches to performing a sensitivity analysis. For our case we will use the approach in Fig. 3.1.



**Figure 3.1:** Explanation of sensitivity analysis steps

### List of sensitivity analysis parameters

The first step of described approach is to choose sensitivity analysis parameters. After some consideration and some preliminary sensitivity analysis it was chosen to vary seven parameters that were considered the most important parameters of the model. As you can see in Fig. 3.2 chosen parameters can be enclosed in four groups:

- **Exchange powers:** evaporator exchange power and condenser exchange power are very important for the model. They allow to simulate heat-pump and enclose all its information
- **Volumetric flow of holes:** in every dryer there are some air leakage. The old MATLAB/Simulink simulate all these leakage with two holes in which get out air, and one hole in which go in air. To have a more clear idea, it is

possible to see Fig. B.1 in Appendix B. These two parameters are two holes in which get out air, one downstream of the drum and the other one at the exit of the drum

- **Evaporation laundry coefficient:** this coefficient depends on laundry type and dynamic of the drum. To calculate it we use its dependence by moisture laundry rate (MLR), so water Kg in laundry divide by total laundry amount. The equation is:

$$k = a * MLR + b \quad (3.5)$$

where  $k$  is the evaporation laundry coefficient,  $a$  is a multiplicative constant and  $b$  is an additive constant

- **Max volumetric flow of the fan:** as the name tells, it is the maximum value of fan volumetric flow

	VARIABLE	PARAMETER VALUE (PV)
1	Evaporator exchange power	1.70 [KW]
2	Condenser exchange power	2.40 [KW]
3	Volumetric flow of the hole downstream of the drum	5 [m <sup>3</sup> /h]
4	Volumetric flow of the hole to the exit of the drum	5 [m <sup>3</sup> /h]
5	Evaporation laundry coefficient (multiplicative value)	0.015
6	Evaporation laundry coefficient (additive value)	0.0003
7	Max volumetric flow of the fan	255 [m <sup>3</sup> /h]

**Figure 3.2:** List of sensitivity analysis parameters

### Variable range

Another important choice is that regards the range of variability for the parameters. It needs to evaluate two important constraints:

- **Parameter range:** it is important do not change a parameter out of its normal range. For example we have a parameter that usually has values from 1 to 5, it is not correct to make a simulation with a parameter value equals to 0.4

- **MATLAB crash:** chosen range do not have to be too much big since a greater parameter variability implies a greater crash probability

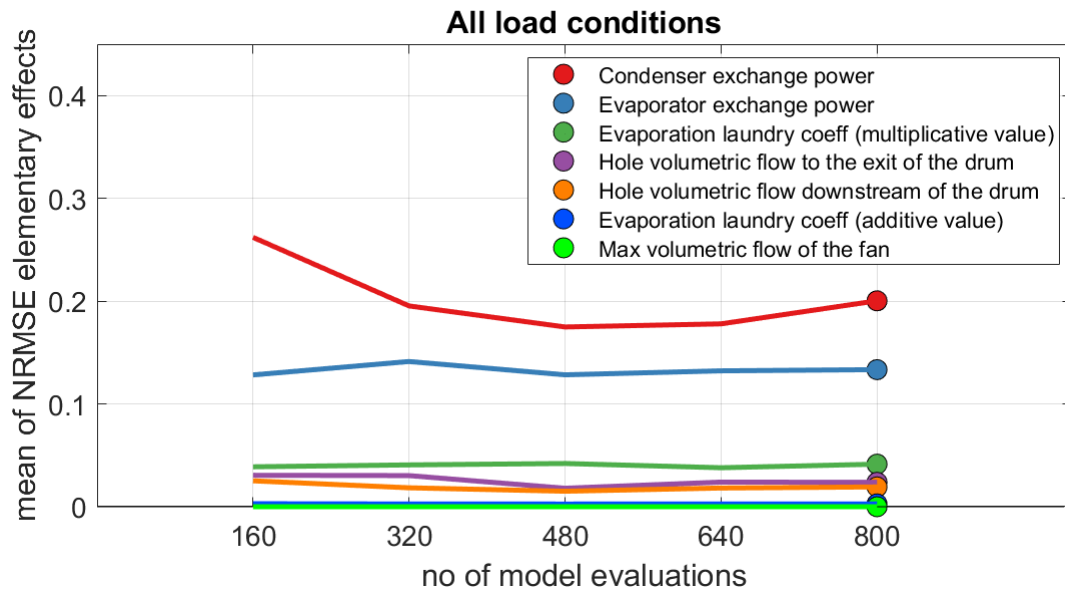
Taking into account all these considerations, we choose a range of  $\pm 15\%$  of nominal value.

### Simulation number issue

The simulation number issue contains the conflict between computational time and precision of model analysis. As regards EEs method, the simple formula to find total simulation number is

$$N = r * (M + 1) \quad (3.6)$$

where  $r$  is the number of variations for each parameter,  $M$  is the number of sensitivity analysis parameters and  $N$  is the total simulation number.



**Figure 3.3:** Graph for verification of the simulation number

For our project we tried various values of  $r$  and at the end we use a range value equals to 50-100. To verify the quality of our parameters we can analyzed different value of  $\mu$  (mean of EEs) during run of sensitivity analysis. As it is possible to see in Fig. 3.3 it was chosen to take five sample points equally spaced between

them (160, 320, 480, 640, 800 in the figure) to evaluate  $\mu_i$  in the time simulation; if, as in figure,  $\mu_i$  values become similar-constant, then the precision of sensitivity analysis can be considered adequate.

### **Model evaluation**

After having implemented previous steps, now we can put into SAFE tool project model (that it was specifically parameterized<sup>2</sup>, so that during sensitivity analysis the chosen parameters were able to vary smoothly). This process was a delicate task since there were different level of workspace and having to repeat more times the same code (one time for every parameter variation) the MATLAB global variables are not always able to work properly.

### **KPI choice**

For a sensitivity analysis needs a KPI on which evaluating EEs. In our case we chose mean NRMSE since we used it as the most important KPI also for comparison, and in general during whole of the project.

---

<sup>2</sup>A MATLAB model is parameterized when the whole model can be controlled with some parameters whose values can be modified through an external support script

## 3.3 Sensitivity analysis

In the following subsection we will tell sensitivity analysis results. It was chosen to make two different analysis:

- **For laundry load condition**
- **For signal output**

Both analysis types are useful since allows to see possible dependencies and issues. The aim of these two sensitivity evaluations is to study the model in detail.

Moreover, in this moment we have a black-box model with look up tables (in reality there are some "white" parts that corresponds to thermodynamic process), so this approach allows us to understand better the whole functioning.

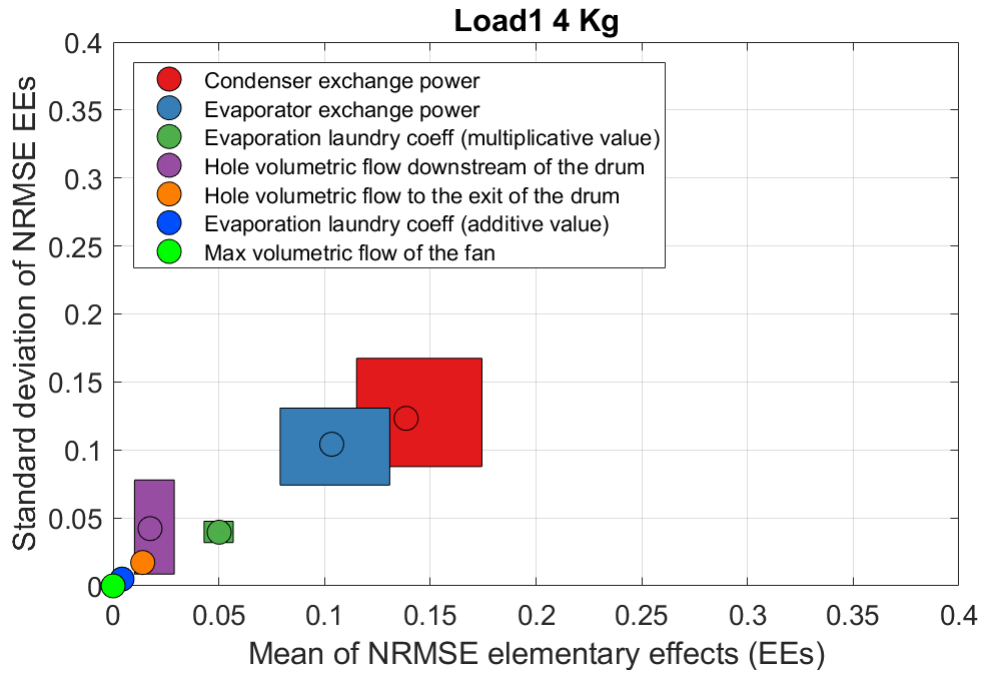
After these two analysis steps we will also make a general sensitivity analysis, comparing it with other results, and a consideration summary.

### 3.3.1 Sensitivity analysis for load condition

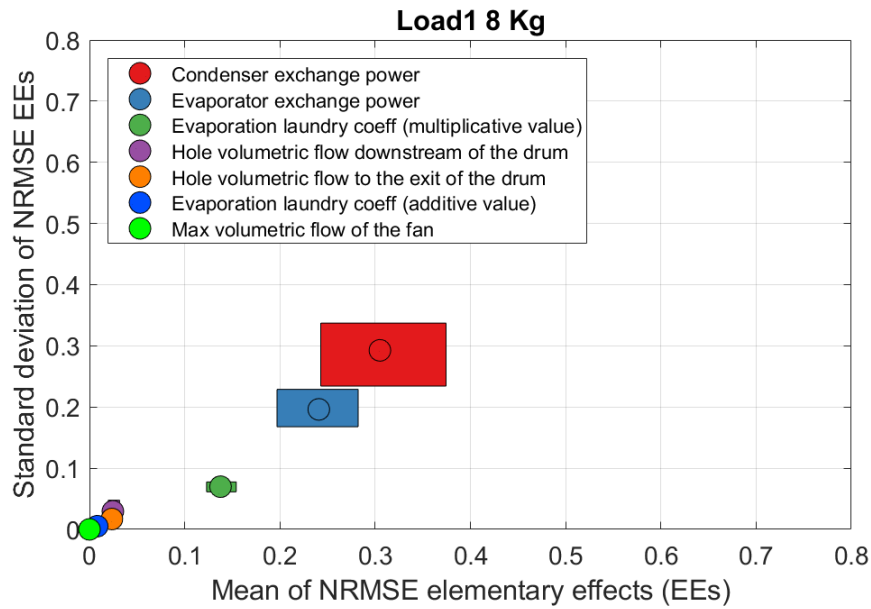
As we can see in Appendix A, the analyzed load conditions during the project are the following:

- Load1 4 Kg
- Load1 8 Kg
- Load2 4 Kg
- Load2 8 Kg
- Load3 5.6 kg
- Load4 3.5 Kg
- Load5 6 Kg
- Cold climatic chamber load 4 Kg (environment temperature equals to  $5^{\circ}C$ )
- Hot climatic chamber load 4 Kg (environment temperature equals to  $35^{\circ}C$ )
- Cold climatic chamber load 8 Kg (environment temperature equals to  $5^{\circ}C$ )
- Hot climatic chamber load 8 Kg (environment temperature equals to  $35^{\circ}C$ )

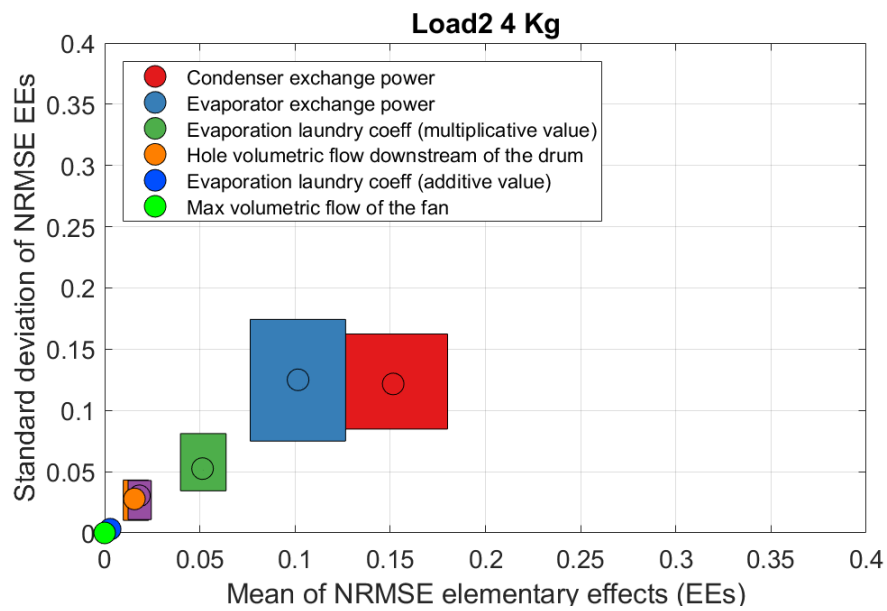
Each of these load condition has different features (threshold, switch rule, ...), program, load, laundry type (cotton, mixed, ...), laundry amount, environment temperature (standard one is  $23^{\circ}C$ ). For these motivations it is not obvious that all will give same results. For analyzing the following figures, it is useful to know that different scales were used, so from give visibility to image features.



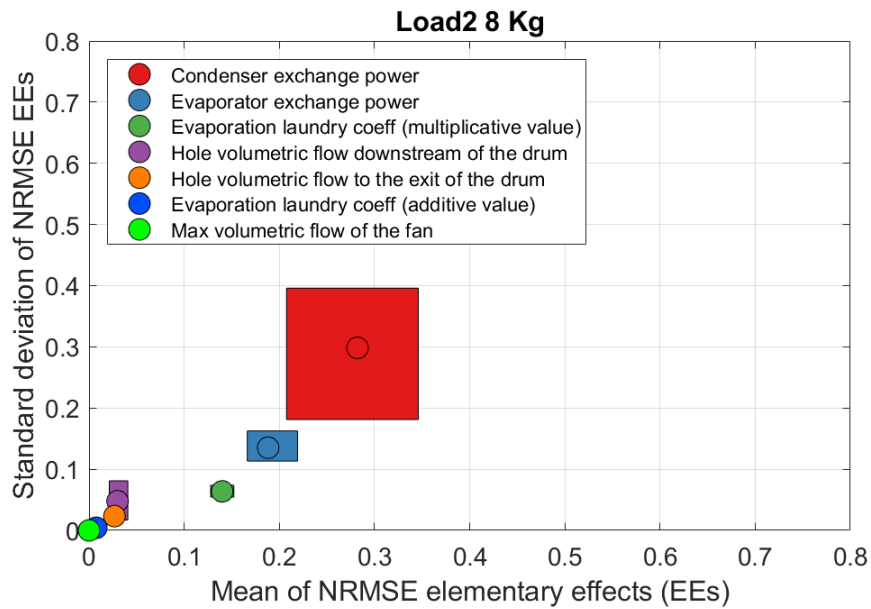
**Figure 3.4:** Sensitivity analysis for Load1 4 Kg



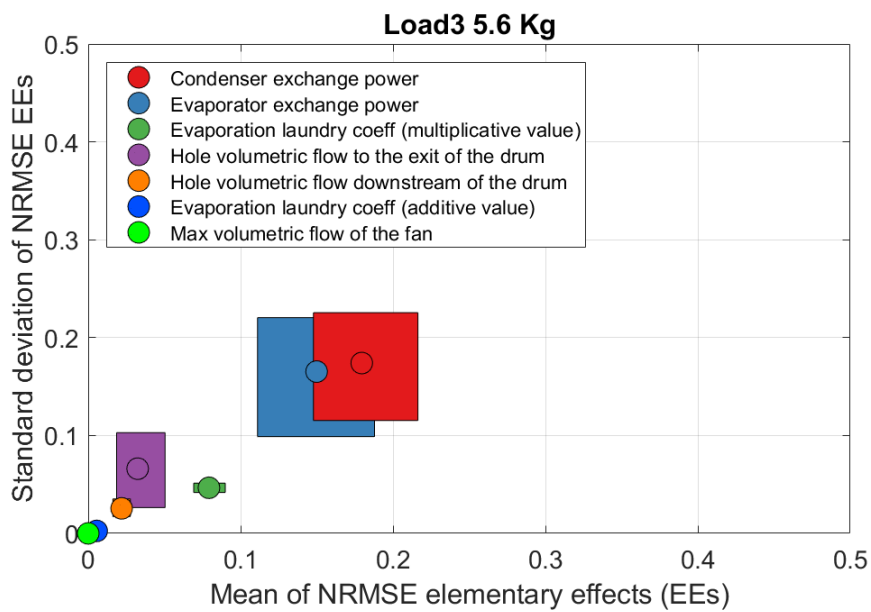
**Figure 3.5:** Sensitivity analysis for Load1 8 Kg



**Figure 3.6:** Sensitivity analysis for Load2 4 Kg

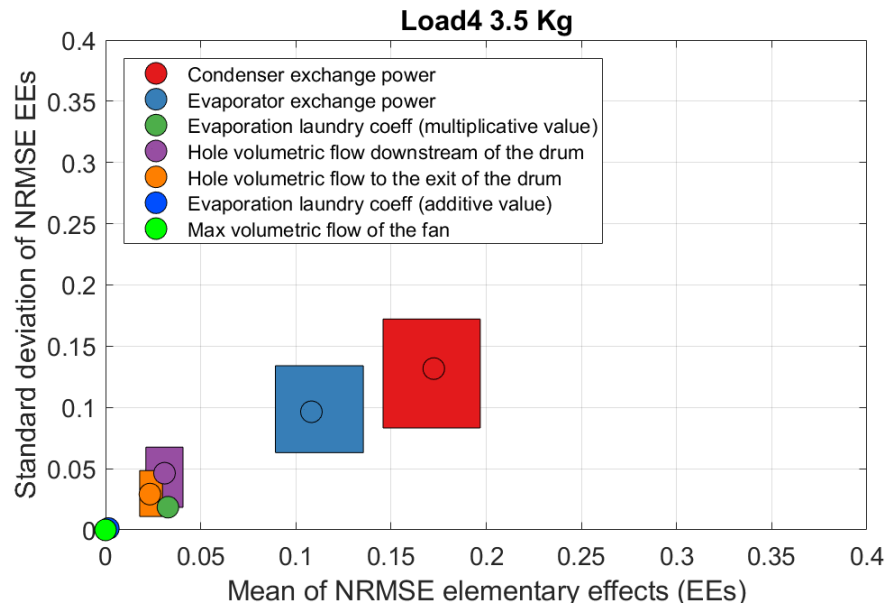


**Figure 3.7:** Sensitivity analysis for Load2 8 Kg

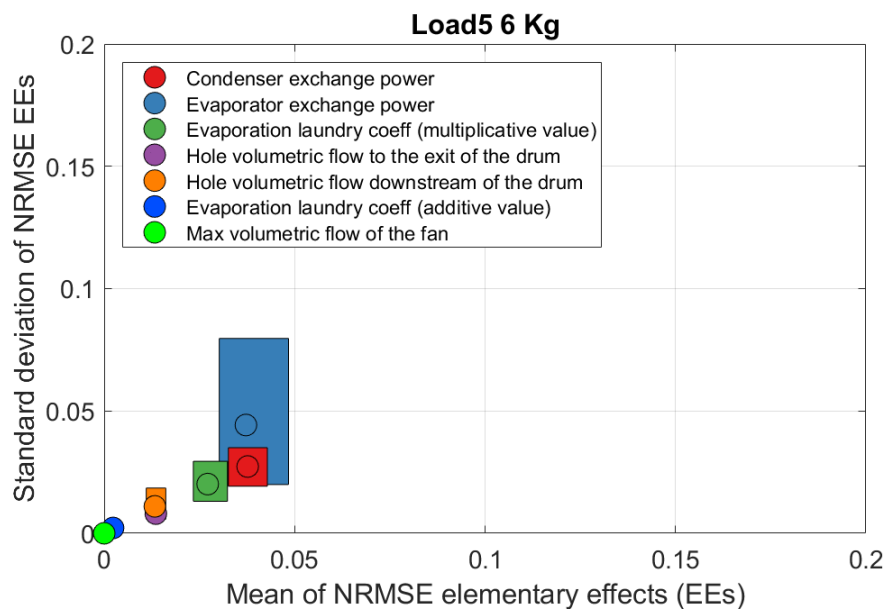


**Figure 3.8:** Sensitivity analysis for Load3 5.6 Kg

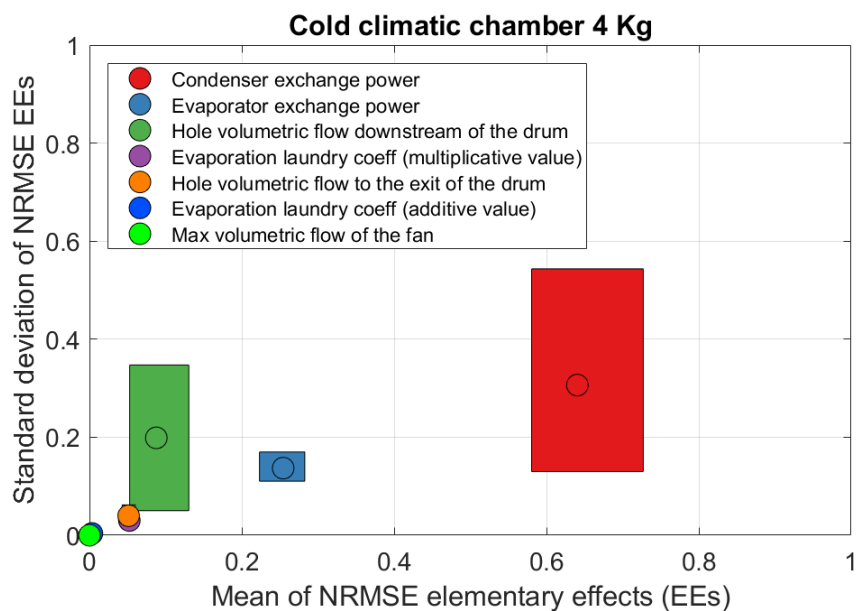




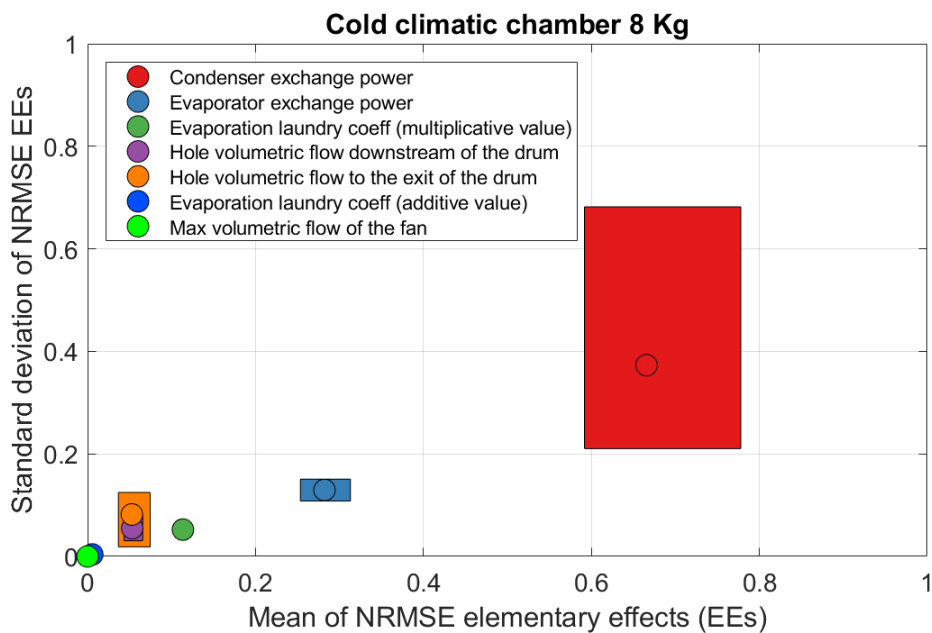
**Figure 3.9:** Sensitivity analysis for Load4 3.5 Kg



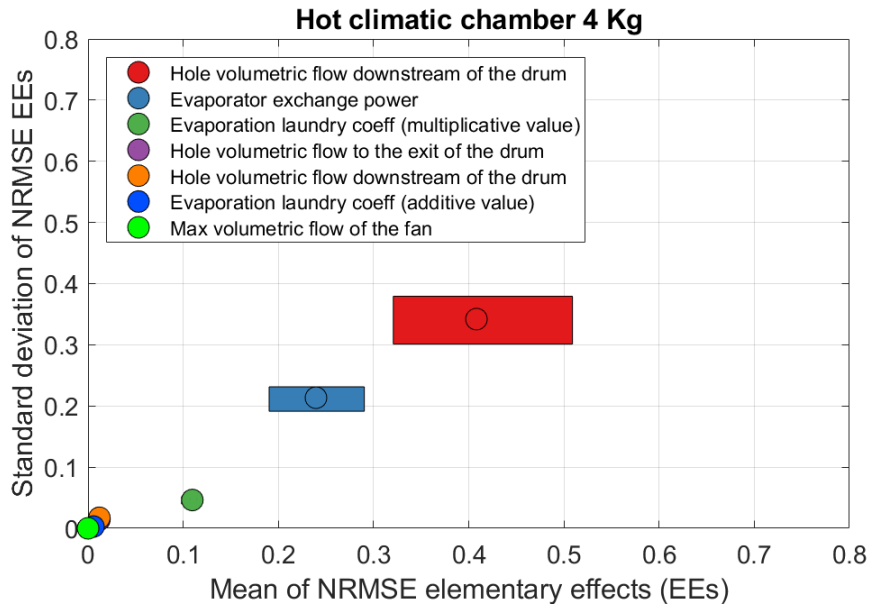
**Figure 3.10:** Sensitivity analysis for Load5 6 Kg



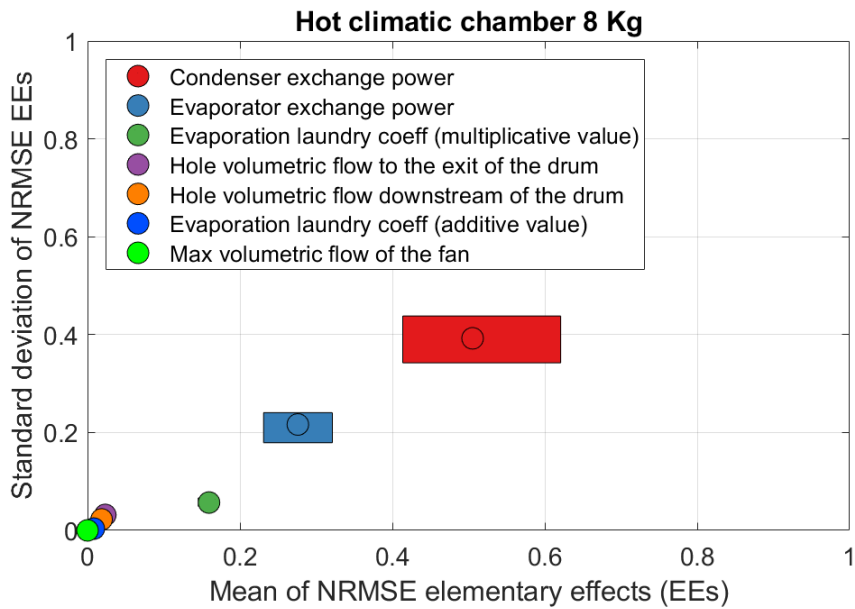
**Figure 3.11:** Sensitivity analysis for Cold climatic chamber load 4 Kg



**Figure 3.12:** Sensitivity analysis for Cold climatic chamber load 8 Kg



**Figure 3.13:** Sensitivity analysis for Hot climatic chamber load 4 Kg



**Figure 3.14:** Sensitivity analysis for Hot climatic chamber load 8 Kg

### 3.4 Sensitivity analysis for signal

As for sensitivity analysis for laundry load condition, this section will be only used for sensitivity analysis graphs. All considerations will make in next section.

For this sensitivity analysis we considered seven of nine output signals; in particular two motor signal (motor feature and motor speed) were not enclosed in evaluation since are divided by model heart, and chosen sensitivity analysis parameters do not influence these outputs. To recap, considered signals are:

- Laundry moisture
- Temperature of condenser exit (air side)
- Temperature of condenser inlet (refrigerant side)
- Temperature of drum exit
- Condensed water
- Humidity sensor 1
- Humidity sensor 2

Following, as sensitivity analysis for load condition, figures can be different scales to give priority to image features.

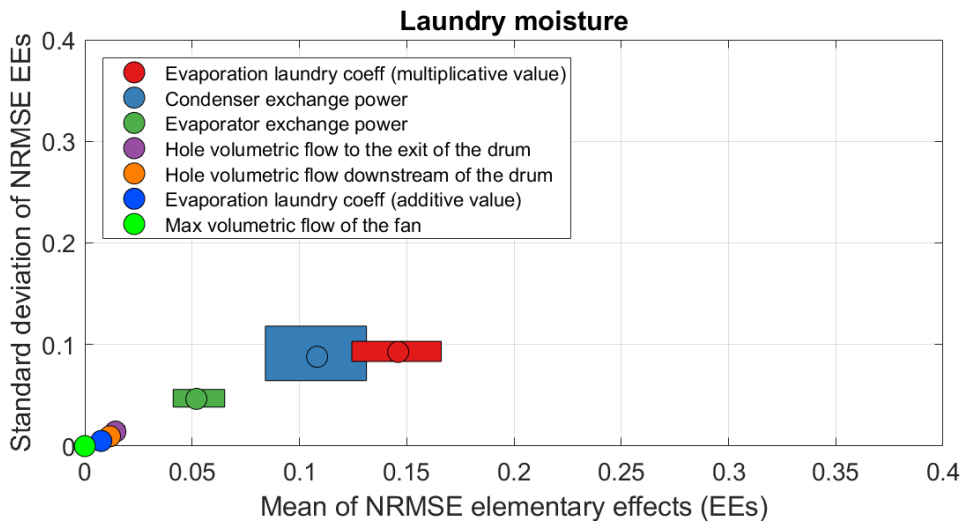
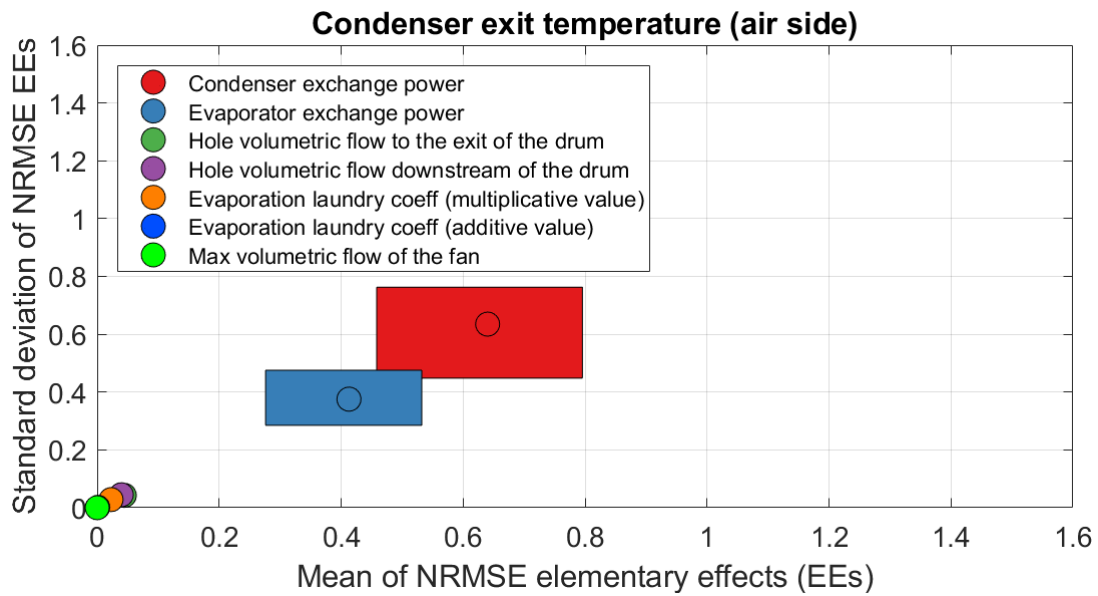
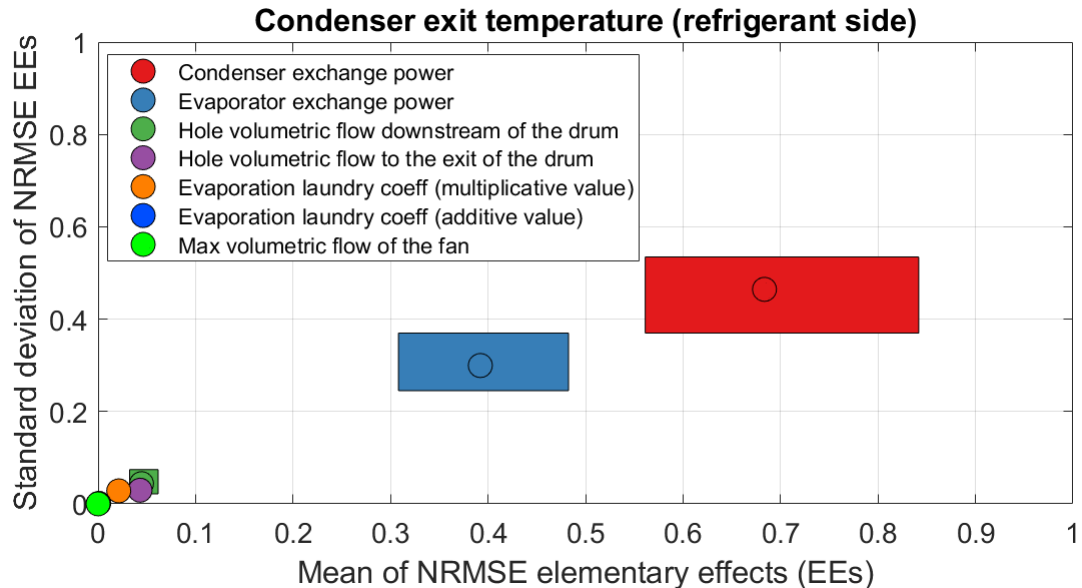


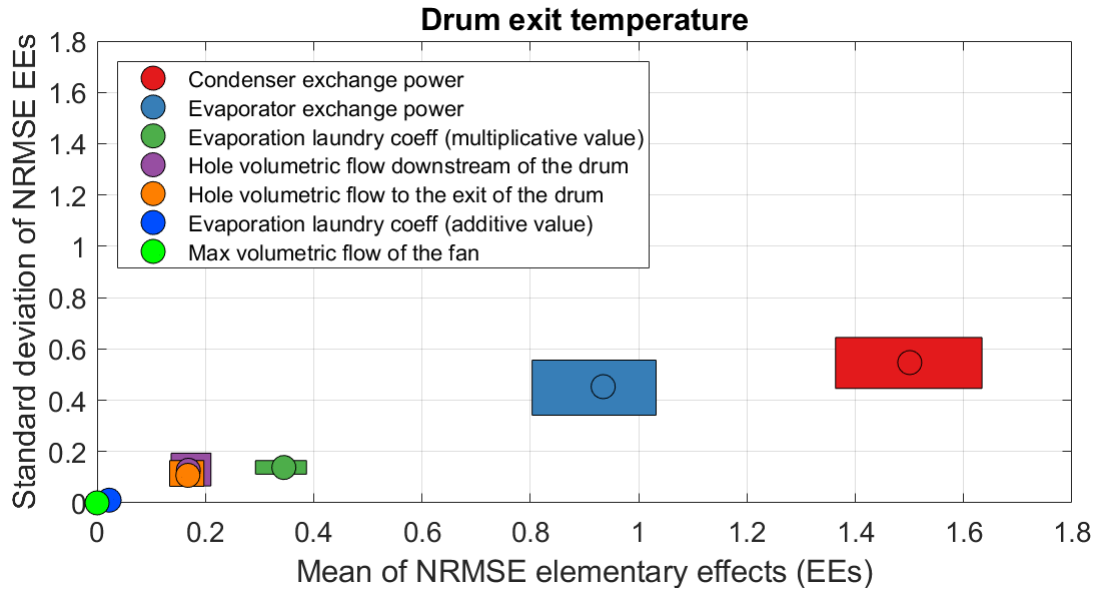
Figure 3.15: Sensitivity analysis for Laundry moisture



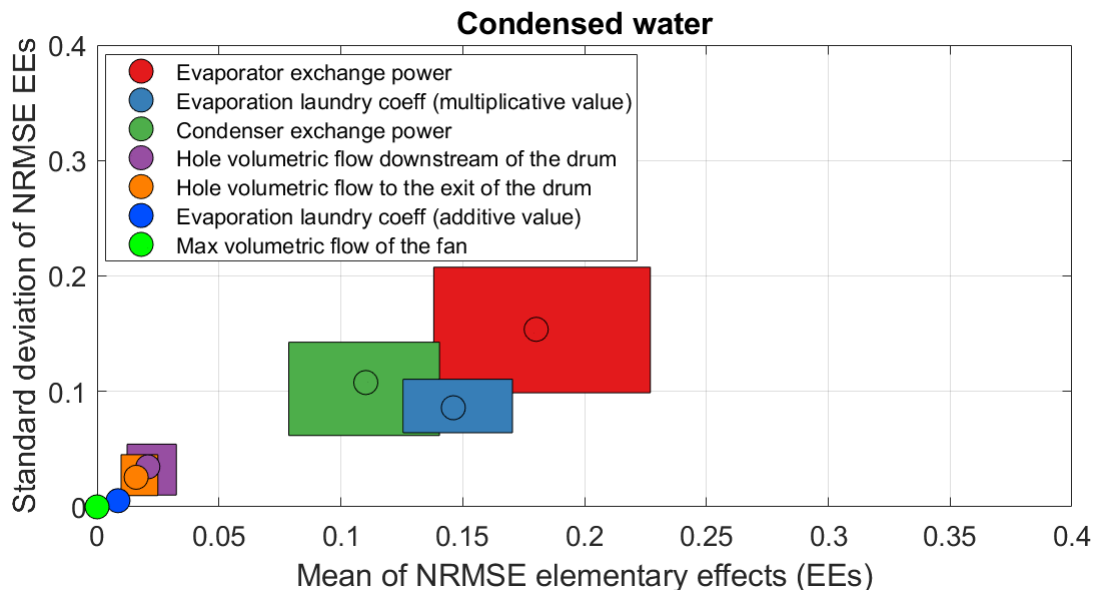
**Figure 3.16:** Sensitivity analysis for Temperature of condenser exit (air side)



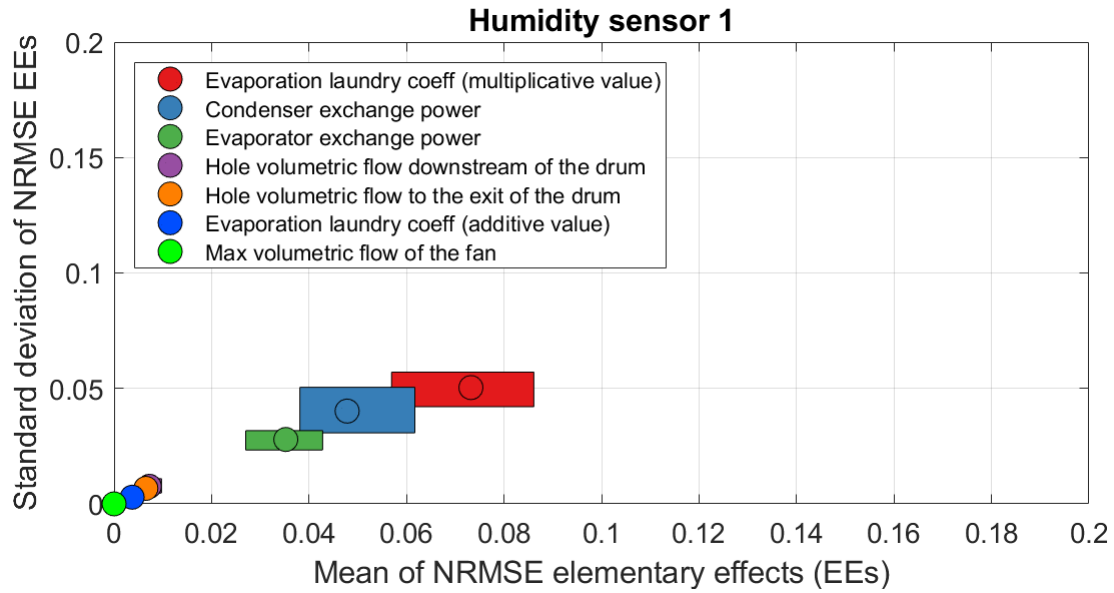
**Figure 3.17:** Sensitivity analysis for Temperature of condenser inlet (refrigerant side)



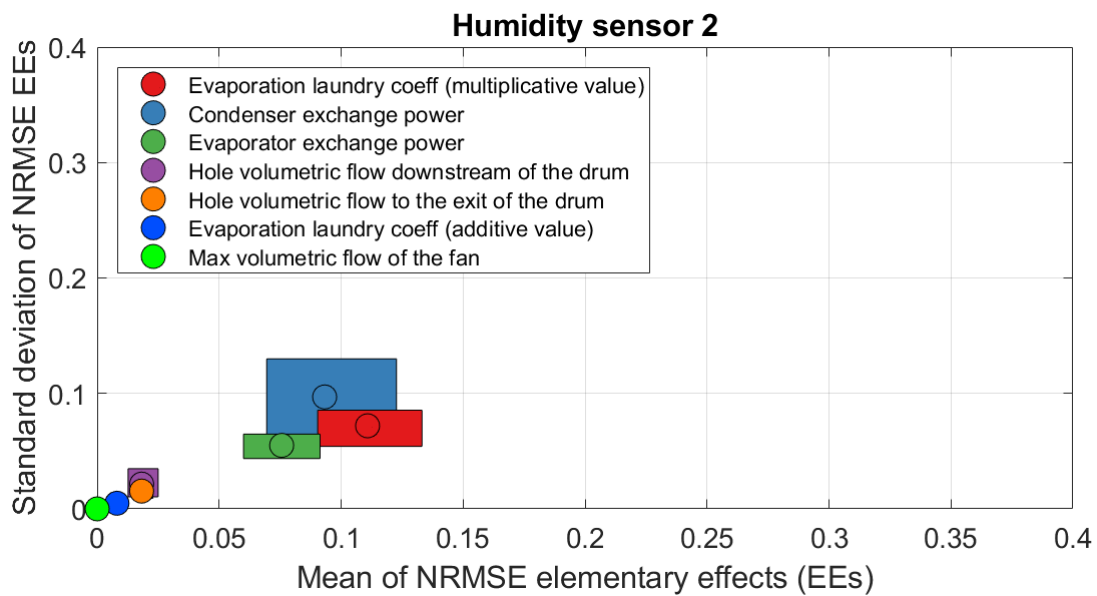
**Figure 3.18:** Sensitivity analysis for Temperature of drum exit



**Figure 3.19:** Sensitivity analysis for Condensed water



**Figure 3.20:** Sensitivity analysis for Humidity sensor 1



**Figure 3.21:** Sensitivity analysis for Humidity sensor 2

### 3.5 Sensitivity analysis summary

In this final chapter section main results and considerations will be listed and summarized briefly.

The sensitivity analysis highlights that the most important parameters are (in order of importance):

- 1) condenser exchange power
- 2) evaporator exchange power
- 3) multiplicative constant of evaporated water coefficient in the drum
- 4) hole volumetric flows

This indication allow so understanding the most important manipulators of the model and gives a priority order for future modifications.

Moreover, it is possible to note an influence on results due to

- laundry load amount
- range of the signal (for sensitivity analysis is divided signal by signal)

and a presence of two parameter "couples" (with similar EEs measures for all made sensitivity analysis), so

- exchange power couple (anyway in general condenser one is a little bit more important)
- hole volumetric flow couple

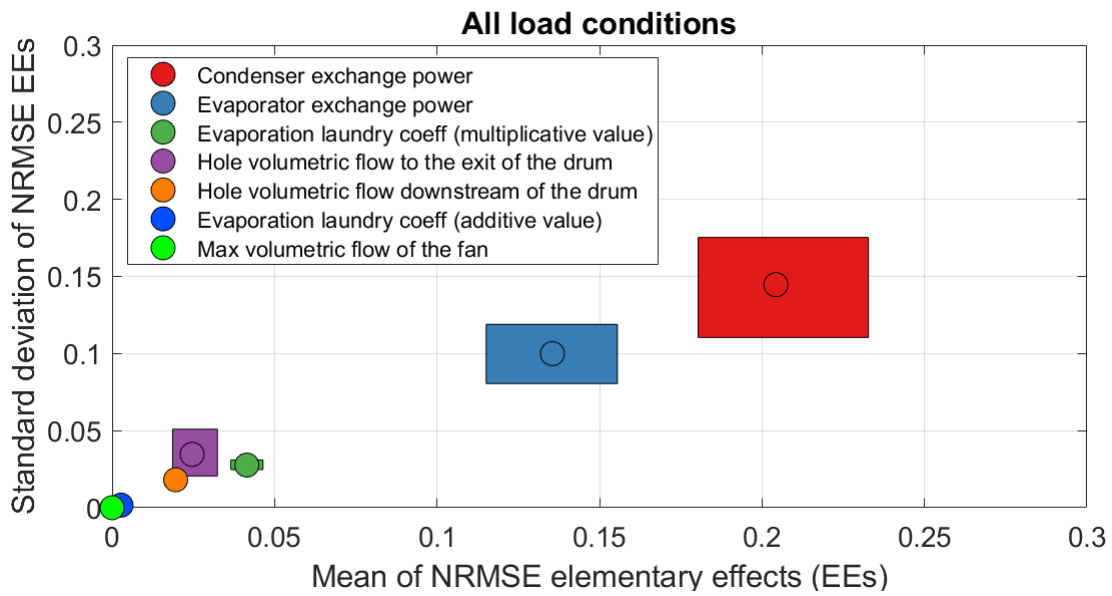
As regards the difference between various sensitivity analysis, it is possible to tell that there are not big ones; importance rank is almost always the same. However making various types of evaluation is a significant step for a sensitivity analysis, since gives possibility to differentiate operation approach for different future modification aim.

The only deviation of interest is present in temperature of condenser exit (air side) analysis and temperature of condenser inlet (refrigerant side) analysis; in this two sensitivity analysis hole volumetric flows are more important than evaporated water coefficient  $k_{ev}$ . This fact is reasonable since  $k_{ev}$  is a coefficient of drum, while these temperatures are to inlet and exit of condenser.

To verify even more considerations of this section, we made a general sensitivity



analysis (for all load conditions and signals). In Fig. 3.22, it is possible to see its Morris graph that confirms given importance order of sensitivity analysis parameters.



**Figure 3.22:** General sensitivity analysis



# Chapter 4

## Phase 2

### 4.1 Code improvements

#### 4.1.1 Black-box model

A black-box model is a model for which interior behaviour is not completely known. In particular, as regards our model, this not clear part consists of look up tables (for example with an interpolation and a look up table we find component temperature with the knowledge of enthalpy and specific humidity). For this motivation in the following sections we work to make more clear the model with some physical formula.

#### 4.1.2 Look up table vs Physical formula

The advantages of a physical formula are several but we can concentrate on three aspects:

- make more clear the model for future modelers
- avoid (or however decrease) the problem of operation range. A look up table is able to find a value as long as its size. Instead, a physical formula has not MATLAB operation range but only a possible physical range. This fact is very important for a MATLAB modeler since allows to avoid MATLAB crash for out of range problem
- increasing of physical base. This fact is very important for future modeler too; a physical base allows to make a general model, also if this model was conceived for a specific machine

The most important changing to increase physical base in our model were:

- 

$$T = \frac{(\frac{h}{4.184} - 596 * x)}{0.24 + 0.46 * x} \quad (4.1)$$

where  $T$  is the temperature in  $^{\circ}C$ ,  $h$  is the enthalpy in Joule and  $x$  is the specific humidity in  $Kg/Kg$

- 

$$P_{sat} = exp[65.81 - \frac{7066.27}{T + 273.15} - 5.976 * ln(T + 273.15)] \quad (4.2)$$

where  $P_{sat}$  is the pressure of saturation in Pascal and  $T$  is the temperature in  $^{\circ}C$

- 

$$h = (h_a + h_v) * 4.184 = (T * 0.24 + x * (596 + 0.46 * T)) * 4.184 \quad (4.3)$$

where  $h$  is the enthalpy in Joule,  $h_a$  is the specific enthalpy of dry air and  $h_v$  is the specific enthalpy of water vapour

Before to finish this section, by way an example it is possible to see a replaced look up table in Fig. 4.1.

```
T = [-10 30 70 110];
x = [0.0001 0.001 0.08 0.15 0.3];

h = [ -9.81      30.44      70.68      110.93 ;
      -7.58      32.73      73.05      113.36 ;
      188.48     234.57     280.66     326.76 ;
      362.2      413.41     464.62     515.84 ;
      734.45     796.64     858.83     921.02 ];

v = interp1(x, h, xin, 'linear', 'extrap');

Tout = interp1(v, T, hin, 'linear', 'extrap');
```

**Figure 4.1:** Look up table for calculating  $T$  from  $h$  and  $x$

### 4.1.3 Grey-box model

Thanks to physical formula, we obtained a model with some look up table and some formula, so we can tell that now the model is a grey-box one, with all advantages that we told before.

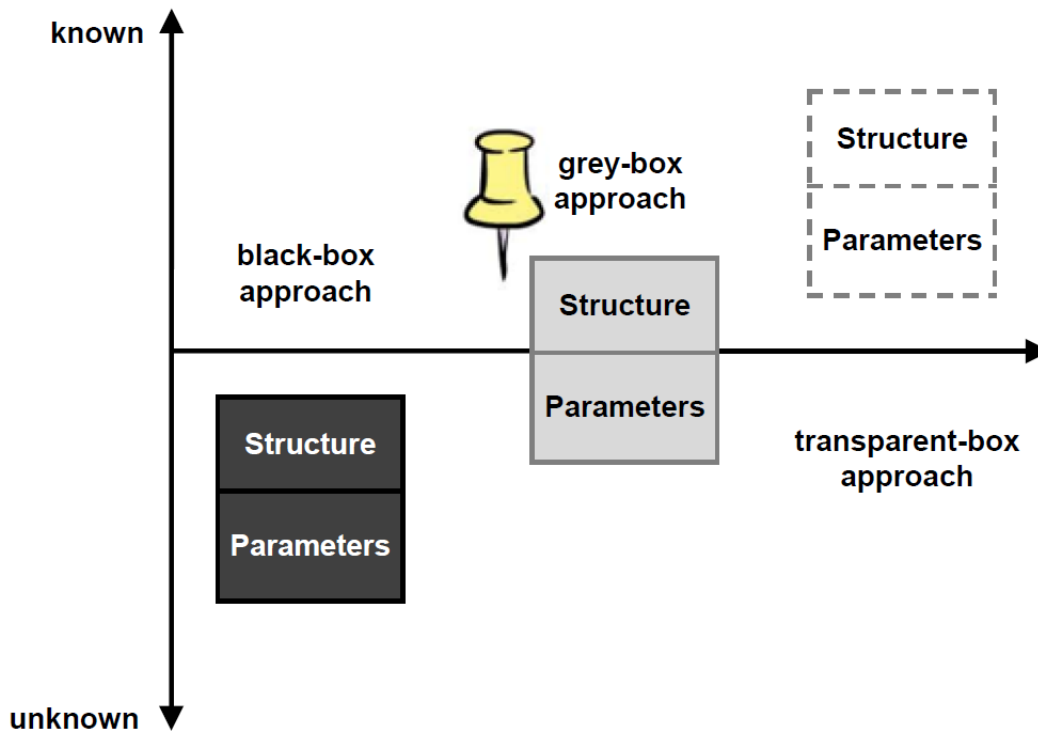


Figure 4.2: Different box model

## 4.2 Least square estimation of motor feature signal

Concluding this work it is necessary to make a modify to the model, for achieving a better motor feature performance. In particular it was chosen to implement a least square estimation.

### 4.2.1 Least square estimation

Least square estimation [9] (LSE) is a method to estimate a signal by data. It is about estimating parameters by minimizing the squared discrepancies between observed data, on the one hand, and their expected values on the other.

The estimated signal  $Y_{stim}$  depends on variation of some variable  $X$  and their coefficients  $K$ . Given the values of  $X$ , the best prediction of  $Y$  is the mean  $f(X)$  (function gives by  $X$  variables and  $K$  coefficients) of  $Y$  given  $X$ . We can summarize this definition in the following formula:

$$Y_{stim} = f(X) = K_0 + K_1X_1 + K_2X_2 + \dots + K_nX_n \quad (4.4)$$

where  $n$  is the number of  $X$  features of output  $Y$ .

We had to decide the features of the output, and using some acquired signal of  $Y$  we found  $K$  values. At the end used LSE formula was:

$$Y_{stim} = K_0 + K_1X_1 + K_2X_2 \quad (4.5)$$

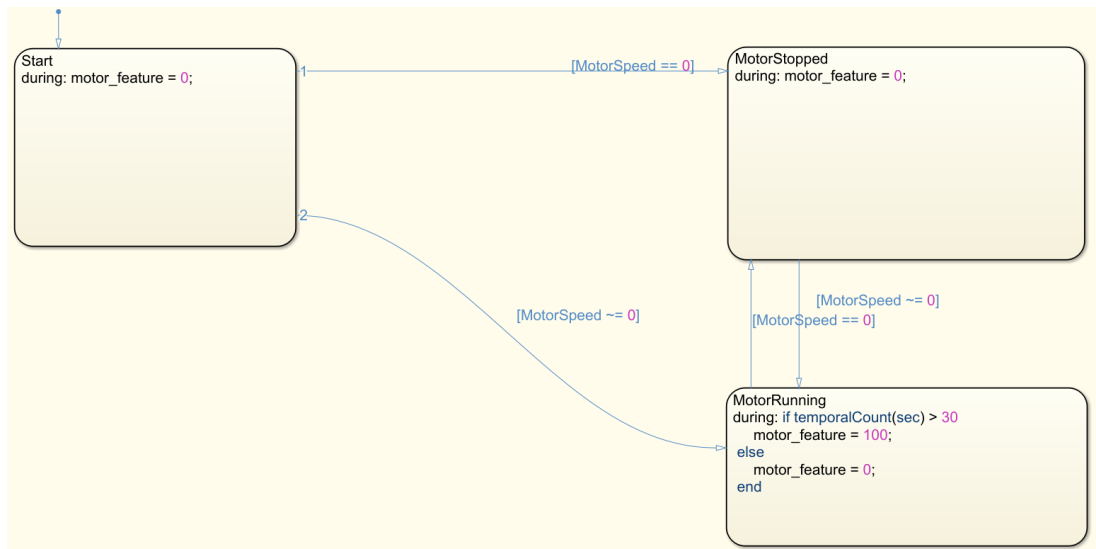
where  $X_1$  is the laundry load amount and  $X_2$  is the laundry initial moisture. As regards  $K$  LSE gave as results

$K_0$	$K_1$	$K_2$
-61.802	39.882	0.466

**Table 1:** Table of  $K$  coefficients

### 4.2.2 Old motor feature calculation

In this subsection it is possible to see old motor feature MATLAB implementation (Fig. 4.3). In practice we wait 30 seconds after motor switch on, and set motor feature signal equals to 100. This approach was enough performing with laundry half-load but not with other load amount.

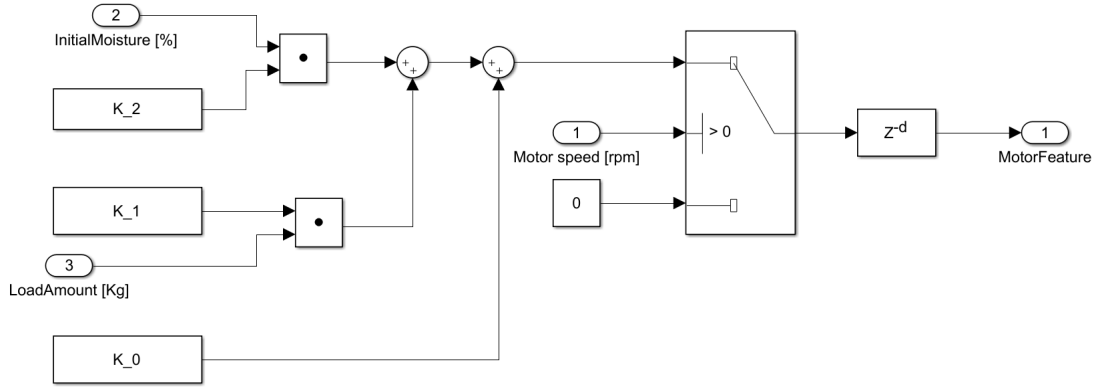


**Figure 4.3:** Old implementation of the motor feature signal

### 4.2.3 New implementation

In new motor feature implementation (Fig. 4.4) we use LSE. As you can see new block is easily a LSE Simulink implementation. However, it is important to note last two parts:

- **Motor speed switch-block:** this block allows to delay the count start. As long as the speed of motor is equal to zero, motor feature signal is all the same; when motor speed is nonzero, motor signal keeps reference value
- **Delay block ( $z^{-d}$ ):** this block allows to delay motor feature signal further, so that simulated signal starts at the same time of acquired one



**Figure 4.4:** New implementation of the motor feature

#### 4.2.4 Comparison of motor feature mean NRMSE

It is possible to compare KPIs before and after the modification. In particular it was chosen to use mean NRMSE as key performance index. The results are written in the following table.

Before modification	After modification
1	0.28

**Table 2:** Table of motor feature signal comparison (mean NRMSE)

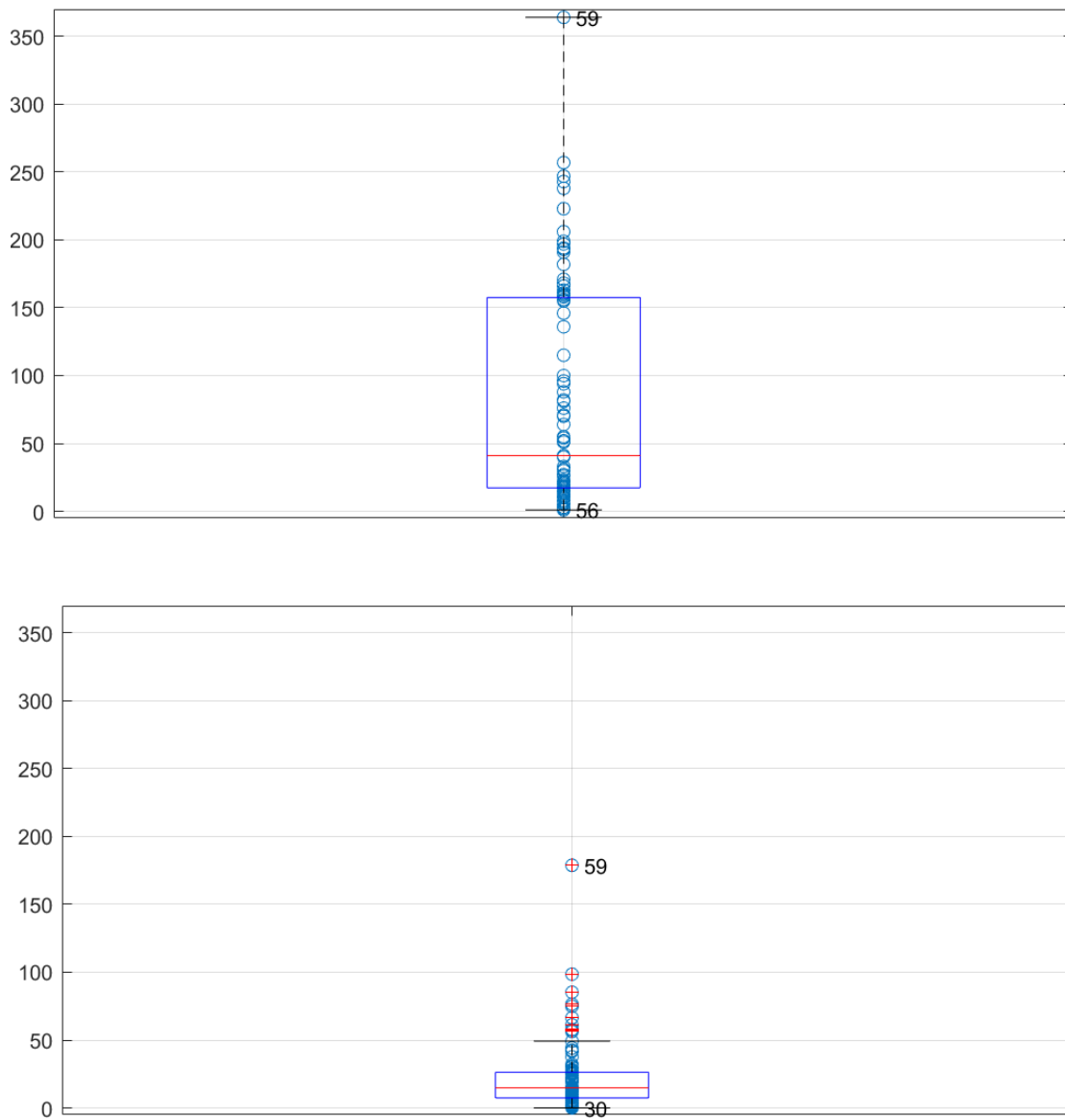
#### 4.2.5 Boxplot evaluation

Another performance parameter is boxplot evaluation. As tells in the previous section 2.6.2 this type of evaluation is very important and encloses in a graph many information.

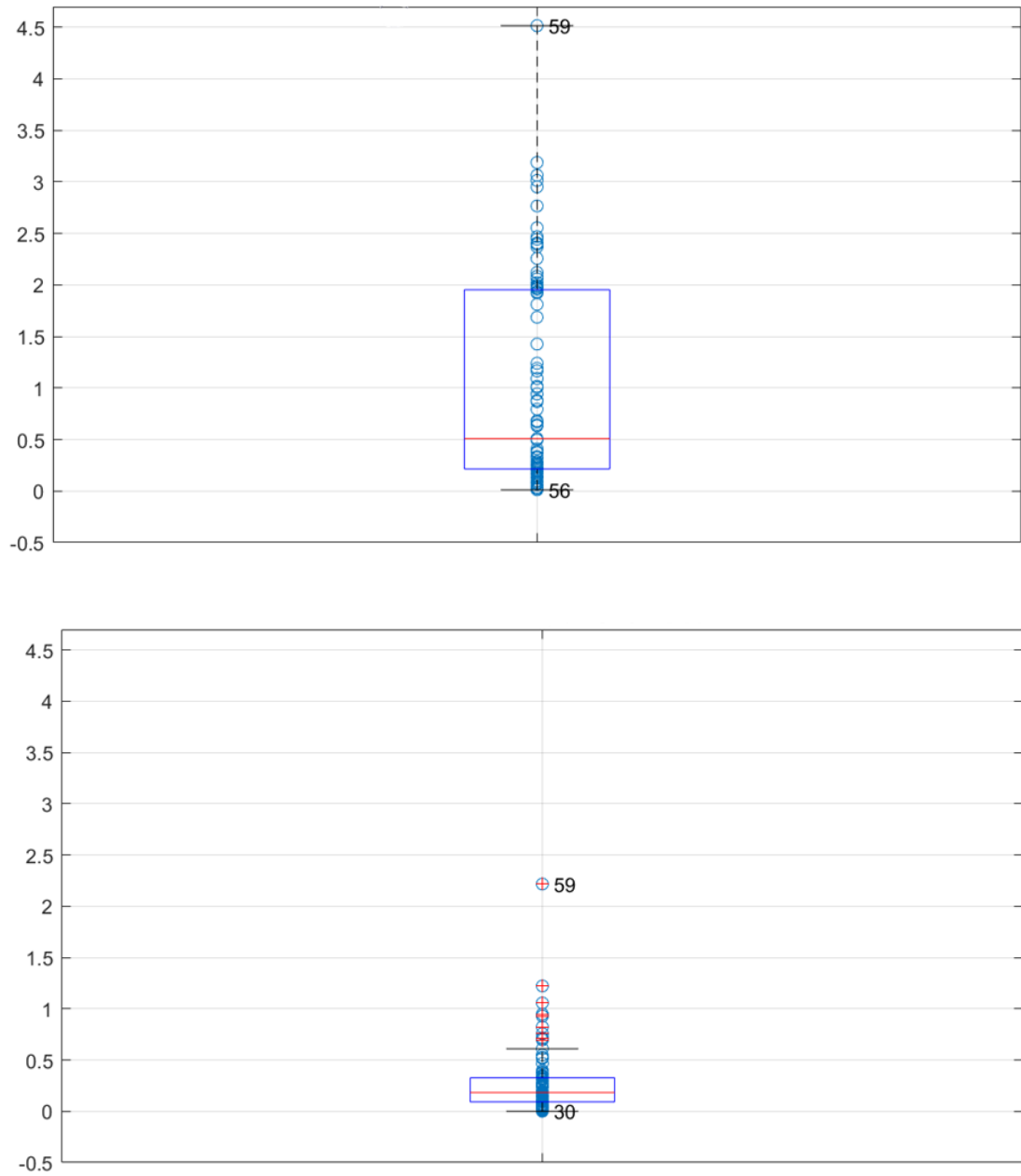
During the company experience were made various boxplots (RMSE, for laundry load amount, ...); in this writing we concentrate on RMSE and NRMSE boxplot because contains more information.

From Fig. 4.5 and Fig. 4.6 is enough easy to verify introduced improvements after modification (for both figures, new error of motor feature signal is represented in the second graph). In fact, for both outliers and mean distribution, there is a significant decreasing of NRMSE, for all tests.





**Figure 4.5:** RMSE boxplot for modification of motor feature signal calculation



**Figure 4.6:** NRMSE boxplot for modification of motor feature signal calculation

### 4.3 Exchange power calculation

The last section of this project will be paid for a physical theoretical exchange power calculation; this calculation is more important to give additional theoretical base to the model and verify correctness of our work.

Two equations [2, 4, 6] from which we started are the following

$$\begin{cases} h = h_a + xh_v = c_{p_a}T + x(r_0 + c_{p_v}T) \\ q + h_1 = h_2 \Rightarrow q = h_2 - h_1 \end{cases} \quad (4.6)$$

where 1 and 2 mean respectively before and after examined component,  $h$  is the enthalpy,  $h_a$  is the enthalpy of dry air,  $h_v$  is the enthalpy of water vapour,  $x$  is the specific humidity,  $T$  is the temperature in  $^{\circ}C$ ,  $c_{p_a} = 1.006KJ/(Kg * ^{\circ}C)$  is the air specific heat at constant pressure,  $q$  is the heat,  $c_{p_v} = 1.875KJ/(Kg * ^{\circ}C)$  is the water vapour specific heat at constant pressure and  $r_0 = 2501KJ/Kg$  is the heat of vaporization.

From this two equations, remembering that  $P_{exchange} = \dot{m}_a q = \rho \dot{V} q$  (where  $\dot{m}_a$  is the air that crosses component,  $\rho$  is the air density and  $\dot{V}$  is the volumetric flow), we can calculate exchange power that is

$$P_{exchange} = \rho \dot{V} [c_{p_a}(T_2 - T_1) + r_0(x_2 - x_1) + c_{p_v}(T_2 x_2 - T_1 x_1)] \quad (4.7)$$

As regards all these terms, many of them are directly calculated by laboratory technicians, but this is not for specific humidity  $x$ . For this motivation we used the following equation [1] to calculate it

$$x = 0.622 \frac{P_v}{P_{tot} - P_v} \quad (4.8)$$

where  $P_{tot}$  (total component pressure) is a data, while  $P_v$  (pressure of vaporization) is derived by

$$P_v = P_{sat} * RH \quad (4.9)$$

where RH is the relative humidity [%] and  $P_{sat}$  is calculated as in section 4.1.2 - equation 4.2.



# Chapter 5

## Conclusions

The results of the project can be considered satisfying. With using of this model will be possible to dominate the increasing complexity of industrial processes and they enable to accelerate innovation cycles, rapidly exploring and exploiting quickly new possible solutions.

It was possible to increase physical base, improving initial model, and to make an in-depth analysis of all most important model aspects. Thanks to this work, feature modelers will be able to modify easily the model to transform it in a model of different dryer (in some case it will not need of any modifications), earning work hours for each revision. Moreover it will be possible use various scripts of this project for most disparate activities (avoid acquisition disturbances, least square estimation of a signal, report for a simulation/acquisition comparison, in-depth analysis with error and boxplot evaluation and sensitivity analysis, ...).

The aim of the project, thus to allow performance evaluation and software debug of the dryer without use of the real machine, was achieved. This will mean a considerable time and cost saving for Electrolux, a greater evaluation of issues and a possible using for hardware in the loop activities.



# Acknowledgements

I would like to thank all people that I allowed to work at this project concluding it. In particular I thank my Electrolux tutor Terenzio Giroto for all precious advices, all Electrolux and university people that in this six months worked with me, my relator Alessandro Beghi and my correlators Gian Antonio Susto and Mirco Rampazzo.





# Appendix A

## Real test dataset

This appendix contains the real test dataset. As said above, during the conduct of the thesis, much time was spend to clean and improve the acquisition signals. The dataset consists of 91 tests divided by laundry load condition (different types, including climatic chamber conditions) and laundry load amount (full and half load, so respectively  $8Kg$  and  $4Kg$ ).

Climatic chamber tests are in turn divided into hot conditions (average lab temperature is  $35^{\circ}C$ ) and cold conditions (average lab temperature is  $5^{\circ}C$ ). The choice of these temperatures is not random but is due to the extreme working dryer temperatures, precisely  $5^{\circ}C$  and  $35^{\circ}C$ .

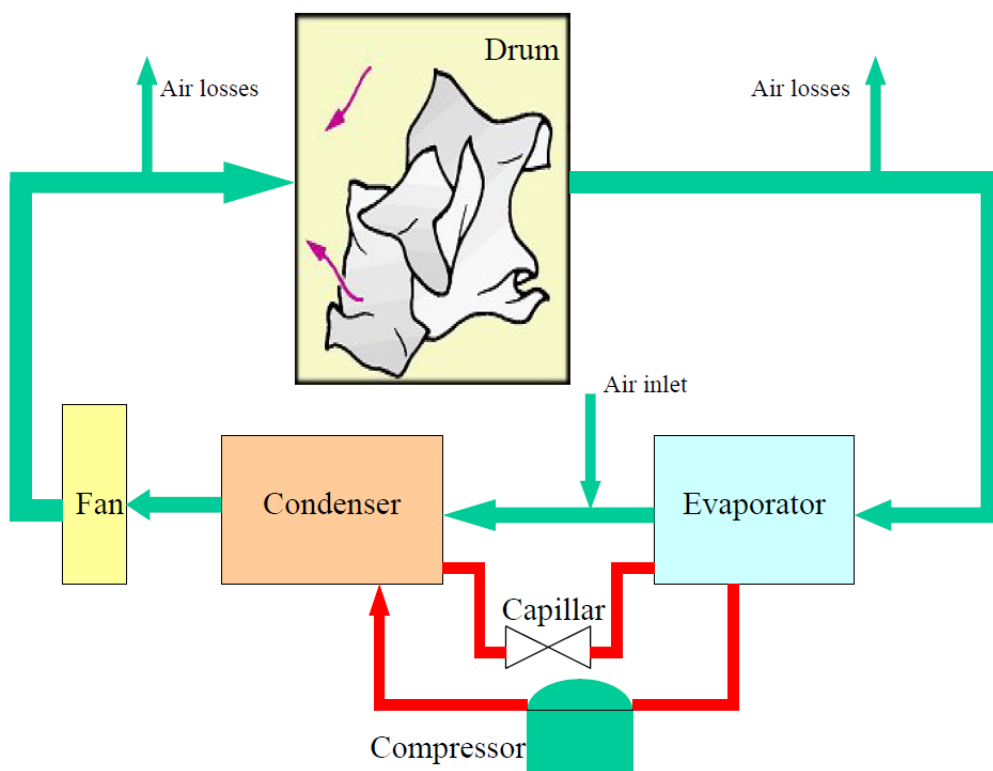
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	<b>LOAD / TEST CONDITION</b>	<b>N° Tests</b>	<b>Program</b>
1	<i>Load1 4 Kg</i>	19	COTTON ECO
2	<i>Load1 8 Kg</i>	15	COTTON ECO
3	<i>Load2 4 Kg</i>	20	COTTON ECO
4	<i>Load2 8 Kg</i>	9	COTTON ECO
5	<i>Load3 5.6 Kg</i>	9	COTTON
6	<i>Load4 3.5 Kg</i>	7	SYNTHETIC
7	<i>Load5 6 Kg</i>	4	MIXED
8	<i>Cold climatic chamber load 4 Kg</i>	2	COTTON ECO
9	<i>Hot climatic chamber load 4 Kg</i>	2	COTTON ECO
10	<i>Cold climatic chamber load 8 Kg</i>	2	COTTON ECO
11	<i>Hot climatic chamber load 8 Kg</i>	2	COTTON ECO

**Figure A.1:** Real test Dataset (91 tests)

## Appendix B

### Holes and circuit in old MATLAB/Simulink model



**Figure B.1:** Holes and circuit in old MATLAB/Simulink model



# Bibliography

- [1] Cavallini. Aria Umida.
- [2] I. Dinçer and C. Zamfirescu. *Drying phenomena - Theory and applications*. 2016. ISBN 9781119975861.
- [3] Ecole CEA-EDF-INRIA. Basics of global sensitivity analysis. 2011.
- [4] IUAV. L’Aria Umida. pages 107–129.
- [5] Odilio Alves-Filho. *Heat pump dryers: Theory, design and industrial applications*. 2000. ISBN 9781498711340.
- [6] U. of Genova. Termodinamica dell’aria umida. pages 1–14. 2012.
- [7] F. Pianosi, F. Sarrazin, and T. Wagener. A Matlab toolbox for Global Sensitivity Analysis. *Environmental Modelling and Software*, 70:80–85, 2015. ISSN 13648152. doi: 10.1016/j.envsoft.2015.04.009. URL <http://dx.doi.org/10.1016/j.envsoft.2015.04.009>.
- [8] G. Rossi. “ ANALISI TEORICO-SPERIMENTALE DI UN ESSICCATORE A POMPA DI CALORE ”, Bachelor Thesis 2004.
- [9] D. Simon. Least squares estimation. *Optimal State Estimation*, 2:79–105, 2006. doi: 10.1002/0470045345.ch3.