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PU Public
PP Restricted to other programme participants (including the Commission Services)
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0	15/02/2016	Draft
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2	15/05/2016	v02
3		

Acronyms	
IFC	International Finance Corporation
IO	Inputs and Outputs
M&CS	Monitoring and Control Sytem
ORC	Organic Rankine Cycle

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1 Executive summary

D4.2 reports the main activities conducted under T4.2, in order to identify potential additional IO to be considered in the system to improve WHRS M&CS increasing systems' availability and performance.

To achieve these objectives, the feasibility of waste flue gases temperatures prediction and additional performance indicators assessment has been analysed.

This deliverable is divided in three main sections. Firstly, chapters 3 and 4 summarize the findings on the literature review and preliminary work conducted to analyse the feasibility of waste flue gases temperature prediction. Next, chapter 5 summarises the review on the current performance indicators as well as the desired ones. Finally, conclusions and next steps from the work done are presented.

2 Introduction

This deliverable aims at determining whether a new control strategy for an ORC system could be created based on heat source modelling. Due to the complexity of both cement industries and heat recovery systems different factors affect their performance; sometimes temperature and mass flow increase suddenly and this can be an issue for the organic fluid stability. Hence, ORC systems present a threshold value (maximum temperature) from which they are disconnected. If the arising of these peaks is known in advance, some countermeasures could be taken (acting on ORC parameters or on gas by-pass valve) to avoid the shut-down of the ORC (and the time needed to restart it). Sometimes temperature or mass flow is too low to allow organic fluid evaporation, so also in these cases the ORC stops.

It may be effective to use different methods to keep the heat recovery system online instead of shutting it down, if the duration of these operational conditions is short and predictable.

For this purpose, a correct modelling of the heat source is of paramount importance and this possibility will be discussed in this deliverable. To do so, the state of the art in, a priori, suitable modelling techniques has been analysed, applying later a simplistic approach of the use of one of the techniques for the problem of cement industry waste heat modelling.

In parallel, an analysis of current performance monitoring strategies and extended potential features were conducted.

The expected outcome of this document are the new, if needed, IO's to be considered during the subsequent tasks of WP4 devoted to the ORC's M&CS specification and implementation.

3 State of the art

Heat source modelling is a task of interest for industries or processes where combustion and burning related phenomena are of importance. In the case of this project, the focus is on the exhaust smoke from a cement factory with the aim of being able to forecast low energy periods in order to decide if the attached ORC should stop working or keep non-optimal conditions for a period of time avoiding, therefore, its stop and restart period. In order to study the feasibility of modelling exhaust gas heat and gain some insight on production processes performed in cement industries, some literature works have been searched. At the beginning "heat source modelling" were the used keywords evolving into "waste heat modelling" for the cement industry. Both searches offered mainly data driven researches, as they will be presented in the following paragraphs. Theoretical models were not found for the explanation of waste heat modelling in the cement industry.

According to Wang, Dai, and Gao (2009) there are two main heat sources in a cement plant. One of them is the suspension preheater exhaust and the other is the hot air from the clinker cooler discharge. Both sources can be used as a heat source for exchangers but part of the heat will be used for drying raw materials thus reducing the available energy.

They also described the typical temperatures and mass flow for different points in different points of the exhaust system in cement industries (Figure 1) as well as a typical ORC set in a cement plant (Figure 2).

Preheater exhaust temperature (°C)	340
SP boiler exhaust temperature (°C)	210
Clinker cooler exhaust temperature (°C)	320
Preheater exhaust mass flow (kg/s)	126.56
Clinker cooler exhaust mass flow (kg/s)	86.2

Figure 1: Cement plant typical exhaust gas conditions; Wang et al. 2009

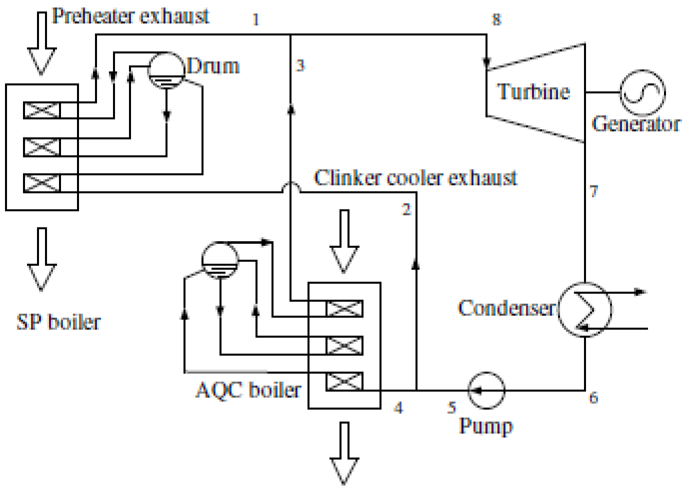

Figure 2: Organic Rankine Cycle set up in a cement factory; Wang et al. 2009

"Sui et al. calculated the power generation per ton clinker of the waste heat as 30.75kWh/t" (Sui et al. in Pradeep Varma and Srinivas, 2015). It is a considerable amount but that is not operational as the information available in order to model the heat source in the exhaust of the system is the exhaust gas temperature and mass flow. Cement production may not be constant over time and production rate changes affect the amount of waste heat produced. Pradeep Varma and Srinivas (2015) demonstrated that increasing productivity linearly increases process heat, increasing generated power as well. The figure below shows the relation between cement production rates, process heat and generated power.

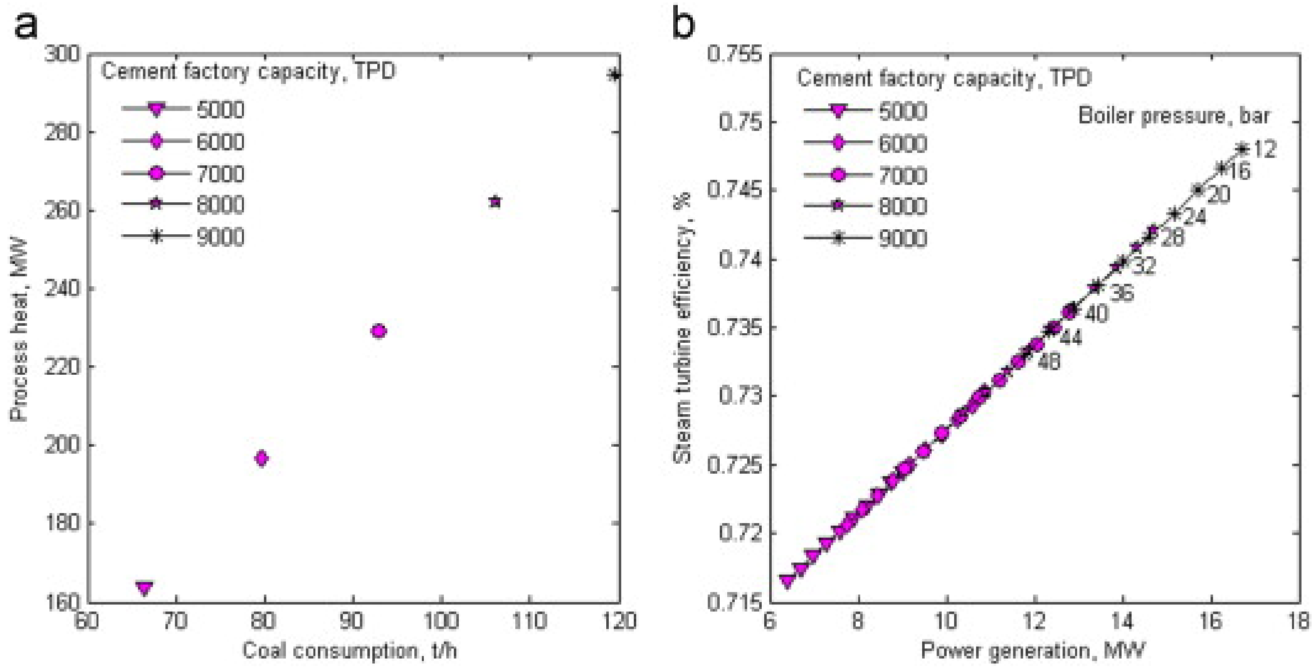

Figure 3: Process heat and productivity (left) and productivity and power generation (right) relation (ibid)

In a report by IFC, member of the World Bank Group, the following factors were determined as influential on the amount of recoverable waste heat generated in cement industries:

- **Moisture** content of the raw material feed. Moisture will have influence on the amount of heat necessary for drying materials and the heat requirement for the kiln.
- Amount of **excess air** in the kiln.
- Amount of **air infiltration**.
- **Preheater stages and their efficiency**. A bigger number of preheaters or a better efficiency of these systems will decrease the amount of recoverable waste heat as excessive heat has already been recovered for its use during the manufacturing process.
- **Cooler system configuration**.

In the following table the influence of the amount of preheater stages is shown.

Parameter	Unit	Preheater kilns	Preheater with precalciner (Number of Stages)		
Number of cyclone stages		4	4	5	6
Kiln capacity range	TPD	1000 - 2500	2000 – 8000		
Top stage exit temperature	Deg C	390	360	316	282
Heat available in preheater exhaust	GJ / tonne clinker (kcal/ kg)	0.904 (216)	0.754 (180)	0.649 (155)	0.586 (140)
Heat available in preheater exhaust	GJ / hr for 1 MTPA* (Mkcal/hr)	113.0 (27.0)	94.3 (22.5)	81.1 (19.4)	73.3 (17.5)
Specific heat consumption	GJ / tonne clinker (kcal/ kg)	3.55 (850)	3.14 (750)	3.01 (720)	2.93 (700)

**MTPA – Million Metric Tonnes per Annum*
Source: Based on "Desk Study on Waste Heat Recovery in the Indian Cement Industry," Confederation of Indian Industry, Final Report, April 2009 (CII 2009)

Figure 4: Influence of the number of preheater stages in the available heat (IFC, 2014)

Linking with the research by Pradeep Varma and Srinivas (2015) mentioned above, this report also points the waste heat produced as a function of the capacity of the factory. A graphical representation of this relation is shown in the following figure.

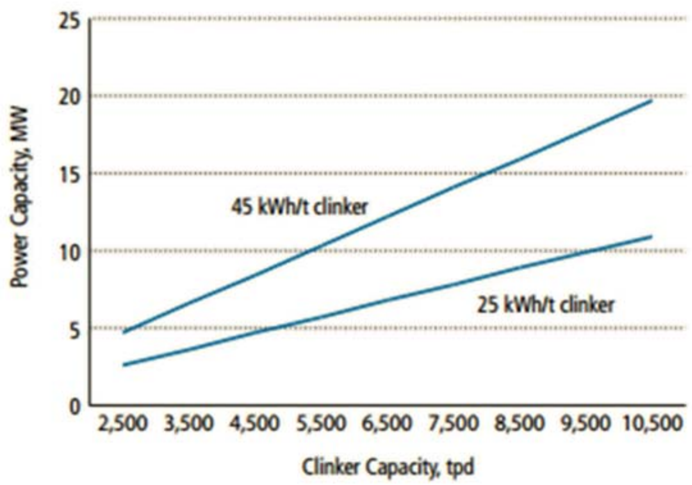

Figure 5: waste heat vs production capacity per day

In the same study, they reported the effect of moisture in raw materials and the heat amount needed to dry them to acceptable levels. In theory, 540kcal/kg is required to dry moisture but in reality this value raises up to 1100kcal/kg depending on the technology of the mills and due to different heat loses during the process. Acceptable moisture values on raw materials are around 1% and needed heat to dry different moisture levels is shown in the following table. A value of 950kcal/kg heat requirement has been considered for the calculations. As shown in the table, used heat amount differs for different moisture levels; therefore, raw material conditions will have a direct impact on the waste energy that can be used for electricity generation.

Kiln Capacity, TPD	2000	3000	4000	5000	6000	7000	8000
Raw Material Flow, TPD	3382	5073	6774	8455	10,145	11,836	13,527
Raw Moisture Content	**Drying Heat Required, GJ/hr**						
2 percent	6.7	10.0	13.4	16.7	20.1	23.9	27.2
4 percent	23.4	35.2	46.9	58.2	69.9	81.6	93.4
6 percent	32.7	49.0	64.9	81.2	97.6	113.9	130.2
8 percent	48.6	73.3	97.6	121.8	146.1	170.4	195.1
10 percent	59.9	91.7	122.3	152.8	183.4	213.9	257.5
12 percent	76.6	114.7	152.8	190.9	229.4	267.5	305.6

Source: "Desk Study on Waste Heat Recovery in the Indian Cement Industry," Confederation of Indian Industry, Final Report, April 2009 (CII 2009)

Figure 6: heat required for drying raw materials

As seen in this section, there are some factors that influence on the amount of available heat for heat recovery systems that go from clinker capacity to the conditions of raw materials and used technologies. Once the most influential factors have been identified and the access to their relative data is assured, problem modelling would be the next challenge.

As it has been presented in the above paragraphs, the main researches make use of data driven models in order to calculate the available waste heat that will be the input for different heat recovery systems. Theoretical models seem to be not popular at the time of modelling such complex processes as cement production. A reason for this may be the different influence that components have in the amount of waste heat; i.e. the bigger the amount of preheaters the smaller the waste heat will be at the exhaust, although there is not a linear relationship between the amount of preheaters and waste heat level. For the reason explained, data driven modelling is foreseen as the most appropriate modelling technique for the case of waste heat in the cement industry,

The following sections of this deliverable will identify and explain some of the techniques that can be applied in order to forecast waste energy aiming at improving the performance of energy recovery systems.

4 Heat source modelling techniques

This section aims at describing some of the modelling techniques that can be of interest to model and analyse heat sources on cement factories. There are two main options for modelling this type of problems: theoretical models and data driven models. Both of them have advantages and disadvantages and the main difference is between them is their origin. Theoretical models, as their nomination indicates, are based on theory and so on mathematical models. Data driven models instead are based on historical data from a process therefore they are created using real data from sensors or productivity indicators. As mentioned before, the advantages of each method are that theoretical models may be easier to use as they can be obtained from product manufacturers while data driven models should represent the actual process with a higher accuracy.

Data driven models are widely used in several industries due to their suitability to face fault detection problems. This modelling method is also applied to control performance assessment problems (Qin, 2012). This modelling technique is dependent on the measured process variables; therefore, knowledge of the process is of paramount importance in order to measure meaningful variables and obtain valid models. When process data is available, pre-processing data is advised in order that correlations can be identified (Yin et al. 2012).

For the case of this project, data driven models are foreseen as a suitable modelling technique as cement factories monitor their process and store its relative data; therefore, there exists historical process data that might be used to describe factory's performance. Machine learning techniques are also interesting as their use would allow creating the most appropriate models as well as adapting existing models to changing initial conditions as raw material state.

In section 4.1 a theoretical thermal system in cement industry with nonlinear ordinary differential equations is shown, in section 4.2 the parameters of the differential equation to fit the system are calculated by metaheuristic techniques. In section 4.3 the applicability of machine learning techniques in the field of thermal systems control is raised.

4.1 Theoretical models

Nonlinear ordinary differential equations are one of the most popular frameworks for describing the temporal evolution of a wide variety of systems. For the case of cement industries, it has not been possible to find specific literature on theoretical waste heat models and therefore, more generalist approach will be taken. There are some scientific papers that describe thermal system as a set of nonlinear differential equations (Fan, Infante Ferreira and Mosaffa, 2014).

Simulating a set of nonlinear ordinary differential equations given parameters and predicting state variables over time has been extensively studied in scientific community. Defining the parameters of nonlinear ordinary differential equations is the first steep to create a data-based-model in data using least squares mythology as stated by Liang and Wu (2008).

Thermal systems are those that involve the transfer of heat from one substance to another. Thermal systems may be analysed in terms of resistance and capacitance. The thermal resistance R for heat transfer between two substances may be defined as follows:

$$R = \frac{d(\Delta T)}{d\dot{Q}} = \frac{\overbrace{k \cdot A}^{Conductivity}}{\Delta x} = \frac{\overbrace{1}^{Convection}}{h \cdot A_s}$$

The thermal capacitance C is defined by

$$C = \frac{\text{change in heat stored}}{\text{change in temperature}} = m \cdot \mathrm{C_p}$$

Where m is the mass of substance considered in kg

As an example consider the problem showed in the figure below where the liquid inside the tank is perfectly mixed and the liquid flow rate is kept constant.

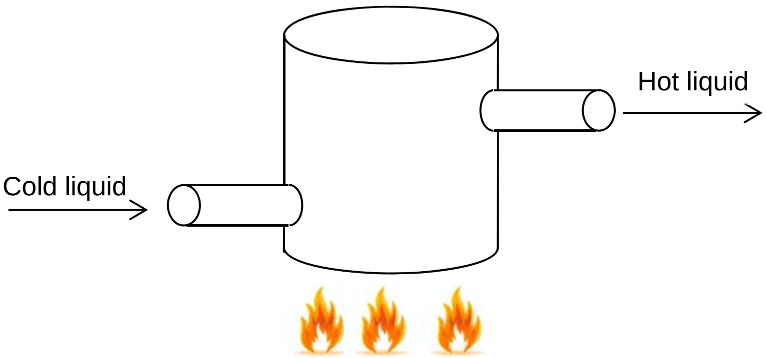

Figure 7: example of thermal system

The change in the temperature of the outflowing liquid can be modelled with a differential equation that use thermal resistance R and thermal capacitance. The following equation is obtained by transforming that differential equation into in Laplace domain.

$$\frac{T_{out}}{T_{in}} = \frac{\frac{1}{(R \cdot C)}}{s + \frac{1}{(R \cdot C)}}$$

Where, T_{out} is the temperature of outflowing liquid and T_{in} is the temperature of inflowing liquid.

A thermal system can be modelled by a set of nonlinear ordinary differential equations with some parameters. Experimentally measured data is used to estimate the unknown parameters of nonlinear ordinary differential equations. In most cases, these data consist of time series, or time courses, of repeated measurements of one or more experimental variables.

The parameters are calculated by minimize the difference between solution of the differential equation and the data provided. Use Metaheuristics technique could be a compromise solution between accuracy and time span to find parameters of differential equations. Least squares based approaches is another technique.

4.2 Model based on Data

Alongside with theoretical models, data driven modelling is one of the most promising methods for the case of forecasting waste heat level at some point of a cement factory. For the specific case under study, some data is available from a cement factory that can be used to create a preliminary model with limited detail. This model is of help in order to determine if the proposed technique may offer promising results. As seen in section 3, one of the most influential factors on the available waste heat is the capacity of the kiln. In this section an approach to the heat source modelling has been performed attending only to the amount of raw material feeding the kiln. In this section, the aim will be determining whether a model based on data can be created with the available data from previous studies in cement factories.

The dataset analysed belongs to the timespan January 2015 to June 2015. This analysis takes into account the tons of material input to the oven and temperature 7 (measured temperature in the exhaust). The following figure shows the input variable (tons of material) depending on the output variable (Temperature 7). This system is a dynamic system and there is no linear dependence or function that explains the output signal based on input signal regardless of the previous state of the system.

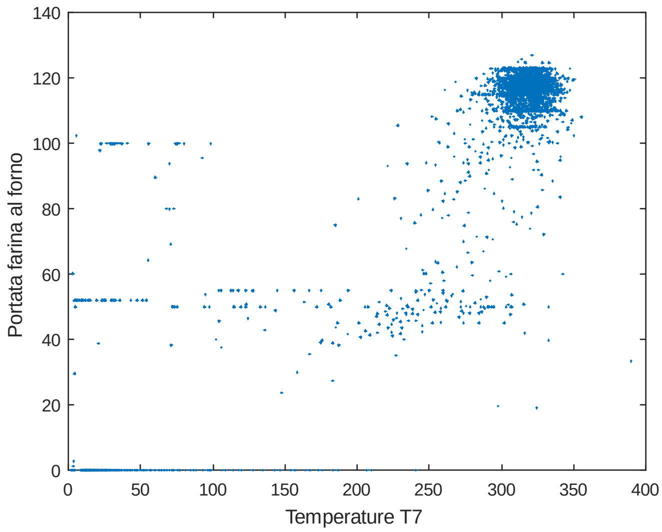

Figure 8: Input material in the oven vs temperature T7

Steady state: The dynamic system has reached a stable regime when the input variable does not present significant variations for several time instants. For example, this event occurs around Easter holidays 2015, from March 13 to April 14.

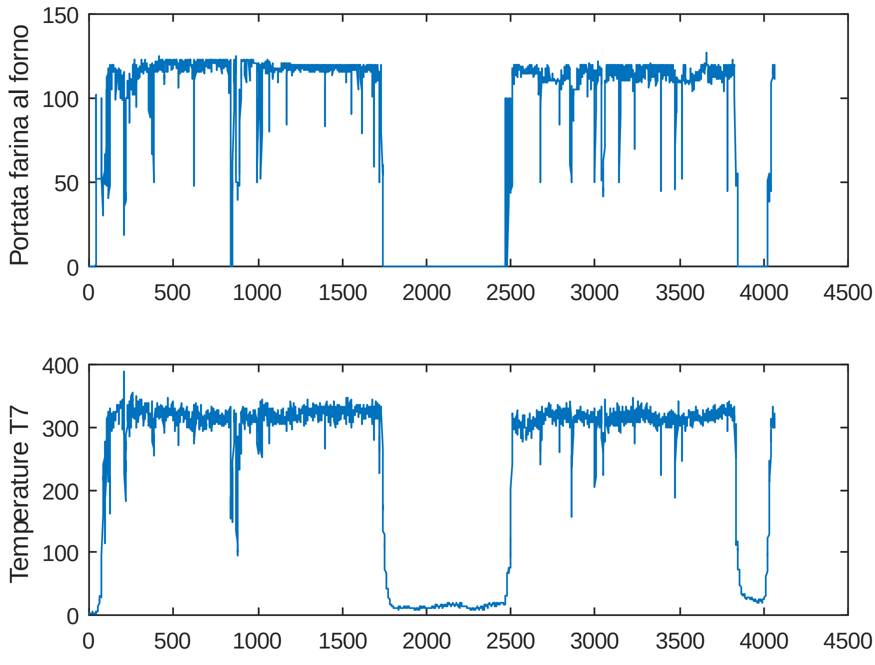

Figure 9: Input material in the oven and temperature T7 over time (2015)

In steady state, the output signal can be expressed as the input signal multiplied by a constant parameter. This is expressed by the following equation.

$$Output = K \cdot Input$$

The output represents the temperature T7 and the input represents the tons of material introduced in the kiln. There are two clear moments of stability within the data available for 2015: the first moment, when there is no input material in the oven, the temperature is constant about 15 °C. The second moment, when there is a constant input material in the oven, the temperature is constant about 320° C. Those moments are shown in the next figure.

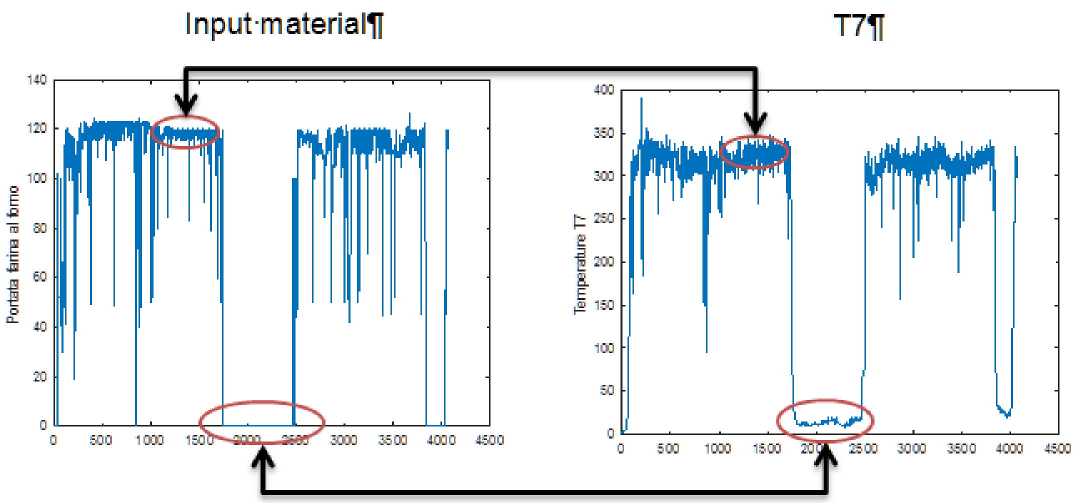

Figure 10: Steady state moments of input material in the oven and temperature T7

Transient states: There are transient states all the time but there are two transient states clearly identified. The first transient state is the boot state of the oven and it shown in the following figure.

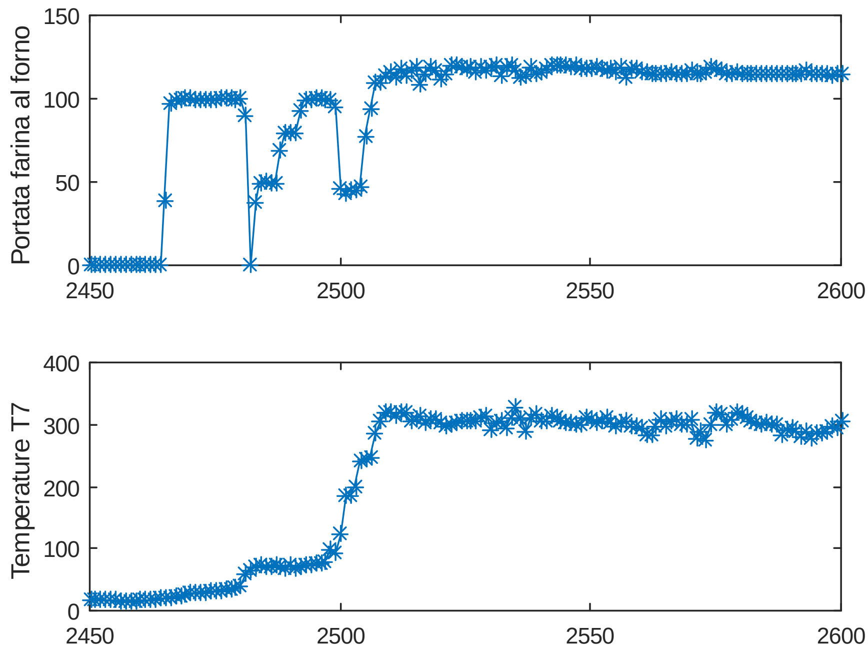

Figure 11Boot state of the oven over time

The second state is the stop state of the oven and it is shown in the following figure.

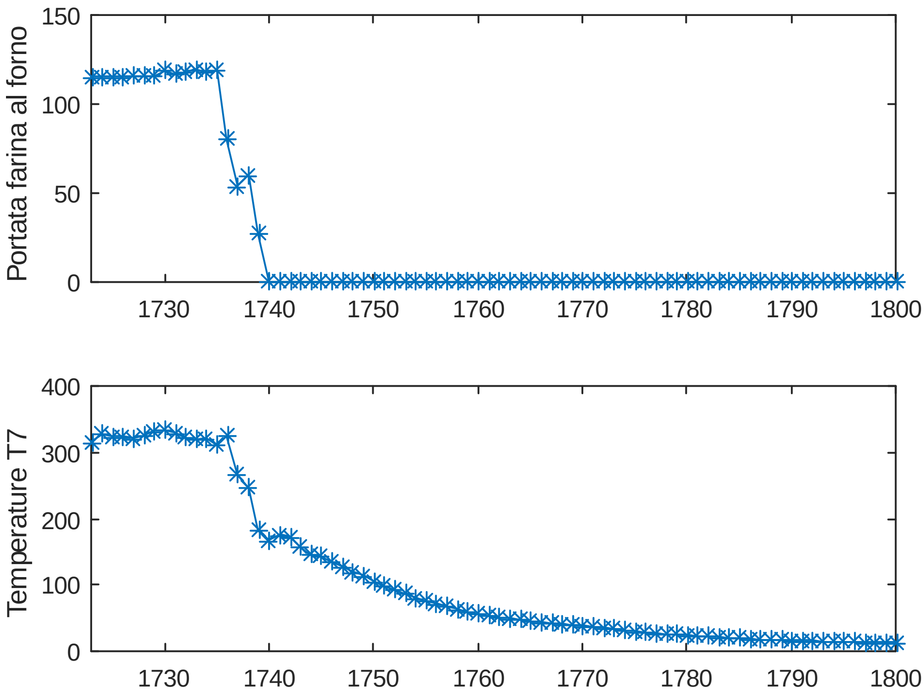

Figure 12: Stop state of the oven over time

Model the system: Once the transfer function of the system is known, it is possible to predict the behaviour of the system. The transfer function of the system can be calculated using evolutionary computation techniques. This concept is shown in the following figure.

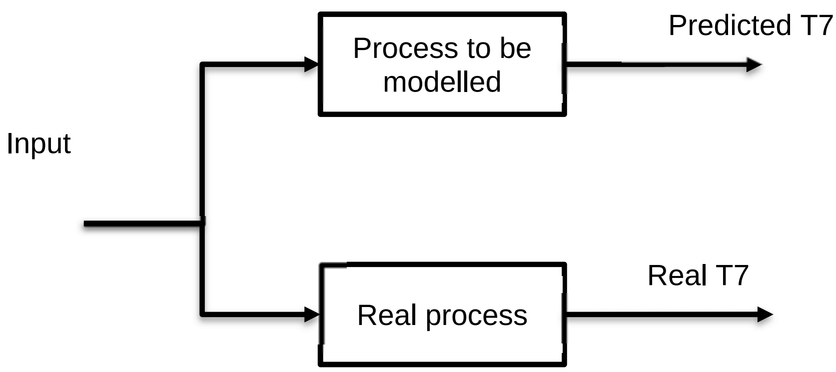

Figure 13: System training scheme

The system is modelled as a first order system with two parameters: “a” and “k”. This proposed model is shown in the following figure.

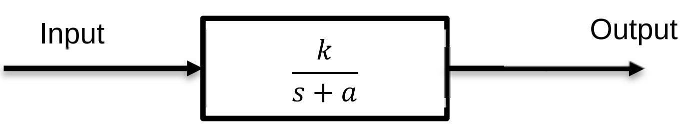

Figure 14: First order model

Where, ‘s‘ it’s a complex number that represents the frequency parameter of Laplace transform. The fitness function revealed in the following equation defines how well or bad the values of parameters ‘a‘ and ‘k‘ describe the real model in contrast of proposed model.

$$Fitness = \sum_{t=0}^{t=t_{end}} \sqrt[2]{(T_{real})^2 - \left(T_{predict}\right)^2}$$

The objective consist of finding a model with values of parameters ‘a‘ and ‘k‘ with a low fitness value. The parameters ‘a‘ and ‘k’ are obtained by applying an evolutionary algorithm.

Parameter	Value
‘a’	1.0
‘k’	2.73

The following figure shows different values of ‘a’ parameter Vs fitness value, where the best value of ‘a’ parameter is when a=1.

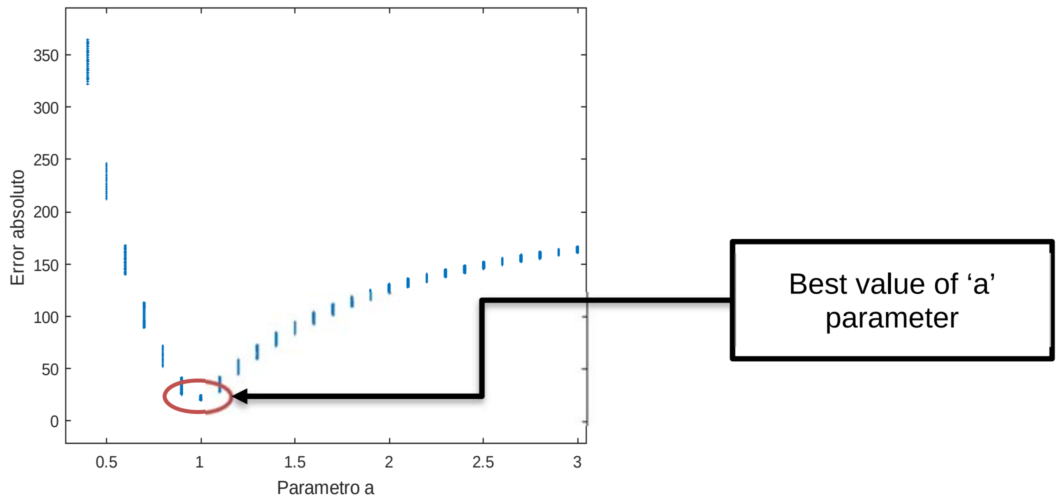

Figure 15: Fitness value vs 'a' parameter

In a similar way, the following figure shows different values of ‘k’ parameter Vs fitness value, where the best value of ‘k’ parameter is when k=2.73.

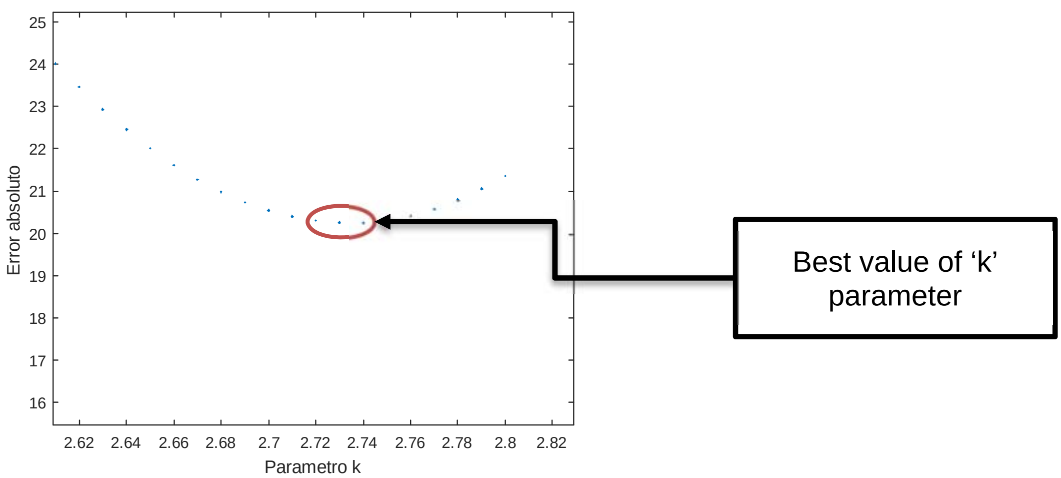

Figure 16: Fitness value vs 'k' parameter

The following figure shows temperature prediction using the same input data (input of material into the oven) on the new calculated model.

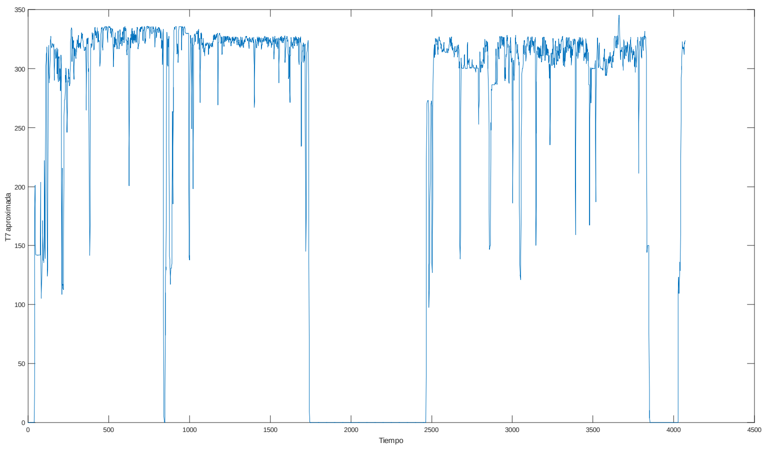

Figure 17: Output of temperature prediction based on input data

The following figure shows the two models (Real model and predicted model).

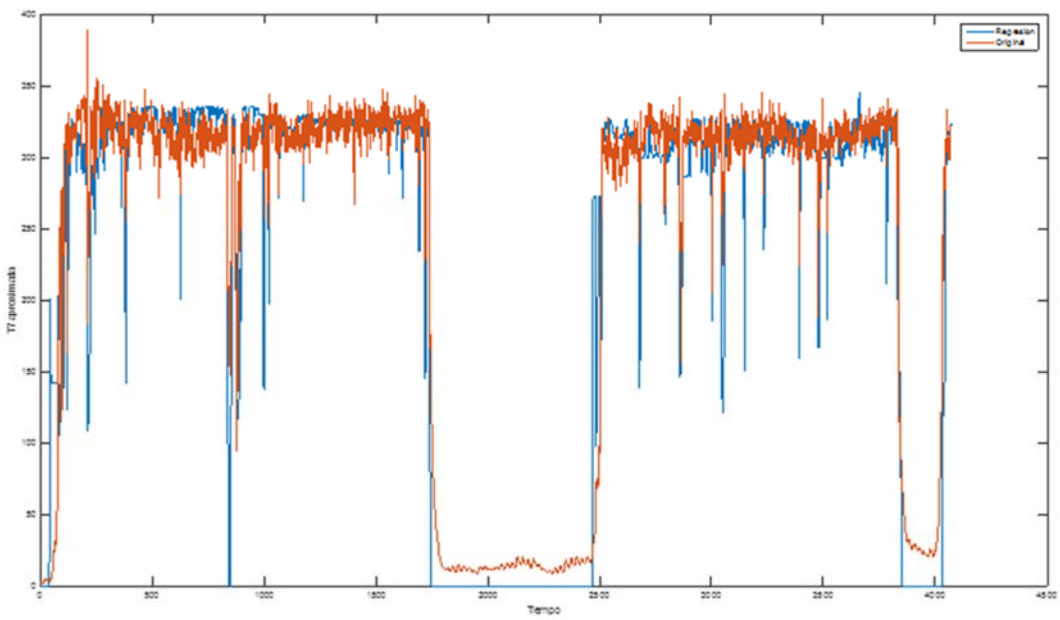

Figure 18: Real model and predicted model over time

As can be seen, the results for the predictive model match with certain reliability the results from the measures. It is worth saying that the only input for the model was the amount of raw material feeding the kiln and variables as raw material moisture have not been taken into consideration. With work that is beyond the scope of this deliverable, a more complete model could be created as well as defining a strategy to optimize the use of ORC systems in the cement industry would be feasible.

4.3 Machine learning

Reinforcement learning is an area of machine learning based on software agents that take actions in an environment to maximize some cumulative reward. Reinforcement learning can be used to control thermal systems as has previously been done by some authors:

- A hybrid control approach of commercial building passive and active thermal storage inventory based on simulated reinforcement learning has been introduced by Liu and Henze (Liu and Henze, 2006).
- Yang et al. (Yang et al., 2015) apply a reinforcement learning control of heating demand, maintaining the optimal operation temperature and compensating more effectively for ground heat for buildings.
- In a work by Stone and Urieli an adaptive reinforcement learning agent which applies a new control strategy for a heat-pump thermostat is presented (Stone and Urieli, 2013).
- Moslem et al. present a robust, efficient and parameter-setting-free evolutionary approach for the optimal design of compact heat exchangers. A learning automata based particle swarm optimization (LAPSO) is developed for optimization task (Moslem et al. 2012).
- In a research performed by Idowu, Åhlund and Schelén, the application of Reinforcement Learning (RL) and online Supervised Learning (SL) to achieve energy optimization in District-Heating (DH) systems is investigated (Idowu, Åhlund and Schelén, 2014).

As explained in the works above, machine learning is a common topic on thermal systems control. The application of theories from the previous works is suitable due to the existing similarity in control systems. With the application of machine learning techniques, more robust controls can be created thus optimising the energy recovery system installed in the companies.

5 Performance Monitoring

Real-time information available from the ORC's control system helps to pinpoint opportunities for performance improvement that would otherwise go unnoticed. This section describes which are the indicators used for this purpose.

ORC's key performance indicator is **cycle efficiency**, defined as the ratio between the generated electrical power and the thermal input

$$\text{Cycle Efficiency} = \eta_{el,gross} = P_{el,gross} / P_{in}$$

Where,

$P_{el,gross}$ is the electrical power measured at the generator output

P_{in} *is the thermal input calculated as* $Pin = Thermal\ Input = Gas\ Mass\ Flow \times \Delta H\ (Gas\ Stream)$

It is usually difficult to calculate P_{in} because gas properties and mass flow sometimes are not available or not reliable. In order to overcome that difficulty thermal input is checked using data coming from the ORC, so P_{in} is estimated also as $Pin = \text{Organic Fluid Mass Flow} \times \Delta\text{H}$

In this case, ΔH is calculated at the inlet and at the outlet of the direct heat exchanger, on the base of temperature and pressure measurements on organic liquid and vapour.

Organic fluid mass flow is calculated using the formula of *Choked flow*. Indeed, the turbine works with a ratio $Pressure_{in} / Pressure_{out}$ higher than critical ratio, so turbine nozzles works in supersonic conditions. Mass flow in choked condition depends only by nozzle area (known) and upstream vapour conditions (pressure and temperature measured at turbine inlet).

Finally, **net cycle efficiency** can be calculated as $\eta_{el,net} = P_{el,net} / P_{in}$

Where, $P_{el,net} = P_{el,gross} - ORC_{consumes}$

ORC consumables are mainly organic pump and fan for air cooled condenser

Moreover, in order to consider different conditions from the nominal one, cycle efficiency has to be calculated; for example, typically ORC efficiency has to be verified at partial load (heat source changes in terms of mass flow and temperature) and at different ambient temperature.

To consider these conditions, specific curves are calculated and following figures show typical values for these curves:

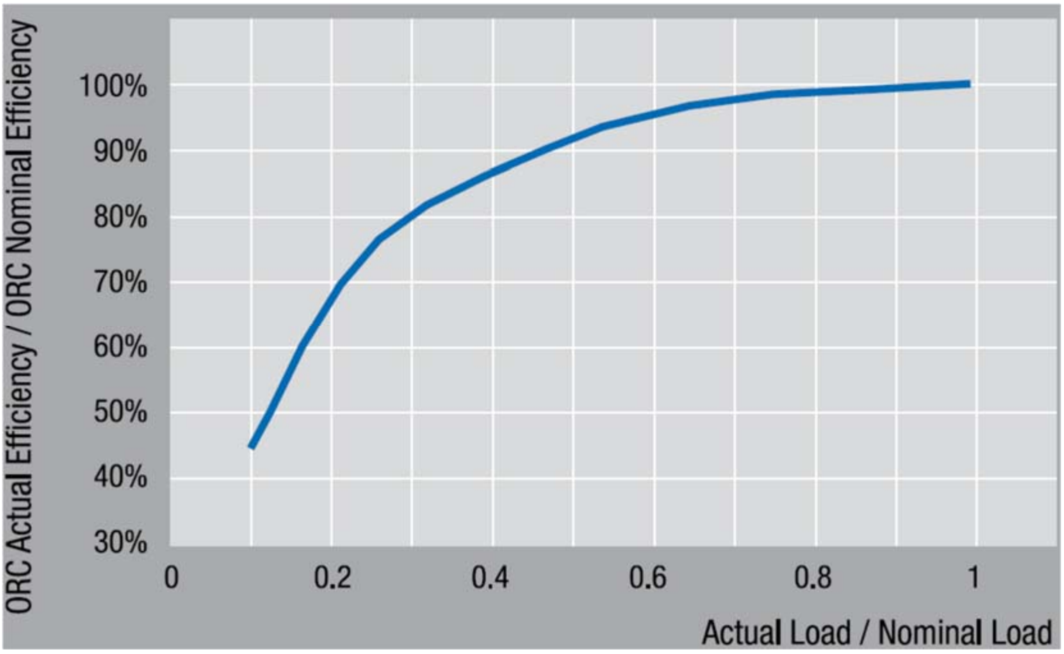

Figure 19: ORC Partial Load Efficiency

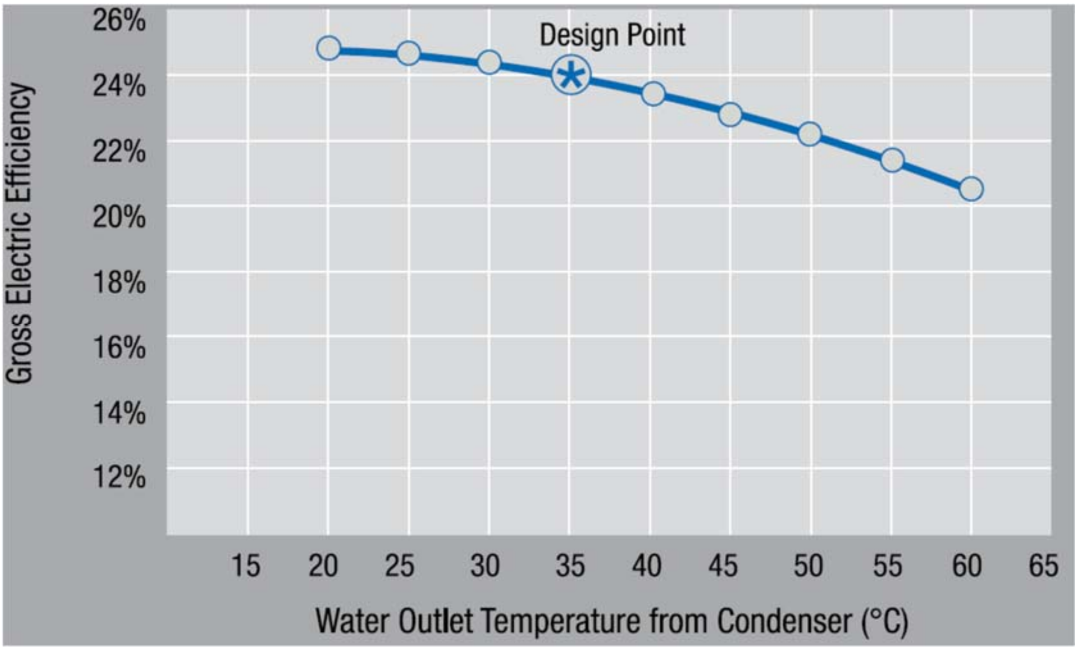

Figure 20: Cooling Water Temperature Effect on Cycle Efficiency (HRS Model)

6 Conclusions

The aim of this deliverable has been to understand the requirements of a thermal recovery system to be modelled. Other related aspects such as the background for the modelling process of its heat source, the waste heat model for cement industries, as well as the creation of a control strategy that will determine whether the energy recovery system should work on non-optimal conditions or should be shut down have also been approached.

There are some previous experiences on energy recovery in the cement industry as well as in other heat exhaustive industries that allow the modelling of the heat source in a reliable way. What is more, a simple model has been performed in the framework of this deliverable using limited data and few of the descriptive factors as input, and its results have been promising. A deeper work could probably result in a better model able to describe and forecast most of the important phenomena existing in cement industry. As stated during the state of the art section, there are several factors that influence waste heat level in this kind of industry and for the limited model created for this deliverable they have not been taken into consideration. As presented for the model, obtained forecasted values seem to match with certain precision real measured values. This fact indicates that a more elaborated model could reliably enough be used as a forecasting tool to determine the correct functioning of a waste heat recovery system. All in all, it can be said that if there is access to information about factors such as raw material conditions and plant configuration, the possibility to create a more reliable model would be high.

Machine learning processes, as described in the work, are widely used for the control of thermal systems. Some examples have been found as candidates in order to replicate them in the cement industry field to try to improve the performance of waste heat recovery systems.

All in all, as per the analysis done, we can conclude that no further sensors have to be considered during T4.3 and T4.4 for the ORC’s M&C system implementation.

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8 Annexes