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# Impact of thermal storage modeling accuracy on the optimal strategy for its management

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**Abstract** – In a context of strong penetration of renewable energies, especially in a multi-energy network, thermocline thermal storage is a relevant solution. However, its operation using heat transfers between several phases is complex. Its precise modeling can therefore only with difficulty be taken into account within the problem of optimal management of a multi-energy network. In this work, we propose to analyze the impact of the precision of the thermal storage model on the efficiency of the management of a heating network. An accurate physical model and two linear models will be compared on a case study, as well as an original metamodel : fast but able to take into account stratification heat or heat loss during the load phase. This metamodel uses the logistic function to reduce the dimensions of the storage condition. It is based on an interpolation matrix previously constructed using the numerous simulations from the precise physical model. In addition, this model can be adjusted to achieve all the trade-offs between accuracy and speed of evaluation.

**Keywords** – thermal storage, model reduction, optimal management, dynamic programming, waste heat, multi-energy networks.

## Nomenclature

$T$	Temperature, $^{\circ}C$
$Q_m$	mass flow rate, $kg s^{-1}$
$(\rho C_p)$	Energy density, $J m^{-3} K^{-1}$
$k^{eff}$	Effective thermal conductivity, $W m^{-1} K^{-1}$
$h_v$	Interstitial transfer coefficient, $W m^{-3} K^{-1}$
$h$	Surface transfer coefficient, $W m^{-2} K^{-1}$
$A$	Surface, $m^2$
$V$	Volume, $m^3$
$u$	Fluid velocity, $m s^{-1}$
$f$	Fluid
$s$	Solid
$w$	wall
ext	Exterior

## 1. INTRODUCTION

In France, 50 to 80 % of electricity (depending on the studied sector) is consumed in the form of heat [1]. There is therefore a strong link between electrical and thermal vectors. Today, the coupling between these two vectors is rarely taken into account when designing and managing energy networks. Decoupling this problem into several single-vector networks results in a sub-optimality of the provided solution. This coupling nevertheless comes up against a great technological complexity, from the design of each of the components required for such a so-called "multi-energy" network, to their modeling and the overall management of the whole system.

Efforts to overcome the difficulties of a multi-energy network are justified by the many storage and conversion resources and technologies, which could then be exploited much more widely than today. This is the case, for example, for the waste heat generated by industries at the margins of their processes. This represents 3500 TWh/year at high temperature ( $> 150^{\circ}C$ )

and the equivalent of 2450 Mt CO<sub>2</sub>/year in terms of global carbon dioxide emissions [2]. Several renewable sources, such as geothermal energy and waste incineration, also have large deposits of heat. Thermal storage is also an important brick in the technological chain of a multi-energy network. Thanks to its low economic (15 \$/kWh) and environmental (GHG : 0.3 kg-eq CO<sub>2</sub>/m<sup>3</sup> over life cycle) cost compared to other storage systems, it is advantageous to partially store energy within such systems [3][4].

Thermal storage can be classified according to several criteria :

- Temperature level : low ( $T < 150^{\circ}C$ ), high ( $150^{\circ} < T < 900^{\circ}C$ ) and ultra high ( $900^{\circ}C < T$ ).
- Physical principle : sensitive heat, latent heat, thermo-chemical.
- Storage medium and transfer fluid used : oil and rock, hot water, molten salt or air and rock.
- geometry : 2 vessels (physical separation between hot and cold media) or thermocline (thermal separation within a single vessel).

In this work, a high temperature sensible heat storage using air and ceramics is considered. This is the EcoStock system<sup>®</sup> (Fig. 1) developed by Eco-Tech CERAM, an engineering company specialized in thermal storage and industrial ecology.

The EcoStock<sup>®</sup> is a containerized and mobile storage with a capacity of 4 MWh<sub>th</sub>. It consists of an eco-designed porous medium with high energy density and capable of withstanding high temperatures.

The charging phase of this technology consists of blowing hot air through the porous medium. The air circulates in direct contact with the solids and transfers its heat to them through heat exchange. As a result, the temperature of the porous medium increases. During discharge, the energy is recovered by cold air flowing in the opposite direction through the porous medium. The air recovers the heat by warming up in contact with the hot solid.



Fig. 1. EcoStock<sup>®</sup> of 4 MWh<sub>th</sub> ( $D = 2m$  and  $L = 4m$ ).

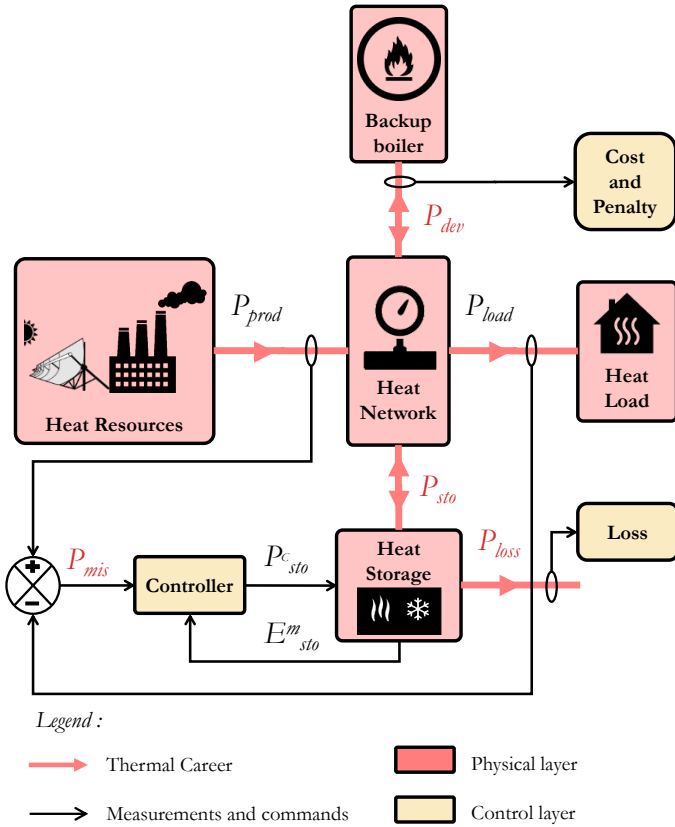


Fig. 2. Synopsis of the reference case study.

The case study described in Fig. 2 consists of an uncontrollable waste heat source  $P_{prod}$  and a high temperature ( $600^{\circ}\text{C}$ ) heat requirement  $P_{load}$ , whose power is variable. Between production and consumption, an EcoStock<sup>®</sup> is inserted in order to minimize both the call to the auxiliary boiler in case of overconsumption and the loss of profit in case of overproduction  $P_{dev}$ . Finally, losses from thermal storage  $P_{loss}$  are also to be minimized.

This work has two main objectives : the first is to develop and validate a high-performance and accurate metamodel. The second aims to compare the performance of the optimized management strategy based on various models on the reference case Fig. 2. The comparison will be done using a Pareto front with two objectives :  $\sum P_{dev}^2$  and  $\sum P_{loss}^2$  over a fixed time horizon. The simulation of the strategies issued from the different models will be done using a precise model (see section 3.1) in order to have a unique basis of comparison. This precise model called 1D - EDP has been experimentally validated on an industrial scale [5].

The section 2. summarizes the state of the art of thermal storage optimization and its most used models in the literature. Section 3. presents the main equations governing the models selected in the literature : 1D - EDP, 0D - Ideal, 0D - Mixed. The elaboration of a metamodel is explained in section 4 as well as its validation via the 1D - EDP model. In the section 5 the reference case is detailed as well as the input data. The management strategies resulting from the studied models are analyzed and compared in section 6. Finally, the conclusions and perspectives of this work are presented in section 7.

## 2. STATE OF THE ART

Thermal storage models range from static 0D models to 2D models derived from the numerical resolution of partial

differential equations (PDEs), which reflect energy conservation within the system. Among the EDP models, 1D models are the most commonly used in the literature. These models are accurate but generally time-consuming to compute. In general, they are used for numerical simulation purposes in order to accurately estimate the technical performance of the storage for a few operating cycles.

In [6], the author has developed 1D models solving the heat equations on the phases constituting the storage. These are the phases : solid (rock), liquid (oil) and wall. The evaluation of the state of the storage and the heat losses via these models is relatively expensive. These models were compared and validated using a prototype with a storage capacity of a few  $\text{kWh}_{th}$ .

An analytical model estimating the state of thermal storage, without going through the resolution of PDEs, has been proposed in [7]. This model significantly reduces the computation time compared to other 1D models. However, the author concludes that there are strong limitations to the analytical modeling of such a system. Such a model works well within the limit of a partial cycle without extraction of the thermocline (partial use is not adapted to industrial reality). Moreover, such a model is not able to estimate heat losses during the load phase.

Hot water storage was modelled using three models of different levels of complexity in [8]. He concludes that the modelling of heat losses and stratification phenomena has a strong impact on the economic feasibility of projects. No comparative optimization work was carried out.

In the literature, optimization work on thermal storage is divided into two categories : management optimization and sizing. Most of this work uses simplified 0D models in order to get rid of the computation time problem.

[9] [10] and [11] suggest a stochastic optimization of the management of a thermal storage coupled with a thermal source feeding a heat network. The storage is represented by an 0D model including, sometimes, a linear term to estimate the heat losses to the outside. In general, the authors do not differentiate the model used for optimization from the model used for performance simulation. They conclude that this type of model is suitable for the optimization of large-scale systems.

The optimization of the design of a multi-energy system at the scale of a region was the subject of the study [12]. The models involved in this tool are of type 0D in order to guarantee, here again, reasonable calculation times.

This brief review of the state of the art shows that the modeling of a thermal storage is essentially on two levels : simplistic models and complex numerical models. These two levels lend themselves, in our opinion, to the management-sizing co-optimization of an energy system with storage. The purpose of this contribution is to propose an intermediate level of storage modeling adapted to such co-optimization studies.

## 3. THERMAL STORAGE STATE AND LOSS MODELING

In order to accurately optimize a thermal storage, it is necessary to estimate the temporal evolution of the state of the storage and the thermal losses. These losses are mainly due to the heat exchanges with the outside via the walls and the losses related to the load phase of the system. The estimation of the temperature evolution within the storage is necessary in order to avoid the assumption of a uniform storage temperature (assumption of the 0D models).

### 3.1. 1D - EDP model

This model was chosen because it faithfully represents high-temperature thermal storage in its three phases. In addition, the experimental results from an industrial scale storage system fit well with the numerical results from this numerical model [5].

This model consists in solving the heat equation on the three phases constituting the storage as shown below by considering only the axial variation of the temperature.

- fluid :

$$\varepsilon (\rho C_p)_f \left( \frac{\partial T_f}{\partial t} + u \frac{\partial T_f}{\partial x} \right) = \quad \text{Eq. 1}$$

$$k_f^{\text{eff}} \frac{\partial^2 T_f}{\partial x^2} + h_v (T_s - T_f) + h_w \frac{A_{f \leftrightarrow w}}{V_f + V_s} (T_w - T_f)$$

- solid :

$$(1 - \varepsilon) (\rho C_p)_s \frac{\partial T_s}{\partial t} = \quad \text{Eq. 2}$$

$$k_s^{\text{eff}} \frac{\partial^2 T_s}{\partial x^2} + h_v (T_f - T_s) + h_w \frac{A_{s \leftrightarrow w}}{V_f + V_s} (T_w - T_s)$$

- wall :

$$(\rho C_p)_w \frac{\partial T_w}{\partial t} = k_w \frac{\partial^2 T_w}{\partial x^2} + h_{\text{ext}} \frac{A_{w \leftrightarrow \text{ext}}}{V_w} (T_{\text{ext}} - T_w) + \quad \text{Eq. 3}$$

$$h_w \left( \frac{A_{f \leftrightarrow w}}{V_w} (T_f - T_w) + \frac{A_{s \leftrightarrow w}}{V_w} (T_s - T_w) \right)$$

The numerical resolution of these equations, by the finite difference method, gives the spatio-temporal evolution of the temperature [6]. With the help of a simple energy balance, it is possible to calculate the thermal losses at the walls and the load losses (the latter are proportional to the storage outlet temperature). An example for a load of 1.5 MW during 1 h is shown in Fig. 3. To simplify, a constant temperature load equal to 600°C is assumed throughout the whole study.

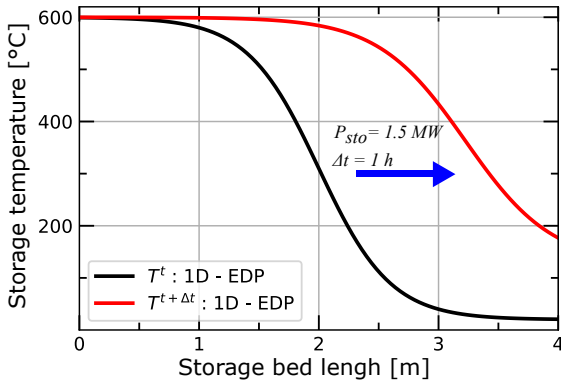


Fig. 3. Evolution of the storage temperature calculated with the 1D-EDP model.

The computation time of the model is relatively long (3 s to simulate 1 h of operation), therefore the model is adapted for short time horizon simulation purposes and not for optimization.

### 3.2. 0D – Ideal storage model

This model assumes a perfect storage without losses at the walls and with a perfect separation between the hot and cold zones (the thickness of the thermocline is zero as shown in Fig. 4).

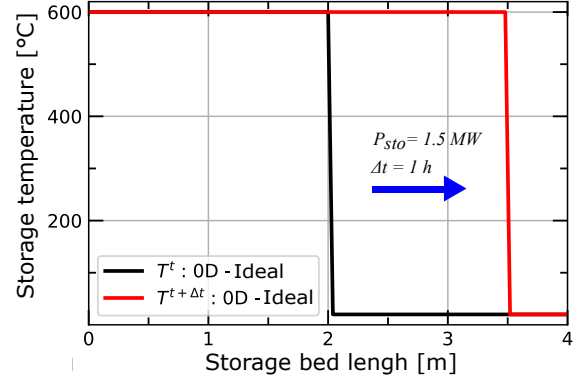


Fig. 4. Evolution of the storage temperature calculated with the 0D-Ideal model.

The dynamics of the system according to this model is expressed as follows :

$$E_{\text{sto}}(t + \Delta t) = E_{\text{sto}}(t) + P_{\text{sto}}(t) \cdot \Delta t \quad \text{Eq. 4}$$

Storage heat losses are zero at all times except when the system is saturated (fully charged storage, in which case the losses are constant and equal to the charging power).

### 3.3. 0D – uniform temperature storage model

In this model, storage is considered, in its entirety, at uniform temperature. Therefore, the thermocline is horizontal as shown in Fig. 5. The evolution of the state of the storage can be calculated with Eq. 5.

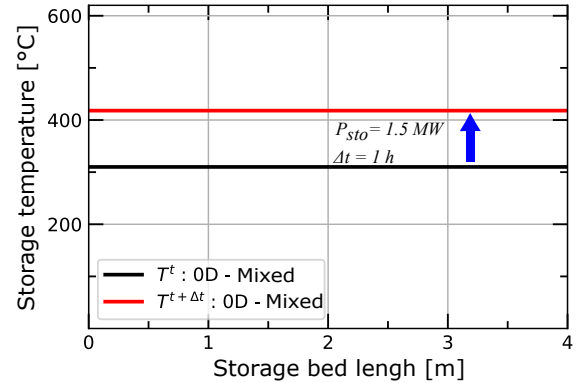


Fig. 5. Evolution of the storage temperature calculated with the 0D model - Mixed.

$$E_{\text{sto}}(t + \Delta t) = E_{\text{sto}}(t) + P_{\text{sto}}(t) \cdot \Delta t - P_{\text{loss}}(T_{\text{moy}}(t), P_{\text{sto}}(t)) \Delta t \quad \text{Eq. 5}$$

with  $P_{\text{loss}}(t) = Q_m C_p (T_{\text{moy}} - T_{\text{ext}})$

and  $T_{\text{moy}} = \frac{E_{\text{sto}}(t)}{C_p m} + T_{\text{ext}}$

The computation time of 0D models is low, which explains their frequent use in energy system optimization work. However, these models poorly estimate the temperature within the storage (e.g. storage outlet temperature for calculating losses).

#### 4. DEVELOPMENT OF A METAMODEL – 1D

This model consists of an analytical approximation of the spatial temperature distribution  $T(x)$ . It takes two input values which are the command  $P_{sto}^t$  and the initial storage temperature curve  $T(x, t)$ . In general, in 1D models, the temperature is a vector of size  $n_x$  ( $n_x = 100$  in [6]). In order to reduce the size of the problem, we use the logistic function that allows to approximate a temperature curve with only four parameters (see Eq. 6).

$$T(x, T_{max}, T_{min}, z_c, s) = T_{max} + \frac{T_{max} - T_{min}}{1 + e^{(x-z_c)/s}} \quad \text{Eq. 6}$$

It is therefore possible to calculate a quadruplet :  $T_{min}, T_{max}, z_c, s$  for each temperature curve as shown in Fig. 6. Linear interpolation, using a previously established matrix (this costly step is performed as explained in 4.1) allows us to calculate the temporal evolution for each quadruplet of values at the instant  $t$ . This gives another quadruplet at instant  $t + \Delta t$ . Finally, using the inverse logistic function allows us to return to the final temperature curve. Therefore, both the state of the storage and the heat losses can be calculated by a simple energy balance.

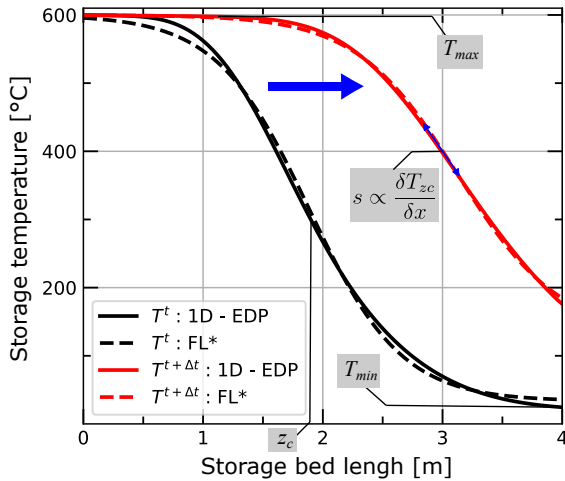


Fig. 6. Evolution of the storage temperature for 1 MW load during 1 h estimated by the 1D - EDP model and approximated by the logistic function\*.

The operation of the metamodel is illustrated in Fig. 7. Its use, once built, is fast because it is a simple linear interpolation according to four parameters (0.001 s to simulate 1 hour of operation). As a result, the model is suitable for use in an optimization and simulation logic over a large time horizon.

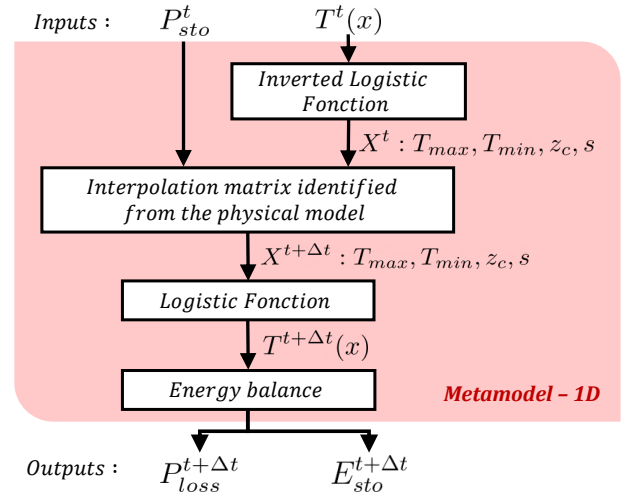


Fig. 7. Metamodel Operating Diagram, illustrating the main steps in the calculation of system state evolution and losses.

#### 4.1. Construction of the metamodel – 1D

The aim is to identify, on the basis of the 1D - EDP model, the interpolation matrix of the temporal evolution of the parameters of the logistic function. The size of this matrix depends on the size of the four discretization vectors  $\overline{T_{min}}, \overline{T_{max}}, \overline{z_c}, \overline{s}$ , in addition to the discretization of the  $\overline{P_{sto}^t}$  command. A simulation, via the expensive 1D - EDP model, is therefore required for each combination of the discretized parameters as shown below.

#### 4.2. Validation of metamodel – 1D

In this section, the simulation results obtained with the 1D - EDP model and the 1D - metamodel for a complete charge and discharge cycle are compared. On the other hand, the sensitivity of the 1D metamodel to the level of discretization, to the time step of the model and to the control is analyzed.

##### 4.2.1. 1D – EDP vs metamodel – 1D for a charge and discharge cycle

Fig. 8 and 9 show, on the basis of a complete load cycle, a concordance between the results from the two models. The mean absolute error is less than 15°C (2.5 %) and 0.1 MW (2.5 %) for the storage temperature and energy state respectively. Therefore, the accuracy of the metamodel - 1D is satisfactory for a load of 1 MW during 5 h.

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#### Algorithm 1: Procedure for the construction of the metamodel identification matrix

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**Data:**  $T_{min}^t \in \overline{T_{min}}, T_{max}^t \in \overline{T_{max}}, z_c^t \in \overline{z_c}, s^t \in \overline{s}, P_{sto}^t \in \overline{P_{sto}}$

**Result:**  $(T_{min}^{t+\Delta t}, T_{max}^{t+\Delta t}, z_c^{t+\Delta t}, s^{t+\Delta t}) = f(T_{min}^t, T_{max}^t, z_c^t, s^t, P_{sto}^t)$

initialization;

**foreach**  $T_{min}^t, T_{max}^t, z_c^t, s^t$  **do**

**foreach**  $P_{sto}^t$  **do**

        calculate  $T(x, t)$  with Eq.6 ;

        calculate  $T(x, t + \Delta t)$  with Eq.1.2.3 ;

        calculate  $T_{min}^{t+\Delta t}, T_{max}^{t+\Delta t}, z_c^{t+\Delta t}, s^{t+\Delta t}$  with Eq.6 inverted

**end**

**end**

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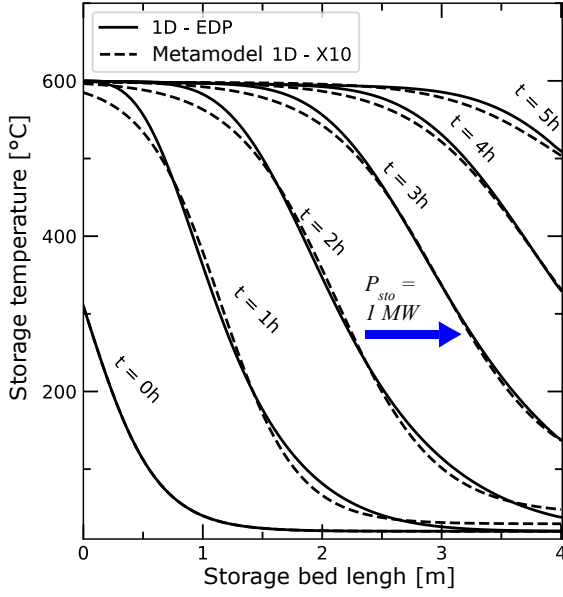


Fig. 8. Simulation of storage temperature for a 1 MW load with two models : 1D - EDP and metamodel - 1D.

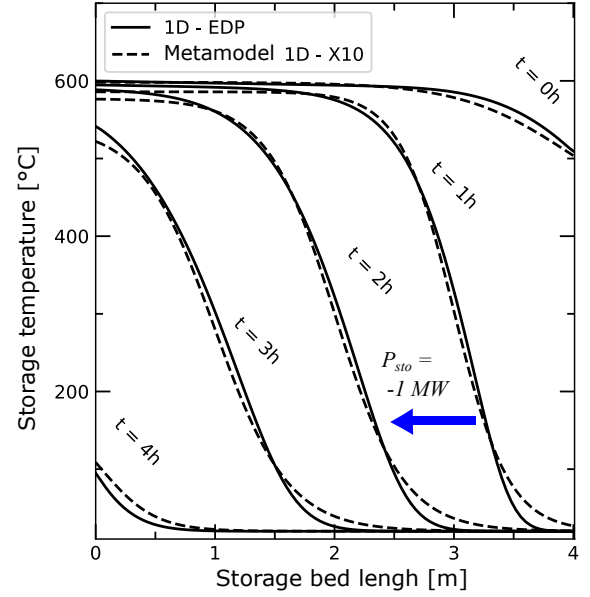


Fig. 10. Simulation of storage temperature for a 1 MW discharge with two models : 1D - EDP and metamodel - 1D.

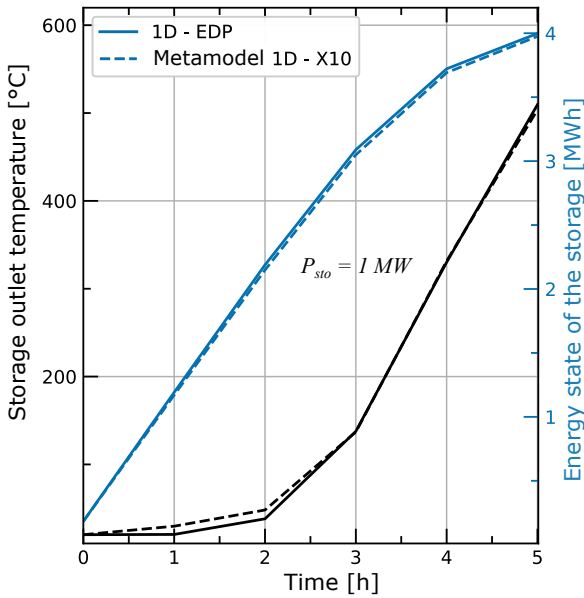


Fig. 9. Simulation of storage energy state and output temperature for a 1 MW load with two models : 1D - EDP and metamodel - 1D.

Fig. 10 and 11 show the same type of result for a complete discharge. In this case, the mean absolute error is 50°C (8.6 %) and 0.1 MW (2.5 %) for temperature and energy state respectively.

#### 4.2.2. Sensitivity study according to the level of discretization

The aim is to vary the level of discretization of the parameters constituting the metamodel - 1D (here four parameters of the logistic function in addition to the control parameter), and to study its impact on the accuracy of the model.

For this study, the charging and discharging of a storage with a power of 0.25 MW during a period of 20 h is simulated. The time step of the model remains unchanged ( $\Delta t = 1h$ ). Table 1 details the different metamodels - 1D used in this study.

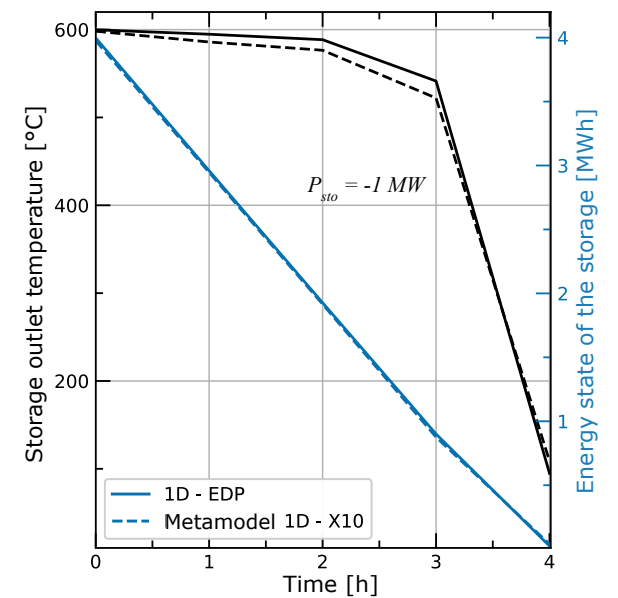


Fig. 11. Simulation of storage energy state and output temperature for a 1 MW discharge with two models : 1D - EDP and metamodel - 1D.

Fig. 12 and 13 show the evolution of the energy state and heat losses during the charging phase respectively. The results are illustrated for different metamodels based on data from the precise model (1D - EDP).

<sup>1</sup> Number of discretization points for each parameter of the logistic function :  $T_{\max}, T_{\min}, z_c, s$ .

<sup>2</sup> Number of discretization points for the power command  $P_{sto}$

<sup>3</sup> Number of expensive simulations required with the 1D model - EDP

<sup>4</sup> Intel® Core i7-6820HQ CPU @ 2.70GHz

Symbol	$n_{log}$ <sup>1</sup>	$n_{com}$ <sup>2</sup>	$N_{sim}$ <sup>3</sup>	Model construction time [s] <sup>4</sup>
X2	2	5	80	112
X3	3	7	567	737
X5	5	11	6 875	6 187
X10	10	21	210 000	207 000

Tableau 1. Description of the level of discretization of metamodels - 1D built during this analysis.

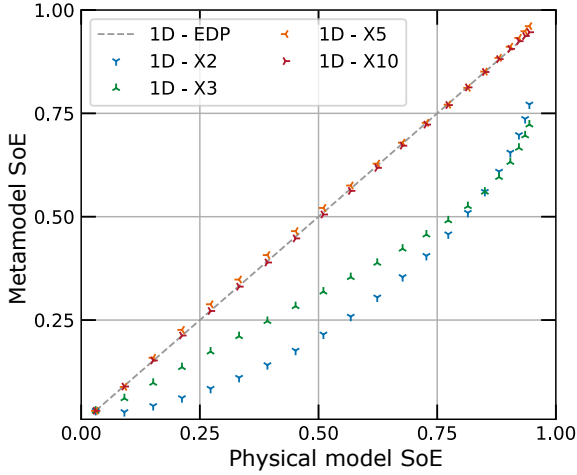


Fig. 12. Evolution of the state of the system during a load, estimated by the metamodels - 1D at different levels of discretization, and compared to the 1D - EDP model.

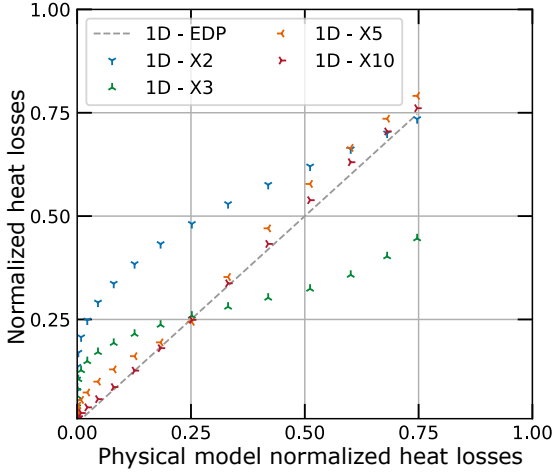


Fig. 13. Evolution of heat losses during a load, estimated by the metamodels - 1D at different discretization levels, and compared to the 1D - EDP model.

The error decreases as the level of discretization of the model increases. The maximum relative error remains less than 7% and 3% for models X5 and X10 respectively (valid for the two quantities in question :  $E_{sto}$  and  $P_{loss}$ ).

Fig. 14 shows the evolution of the energy state during a complete discharge. Starting from the X5 model, the maximum relative error remains below 4%. The accuracy is therefore considered satisfactory for simulation or optimization purposes.

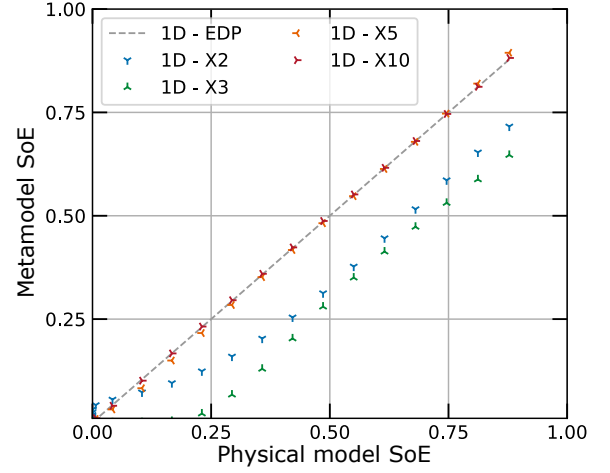


Fig. 14. Evolution of the state of the system during a discharge, estimated by the metamodels - 1D at different levels of discretization, and compared to the 1D - EDP model.

#### 4.2.3. Sensitivity study as a function of storage power.

This study consists in simulating, via the 1D - EDP model and the metamodel, the load of a thermal storage for a power that varies between 0.25 and 4 MW (maximum allowed power) as shown in Fig. 15.

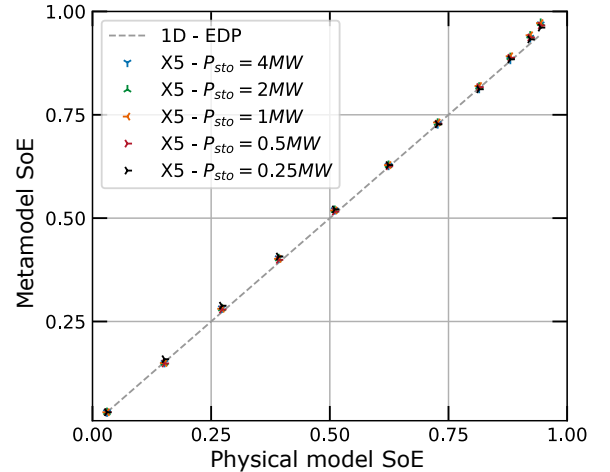


Fig. 15. Evolution of the state of the system during a variable power load, estimated by the metamodel - 1D - X5, and compared to that of the 1D - EDP model.

The discretization of the model with respect to the power is done with variable steps, which implies a strong discretization for values close to 0. Consequently, the model maintains the same level of accuracy for the different values of power injected into the storage. Thus the metamodel - 1D X5 is efficient for both low and high power values.

## 5. CASE STUDY

In this section, the case study used for the optimization work is presented. This is the case study illustrated in Fig. 2. As a reminder, this is a production source and another consumption source, both of which are time-varying. The control to be optimized is that of thermal storage in order to minimize both the call on the auxiliary boiler in case of overconsumption and the loss of profit in case of overproduction  $P_{dev}$ . In the end, thermal losses related to storage should also be minimized.

For simplicity, an adjusted time series of the wind forecast error, from BPA (Bonneville Power Administration) in the Pacific Northwest region of the United States is chosen (see Fig. 16). This power series is assumed to be equivalent to the difference between production and consumption  $P_{mis}$ . Throughout this study, the optimization problem is assumed to be deterministic.

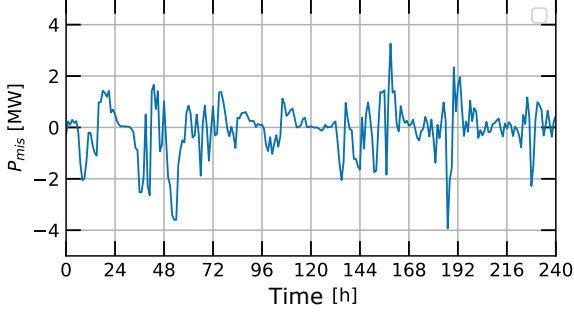


Fig. 16. Time series of the forecast error of wind power assimilated to the difference between production and consumption power on the heat network.

### 5.1. Mathematical formulation and method of resolution

We seek to optimize the management of thermal storage, described above, over a fixed time horizon. The objective of the optimization is to minimize, the sum of the deflection power on the grid squared and the thermal losses related to the storage squared. It is a mono - objective optimization including two terms weighted with the value  $\alpha$ . This problem is subject to physical constraints which are described below.

$$\min_{P_{sto}^{t,c}} \sum_{t=0}^T \alpha P_{dev}^2(t) + (1 - \alpha) P_{loss}^2(t)$$

such as  $\forall t \in [0, T]$

$$P_{mis}(t) = P_{prod}(t) - P_{load}(t)$$

$$P_{dev}(t) = P_{mis}(t) - P_{sto}(t)$$

$$P_{dev}(t) = P_{prod}(t) - P_{load}(t) - P_{sto}(t)$$

$$-P_{rated} \leq P_{sto}(t) \leq P_{rated}$$

$$0 \leq E_{sto}(t) \leq E_{rated}$$

$$\text{with } P_{rated} = 4\text{MW et } E_{rated} = 4\text{MWh}$$

Eq. 7

The storage dynamics that link storage condition and heat loss to control is estimated using one of the three models described in the previous sections.

The problem is solved numerically using dynamic programming (Bellman principle). The equation below shows the two terms to be minimized : the instantaneous cost and the anticipation of the future cost.

$$J_t(E_{sto}^t) = \min_{P_{sto}^t} \left\{ \underbrace{c_t(E_{sto}^t, P_{sto}^t)}_{\text{instantaneous cost}} + \underbrace{J_{t+1}(f(E_{sto}^t, P_{sto}^t))}_{\text{future cost}} \right\} \text{ Eq. 8}$$

## 6. RESULTS AND MODEL COMPARISON

The optimal management resulting from dynamic programming manifests itself as a two-dimensional matrix (time  $t$  and energy state  $SoE$ ) for linear 0D models as shown in Fig. 17. On the other hand, the management matrices corresponding to the metamodels are 5-dimensional ( $t, T_{max}, T_{min}, z_c$  and  $s$ ). To simplify reading, we plot the latter as a function of time and only one state dimension  $z_c$ . These matrices are calculated for a value of  $\alpha = 0.5$  and over a 24-hour time horizon.

When the storage is empty ( $SoE = 0$ ), the optimal command is always positive or zero. On the other hand, when the storage is saturated ( $SoE = 1$ ), the optimal command can be positive. This is a particularity of this technology : we can continue charging after saturation by sending hot air to the storage which will also come out hot and will be taken into account as heat loss.

It is possible to notice that the discretization of the metamodel helps to obtain a less approximate management strategy. The most discretized metamodel management matrix (here X10) strongly resembles the management from discretized 0D models ( $n_{SoE}^{0D} = 101$ ).

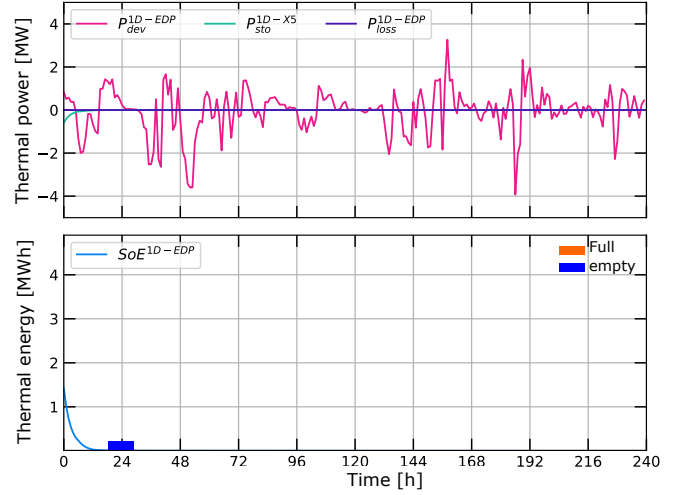


Fig. 18. Simulation of the case study, using the 1D - EDP model, of the management strategy resulting from the metamodel - 1D - X5, for  $\alpha = 0$  and over a time horizon of 240 h.

In the rest of this article, all the optimization results come from the simulation of the 1D - EDP model. The goal is to validate and compare these management strategies with each other in a simulation environment that is as close as possible to reality.

The figures Fig. 18, 19, and 20 show the simulation results of the management resulting from an X5 metamodel for  $\alpha = 0, 0.5$  and 1 respectively. The time horizon of the simulation is 240 h. For  $\alpha = 0$ , we notice that the storage discharges from the first steps of time and remains without energy in order to minimize its losses. For  $\alpha = 0.5$ , the storage is managed in a way to minimize both the deviation on the network but also the thermal losses. Finally, with a  $\alpha = 1$ , the only objective taken into account by the storage is the deviation on the network. We note that this last management mode generates non-negligible losses of the same order of magnitude as the deviation on the network.

In order to see the impact of the choice of model as a function of the value of  $\alpha$  (weight of the deviation in front of the thermal losses in the objective function), we have chosen to plot a Pareto front. In Fig. 21, the y-axis represents the sum of the deflected powers on the grid squared, the x-axis represents the sum of the heat losses over the time horizon studied (here 24 h) squared. The different groups of points correspond to the different models used for management optimization. The points belonging to the same group correspond to the different values of  $\alpha$  (ranging from 0 to 1).

From the X5 metamodel, a better performance over the studied time horizon is obtained, compared to the Ideal and Mixed 0D models. An asymptote close to the metamodel - X10 appears, which shows that the gain from this last level of discretization becomes negligible.

It should be noted that the 0D - Ideal model does not allow to cancel the thermal losses : the total cost of losses corresponding



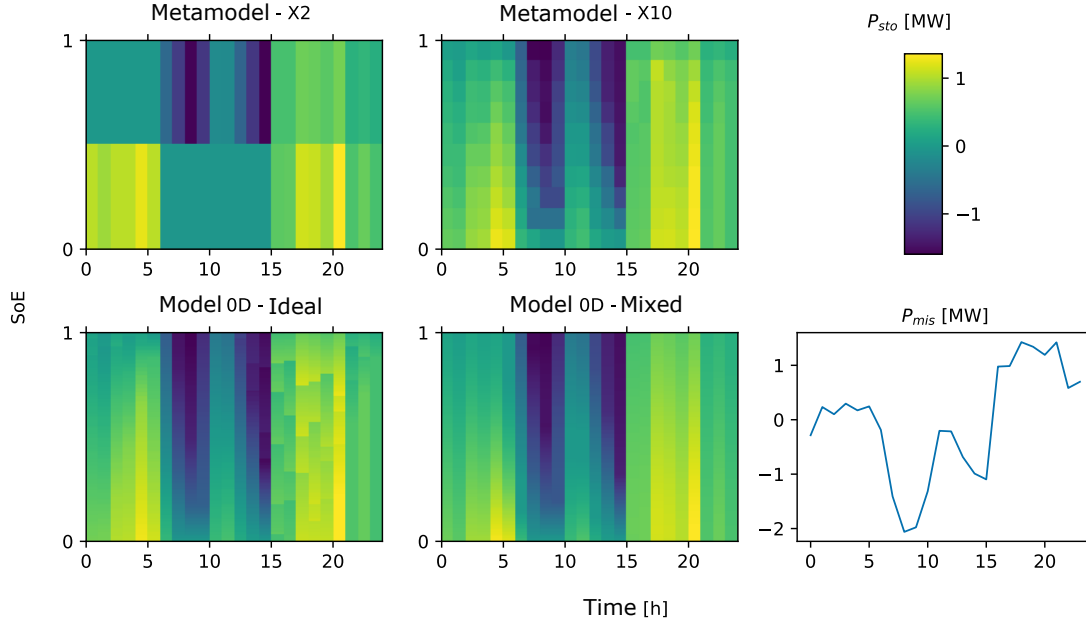


Fig. 17. Example of management matrices from different models : 0D - Ideal, 0D - Mixed, Metamodels - 1D.

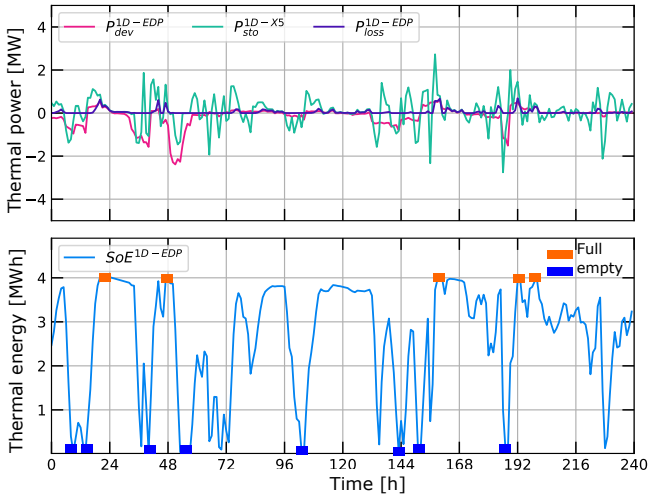


Fig. 19. Simulation of the case study, using the 1D - EDP model, the management strategy derived from the metamodel - 1D - X5, for  $\alpha = 0.5$  and over a time horizon of 240 h.

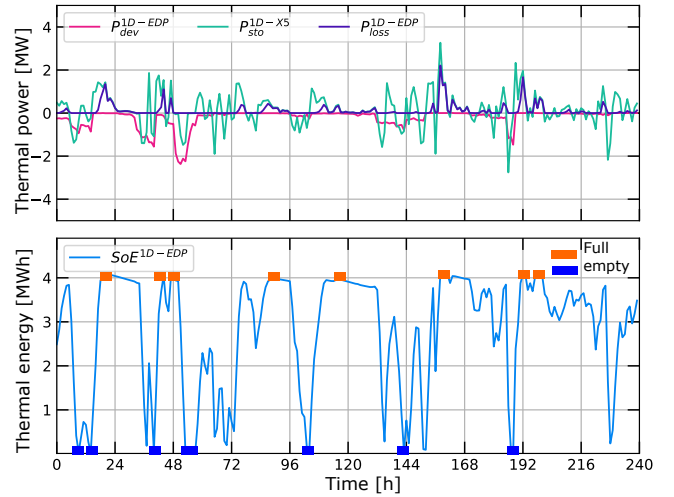


Fig. 20. Simulation of the study case, using the 1D - EDP model, of the management strategy derived from the metamodel - 1D - X5, for  $\alpha = 1$  and over a time horizon of 240 h.

to this model never reaches zero (on the left of the curve) because it does not model them.

In Table 2, the value of  $\alpha$  is set to 0.5 (identical weight for the deviation and for the heat losses in the objective function). The sensitivity study shows the evolution of the total cost of management as a function of the calculation time required, and the level of discretization of the metamodel.

In this case, it is noteworthy that an optimal management allows to reduce the cost by 48% compared to a simplified management (load as much as possible and ditto for the discharge). The calculation time for optimal management using the metamodel increases exponentially with the level of discretization. For a slightly discretized metamodel (X2) this time is of the same order of magnitude as for linear 0D models. The total cost of the optimization decreases largely up to the X3 model, and slightly up to the X10 model. The total cost related to the X3 model corresponds to that related to the 0D models.

The use of the metamodel - X10 in an optimization logic

makes it possible to reduce the total cost of management by 2 and 4% compared to management using 0D - Ideal and 0D - Mixed models respectively. This is to the detriment of a longer calculation time : 7 s for 0D models, 50 s for 1D - X3 and 6,557 s for 1D - X10.

## 7. CONCLUSIONS AND PERSPECTIVES

In this work, a metamodel - 1D for thermocline thermal storage is proposed and validated on a precise 1D - EDP model, itself experimentally validated on an industrial system, an EcoStock<sup>®</sup> of 4 MWh. Sensitivity studies of the metamodel validate its performance and show a good compromise between computing speed and model accuracy. The metamodel significantly reduces the calculation time : 1 ms to simulate 1 hour of load via the metamodel - 1D and 3 s for the 1D - EDP model. This model is useful for simulating storage performance over a very large time horizon (several years).

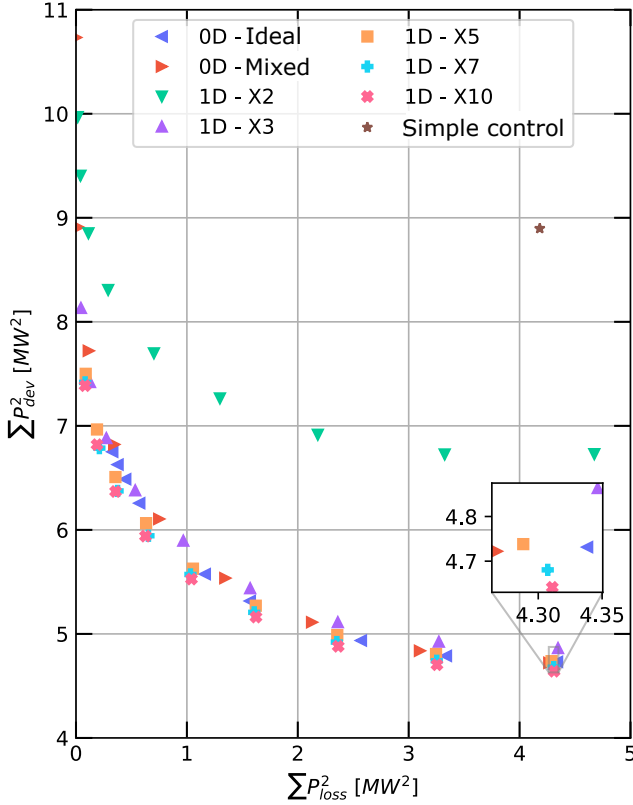


Fig. 21. Front of Pareto composed of the sum of the two objectives : the deviation power on the network and the heat losses squared, accumulated over 24 hours. The simulation uses the 1D - EDP model but the management strategies are calculated using the models - 0D and the metamodels - 1D.

Tableau 2. Comparison of computation time and optimality of results between the different 0D models and metamodels studied.

Model	Calculation time [s]	Optimal cost [ $MW^2$ ]	Cost reduction / simple control [%]
Simple control	-	13.1	0
0D-Ideal	7	6.8	48
0D-Mixed	7	7	46.7
1D-X2	12	8.4	35.5
1D-X3	50	6.9	47.5
1D-X5	310	6.7	49
1D-X7	884	6.6	49.7
1D-X10	6 557	6.5	50

On a typical case study, the metamodel is compared to the different models commonly used in the literature. To do this, optimal management strategies are calculated using dynamic programming. These cases are then simulated using the precise 1D - EDP model. The results show that the 0D models give satisfactory results and that the metamodel allows a slight increase in accuracy compared to the 0D models.

The use of 0D models is sufficient to optimize management. However, this model remains insufficient to simulate the spatial distribution of temperature and to integrate finer cost functions such as ageing.

This work deals with an optimization problem solved using dynamic programming. In perspective, it is possible to ask : to what extent are these conclusions valid for other optimization

techniques (online optimization such as MPC).

This work will be used as a basis for dealing with an optimization problem of a multi-energy network. It is a coupling of the sources of production and consumption of heat and electricity, integrating thermal and electrical storage and "Power To Heat" and "Heat To Power" conversion systems with uncertainties.

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