Demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility

IES Simulation Ecosystem Control System Development

Nuclear Science and Engineering Division
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Demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility

IES Simulation Ecosystem Control System Development

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ABSTRACT

The goal of the power dispatch problem for an Integrated Energy System (IES) is to adjust the power output and the heat flow of each component to maximize the profitability of the whole unit. Facilities that can integrate real-time digital signals, mock nuclear power, thermal energy storage and industrial heat use via high-temperature electrolysis were constructed at INL to support the research activities. The Dynamic Energy Technology and Integration Laboratory (DETAIL) houses the Microreactor Agile Non-nuclear Experimental Test Bed (MAGNET) and the Thermal Energy Distribution System (TEDS).

In this report, the hierarchical control system architecture proposed in June 2023 milestone for the flexible operation of DETAIL facility is finalized and demonstrated. A brief description of the components and the corresponding Dymola models from the HYRBID repository is first provided. Then, the current control strategy is presented. In particular, the approach for generating the set-point trajectories to be fed to the PI controllers is analyzed, and its limits were identified. To preserve safe operation over both long-time and real-time horizons, the integration of a Supervisory Control layer embedding a modified version of FARM (Feasible Actuator Range Modifier) module is proposed. FARM is a component of the RAVEN-based FORCE framework designed to support HERON module at optimizing the operation of IES units. The proposed control system for DETAIL foresees FARM to be applied twice, i.e., the original version (“FARM-Validator”) aiding the solution of the power dispatch problem, and a modified version (“FARM-Supervisory”) coordinating the PID controllers. Despite the kernel of the two modules is the same, their tasks are quite different. The former intervenes at the beginning of each hour to prevent constraint violations over long time periods, the latter addresses real-time control tasks and monitors the response of constrained variables at a much finer time resolution. A tentative procedure for training the embedded Digital Twins with the experimental data is also proposed. Finally, the capabilities of the designed architecture and the impact of the added Supervisory Control layer are demonstrated by simulating a representative power dispatch scenario.
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1. INTRODUCTION

The goal of the power dispatch problem for an Integrated Energy System (IES) is to adjust the power output and the heat flow of each component to maximize the profitability of the whole unit. Facilities that can integrate real-time digital signals, mock nuclear power, thermal energy storage and industrial heat use via high-temperature electrolysis were constructed at INL to support the research activities. The Dynamic Energy Technology and Integration Laboratory (DETAIL) houses the Microreactor Agile Non-nuclear Experimental Test Bed (MAGNET) and the Thermal Energy Distribution System (TEDS) (Figure 1-1) [1].

![Figure 1-1. Photo of DETAIL facility at INL’s Energy Systems Laboratory [2].](image)

MAGNET is an experimental design to aid in the development, demonstration, and testing of various microreactor technologies. It houses an electrical heating element that enables it to simulate nuclear reactor cores with microreactor test elements inside the environmental chamber. This provides inputs for primary heat exchanger performance as well as passive decay heat removal for heat-pipe and gas-cooled microreactors. To test and prove microreactor/hybrid technologies, MAGNET was designed to be integrated with a power conversion unit (PCU) constituted by a 30 kW_e gas turbine, and a thermocline-based energy storage system named TEDS. To aid the design and operation of experimental facilities, the IES team continues to create high-fidelity dynamic models in HYBRID [3] open-source repository using Modelica [4], an equation-based acausal
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language for engineering applications. HYBRID modelers can quickly develop new systems by utilizing building block structures created either internally, in the open-source Modelica Standard Library, or using ORNL’s open-source TRANSFORM library [5]. A system-wide ramping capability, thermal and electrical integration methods, control, and feedback are observable via the HYBRID output [1]. In the milestone completed in June 2023 [6], hierarchical control system architecture for the operation DETAIL was proposed. First, the current control strategy was presented. In particular, the approach for generating the set-point trajectories to be fed to the PI controllers was analyzed, and its limits were identified. To preserve the system safe operation over both long-time and short-time horizons, a Supervisory Control layer embedding a modified version of the FARM (Feasible Actuator Range Modifier) algorithm [7] was designed.

The kernel of FARM module is the Command Governor (CG), i.e., the Multiple Input Multiple Output (MIMO) version of the Reference Governor algorithm [8][9]. It is a discrete-time device that is used in the field of feedback control of dynamic systems. It is an add-on scheme that enforces pointwise-in-time constraints by modifying the set-point signals fed to a closed-loop, dynamic system. In this way, the problem of designing the control system is addressed as a two-step process. The primal regulator is tasked to stabilize the system and provide tracking properties in the absence of constraints. It can be a set of PI controllers, as in the case of DETAIL facility. The constraint fulfillment task is left to the CG, i.e., a nonlinear device which is added to the primal compensated nonlinear system. As shown in Figure 1-2, the CG modifies the reference, set-point signals ($\hat{r}(t)$) by providing the primal regulators with adjusted signals ($\hat{v}(t)$) to enforce the constraints, whenever necessary. In FARM, the CG is tasked with favoring the convergence of the power dispatch optimization algorithm to a feasible solution. It constitutes a sort of validator downstream of the HERON Power Dispatcher by assessing that the calculated set-point trajectories meet both explicit and implicit constraints (Figure 1-3). In case the imposed constraints are violated, the operational margin is evaluated and returned for re-optimization.

Figure 1-2. Traditional configuration of a feedback control loop embedding the CG algorithm.
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Figure 1-3. Implementation of the FARM module into the power dispatch optimization scheme.

The hierarchical control system architecture proposed for DETAIL foresees the CG to fulfil its traditional task of modifying the reference, set-point signals supplied to the primal regulators. In this way, FARM module would be applied twice, i.e., the original version (“FARM-Validator”) aiding the solution of the power dispatch problem, and the modified version (“FARM-Supervisory”) coordinating the PID controllers (Figure 1-4). Despite the kernel of the two modules is the same, their tasks are quite different. A detailed description of the role of FARM at addressing real-time control tasks is provided, along with tentative procedures for training the models embedded into the algorithm by using the collected experimental data.

Figure 1-4. Graphical representation of the proposed hierarchical control system architecture adopting two instances of FARM, i.e., FARM-Validator and FARM-Supervisory.
2. DESCRIPTION OF DETAIL FACILITY AND PROPOSED CONTROL SYSTEM

In this Section, the components that constitute DETAIL facility and the corresponding Modelica models contained in the HYBRID repository are described. In addition, the currently adopted control strategy for the operation of the facility was presented, and the list of adopted feedback controllers was provided.

2.1. MAGNET

2.1.1. Description of the Component

MAGNET is a combination of subsystems and components working in tandem via a control system. These components and subsystems include a 250 kW electrically heated core, an environmental chamber, a 350-kW recuperator, a 265-kW heat rejection chiller, a compressor to control the coolant flow rate, and a series of insulated pipes. In Figure 2-1, a scheme of the MAGNET process flow is shown.

![Figure 2-1. Scheme of the MAGNET process flow [1].](image-url)
2.1.2. Description of the Modelica model

The graphical user interface of the Modelica model of MAGNET is shown in Figure 2-2. The main components described in Section 2.1.1 are modeled:

- the 250 kW electrically heated core and the environment chamber are modeled by a volume “vc”.
- the 350-kW recuperator and the 265-kW heat rejection chiller are modeled by two heat exchangers “rp” and “hx”, respectively.
- the compressor controlling the coolant flow rate is modeled by a pump “co”.

Components are interconnected through insulated pipes. MAGNET is cooled by a nitrogen flowrate that is pumped into the environmental chamber “vc” (363 °C, 11.5 bar), where it is heated up by the core at a maximum rate of 250 kWth. The hot coolant leaves the chamber (602 °C), and it gets distributed to external processes (i.e., gas turbine, heat exchangers) through a flange after passing through the insulated pipe “pipe_vc_TEDS”. The returned coolant is fed to the recuperator “rp” to preheat the cold coolant before entering the environmental chamber. The hot coolant leaves the recuperator (284 °C, 11.1 bar), and it is cooled by water at the heat rejection chiller “hx”. The cold coolant then leaves the heat rejection chiller (20 °C, 10.8 bar). A tank of nitrogen is connected to the loop via a pressure-reducing valve as a buffer. The cold coolant then passes through the recuperator so it can be preheated before entering the environmental chamber. Two PI controllers are used to control the mass flow rate of the chilled water and the nitrogen within the MAGNET loop to maintain the desired temperature of nitrogen when entering and leaving the environmental chamber “vc”. For more details about MAGNET operation, the reader may refer to [1].
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![Graphical representation of the Modelica model of MAGNET [3].](image)

### 2.2. Power Conversion Unit (PCU) and Thermal Energy Distribution System (TEDS)

#### 2.2.1 Description of the Components

In DETAIL, MAGNET acts as a heat source, with nitrogen serving as the coolant to transport the thermal power generated inside the vacuum chamber to the gas turbine to meet the electricity demand. If the thermal power is more than what is needed to meet the electricity demand, it will be transferred to TEDS. This is accomplished through a helical coil heat exchanger that transfers the heat from MAGNET to TEDS. TEDS can use this excess heat to meet the heat demand or can store it in the thermocline thermal storage. Ther thermocline in TEDS can also discharge in case the heat demand exceeds the thermal power generated by MAGNET.
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2.2.2 Description of the Modelica model

In Figure 2-3, the graphical user interface of the PCU model is shown. The coolant leaving MAGNET’s environmental chamber is expanded through the gas turbine by producing up to 30 kW. The fluid is then cooled and compressed back to the original pressure and returned to the MAGNET loop for reheating. A valve controls the coolant flow rate into the gas turbine to meet the electricity demand set by the market. The major component of TEDS is the single-tank packed-bed thermocline system that can store up to 200-kWth. A thermocline storage system stores heat via hot and cold fluid separated by a thin thermocline region that arises because of a fluid density differential. This thermocline region can be kept relatively small in comparison with the size of the tank, given the low mixing via internal flow characteristics and structural design. Additionally, large buoyancy changes and low internal thermal conductivity are also extremely useful in maintaining small relative thermocline thickness. To increase the cost-effective nature of these designs, it is common to fill the tank with a low-cost filler material, such as concrete or quartzite. These filler materials are inexpensive, have high density, and high thermal capacity. By using such material, a reduction in the amount of high-cost thermal fluid can be achieved, thereby increasing

Figure 2-3. Graphical representation of the Modelica model of the PCU [3].
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the economic competitiveness of such designs. A model of this thermocline system with filler material was developed in [10], and the graphical representation is shown in Figure 2-4.

![Graphical representation of the Modelica model of the Thermocline](image)

**Figure 2-4. Graphical representation of the Modelica model of the Thermocline [10].**

To ensure all operational modes are possible while maintaining component properties within acceptable limits, a set of valves, sensors, heat exchangers and control algorithms is required. A representation of the Modelica model of TEDS is provided in Figure 2-5. The heat is transferred from MAGNET circuit to TEDS through the helical coil heat exchanger and then distributed for either storage purposes or heat removal through 8 valves, i.e., “valve1” through “valve6” in the original design, and 2 newly added bypass valves (“valve10” and “valve11”). A dedicated heat exchanger “Glycol_HX” is used to dispose heat from TEDS, where 50% ethylene glycol is heated up by the hot thermal storage fluid to meet the non-zero heat load demand. During zero heat load demand scenarios, the very heat exchanger is bypassed. To adjust the valve openings to meet the heat load demand and store excessive heat to thermocline system, a unified control system was developed. Two addition PI controllers are used to regulate the mass flow rate of Ethelyn glycol and thermal storage fluid to maintain a constant temperature of thermal storage fluid when entering (225 °C) and leaving (325 °C) the helical coil heat exchanger. A more detailed description of TEDS model can be found in [10].
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2.3. **Current control strategy of DETAIL facility**

The integration of MAGNET, TEDS and PCU is meant to provide DETAIL with superior performance in terms of operational flexibility. In response to market conditions, the thermal power produced by MAGNET can be directed to electricity production, heating demand, thermal storage, or any combination of the three. In the case of high-demand scenarios, the thermal power stored in TEDS can also be discharged. Five different operating modes for DETAIL were then identified (Table 2-1). In all of them, a portion of the thermal power produced by MAGNET is directed to meet the electricity load, i.e., the PCU is always running to meet the electricity demand. A more complex operating scheme for accommodating scenarios in which there is no electricity demand, with the heat source instead directing all its energy toward the heat load and/or thermal storage is currently being investigated [1]. As shown in Table 2-2, the decision of operating DETAIL in a certain mode is determined by comparing the heat demand level ($P_{Heat}$) with the heat disposed to TEDS through the helical coil heat exchanger ($Q_{MT,HX}$).
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Table 2-1. Description of the identified Operating Modes for DETAIL facility.

<table>
<thead>
<tr>
<th>Mode</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode 1</td>
<td>It simulates the heat generation with no energy storage. This mode is equivalent to a standard load-following mode.</td>
</tr>
<tr>
<td>Mode 2</td>
<td>It simulates a full charging scenario, i.e., all the heat transferred to TEDS is disposed to the thermal storage unit.</td>
</tr>
<tr>
<td>Mode 3</td>
<td>It simulates a full discharging scenario, i.e., no heat is disposed to TEDS and the thermal storage unit is the sole unit providing heat to the glycol heat exchanger.</td>
</tr>
<tr>
<td>Mode 4</td>
<td>It is a combination of modes 1 and 2, i.e., the heat transferred to TEDS is distributed to both the heat load and the storage. Typically, this operational unit provides heat to the load first and then dumps excess heat into the thermal storage unit for use later.</td>
</tr>
<tr>
<td>Mode 5</td>
<td>It involves a combination of Modes 1 and 3. Both the MAGNET and the thermal storage tank supply the heat load. This mode would be common in an area that utilizes a large amount of variable renewable energy.</td>
</tr>
</tbody>
</table>

Table 2-2. List and features of the Operating Modes.

<table>
<thead>
<tr>
<th>Mode</th>
<th>Condition</th>
<th>Heat Source to Electrical Load</th>
<th>HX to Heat Load</th>
<th>Charging (HX to Storage)</th>
<th>Discharging (Storage to Heat Load)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode 1</td>
<td>$Q_{MT,HX} = P_{Heat}$</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Mode 2</td>
<td>$Q_{MT,HX} &gt; P_{Heat} = 0$</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Mode 3</td>
<td>$P_{Heat} &gt; Q_{MT,HX} = 0$</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Mode 4</td>
<td>$Q_{MT,HX} &gt; P_{Heat} &gt; 0$</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Mode 5</td>
<td>$P_{Heat} &gt; Q_{MT,HX} &gt; 0$</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

In Figure 2-6, the Piping and Instrumentation Diagram (P&ID) of the MAGNET-PCU-TEDS integrated system is shown. The red labels represent the actuators, the dash blue lines represent the pairings between the control and the controlled variables. Overall, the system is characterized by 10 actuators (7 valves, 2 pumps, 1 compressor). The number of actuators is lower than the number of variables to be controlled (i.e., these systems are called “underactuated”). Some of these temperatures are controlled by adopting PI controllers issued with constant set-points (the corresponding values are displayed). At the same time, oscillations of the temperatures of the working fluids in some crucial positions need to be avoided to ensure the safe operation of the system. The temperatures that cannot be controlled are constrained (the values of the corresponding limits are represented by orange displays).

From an operational standpoint, DETAIL is addressed as a whole, single dynamic system, since the proposed control strategy needs to inherently account for the impact that MAGNET, TEDS and PCU have on each other. A decentralized control scheme structure is adopted. Traditionally, this means that all the plant subsystems are separately controlled by their own local controller. In
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decentralized schemes, the roles of all the local controllers are the same, and none of them has a more important role. Compared with the centralized control, this scheme has higher reliability because it does not have a centralized controller with excessive communication. With respect to the current implementation, it means that each actuator is tasked with controlling a specific process variable. The control system is then constituted by a set of Single Input Single Output (SISO) regulators, i.e., 10 control variables are adjusted to govern the response of 10 controlled variables. A comprehensive description of the current control strategy and the foreseen regulators is here reported (Table 2-3). For further details, the reader may refer to [1].

- The first column lists the controlled variables \( (y) \). The corresponding labels used in the Modelica model are provided.
- The second column lists the control variables \( (u) \), i.e., the variables that can be adjusted for governing the system response.
- The third column lists the actuators performing the control actions. 8 of these actuators are governed by PI controllers and one of them by an algebra-based interlock that is aligned with the response of one of the PI controllers.
- The fourth column lists the types of adopted SISO regulators.
- The fifth column lists the relationship/equation used to derive the 8 set-point values fed to the regulators \( (y^{ref}) \). Here is a summary of how they are derived:

  - 1 is user-defined signal \( (P_{Elec}) \).
  - 1 is calculated from another user-defined signal \( (P_{Heat}) \) to preserve a mass or an energy balance.
  - 4 are constant temperatures.
  - 2 are binary values depending either on the other set-points or on the actuator values.

PI controllers are assigned either regulation or tracking duties. As for the former, the controller is programmed to ensure that a specific controlled variable remains close to a pre-defined set-point; as for the latter, the controller keeps modifying its action to ensure the controlled variable reaches a time-dependent set-point. The duties of the controllers foreseen by the control strategy then depend on the nature of the set-point signals, which can be divided into two sets. The former set is constituted by two signals that are adjusted during operation \( (P_{Elec} \text{ and } m^{TES}_{charge}) \); the latter set is constituted by six signals that are either constant or dependent on the others. In Table 2-4, the equations defining the set-point values governing the charging and discharging phases of TEDS are reported. In Table 2-5, the involved variables and the parameters are listed and described.

The proposed hierarchical control system preserves the pairings between control and controlled variables foreseen by the current control strategy, despite some features might be improved. For example, some temperatures are supposed to be maintained constant during operation. Instead of
controlling these temperatures, they just might be constrained by ensuring more flexibility. Another aspect concerns the control of MAGNET. In particular, a portion of the coolant flow rate at the heater outlet is sent to the PCU, and the left portion passes through the heat exchanger at the interface with TEDS. The process is governed by three valves regulating the flow rates, i.e., the one at the flow-split inlet and the two at the flow-split outlets. This control problem is over constrained, i.e., if the opening of two valves is imposed, the corresponding flow rates are imposed, and the flow rate through the third one is automatically defined. For this reason, controlling the pressure on one of the outlet lines would be more effective.
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Figure 2-6. P&ID of the MAGNET-PCU-TEDS integrated system.
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Table 2-3. Current control strategy for DETAIL. The labels used in the P&ID shown in Figure 2-6 for control and controlled variables are adopted here as well.

<table>
<thead>
<tr>
<th>Controlled variable (y)</th>
<th>Control variable (u)</th>
<th>Actuator</th>
<th>SISO regulator</th>
<th>Set-Point variable (y&lt;ref&gt;)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GT_Power (Generated electrical power)</td>
<td>Opening&lt;sub&gt;7&lt;/sub&gt;</td>
<td>valve_vc_GT (Nitrogen valve at Gas Turbine inlet)</td>
<td>PID (PIDV8)</td>
<td>PCU_Elec_Demand_W (F&lt;sub&gt;Elec&lt;/sub&gt;) (User-defined)</td>
</tr>
<tr>
<td>pT_pipe_vc.T (T3) (Nitrogen temperature at MAGNET inlet)</td>
<td>m&lt;sub&gt;11&lt;/sub&gt; (F11)</td>
<td>Water Pump (Chilled water mass flowrate source)</td>
<td>PID (cw_mf_control)</td>
<td>data.T_rp_vc (363 °C)</td>
</tr>
<tr>
<td>pT_vc_pipe.T (T4) (Nitrogen temperature at MAGNET outlet)</td>
<td>m&lt;sub&gt;10&lt;/sub&gt; (F10)</td>
<td>Compressor (Nitrogen Compressor)</td>
<td>PID (N2_mf_control)</td>
<td>data.T_vc_rp (602 °C)</td>
</tr>
<tr>
<td>FM_202.m_flow (FM-202) (Therminol-66 flow rate through valve PV-049 and PV-052)</td>
<td>Opening&lt;sub&gt;1&lt;/sub&gt;</td>
<td>PV-052 (Valve at Thermocline charging outlet)</td>
<td>PID (PIDV1)</td>
<td>m&lt;sub&gt;TES&lt;/sub&gt;_charged (&lt;i&gt;m&lt;/i&gt;&lt;sup&gt;TES&lt;/sup&gt; &lt;i&gt;charge&lt;/i&gt;) (Eq.(1))</td>
</tr>
<tr>
<td>N/A</td>
<td>Opening&lt;sub&gt;4&lt;/sub&gt;</td>
<td>PV-049 (Valve at Thermocline charging inlet)</td>
<td>PID (PIDV4)</td>
<td>(-1^*m_TES_charged (-1 * m^{TES}_{charge}))</td>
</tr>
<tr>
<td>FM_201.m_flow (FM-201) (Therminol-66 flow rate through PV-050 and PV-051)</td>
<td>Opening&lt;sub&gt;3&lt;/sub&gt;</td>
<td>PV-051 (Valve at Thermocline discharging inlet)</td>
<td>PID (PIDV3)</td>
<td>Aligned with PV-052. Binary values, i.e., (+1) when PV-052 is opened, (-1) when fully closed.</td>
</tr>
<tr>
<td>N/A</td>
<td>Opening&lt;sub&gt;5&lt;/sub&gt;</td>
<td>PV-050 (Valve at Thermocline discharging outlet)</td>
<td>PID (PIDV5)</td>
<td>Aligned with PV-051. Binary values, i.e., (+1) when PV-051 is opened, (-1) when fully closed.</td>
</tr>
<tr>
<td>TC_006.T (TC-006) (Therminol-66 temperature at pump P-001 inlet)</td>
<td>Opening&lt;sub&gt;11&lt;/sub&gt;</td>
<td>PV-012 (Valve at Glycol Heat Exchanger tube side outlet)</td>
<td>PID (PIDV10)</td>
<td>data.T_cold_design (225 °C)</td>
</tr>
<tr>
<td>N/A</td>
<td>Opening&lt;sub&gt;10&lt;/sub&gt;</td>
<td>PV-009 (By-pass valve for Glycol Heat Exchanger)</td>
<td>Algebra-based Interlock</td>
<td>Aligned with PV-012, i.e., Opening&lt;sub&gt;10&lt;/sub&gt; = 1 − Opening&lt;sub&gt;11&lt;/sub&gt;</td>
</tr>
<tr>
<td>TC_003.T (TC-003) (Therminol-66 Temperature at MAGNET_TEDS_HX outlet)</td>
<td>p&lt;sub&gt;1&lt;/sub&gt;</td>
<td>P-001 MOS Pump (Therminol-66 pump)</td>
<td>PID (TEDS_pump_Control)</td>
<td>data.T_hot_design (325 °C)</td>
</tr>
</tbody>
</table>
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Table 2-4. Equation defining the set-point issued to the PI controller governing the flow rate entering the thermocline thermal energy storage.

<table>
<thead>
<tr>
<th>PI controller</th>
<th>Equation defining the set-point value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIDV1 (controls valve1)</td>
<td>[ m_{\text{tes charged}} = \frac{Q_{MT_HX} - P_{\text{Heat}}}{c_p \cdot (T_{\text{hot design}} - T_{\text{cold design}})} ] (1)</td>
</tr>
</tbody>
</table>

Table 2-5. Description of the variables and parameters involved in the definition of the set-point values.

<table>
<thead>
<tr>
<th>Variables/Parameters</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_{\text{Heat}} )</td>
<td>User defined heat load demand, (W)</td>
</tr>
<tr>
<td>( c_p )</td>
<td>Specific heat capacity of Therminol-66, (J/kgK)</td>
</tr>
<tr>
<td>( Q_{MT_HX} )</td>
<td>Heat flow transferred from nitrogen to Therminol-66 through the heat exchanger at the interface between MAGNET and TEDS (MAGNET_TEDS_HX), (W)</td>
</tr>
<tr>
<td>( T_{\text{hot design}} )</td>
<td>Reference temperature of the thermal storage fluid when entering MAGNET_TEDS_HX (325 °C)</td>
</tr>
<tr>
<td>( T_{\text{cold design}} )</td>
<td>Reference temperature of the thermal storage fluid when leaving MAGNET_TEDS_HX (225 °C)</td>
</tr>
</tbody>
</table>
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3. APPLICATION OF FARM TO THE SUPERVISED OPERATION OF DETAIL

To operate the DETAIL facility by ensuring that each component meets its individual operating limits, a Supervisory Control layer is proposed. It is designed to meet the overall demand of the grid, both electrical and thermal, with any excess thermal energy being disposed to and stored within the thermocline thermal storage. The electrical power demand is met by the PCU, and the heat demand is met by the excess thermal energy from MAGNET. As the two demands oscillate in time, the amount of excess heat redirected to TEDS will also vary. To determine the heat to be sent to TEDS after meeting the electricity demand, the amount of heat provided via the helical coil heat exchanger between MAGNET and TEDS is used as an input to the Supervisory Control scheme.

The idea of embedding a modified version of the FARM scheme into a Supervisory Control layer for the operation of DETAIL was suggested in [3]. In this report, the solution was implemented and demonstrated by simulating both the initial training of the needed Digital Twin (DT) and the power dispatch problem. The proposed paradigm then foresees the FARM module to be applied twice, i.e., the original version (“FARM-Validator”) aiding the solution of the power dispatch problem, the modified version (“FARM-Supervisory”) coordinating the PI controllers to address real-time control tasks. The main advantages to be accomplished by integrating FARM-Supervisory into the control system architecture are reported below.

- **Refinement of the set-point trajectories**
  In DETAIL, there are two sets of set-point signals. The former set is constituted by 2 signals that are continuously adjusted during operation ($P_{Elec}$ and $m^{TES}_{charge}$); the latter set is constituted by the other 6 signals that are either constant or dependent on the others. Let us focus on the former set. The set-point preserving the energy balance ($m^{TES}_{charge}$) is derived by solving the steady-state version of this equation. Though effective during slow transients, such an approach might fail during other operational scenarios. FARM-Supervisory can then refine the tentative trajectories.

- **Reduction of the disturbances due to other feedback control loops**
  The validator can help limit the disturbances on process variables. As mentioned in Section 2.3, the set of PI controllers constitutes a decentralized control scheme, i.e., each controller fulfills its task with no regard for the other ones. Interferences are inevitable, given that each control action affects the response of different process variables. To this end, the validator can adjust the set-points so that tight constraints on the most affected process variables are enforced.

- **Compensation in case of PI performance degradation**
  Wear and tear phenomena degrade components performance during unit operation. If the gains of the PI controllers are not adjusted to the new operating conditions, their
Demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility

effectiveness might degrade as well, causing oscillating behavior and even instabilities. FARM-Validator can limit the consequences since the embedded data-driven algorithm continuously updates the DT.

Despite FARM-Supervisory and FARM-Validator having the same kernel (the same set of algorithms embedded into FARM-Validator are embedded into FARM-Supervisory), their roles, tasks, and capabilities are quite different. They are described in Table 3-1.

Table 3-1. List of roles, tasks, and capabilities of FARM-Validator and FARM-Supervisory.

<table>
<thead>
<tr>
<th>Problem to solve</th>
<th>FARM-Validator</th>
<th>FARM-Supervisory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supports HERON power dispatcher by providing fine time resolution characterization of the system flexible operation capabilities.</td>
<td>Performs low-level control tasks by feeding admissible set-point signals to the PI controllers addressing noise/disturbances</td>
<td></td>
</tr>
<tr>
<td>Frequency of activity</td>
<td>It intervenes at the beginning of each dispatch interval. It validates the power set-points to be issued to the system and enforces the constraints over the next dispatch interval.</td>
<td>It is active all the time. It checks/adjusts the set-point signals to the PI controllers every few seconds to avoid abrupt violation of constraints (e.g., overshooting or oscillations).</td>
</tr>
<tr>
<td>Description of performed tasks</td>
<td>It uses an LPV model. The inputs are the power set-points issued by HERON power dispatcher. FARM-Supervisory layer does not need to be accounted for when deriving the LPV model for FARM-Validator.</td>
<td>It adjusts the set-points from the upper layer. Tentative trajectories issued to the PI controllers governing the active valves are derived from steady-state heat balances. FARM-Supervisory is only involved when the whole HERON-FARM architecture is coupled with either the real experimental facility or the high-fidelity model.</td>
</tr>
<tr>
<td>Adopted state-space representation models</td>
<td>LPV model derived from simulation data. To solve the power dispatch problem, the LPV model needs to be provided with an exhaustive characterization of the system dynamics. A large set of simulations is then required.</td>
<td>A data-driven model derived from experimental data is used. To perform its task, FARM-Supervisory only needs an accurate description of the current system state and the recent past dynamics retrieved from previous transients.</td>
</tr>
<tr>
<td>Model complexity</td>
<td>Given the number of iterations between FARM-Validator and HERON power dispatcher, the embedded model cannot be too large.</td>
<td>Since FARM-Supervisory is merely a once-through filter, the size of the model does not represent a real issue in computational time.</td>
</tr>
<tr>
<td>Time horizon and time resolution</td>
<td>The prediction time horizon is set equal to one hour. The time resolution is coarse (usually ~ 600 seconds).</td>
<td>The prediction time horizon is set equal to one minute. The time resolution is fine (usually ~ 10 seconds).</td>
</tr>
</tbody>
</table>

3.1. Description of “FARM-Validator” aiding HERON Power dispatcher

In this Section, the list of algorithms embedded in FARM, along with the latest improvements to FARM-Delta [11], are described. A brief overview of the method and the outcome will be provided for each of them. For more details, the reader is referred to dedicated publications.
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- **Command Governor (CG):** optimization of the set-point trajectories (Section 3.1.2).
- **Dynamic Mode Decomposition with control (DMDc):** derivation of the state-space matrices (Section 3.1.2).
- **Recursive Feature Elimination with DMDc (RFE-DMDc):** data-driven selection of the state variables starting from the Modelica model simulation outcomes (Section 3.1.3).
- **Convex Hull:** elimination of the redundant constraints (Section 3.1.4).

### 3.1.1. Command Governor (CG) algorithm for enforcing implicit constraints

The CG algorithm is the kernel algorithm of the FARM module. Its task consists of assessing the set-point trajectories. In case the imposed constraints are violated, the operational margin is evaluated and returned to the HERON power dispatcher for re-optimization. At each time-step, the CG constructs a Maximum Output Admissible Set (MOAS) by using the state-space matrices, the current values of the state variables ($\hat{x}(k)$) and the constraints on the output variables ($\hat{y}(k)$). The MOAS represents a multi-dimensional, feasible region for the set-point issued at the beginning of the prediction time horizon, i.e., any point $\hat{v}(k)$ within MOAS is considered feasible since it does not lead to violation of either explicit or implicit constraints over the considered time horizon. The MOAS is defined by a set of constraints in the form of linear inequalities ($H \cdot \hat{v} \leq h$). For further details about the derivation of the MOAS for multi-dimensional actuator signal, the reader may refer to [12]. The CG solves a Quadratic Programming (QP) [13] problem, i.e., it finds a vector of adjusted set-points ($\hat{v}(k)$) by minimizing the geometric distance to the tentative set-points ($\tilde{r}(k)$) within the MOAS (Eq. (2)).

$$\hat{v}(k) = \arg\min_{\tilde{v}(k)} (\hat{v}(k) - \tilde{r}(k))^2, \hat{v}(k) \in MOAS$$ (2)

To solve for the adjusted set-points, the CG runs a quadratic optimization with no initial guesses. The time-dependent trajectories are re-calculated. At the end of the needed iterations, it might occur that very different set-point trajectories with respect to the tentative ones are returned.

### 3.1.2. Dynamic Mode Decomposition with Control (DMDc) for deriving the state-space matrices

FARM requires a Linear Parameter Varying (LPV) state-space model to describe the dynamics of the system to be controlled. An LPV model consists of a set of Linear Time Invariant (LTI) models representing the dynamics around selected reference conditions [14]. It is then given by sets of matrices depending on certain parameters (scheduling parameters) (Eqs. (3)(4)).

$$\hat{x}(k + 1) = A(p)\hat{x}(k) + B(p)\hat{v}(k)$$ (3)

$$\hat{y}(k) = C(p)\hat{x}(k) + D(p)\hat{v}(k)$$ (4)
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where \( A(p), B(p), C(p) \) and \( D(p) \) are the parametrized state-space representation matrices, which models the evolution of system state vector under the influence of the system input vector as well as the response of system output vector.

To derive the set of LTI matrices representing the dynamics around selected operating conditions, the DMDc was used. This technique allows obtaining the \( A^d \) and \( B^d \) state-space representation matrices, resulting in accurate input-output models. For more details, the reader may refer to [15]. To complete the state-space representation model, matrices \( C^d \) and \( D^d \) need to be derived as well. These matrices express the evolution of the output variables (\( \tilde{y}(k) \)) as a linear combination of state and input variables, i.e., \( C^d \) matrix represents the influence of \( \tilde{x}(k) \), \( D^d \) represents the influence of \( \tilde{v}(k) \). For more details, the reader may refer to [2]. The derived matrices derived constitute an approximation of the system dynamics close to the operational conditions of the realization (time series) that was used. Since the models fed to the CG need to represent the system response over a wide range of operating conditions, an augmented approach was derived. A method, called parametric dynamic mode decomposition with control (PDMDc) for allowing the DMDc-based method to capture the distortion of the underlying matrices in case of operational condition deviations, was developed. The basic idea behind the PDMDc algorithm is to segment the operational condition domain into multiple sub-domains, characterized by specific coordinates in the phase space (e.g., power levels). For each coordinate in the phase space (parameters), the system matrices are evaluated via the DMDc method, resulting in a set of matrices that are now dependent on the scheduling parameter \( p \) (Eq.(5)).

\[
[A^d(p) \ B^d(p) \ C^d(p) \ D^d(p)]
\]  

With this LPV model, FARM trains a \( k \)-nearest neighbor classifier to map the scheduling parameters to corresponding matrices. When a tentative vector set-point is issued, the corresponding scheduling parameter will be calculated and fed to this \( k \)-nearest neighbor classifier, and the most suitable set of matrices will be selected and provided to CG for further processing. The algorithm here reported has been deployed in the RAVEN framework.

3.1.3. Recursive Feature Elimination (RFE)-based scheme for selecting the state variables

As discussed in Section 3.1.2, the state-space representation matrices are derived by tracking the evolution of state variables, the input variables and the output variables during a given set of transients. While the input and the output variables can be easily identified, the identification of the variables that exhaustively describe the system dynamics at any time (state variables) is not straightforward. A novel and efficient algorithm for selecting state variables that corporates recursive feature elimination and DMDc (RFE-DMDc) was developed in RAVEN framework [16]. RFE is an iterative method based on a batching modification of a backward feature elimination algorithm. The backward elimination method is an effective way to select a subset of variables for a supervised regression (or classification) model and has been extensively applied for space
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dimensionality reduction [17]. As for the selection of state variables, feature-ranking techniques are particularly attractive since they allow selecting a fixed number of top ranked features for constructing representative models and/or identifying important dimensions/inputs for the figure of merits. To this aim, the cost function accounting for the accuracy of both state variable and output variable predictions is defined as follows. Let us consider \( n \) state variables and \( p \) output variables. \( \sigma(x_i) \) and \( \sigma(y_j) \) represent the standard deviation of the \( i \)-th dimension of known state variables and \( j \)-th dimension of known output variables, and they are used for normalization purposes. The cost function is obtained by summing the weighted mean square error (MSE) between the predicted values and the known values of candidate state variables, and the weighted MSE between the predicted values and the known values of output variables sampled at each time-step (Eq. (6)). This cost function is also used to assess the accuracy of the derived matrices predictions against the testing dataset. Being used for assessing both the RFE-DMDc and the GA-DMDc results, it is used to estimate the information content of the sets of variables selected by the two algorithms. For more details, the reader may refer to [16][18]. The presented methodology was developed in RAVEN framework [19]. The code is available at https://github.com/idaholab/raven.

\[
\text{Cost function} = \frac{1}{n \cdot l} \sum_{i=1}^{n} \sum_{k=1}^{l} \left( \frac{x_i(k) - \hat{x}_i(k)}{\sigma(x_i)} \right)^2 + \frac{1}{p \cdot l} \sum_{j=1}^{p} \sum_{k=1}^{l} \left( \frac{y_j(k) - \hat{y}_j(k)}{\sigma(y_j)} \right)^2 \quad (6)
\]

3.1.4. Convex Hull approach for removing the redundant constraints

When defining the power dispatch problem, implicit constraints are imposed to limit the thermomechanical loads. Since the components that constitute an IES unit are thermally coupled, the constraints on the process variables of a component might affect the operation of another component. As a result, some constraints defining the MOAS might be redundant. If they are not removed, they will increase the computational burden and cause the QP solver to return a suboptimal solution [2]. A new method was then implemented into FARM-Delta to efficiently remove the redundant constraints from the original MOAS. The “convex hull” concept was borrowed from geometry [20]. The expression of the normalized MOAS for \( m \)-dimensional actuator signal with \( q \) constraints is reported in Eq.(7).

\[
\begin{bmatrix}
H_{11} & H_{12} & \cdots & H_{1m} \\
H_{21} & H_{22} & \cdots & H_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
H_{q1} & H_{q2} & \cdots & H_{qm}
\end{bmatrix}
\begin{bmatrix}
v_1 \\
v_2 \\
\vdots \\
v_m
\end{bmatrix}
\leq
\begin{bmatrix}
h_1 \\
h_2 \\
\vdots \\
h_q
\end{bmatrix}
\quad (7)
\]

Let assume that both the \( H \) matrix and the \( h \) vector are normalized, i.e., each row of \( H \) matrix shares the same magnitude (Eq.(8)).

\[
\sqrt{H_{i1}^2 + H_{i2}^2 + \cdots + H_{im}^2} = 1, \quad (i = 1, 2, \ldots, q). \quad (8)
\]
Eq.(7) defines an $m$-dimensional convex polytope. Once found an inner point ($\mathbf{c}$) meeting all the $q$ constraints, a translatory motion is performed to include the origin point (Eq.(9)).

$$
\begin{bmatrix}
H_{11} & H_{12} & \cdots & H_{1m} \\
H_{21} & H_{22} & \cdots & H_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
H_{q1} & H_{q2} & \cdots & H_{qm}
\end{bmatrix}
\begin{bmatrix}
v_{c,1} \\
v_{c,2} \\
\vdots \\
v_{c,m}
\end{bmatrix}
\leq
\begin{bmatrix}
h_1 \\
h_2 \\
\vdots \\
h_q
\end{bmatrix}
- 
\begin{bmatrix}
H_{11} & H_{12} & \cdots & H_{1m} \\
H_{21} & H_{22} & \cdots & H_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
H_{q1} & H_{q2} & \cdots & H_{qm}
\end{bmatrix}
\begin{bmatrix}
c_1 \\
c_2 \\
\vdots \\
c_m
\end{bmatrix}
$$

(9)

where $v_{c,j} = v_j - c_j$ ($j = 1, 2, ..., m$).

Eq.(9) can then be simplified as shown in Eq.(10).

$$
\begin{bmatrix}
H_{11} & H_{12} & \cdots & H_{1m} \\
H_{21} & H_{22} & \cdots & H_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
H_{q1} & H_{q2} & \cdots & H_{qm}
\end{bmatrix}
\begin{bmatrix}
v_{c,1} \\
v_{c,2} \\
\vdots \\
v_{c,m}
\end{bmatrix}
\leq
\begin{bmatrix}
h_{c,1} \\
h_{c,2} \\
\vdots \\
h_{c,q}
\end{bmatrix}
$$

(10)

where $h_{c,i} = h_i - \sum_{j=1}^{m} H_{ij} \cdot c_j$ ($i = 1, 2, ..., q$).

It is worth stressing that the origin point ($\mathbf{0} \in \mathbb{R}^m$) is within the $m$-dimensional polytope defined by Eq.(10), i.e., $h_{c,i} \geq 0$. A new matrix $M$ is defined as the element-wise division between $H$ and $h_c$ (Eq.(11)).

$$
M = 
\begin{bmatrix}
H_{11}/h_{c,1} & H_{12}/h_{c,1} & \cdots & H_{1m}/h_{c,1} \\
H_{21}/h_{c,2} & H_{22}/h_{c,2} & \cdots & H_{2m}/h_{c,2} \\
\vdots & \vdots & \ddots & \vdots \\
H_{q1}/h_{c,q} & H_{q2}/h_{c,q} & \cdots & H_{qm}/h_{c,q}
\end{bmatrix}
$$

(11)

The $i^{th}$ row of matrix $M$ is an $m$-dimensional vector. Its direction follows the $m$-dimensional normalized vector composed by the numerators (Eq.(12)), and its magnitude is inversely proportional to the value of $h_{c,i}$.

$$
\mathbf{H}_{i,\text{Direction}} = [H_{i1}, H_{i2}, \cdots, H_{im}]
$$

(12)

The convex hull is built by using all the $q$ rows of $m$-dimensional vectors. Among all the $m$-dimensional vectors that share the same direction, the one with largest magnitude corresponds to the tightest constraint. This property can be used to define a ranking criterion. The convex hull is the smallest convex set that contains all the provided points, i.e., the points on the vertices of such convex polytope correspond to the tightest constraints in MOAS. For visualization purposes, a
convex hull corresponding to the two-unit test case reported in [12] was built. An IES unit constituted by two power plants, i.e., a Balance of Plant (BOP) constituted by a 1350-MW Rankine energy conversion cycle, and a Secondary Energy Source (SES) constituted by a 50-MW gas turbine cycle, is considered. The power dispatch problem consists of optimizing the corresponding power outputs at the beginning of each hour to meet the load demand for electrical power. Since we are operating in a discrete-time domain (sampling period equal to 10 seconds), the prediction time horizon is constituted by 361 time-steps. Besides, we are constraining the dynamic response of 4 process variables by imposing upper and lower bounds (2 linear inequalities). Therefore, the built MOAS has 2,888 rows, and the $M$ matrix has 2,888 rows of 2-dimensional vectors (blue points in Figure 3-1). The four blue points on the vertices of the convex polygon correspond to the 4 tightest constraints in MOAS, whereas all the other 2884 blue points inside the polygon correspond to constraints that can be dropped.

The ConvexHull function is available from scipy python package [21]. It allows constructing a convex hull from a given $M$ matrix and returning the indexes of the points on the vertices which correspond to the non-redundant constraints in MOAS. The final set of constraints is equivalent to the original MOAS. Let us consider the results reported in Figure 3-2. The original MOAS defined by 2,888 constraints and the MOAS returned by the ConvexHull feature defined by 4 non-redundant constraints evaluated at $t = 8$ hr are shown. They delimit the same feasible region for the multi-dimensional set-point signal. Besides reducing the computational burden, the dimensionality reduction has a second benefit, i.e., it favors the convergence to the optimal solution. When redundant constraints are present, the QP solver is challenged, and a sub-optimal solution is returned occasionally (black square in Figure 3-2a). Thanks to the ConvexHull feature, the returned solution is within the feasible region and has a minimized distance from the original actuator (black square in Figure 3-2b).
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![Figure 3-2. Comparison of the constrained optimization problem defining the same feasible region at t = 8 hr. (a) The original 2,888 constraints configuration and the sub-optimal solution, and (b) the 4 non-redundant constraints calculated by the Convex Hull method and the optimal solution are shown.](image)

3.1.5. Performance of the final version of FARM-Validator

The latest release of FARM module embedding the Convex Hull algorithm for redundant constraint removal is called “FARM-Epsilon”. The previous release was called FARM-Delta [11]. In this Section, the performance of these two versions of FARM-Validator is compared in terms of computational costs and quality of the solution of the power dispatch problem. To obtain an accurate evaluation, a simple test-case problem was selected, i.e., the 12 hour-long dispatch problem described in Section 3.1.4 was simulated by adopting both FARM-Delta and FARM-Epsilon. As for the assumptions, they adopted the same LPV model with 2 state variables, i.e., one for the BOP and one for the SES. In addition, to isolate the computational cost benefits due to the Convex Hull algorithm, no Functional Mock-Up (FMU) units were used for simulating the power transients. To benchmark the computation speed, a 2.7GHz Intel Xeon 8168 processor was used. In Table 3-2, the main results are shown. The reported values for the computational cost do not include the training of the LPV models, i.e., they refer to the solution of the power dispatch problem.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FARM-Delta</th>
<th>FARM-Epsilon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Final number of constraints defining the MOAS, (-)</td>
<td>2,888</td>
<td>less than 6</td>
</tr>
<tr>
<td>Computational time, (s)</td>
<td>14.85</td>
<td>14.15</td>
</tr>
</tbody>
</table>

Table 3-2. Comparison of performance of FARM-Delta and FARM-Epsilon releases.
Demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility

As mentioned in Section 3.1.1, at every time-step, the CG builds the MOAS by using the state-space matrices, the current values of the state variables and the constraints on the output variables. In FARM-Delta, the size of the MOAS is constant at each time-step. In particular, for the studied test-case, it is equal to 2,888, i.e., the prediction time horizon is constituted by 361 time-steps, 4 process variables are constrained by imposing 2 linear inequalities. In FARM-Epsilon, the size of the MOAS is not constant, since the ConvexHull feature intervenes at each time-step to remove all the redundant constraints. For the studied test-case, sometimes it returns 4 non-redundant constraints, sometimes 6. Overall, the final number of constraints is always lower than 6.

![Graph](image)

**Figure 3-3.** Results of the power dispatch problem calculated by FARM-Delta (blue curves) and FARM-Epsilon (red curves).

As for the computational cost, the difference between FARM-Delta and FARM-Epsilon is not significant, i.e., the former takes 14.85 seconds to finish the simulation, the latter takes 14.15 seconds (~4.7% improvement). Though the computational time may increase by adopting larger MOAS (i.e., by adopting LPV models characterized by a larger number of state variables), the most beneficial effects of the ConvexHull feature concern the quality of the solution. In Figure 3-2, the position of the black square representing the solution of the power dispatch problem was influenced by the presence of redundant constraints. This trend can be clearly observed by looking at the optimized power outputs in Figure 3-3.

The trajectories of the electrical power outputs of the BOP and the SES calculated by FARM-Delta and by FARM-Epsilon do not always overlap. To verify the quality of the solution returned
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by FARM-Epsilon, the power generation costs (USD/h) was adopted as metrics. The corresponding trajectories during the simulated dispatch problem were plotted in Figure 3-4. Given that both FARM-Delta and FARM-Epsilon return a feasible solution, i.e., they successfully enforce explicit and implicit constraints, the power generation costs for the found solution assumes lower values when adopting FARM-Epsilon. This result demonstrates that, given the same LPV model to FARM-Delta and FARM-Epsilon, the adoption of the ConvexHull feature allows FARM-Epsilon to obtain higher quality solutions.

![Figure 3-4. Evolution of the power generation costs during the simulated dispatch problem solved by using FARM-Delta (blue curve) and FARM-Epsilon (red curve).](image)

3.2. **Description of FARM-Supervisory coordinating the PID controllers**

3.2.1. **Configuration of the proposed control system architecture**

In Figure 3-5, the current configuration of the control system architecture is shown. At the top level, FARM-Validator supports HERON at solving the power dispatch problem (orange triangle). Once a feasible solution is found, the market electrical power demand ($P_{elec}$) and the heat demand ($P_{heat}$) are returned. The task of the low levels of the architecture consists of adjusting the control actions to get the DETAIL components to satisfy these requests. The grey layer (“Control Layer #1”) converts the demand signals into two, time-dependent set-point signals ($r_1$ and $r_2$) that are fed to the PI controllers contained in the Modelica model mimicking the presence of DETAIL (“PID & DETAIL Modelica model”). The set-point signals are the electrical power demand ($P_{Elec}$) and the Therminol-66 flow rates entering the thermocline thermal storage ($m_{TES}^{charge}$) during charging transients, respectively. As shown in Eqs. (1), the latter signal is calculated from $P_{Heat}$ and the value of the thermal power disposed through the heat exchanger at the interface between MAGNET and TEDS ($Q_{MT, HX}$) obtained from “PID & DETAIL Modelica model” (blue line). In addition to this variable, the Modelica model returns the value of five process variables whose response needs to be constrained ($\vec{y}_{constrained}$). They are listed, described and the corresponding operational bounds are reported in Table 3-3.
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Figure 3-5. Representation of the current control system architecture.

Table 3-3. Description of the output variables and corresponding operational bounds.

<table>
<thead>
<tr>
<th>Output Variable</th>
<th>Description</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_1$ (TC_003_Temp)</td>
<td>Therminol-66 temperature at MAGNET-TEDS HX outlet</td>
<td>225 °C</td>
<td>326 °C</td>
</tr>
<tr>
<td>$y_2$ (Thermocline_Node0_Temp)</td>
<td>Therminol-66 temperature in the top node of thermocline tank</td>
<td>300 °C</td>
<td>325 °C</td>
</tr>
<tr>
<td>$y_3$ (Glycol Exit Temp)</td>
<td>50% Ethylene Glycol temperature at the Glycol HX outlet</td>
<td>0 °C</td>
<td>107 °C</td>
</tr>
<tr>
<td>$y_4$ (FM_003_m)</td>
<td>Therminol-66 mass flow rate at the MAGNET-TEDS HX inlet</td>
<td>0 kg/s</td>
<td>2.19 kg/s</td>
</tr>
<tr>
<td>$y_5$ (PCU Flow)</td>
<td>Nitrogen mass flow rate at the inlet of PCU (Gas Turbine)</td>
<td>0.38 kg/s</td>
<td>0.46 kg/s</td>
</tr>
</tbody>
</table>

The bounds on the constrained variables reported in Table 3-3 are determined by thermomechanical limits.

- Therminol-66 temperature at MAGNET-TEDS HX outlet (TC_003_Temp) needs to be lower than 326 °C to prevent damages to TEDS components.
- Therminol-66 temperature in the top node of thermocline tank needs to be higher than 300 °C to maintain acceptable exergy level of the discharging flow.
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- 50% Ethelyne Glycol temperature at the Glycol HX outlet (Glycol_Exit_Temp) needs to be lower than 107 °C to avoid boiling.
- Therminol-66 mass flow rate at the MAGNET-TEDS HX inlet needs to be lower than 2.19 kg/s (40GPM) according to the pump capacity.
- Nitrogen mass flow rate at PCU inlet (PCU_Flow) needs to be higher than 0.38 kg/s to maintain a minimum power output thus avoiding cold start.

![Figure 3-6. Representation of the proposed architecture embedding the FARM-Supervisory control layer (“Control Layer #2”).](image)

In Figure 3-6, the proposed configuration of the control system architecture is shown. The structure is basically the same, i.e., the PI controllers, the corresponding set-points, and the output variables have not been changed. The Supervisory Control layer embedding FARM-Validator (yellow layer) is placed between “Control Layer #1” and “PID & DETAIL Modelica model”. As inputs, it receives the tentative, time-dependent set-point signals \( r_1 \) and \( r_2 \); as outputs, it returns the adjusted signals \( v_1 \) and \( v_2 \) that will be issued to the dynamic system embedded into the “PID & DETAIL Modelica model” layer. It returns (1) the thermal power disposed to TEDS \( Q_{MT,HX} \), (2) the output variables \( \tilde{y}_{constrained} \), and (3) the current values of the state variables to be provided to FARM for predicting the system response \( \tilde{x} \). As for the implemented algorithms, they are the same as those that are implemented in FARM-Validator, i.e., the RFE-DMDc, the DMDc and the CG.
3.2.2. Implementation of FARM-Supervisory layer and generation of the needed FMUs

As for the implementation, FARM-Supervisory is run as a RAVEN external model. Unlike FARM-Validator, it is not connected in a feedback loop with the HERON Power Dispatcher. Therefore, there are no iterations with it. As shown in Figure 3-6, once the feasible demands are calculated by the Power Dispatcher, they will not be modified any further, and the control system architecture (layers grey and yellow) will take the needed actions to satisfy them without violating the imposed limits. Secondly, FARM-Supervisory is deployed over shorter time horizons (1 minute) and has a much finer time resolution (10 seconds). As for the simulation of the power dispatch, along with a RAVEN external model, three, interacting FMUs are meant to be derived to get real-time values of the system state variables. The models embedded in these three FMUs are described below. At the same time, the available Dymola model of DETAIL facility contains two deeply hidden errors, which prevent the generated FMU executables from completing the simulations via the FMPy Python package [22] used in FARM. More detailed discussion is provided in Section 4.5.2, and an alternative approach was provided in the same section.

- **MAGNET-PCU-TEDS integrated simulator (FMU #1)**
  In Figure 3-5, it is the portion wrapped by the black dashed line. The input variables are the electrical power and the heat demands ($P_{Elec}$ and $P_{Heat}$). The outputs are the constrained process variables ($\vec{y}$). This FMU will be used to derive the LPV model required by HERON-FARM power dispatcher.

- **“Control Layer #1” (FMU #2)**
  In Figure 3-6, it is depicted by the grey layer. The input variables are the electrical power and the heat demands ($P_{Elec}$ and $P_{Heat}$); the outputs are the tentative set-points ($r_1$ and $r_2$) for the PI controllers. To this aim, FMU #2 is provided by FMU #3 with the sampled values of the process variables on 1-second time resolution that are needed to translate $P_{Elec}$ and $P_{Heat}$ into the tentative set-points.

- **“Control Layer #2” (RAVEN external model)**
  It embeds FARM-Supervisory. In addition, it has the capability of simulating the other two FMUs at same time. Finally, “Control Layer #2” is used to generate the adjusted set-points ($v_1$ and $v_2$) and to issue them to FMU #3 for simulating the power dispatch.

- **“PID & DETAIL Modelica model” (FMU #3)**
  In Figure 3-6, it is depicted by the blue layer. The inputs are the adjusted set-points ($\vec{v}$) for the PID controllers; the outputs are the constrained process variables ($\vec{y}$), the state variables to be fed to “Control Layer #2” ($\vec{x}$), and the process variables to be fed to FMU #2 ($Q_{MT,HX}$).
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4. DEMONSTRATION OF THE PROPOSED CONTROL SYSTEM ARCHITECTURE

4.1. Description of the training procedure of the LPV models embedded into FARM-Validator and FARM-Supervisory

As described in Section 3.1.2, the DMDc is the data-driven algorithm embedded into FARM for deriving the state-space representation matrices. Being the characterization of the system dynamics based on the collected data, when starting the optimization of the power dispatch, the database of matrices is empty, i.e., FARM has no information about the dynamics of the supervised system. To address this problem, a preliminary stage ("Self-learning") was included in the procedure. During this step, a set of representative power transient is simulated by the corresponding FMU to collect the responses of both state and output variables over a wide range of operational conditions. As a result, the state variables are selected and the very initial set of matrices constituting the LPV model is derived. The CG optimization problem can then be initialized using these sets of matrices. In the latest release of FARM, the Self-learning stage was integrated into the workflow to automate the selection of the state variables.

![Figure 4-1. Representation of the workflow integrating the different tasks, i.e., the state variable selection, the “Self-learning” and the set-point validation.](image)

The workflow shown in Figure 4-1 only requires to the user two steps to select the state variables.

1. Provide the FMU model of the feedback loop (IES unit and the corresponding PI controllers) and associated fundamental information (i.e., input/output variables, representative power transients, time range of simulation) to a state variable selection template writer. Then, RAVEN simulates the power transients, collects the simulation results, indexes them using the power levels, and performs the state variable selection
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using the RFE-DMDc algorithm. Once completed, the selected state variables and the database of matrices constituting the LPV model are saved to a file.

(2) Specify the location of this database in HERON input file. Then, FARM retrieves these state variable names and uses the LPV matrices for optimizing the power dispatch.

As explained in Section 3.2.2, FARM-Validator and FARM-Supervisory supervise the operation of two different dynamic systems, i.e., the former supervises the dynamic system constituted by “Control Layer #1” (grey layer) and “PID & DETAIL Modelica model” (blue layer) (Figure 3-5), the latter only supervises “PID & DETAIL Modelica model” (Figure 3-6). A second “Self-learning” stage for deriving the LPV model embedded in FARM-Supervisory is then necessary. Accordingly, during the “Self-Learning” stages for FARM-Validator and FARM-Supervisory, two sets of transients will be generated by running FMU #1 and FMU #3, respectively.

4.2. Definition of a procedure for applying FARM-Supervisory to the experimental facility

The procedures described in Section 4.1 for the “Self-learning” stages assume the presence of a Modelica model mimicking the presence of the actual system (DETAIL and the corresponding PI regulators). In [3], a tentative procedure for the application of FARM-Supervisory to the actual DETAIL facility was proposed. Two approaches were identified for the generation of the training dataset for the derivation of the LPV models. In this work, the “Experimental data-based approach” is further developed.

Figure 4-2. Graphical representation of the four steps that constitute the proposed procedure for the supervised operation of DETAIL facility.

The shakedown is a period of testing undergone by an engineering system before being declared operational. In [23][24], a shakedown test of DETAIL by using the Modelica model contained in HYBRID was simulated. It is a 5-hour long simulation during which all five potential operating
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modes are explored, and the ability of valving, control sensors, and component controllers to meet the system demands is demonstrated. With respect to the derivation of LPV models, this phase of deployment of the facility can be exploited, i.e., the experimental data constituting the training dataset can be collected during this phase. In Figure 4-2, the steps constituting the proposed procedure for the supervised operation of DETAIL facility are represented. First, the system components are “warmed up” from the initial cold shutdown conditions (“Start-up” phase). Then, the shakedown tests are performed. As shown, during this phase, the “Self-learning” processes for both FARM-Supervisory and FARM-Validator are completed. Finally, once the LPV models are trained, the power transients demanded by the power dispatch can be safely performed. To maintain the dispatchability of the system, it is essential that the system conditions at the end of the “Start-up” phase are restored at the end of the “Shakedown testing” phase. To this aim, the power trajectory during the “Shakedown testing” needs to be carefully designed. A second requirement is that the system conditions at the end of the “Start-up” phase are restored at the end of both the “Self-learning” processes, so that both the LPV models share the same initial system state and provide a consistent mathematical description of the DETAIL facility that is ready to be dispatched.

Figure 4-3. Configurations of the control system architecture at each step of the procedure shown in Figure 4-2, (a) “Start-up” and “Self-learning for FARM-Supervisory”, (b) “Self-learning for FARM-Validator” and (c) “Dispatch”.

A different configuration of the of the control system architecture corresponds to each step of the procedure. The adopted criterion consists of employing the basic version of the architecture for the “Start-up” phase, and then enabling one or more layers at each of the following steps. Such a paradigm is favored by the modularity of the hierarchical structure.

(1) Start-up
The configuration of the control system architecture in this phase is shown in Figure 4-3a. The power set-point signals \( r_1 \) and \( r_2 \) are manually issued. Their trajectories are slowly increasing to avoid excessive thermal loads. Since the Supervisory control layer constitutes a sort of filter to adjust the set-point trajectories, it can always be disabled.
demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility during system operation, and have the trajectories directly fed to the PID controllers. It is then up to the operators to ensure the respect of the operational limits during transients.

(2) “Self-learning” for FARM-Supervisory LPV model
The same configuration adopted during the “Start-up” phase is used (Figure 4-3a). The goal is deriving the LPV model for the dynamic system supervised by FARM-Supervisory. The studied feedback loop is constituted by the blue layer, which represents the facility and the implemented PI controllers. To avoid the singularity issue described in Section 4.1, the grey layer (“Control Layer #1”) is disabled, i.e., the set-point signals are manually issued.

(3) “Self-learning” for FARM-Validator LPV model
The configuration of the control system architecture in this phase is shown in Figure 4-3b. The goal is deriving the LPV model for the dynamic system supervised by HERON-FARM scheme. Therefore, it is constituted by both the blue and the grey layers, i.e., the set-point signals are derived by adopting the equation-based approach described in Section 2.3. Since the input of the adopted configuration of the architecture are the demand trajectories, it is possible to get the system to explore all the operating modes by providing suitable combinations of $P_{elec}$ and $P_{heat}$, i.e., the shakedown tests will be performed in this phase.

(4) Dispatch
The configuration of the control system architecture in this phase is shown in Figure 4-3c. Once the LPV models are trained, the FARM-Supervisory (yellow layer) can be enabled. The architecture shown in Figure 4-3c will be adopted from that moment on.

4.3. Outcomes of the state variable selection process

As mentioned in Section 4.1, FARM-Supervisory and FARM-Validator govern the operation of two different dynamic systems. The former adjusts the inputs to “PID+DETAIL Modelica Model” (blue layer in Figure 4-3a) at fine time resolution (every 10 seconds); the latter adjusts the inputs of the system given by the blue layer and the grey layer in Figure 4-3b at low time resolution (every 600 seconds). Two sets of state variables need to be identified from the pool of the process variables of the corresponding dynamic systems. For this task, two algorithms are available, i.e., RFE-DMDc and GA-DMDc [18]. The decision of the algorithm to be used is mainly driven by the computational cost. As shown in Figure 4-4, the computational cost associated with RFE-DMDc dramatically increases when the maximum number of candidate state variables exceeds 15, whereas the computational cost associated with GA-DMDc is not significantly affected by this parameter. In this work, RFE-DMDc was initially adopted. Unfortunately, the predictions of the state-space models characterized by less than 15 state variables were not accurate enough for the data with fine
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time resolution. The trend of the computational cost as function of the maximum number of state variables shown in Figure 4-4 discourages the adoption of more state variables. The GA-DMDc scheme was then adopted. Let us start with the system governed by FARM-Supervisory ("PID+DETAIL Modelica Model"). It is characterized by 2,562 process variables. The selection criterion implemented in GA-DMDc is based on the minimization of the cost function reported in Eq.(6). It estimates the accuracy of the predictions of the associated state-space model. In Table 4-1, the results of the sensitivity analysis performed with GA-DMDc are reported.

Figure 4-4. Computational costs of RFE-DMDc and GA-DMDc as function of the maximum number of state variables [18].

Table 4-1. Results of the sensitivity analysis on the maximum number of candidate state variables performed with GA-DMDc.

<table>
<thead>
<tr>
<th>Number of variables</th>
<th>Cost function value (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>2.89</td>
</tr>
<tr>
<td>23</td>
<td>2.88</td>
</tr>
<tr>
<td>30</td>
<td>3.10</td>
</tr>
</tbody>
</table>

Given the values of the cost function, the decision of adopting 21 variables to exhaustively describe the dynamics of an engineering system with 2,562 process variables (less than 1%) was identified as a good compromise. The selected variables are reported in Table 4-2 (first column). They are broken among the different subsystems that constitute DETAIL as follows:

- MAGNET: 10 variables
- PCU: 1 variable
- Glycol HX: 1 variable
- TEDS thermocline: 9 variables
A qualitative explanation of these results is provided here. MAGNET is thermally coupled with the PCU. This means that some of MAGNET process variables describe the dynamics of the PCU and vice versa. When selecting state variables for a dynamic system constituted by multiple subsystems, it often happens that two variables, i.e., one from a subsystem and the other from another subsystem, are collinear. Since they have the same information content, the selection criterion will drop one of them. With regard to DETAIL, it likely occurred that variables from MAGNET were selected because they provided information about the PCU as well. As for the number of state variables representing TEDS thermocline, the reason is that the dynamics of a thermocline is much more complicated than traditional energy storage systems. From a modeling standpoint, the dynamics of energy storage systems is similar to the dynamics of a capacitor. Such analogy works for TES constituted by a couple of coordinated tanks [7], but it does not for a thermocline because of the nonlinear effects. In addition, the model from the HYBRID library provides a one-dimensional description of the thermocline, and several variables are required to properly represent these spatial effects.

In Table 4-2, the lists of process variables to be tracked to derive the LPV models for FARM-Validator and FARM-Supervisory (selected state variables) are provided. The two state-space models are characterized by 9 and 21 state variables, respectively. This result might sound suspicious. Apart from the algebraic equations converting the market demands into set-point signals in the grey layer, FARM-Validator and FARM-Supervisory refer to the same dynamic system. The explanation lies in the different sampling frequency adopted for recording the process variable responses. Since FARM-Validator aids the solution of power dispatch problem on hourly-basis, the adopted sampling period is equal to 600 seconds. Since FARM-Supervisory needs an accurate representation of dynamics modes, a sampling period equal to 10 seconds is adopted. The Nyquist-Shannon sampling theorem imposes a lower threshold on the needed sampling frequency for obtaining a correct reconstruction of the monitored continuous-time signals. In our case, the sampling frequency adopted by FARM-Validator is too low to capture certain oscillations. As a result, they are not accounted for in the used training dataset to derive the corresponding LPV model, and fewer state variables are selected for reproducing the captured frequencies.
Demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility

Table 4-2. List of state variables for the LPV models embedded in FARM modules.

<table>
<thead>
<tr>
<th>State variables for the LPV model in FARM-Supervisory</th>
<th>Subsystem</th>
</tr>
</thead>
<tbody>
<tr>
<td>sensor_hx_co.port_a.p Nitrogen pressure, MAGNET HX outlet</td>
<td>MAGNET</td>
</tr>
<tr>
<td>MAGNET_TEDS_simpleHX1.volume_1[7].port_a.der(h_outflow) Nitrogen specific enthalpy time derivative, MAGNET-TEDS HX, axial node [7]</td>
<td>MAGNET</td>
</tr>
<tr>
<td>MAGNET_TEDS_simpleHX1.volume_1[9].port_b.m_flow Nitrogen mass flow rate, MAGNET-TEDS HX, axial Node [9]</td>
<td>MAGNET</td>
</tr>
<tr>
<td>valve_vc_GT.opening Valve opening, PCU</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>State variables for the LPV model in FARM-Validator</th>
<th>Subsystem</th>
</tr>
</thead>
<tbody>
<tr>
<td>sensor_hx_co.port_a.p Nitrogen pressure, MAGNET HX outlet</td>
<td>MAGNET</td>
</tr>
<tr>
<td>MAGNET_TEDS_simpleHX1.volume_1[7].port_a.der(h_outflow) Nitrogen specific enthalpy time derivative, MAGNET-TEDS HX, axial node [7]</td>
<td>MAGNET</td>
</tr>
<tr>
<td>MAGNET_TEDS_simpleHX1.volume_1[9].port_b.m_flow Nitrogen mass flow rate, MAGNET-TEDS HX, axial Node [9]</td>
<td>MAGNET</td>
</tr>
<tr>
<td>valve_vc_GT.opening Valve opening, PCU</td>
<td></td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Therminol-66 speed, Thermocline tank, axial Node [5]</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>thermocline_Insulation_An.simpleWall[2].R</th>
<th>TEDS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal resistance, Thermocline tank wall, axial Node [2]</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>thermocline_Insulation_An.simpleWall[6].lambda</th>
<th>TEDS</th>
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<tbody>
<tr>
<td>Heat conductivity, Thermocline tank wall, axial Node [6]</td>
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<tr>
<th>thermocline_Insulation_An.simpleWall[8].R</th>
<th>TEDS</th>
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<td>Thermal resistance, Thermocline tank wall, axial Node [8]</td>
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<thead>
<tr>
<th>thermocline_Insulation_An.simpleWall[13].R</th>
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<tbody>
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<table>
<thead>
<tr>
<th>nonLinear_Break2.boundary_medium.T</th>
<th>Glycol HX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Therminol-66 temperature, Glycol HX pump inlet</td>
<td></td>
</tr>
</tbody>
</table>
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4.4. Derivation of the LPV models of the studied portions of DETAIL facility

The same set of combinations of scheduling parameters was adopted for deriving both FARM-Validator and FARM-Supervisory LPV models. The adopted values are reported in Table 4-3 and graphically represented in Figure 4-5. Thanks to this alignment, the risk that the two reduced order models might refer to different operating conditions is prevented.

Table 4-3. List of combinations of scheduling parameters used for deriving FARM-Validator and FARM-Supervisory LPV models.

<table>
<thead>
<tr>
<th>Case Number</th>
<th>$P_{elec}$ (kW)</th>
<th>$P_{heat}$ (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.0</td>
<td>26.3</td>
</tr>
<tr>
<td>2</td>
<td>10.0</td>
<td>36.3</td>
</tr>
<tr>
<td>3</td>
<td>10.0</td>
<td>46.3</td>
</tr>
<tr>
<td>4</td>
<td>10.0</td>
<td>56.3</td>
</tr>
<tr>
<td>5</td>
<td>10.0</td>
<td>76.3</td>
</tr>
<tr>
<td>6</td>
<td>10.0</td>
<td>96.3</td>
</tr>
<tr>
<td>7</td>
<td>10.0</td>
<td>116.3</td>
</tr>
<tr>
<td>8</td>
<td>15.0</td>
<td>17.5</td>
</tr>
<tr>
<td>9</td>
<td>15.0</td>
<td>20.5</td>
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<td>40.5</td>
</tr>
<tr>
<td>12</td>
<td>15.0</td>
<td>50.5</td>
</tr>
<tr>
<td>13</td>
<td>15.0</td>
<td>60.5</td>
</tr>
<tr>
<td>14</td>
<td>15.0</td>
<td>65.5</td>
</tr>
</tbody>
</table>

Figure 4-5. Graphical representation of the set of combinations of scheduling parameters for deriving FARM-Validator and FARM-Supervisory LPV models.
Demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility

4.4.1. LPV models for FARM-Validator

Overall, 14 combinations of scheduling parameters were used for deriving FARM-Validator and FARM-Supervisory LPV models, i.e., 2 values for $P_{elec}$ and 7 values for $P_{heat}$ (Figure 4-5). It is worth noting that the range of $P_{heat}$ values depends on $P_{elec}$ values. In particular, larger values of $P_{elec}$ require higher temperature nitrogen to be directed to the PCU unit. Therefore, less heat can be disposed to TEDS via MAGNET-TEDS-HX. Smaller values of $P_{heat}$ were then selected to prevent the saturation effects in thermocline tank, i.e. over filling or over drain. The adopted sampling period when recording the state variable responses in the training dataset was set equal to 600 seconds.

4.4.2. LPV models for FARM-Supervisory

The same set of simulation data adopted for deriving FARM-Validator LPV model was used for deriving FARM-Supervisory LPV model. A different sampling period when generating the training dataset was used (10 seconds). In addition, the two PID set-point signals ($P_{Elec}$ and $m^{TES}_{charge}$) were used as input variables.

4.5. Solution of the power dispatch problem

4.5.1. Description of the selected test-case

Here below the features of the power dispatch test-case to assess the performance of the proposed control system architecture are reported:

- The DETAIL facility is expected to provide direct heat (and/or convert electricity to heat) to meet a 12-hour time-dependent heat power demand.
- TEDS and PCU are assumed to have different power generation costs (Table 4-4).
- The goal is to dispatch the thermally coupled TEDS and PCU to meet the heat demand, without violating any operational constraints listed in Table 2-5, and minimizing the total power generation cost.

<table>
<thead>
<tr>
<th>Subsystem</th>
<th>Power Generation Cost (USD/MWth)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TEDS</td>
<td>100</td>
</tr>
<tr>
<td>PCU*</td>
<td>200</td>
</tr>
</tbody>
</table>

* PCU generates electricity, and the cost is based on thermal power equivalent.

To obtain a representative scenario, the heat power demand was obtained by scaling a trajectory retrieved from the New York Independent System Operator - Load Data [25]. The final trajectory covers the range from 47.1 kW to 57.4 kW over the 12-hour dispatch period.
4.5.2. Description of solving process, and Issues with the physical model

In this work, the same procedure for solving the power dispatch based on the scheme integrating HERON and FARM-Delta [11] was originally attempted. It adopts the FMU as high-fidelity model of the controlled engineering system. Here below the main steps are reported.

**Step 1.** HERON-FARM power dispatcher solves the power dispatch problem. HERON proposes 12-hour trajectories for the power set-points, FARM-Delta validates them by using LPV model together with the instantaneous values of state variables retrieved from the FMU. The validated trajectories are issued to the FMU for simulating the system response on hourly basis. In the end, the hourly trajectories for the electric power demand and heat power demand ($P_{\text{Elec}}$ and $P_{\text{Heat}}$) are generated for a 12 hour-long dispatch time horizon.

**Step 2.** The 12 hour-long trajectories for $P_{\text{Elec}}$ and $P_{\text{Heat}}$ “approved” by FARM-Validator are issued to the control system architecture shown in Figure 3-6. By retrieving the $Q_{MT,HX}$ value from FMU, $P_{\text{Elec}}$ and $P_{\text{Heat}}$ are converted into two set-points signals ($P_{\text{Elec}}$ and $m^{TES}_{\text{charge}}$) that will be validated by FARM-Supervisory.

**Step 3.** The set-point signals validated by FARM-Supervisory are issued to the PI controllers contained into the FMU of the Dymola model of DETAIL. These simulations return the system response on fine time resolution.

During the development of the simulation framework, multiple modeling issues prevented the implementation of the procedure described above.

- The Dymola model of DETAIL contains two deeply hidden errors. Though they do not constitute an issue when running simulations in Dymola, they prevent the generated FMU executables from completing the simulations in FMPy package used by FARM. First, the numerical solver occasionally tries a Reynolds number with negative values when calculating the flow conditions through the Glycol HX. After attempting several times these conditions, the FMU simulations crash. Secondly, a co-monotonic, C1 smooth regularization function in TRANSFORM package called “regFun3” have quite strict restrictions for the values assumed by the input variables [5]. When simulating a mass flow rate with static head in Glycol HX, these bounds are occasionally violated by causing the FMU simulations to crash. These modeling issues are currently under investigation, but the FARM-Delta cannot retrieve the values of state variables or simulate the system response with the generated FMUs.

- An alternative solution was proposed. Given the unavailability of the Dymola-derived FMU, an LPV model is adopted for mimicking the response of the physical system and
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provide the instantaneous values of the state variables. However, such an approach is feasible only when the asymptotic stability is verified for all the LTI models that constitute the LPV model. This assumption is not verified for DETAIL because of the presence of the thermocline-based energy storage system. From a dynamic standpoint, the thermocline behaves as an integrator with respect to the charging mass flow rate. This entails that abrupt variations of the corresponding state variables are not feasible. When the level of charge is close to either bounds at the end of an hour, the adoption of the new set of matrices significantly affects the feasible region for adjusted set-points (\(\hat{\mathbf{v}}\)), i.e., the MOAS calculated with the previous \(A, B, C\) matrices. Occasionally, given the same value of state variables (\(\hat{x}\)), the MOAS calculated with the new set of matrices may shrink to a singularity indicating no feasible region. Such a scenario prevents the CG algorithm from performing the quadratic optimization.

- Given these limitations and issues, the only alternative to demonstrate the performance of the developed architecture consists of using an LTI model. In particular, we adopted the one referred to the operating conditions identified by Case #11 in Table 4-3. Since the \(Q_{MT, HX}\) value is needed by FARM-Supervisory, this variable was added to all the LTI models as an un-constrained output variable.

4.5.3. Description of power dispatch results using HERON and FARM-Validator

In Figure 4-6, the results of the simulation of the power dispatch problem by using the LTI model of DETAIL is shown. The blue and yellow bars indicate the power outputs of TEDS and PCU, respectively. The solid, purple line represents the imposed heat demand, which is met by the sum of the two contributions.
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Figure 4-6. Results of the power dispatch for DETAIL calculated by HERON-FARM power dispatcher.

To show the feasibility of this obtained results, the response of the five constrained variables are shown in Figure 4-7. All the five constrained variables fall between the values of the lower and upper bounds of the corresponding operational constraints reported in Table 3-3 throughout the entire dispatch period. A qualitative explanation of the dispatch priorities is provided. Given the lower power generation cost, TEDS is the economically preferred source of heat.

- From \( t = 0 \, \text{hr} \) to \( t = 6 \, \text{hr} \), PCU is operating at minimum allowed power (\( y_5 \) is at its lower bound in Figure 4-7), and TEDS output power was adjusted to meet the heat demand. During this period, the heat input to TEDS (\( Q_{MT, HX} \)) is larger than the \( P_{Heat} \), and TEDS was operating at Mode 4 (Table 2-1), i.e., therocline tank is charged, as confirmed by the increasing value of \( y_2 \).

- At \( t = 6 \, \text{hr} \), \( y_2 \) was approaching the corresponding upper bound. This indicates that the therocline tank is about to be fully charged. Starting from \( t = 6 \, \text{hr} \), less heat should then be disposed to TEDS to avoid overcharging of the therocline tank. Accordingly, an increase of the PCU power is necessary to consume more high-temperature nitrogen from MAGNET, which is confirmed by the increasing value of \( y_5 \). On the other hand, the power of TEDS needs to be lowered to meet the decreasing heat demand, but it needs to be carefully calculated to meet the heat balance and avoid overcharging. Despite the difficulties of solving the power dispatch problem for such a tightly coupled system, FARM-Delta succeeded in enforcing the operational constraints by using the CG algorithm.
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Figure 4-7. Response of the constrained output variables during the 12-hour dispatch period. Traces are calculated by adopting the same time discretization (600 seconds time steps).
4.5.4. Description of the impact of FARM-Supervisory

The hourly trajectories for the electric power demand and heat power demand optimized by FARM-Validator \((P_{Elec} \text{ and } P_{Heat})\) are calculated by using an LTI model with a coarse time resolution (600 seconds time steps). Such a level of detail might not allow obtaining accurate predictions of the system responses. To address this limit, Control Layer #1 converts the hourly trajectories of \(P_{Elec}\) and \(P_{Heat}\) into two, tentative set-points signals, i.e., \(\mathbf{r} \equiv (P_{Elec}, m_{\text{TES}}^{\text{charge}})\), as shown in Figure 3-6. These signals are then adjusted \((\mathbf{v})\) by FARM-Supervisory using an LTI model with fine time resolution (10 seconds time steps), and then issued to the LTI model of DETAIL facility for testing. Better results in terms of constraint enforcement are then obtained. In Figure 4-8, both the tentative and the adjusted set-point signals are shown. In general, these two traces tend to be identical, but local discrepancies may be occasionally noted. If the \(\mathbf{r}\) signal does not result in any constraint violations during simulations with fine time resolution, the \(\mathbf{v}\) signal will match; otherwise, \(\mathbf{v}\) will exhibit certain local adjustments required to uphold operational constraints.

Figure 4-8. Tentative (solid, red line) and adjusted (solid, green line) set-point signals. Traces are calculated by adopting the same time discretization (10 seconds time steps).
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Figure 4-9. Responses of the constrained, output variables when tentative set-point (solid, red line) and adjusted set-point (solid, green line) signals are issued. Traces are calculated by adopting the same time discretization (10 seconds time steps).
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The system responses deriving from issuing tentative and adjusted set-point signals were calculated with fine time resolution simulations. In Figure 4-9, the responses of the constrained output variables are illustrated. The red traces and green traces represent the system responses when tentative set-point signals and adjusted set-point signals are applied, respectively. It is evident that the operational constraints placed on the first four variables \((y_1, y_2, y_3, y_4)\) are satisfied with the issuance of either \(r\) or \(v\). Concurrently, the fifth variable \((y_5)\) violates the constraints at \(t = 0 \text{ hr}\), \(t = 5 \text{ hr}\) and \(t = 6 \text{ hr}\) when \(r\) is applied. These violations result from abrupt changes in the PCU power set-point and are discernible only when simulating the system response with fine time resolution. In Figure 4-10, the comparison between the two \(y_5\) trajectories around \(t = 6 \text{ hr}\) is represented. The entity of constraint violations deriving from issuing the \(r\) signal is almost negligible. We are aware that, in case the \(r\) signal was directly issued to the PID controllers, the damages to the components would have been limited. Still, the adjustments of set-point trajectories to prevent the violation of the constraints imposed on \(y_5\) demonstrate the significance of the role played by FARM-Supervisory. This layer constitutes the final check-point that evaluates the feasibility of the optimized power transients with the highest level of accuracy. In this work, due to the modeling challenges outlined in Section 4.5.2, a fundamentally identical LTI model was employed. This model served multiple purposes, including the validation of HERON power set-point trajectories (FARM-Validator), the validation of PID set-point signals (FARM-Supervisory), and the simulation of DETAIL responses. The only reason because these small entity constraint violations were observed is that the identical LTI model was simulated on two different timescales. In Table 4-5, the DTs used for solving the power dispatch problem are reported. The models used in both the proposed implementation and the actual one are presented. It is probable that adopting more accurate DTs for optimizing the set-point trajectories and simulating the response of the DETAIL facility would have revealed more pronounced discrepancies.

Figure 4-10. Response of output variable \(y_5\) when tentative and adjusted set-points are imposed. Thanks to the fine time resolution evaluation of the system response, a constraint violation was detected and successfully prevented by FARM-Supervisory.
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Table 4-5. Description of the DTs used in the solution of the power dispatch problem. The proposed implementation and the actual one described in the report are presented. The mentioned layers refer to the ones represented in Figure 3-5.

<table>
<thead>
<tr>
<th>Digital Twin</th>
<th>Proposed implementation</th>
<th>Current implementation</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT embedded into FARM-Validator</td>
<td>LPV model of the system given by blue and grey layers</td>
<td>LTI of the system given by blue and grey layers</td>
</tr>
<tr>
<td>DT embedded into FARM-Supervisory</td>
<td>LPV model of blue layer</td>
<td>LTI model of blue layer</td>
</tr>
<tr>
<td>DT for testing</td>
<td>Dymola-derived FMU of the blue layer</td>
<td>LTI model of blue layer</td>
</tr>
</tbody>
</table>
5. CONCLUSIONS

In this report, the hierarchical control system architecture proposed in June 2023 for the flexible operation of DETAIL was finalized and demonstrated. Once summarized the features of the subsystems that constitute the facility (MAGNET, TEDS, PCU), the currently adopted control strategy was analyzed. The set of pairings between control and controlled variables, the list of constraints to be enforced and the equations for deriving the set-point trajectories were reported. A tentative, operational procedure for training the DTs embedded into the power dispatcher and the control system architecture with the experimental data (“Self-learning” stage) was proposed. Afterwards, the latest version of FARM (FARM-Epsilon) was presented. Thanks to the implementation of a scheme for removing the redundant constraints, significant improvements in the quality of the solution to the power dispatch problem were obtained.

Then, the implementation and the demonstration of the control system architecture integrating a modified version of FARM module (FARM-Supervisory) was presented. First, the most significant process variable for the characterization of DETAIL dynamics (state variables) were selected. As for the derivation of DT embedded into FARM and the high-fidelity DETAIL simulator, multiple modeling issues prevented the implementation of the scheme based on the adoption of Dymola-derived FMUs that was successfully adopted in the past. For this reason, an alternative, simplified scheme was used. Then, a representative demand scenario was identified, and the power dispatch problem was solved, i.e., first the trajectories for electrical and thermal power contributions were optimized, and then they were “translated” into set-point signals and issued to the PI controllers. Despite the reduced-order of the adopted DT, the observed adjustments of set-point trajectories to prevent the violation of the imposed limits on process variables demonstrated the significance of the role played by FARM-Supervisory. This layer constitutes the final check-point that evaluates the feasibility of the optimized power transients with the highest level of accuracy.
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REFERENCE


Demonstrate FARM supervisory capabilities for a thermal energy storage problem for the DETAIL facility
