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Changing the World's Energy Future

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ABSTRACT

The integrated energy system (IES) refers to the combination of nuclear energy generation with other energy sources to enable the efficiency and reliability of power generations. To create technologically viable and economically competitive systems, supervisory control strategies are critical for optimizing performance and ensuring stability across different energy generation, transportation, and utilization. This work focuses on the control strategies for the thermal energy distribution system (TEDS), which is a cornerstone of the Dynamic Energy Transport and Integration Laboratory at Idaho National Laboratory. TEDS currently relies on operators to coordinate across different components to manage energy storage and ensure efficiency. This work demonstrates the use of model predictive control (MPC) with surrogate models in determining optimal setpoints for major TEDS components. The capability of MPC-based supervisory control system is evaluated by autonomously matching the power outputs from a Dymola-based TEDS with target heat demands.

Keywords: Supervisory Control, Integrated Energy System, Thermal Energy Distribution System

1. INTRODUCTION

Traditionally in nuclear systems, the generation, transport, and usability of energy are considered and operated independently. The integrated energy system (IES) is a heterogeneous multi-component coupled system, where energy flows from different components that are coordinated and managed together to improve energy use, peak-load regulation, and demand-side responses.

The objective of supervisory control for an IES is to maximize profitability by controlling and coordinating various components. Such a control system must account for the explicit constraints of each component, including the operational limits, maximum, and minimum rates of variations. The control system should also account for the physical constraints of each component and the interactions among them. Such constraints include dynamic behaviors and correlations among key state variables of temperatures, pressures, and flow rates.

The Thermal Energy Distribution System (TEDS) acts as the cornerstone of the Dynamic Energy Transport and Integration Laboratory (DETAIL). DETAIL, which was established by Idaho National Laboratory (INL), tests heat-transfer components, distribution systems, instrumentation, and controls for the hybrid generation of electrical power and nonelectrical products [1]. Currently, TEDS relies on a list of Proportional-Integrator (PI) controllers to adapt each component to user-defined setpoints, including fluid temperatures at heater outlets, mass flow rates through pumps, and fluid temperatures at chiller outlets. The connections between these setpoints and the overall power outputs from TEDS are currently missing.

Of the various operating strategies currently available, predictive control strategies—optimizing reactor operations based on predictions of future conditions—can be suitable for IES because they can anticipate fluctuations in renewable energy outputs and adjust energy sources or storage systems accordingly to maintain safety and stability [2] [3]. Moreover, unlike reactive or feedback control systems, predictive control explicitly accounts for constraints in operations and system dynamics when solving for optimal actions. This allows for reconfigurations with new technologies, regulatory changes, or modifications in IES structures. At the same time, for forecasting demands based on patterns, predictive control allows for pre-emptive adjustment to energy production and distribution and thus results in better efficiency and profitability.

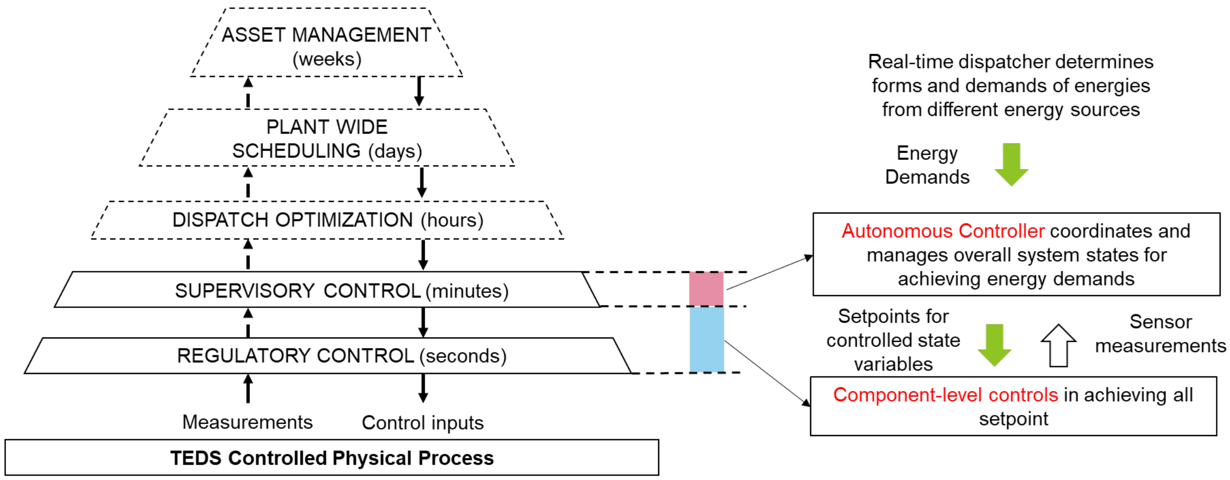

Figure 1. Architecture of TEDS control system.

The paper contributes a supervisory control system that autonomously searches for optimal setpoints to bridge the gaps between TEDS component-level controls and TEDS power outputs to meet external demands. This paper first describes the systems and operating modes that the supervisory control will be deployed at. Section 3 discusses the development of a model predictive control (MPC) system and surrogate models for the IES. Section 4 presents the control results on a virtual TEDS system in Dymola. Section 5 summarizes key findings and discusses future plans.

2. System Descriptions

The TEDS facility is composed of three primary components: a 200 kW Chromalox heater, a single-tank packed-bed thermal energy storage (TES) system filled with 0.125-inch alumina beads, an ethylene-glycol-to-therminol-66 heat exchanger, system piping, five control valves, and associated temperatures and flow sensors. The system dynamics of TEDS are simulated using various approaches in Dymola model [4].

2.1. Dymola Model

The TES contains hot and cold fluid separated by an intermediate temperature zone with a temperature gradient (called a thermocline). The physical stratification between hot and cold fluid is maintained by buoyancy forces due to the density difference. The pack-bed TES uses solid fillers with high thermal conductivity and specific heat capacity as the main storage media, exchanging heat with heat transfer fluid through direct contact, which decreases the total amount of fluid required and increases storage efficiencies [5]. The charging of the thermocline consists of sending hot fluid from the top of the tank and extracting cold fluid from the bottom, while discharging happens in reverse. In the current Dymola model, Schumann equations are adopted for describing the energy conservation of fluid flow through porous media. Meanwhile, the energy balance of filler materials with convective heat transfer between filler and fluid flows are added to account for temperature differences at any local location during the transient (charging and discharging) processes. It is assumed that the radial and axial distributions of fluid flow and filler materials are uniform throughout the storage system with relatively slow flow speeds. Both heat diffusion inside TES and heat conduction inside a single filler material are considered negligible. The wall and insulation are added with conductive heat transfer, and the radiative heat transfer from TES to the environment is neglected.

The Chromalox heater is modeled as a multinode pipe with heat inputs equally distributed along all pipe nodes. The heater mass flow is assumed to be fully developed with pressure loss due to wall friction only. The heating element is also assumed to be in direct contact with the fluid, and energies are added instantaneously into the fluid without any losses or delays. The ethylene glycol heat exchanger (GHX) is modeled using shell and tube heat exchanger model in a TRANSFORM library [6]. Therminol-66 [7] flows on the shell side, while ethylene glycol flows on the tube side with constant flow rates. The heat transfer on the tube side is modeled using a Dittus-Boelter correlation, and a single-phase heat transfer model with correction factors is used on the shell side. The pump is modeled using a TRANSFORM pump pressure booster model, where constant pressure is maintained. The Dymola model is available at https://github.com/idaholab/HYBRID.

The control of TEDS relies on three component-level controllers, each of which is to meet user-defined setpoints for specific state variables. Figure 2 shows the schematic plot of the TEDS loop with control systems during discharging mode. The Chromalox heater's power is controlled by matching heater outlet temperatures $T_{heater,out}$ with a reference temperature. The flow rates through the pump are controlled by changing the positions of a valve near the pump outlet so that the flowrate setpoint $\dot{m}_{pump,out}$ can be achieved. The chiller combines flow-through and bypassing the GHX, which is controlled by matching the chiller outlet temperature $T_{chiller,out}$, with a reference temperature. The controlling objective is achieved by changing the valves' positions in the flow through and bypassing GHX. All component-level controllers are implemented with proportional-integral (PI) controls. Moreover, since the overall goal of TEDS is to ensure that power extracted from GHX's tube side matches the power demands from external applications, a supervisory controller is needed to determine the setpoints for heat outlet temperatures, pump outlet flow rates, chiller outlet temperatures, and the pressure valve (PV) positions for discharging TES.

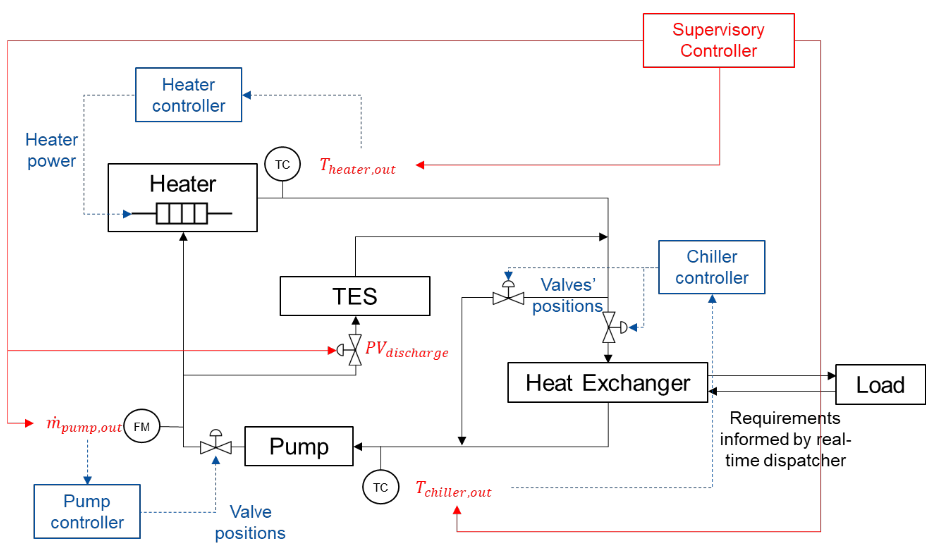

Figure 2: Schematic plot of TEDS and control systems when discharging heat.

2.2. Simulation Results

To understand the system dynamics, especially how the system responds to changes in setpoints, all four setpoints are randomly perturbed to ensure sufficient variations in simulation results. To ensure consistency, this work uses experimental measurements as setpoints for heat outlet temperatures, pump outlet flow rates, chiller outlet temperatures, and the PV positions. Moreover, to ensure computational efficiency, the temporal resolutions of experimental data are coarsened using linear segment-fitting methods. In this method, all data points are partitioned into a fixed number of intervals, and a linear function is fitted to each interval. The selections of breakpoints are determined by minimizing the averaged errors between fitted functions and experimental data. Figure 3 compares the experimental data against segment fitting with a different number of intervals. The user-defined setpoints from the original TEDS Dymola model are also included, and the segment fitting results in smaller subjective errors due to user biases. Although a higher number of intervals yields better agreements, the piecewise function is more likely to overfit noises and biases from experimental measurements. This work selects 10 segments to fit flow rates, chiller outlet temperatures, and heater outlet temperatures. Since the transient of PV positions only has six data points, segment fitting is not applied.

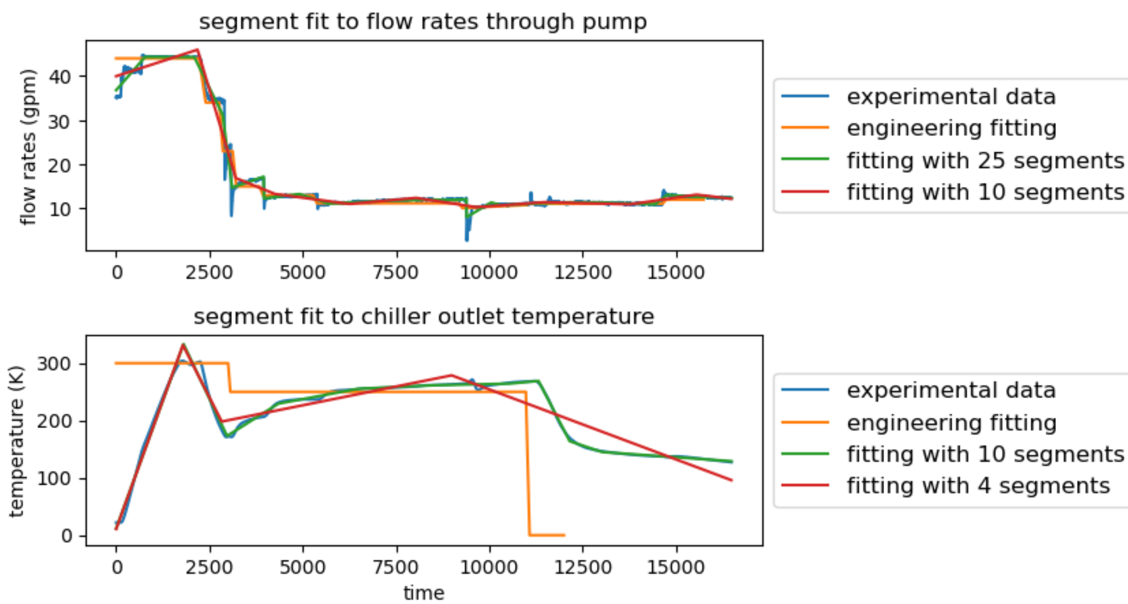

Figure 3. Comparisons of segment fittings with different number of intervals.

For setpoints, the number of intervals is randomly perturbed, and random noises are added to each breakpoint. Figure 4 shows the perturbed setpoints for temperatures at heater outlet and pump inlet (chiller outlet). Note that the discharge process, modeled in this work, starts from 9180 seconds and ends at 14640 seconds. The entire startup, charging, discharging, and cool-down process is perturbed to ensure consistent initial and boundary conditions.

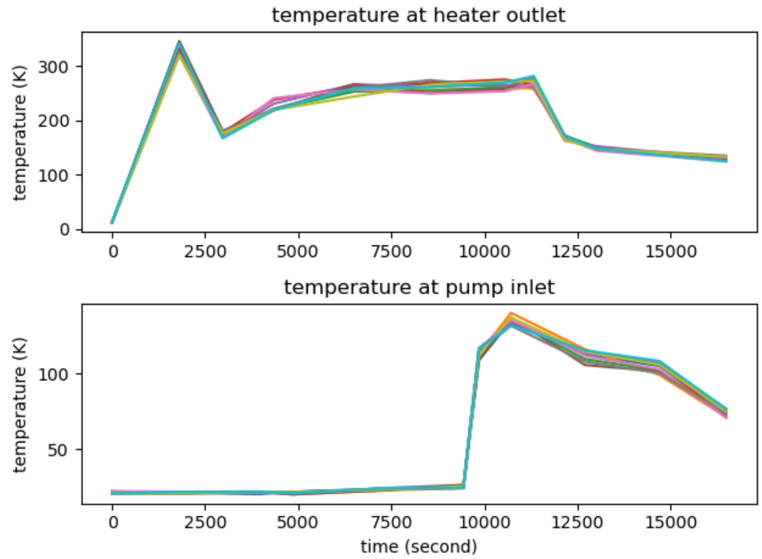

Figure 4: Transients of user-defined setpoints with random noises.

3. Methods and Algorithms for TEDS Autonomous Control

This section describes the model predictive control (MPC) methods used for determining the optimal setpoints to achieve external power demands. Since MPC relies on predicted state variables to search for optimal setpoints, a surrogate model is needed to approximate the dynamics of each component in TEDS. This work builds surrogate models for each component. After training, these models are combined and solved together for the transient of temperatures, flow rates, and TEDS power, and for determining the optimal setpoints.

3.1. Model Predictive Control

The essence of MPC is to minimize—over the manipulatable inputs—the discrepancies between predicted and target setpoints of process behaviors while accounting for the equality and inequality constraints. This forecasting is performed by employing a process model (i.e., a predictor) over a finite time interval of length P. The present work developed two models for chiller and TES, respectively. Eq. (1) and (2) show a generic process model for predicting selected state variables x at the next time step based on the control actions and current state of each component in TEDS:

$$(x_{chiller})_{k+1|j} = f_{chiller}\left((x_{chiller})_{k|j}, u_{chiller_{k|j}}\right) \tag{1}$$

$$(x_{TES})_{k+1|j} = f_{TES}\left((x_{TES})_{k|j}, u_{TES_{k|j}}\right) \tag{2}$$

where j represents the time step at which the MPC is activated to find the optimal control action, and $k = 1, \dots, P$ represents the number of steps ahead of j that system states are being predicted at by the process model. For convenience, we use $k|j$ to denote k steps ahead of the real-time j, and the initial states of x—when $k = 0$ ($x_{0|j}$ or x_j)—are obtained from real-time measurements conducted on the (simulated) TEDS. $x_{chiller}$ and x_{TES} are the state variables of chiller, heater, and TES, respectively. Specifically, $x_{chiller}$ includes the mass flow rates that bypass the GHX, denoted as $\dot{m}_{GHX,bp}$, and the power extracted by GHX to meet external demands $Q_{GHX,in}$. $u_{chiller}$ includes the total mass through chiller $\dot{m}_{u,chiller}$, which is designated by the operator and supervisory controller. Other control actions include inlet $T_{u,chiller,in}$ and outlet $T_{u,chiller,out}$ temperatures of the chiller. Chiller outlet temperatures are set by operators, while the inlet temperatures depend on the state variables of heaters and TES, as in Eq. (3).

$$\dot{m}_{u,chiller} \cdot T_{u,chiller,in} \approx \dot{m}_{tes,out} \cdot T_{tes,out} + \dot{m}_{heater} \cdot T_{u,heater,out} \tag{3}$$

$$\dot{m}_{heater} + \dot{m}_{tes} = \dot{m}_{u,chiller} \tag{4}$$

x_{TES} include mass flow rates through TES $\dot{m}_{tes}$, outlet temperatures $T_{tes,out}$, and fluid temperatures at top ($T_{tes,top}$), middle ($T_{tes,mid}$), and bottom ($T_{tes,bot}$) of the TES, representing the state of the charge of TES. u_{tes} includes the pressure valve positions that are directly controllable by the operator or supervisory controller. Another control action is the inlet temperatures to TES, which are equal to the chiller outlet temperatures.

$$T_{u,TES,in} = T_{u,chiller,out} \tag{5}$$

Based on the predictions of state variables for all components over the prediction horizon, optimization can be performed over a control sequence $U = \left[u_{1|j}, \dots, u_{N|j}\right]$ by minimizing the summation J for stage cost function l over the entire prediction horizon:

$$J^* = \min_{U} \left[\sum_{k=1}^{P} l\left(x_{k|j}, u_{k|j}\right) \right] \tag{6}$$

subject to

$$x_{k+1|j} = f\left(x_{k|j}, u_{k|j}\right)$$

$$\boldsymbol{U} = \left[\boldsymbol{u_{1|j}}, \dots, \boldsymbol{u_{P|j}}\right] \in \mathbf{U}_{\boldsymbol{i}} \text{ for all } i = 1, \dots, n_{c_u}$$

$$\boldsymbol{X} = \left[\boldsymbol{x_{1|j}}, \dots, \boldsymbol{x_{P|j}}\right] \in \mathbf{X}_{\boldsymbol{i}} \text{ for all } i = 1, \dots, n_{c_x}$$

$$x_{0|j} = x_j$$

where J^* is the minimized summation of the stage cost function. The present work uses a weighted quadratic function as the stage cost function l in order to approximate the actual multiobjective, sparse, and nondifferentiable cost function because of the discrete and nonlinear natures for the optimization problem. The present work focuses on reference tracking problems, and the cost function measures the squared differences between the achieved and target powers extracted from GHX. Such an optimization is subject to constraints on system dynamics as in Eq. (1)–(5). $\mathbf{U}_{\boldsymbol{i}}$ and $\mathbf{X}_{\boldsymbol{i}}$ are vectors of constraints on the multiple control actions and state variables, respectively. n_{c_u} and n_{c_x} are the numbers of constraints on the control actions and state variables, respectively. GEKKO optimization packages [8] are used to solve Eq. (6). A Python script is created to transfer information back and forth between the supervisory controller and the Dymola TEDS model and to drive these programs forward.

3.2. Surrogate Models

To represent the dynamic behaviors of state variables in TEDS, this work uses Sparse Identification of Nonlinear Dynamics with Control (SINDyc) for generating governing dynamic equations based on a set of training data from simulation results. SINDyc is a model-discovery method which uses sparse regression to infer nonlinear dynamical systems from measurement data [9]. SINDYc reduces to dynamic mode decomposition if formulated in discrete time—with only linear functions, and without a sparsity-promoting L1 penalty term. This work uses linear state-space models for representing Eq. (1)–(2). Meanwhile, physical correlations among state variables of different components are considered. Eq. (7)–(11) show the models for TES, the chiller, and three physical correlations. The coefficient matrix (A, B, and C) for each component is calibrated using Least Absolute Shrinkage and Selection Operator with second norm (Eq. (12)) implemented in PYSINDY package [10].

TES

$$\frac{d}{dt}\begin{pmatrix} \dot{m}_{TES} \\ T_{TES,out} \\ T_{top} \\ T_{mid} \\ T_{bot} \end{pmatrix} = A_{TES}\begin{pmatrix} \dot{m}_{TES} \\ T_{TES,out} \\ T_{top} \\ T_{mid} \\ T_{bot} \end{pmatrix} + B_{TES}\left(PV_{discharge}\right) \tag{7}$$

Chiller

$$\frac{d}{dt}\begin{pmatrix} Q_{GHX} \\ \dot{m}_{GHX,bp} \end{pmatrix} = A_{GHX}\begin{pmatrix} Q_{GHX} \\ \dot{m}_{GHX,bp} \end{pmatrix} + B_{GHX}\begin{pmatrix} \dot{m}_{pump} \\ T_{pump} \\ T_{chiller} \end{pmatrix} \tag{8}$$

$$\dot{m}_{chiller} \cdot T_{chiller} = \dot{m}_{TES} \cdot T_{TES,out} + \dot{m}_{heater} \cdot T_{heater,out} \tag{9}$$

$$\dot{m}_{heater} = \dot{m}_{pump} - \dot{m}_{TES} \tag{10}$$

$$\dot{m}_{chiller} = \dot{m}_{pump} \tag{11}$$

$$\Theta = \min_{\hat{\xi}_K} \frac{1}{2}\left|x'_k - \hat{\xi}_k \Theta^T(x_k, u_k)\right|_2^2 + \lambda\left|\hat{\xi}_k\right|_1 \tag{12}$$

where $\dot{m}_{TES}$ are mass flow rates in kg/s through TES; $T_{TES,out}$ are fluid temperatures at the outlet of TES; $T_{top}, T_{mid}, T_{bot}$ are fluid temperatures at the top, middle, and bottom of TES; $PV_{discharge}$ is the opening rea of pressure valve; Q_{GHX} are total heats rejected by chiller to meet external demand; $\dot{m}_{GHX,bp}$ are the mass flow rates bypassing the chiller; $\dot{m}_{pump}$ and T_{pump} are mass flow rates ad temperatures of fluid through the pump; $\dot{m}_{chiller}$ and $T_{chiller}$ are mass flow rates and temperatures at chiller inlet; $\dot{m}_{heater}$ and $T_{heater,out}$ are fluid mass flow rates and temperatures at the outlet of heater; k is number of observations or predictions, x' are observations, x and u are predictions and control actions, respectively, ξ represents the sparsity coefficients for a dynamic system, λ is the penalty coefficient for the sparsity-promoting term, and Θ is the coefficient matrix (A, B, and C) of the SINDYc surrogate.

4. Demonstration Results

To demonstrate the capability of supervisory control systems, this work builds a class of application program interfaces (APIs) to pass information between the control system, a Dymola model for TEDS, and for driving both programs using command lines. Figure 5 shows the operational workflow for demonstrating the controller's capabilities in finding optimal setpoints and achieving external energy demands.

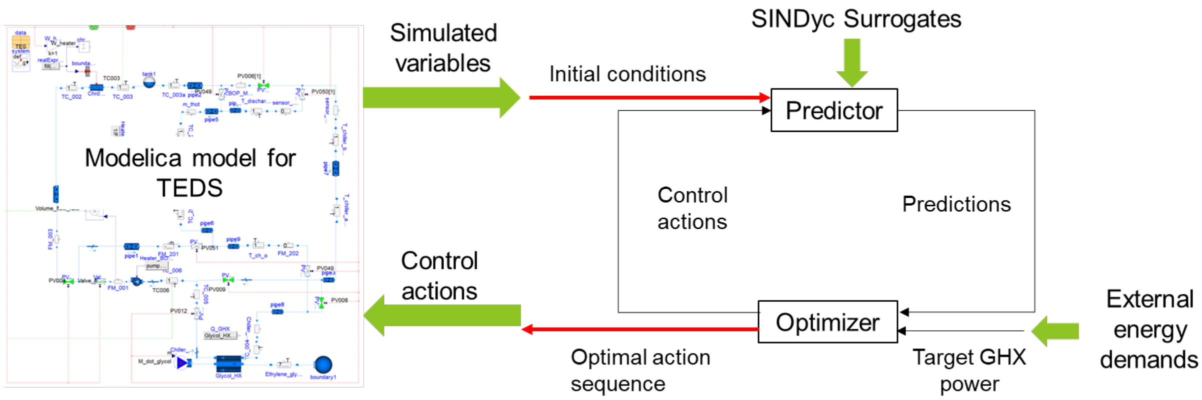

Figure 5: Operational workflow for demonstrating the controller's capabilities in achieveing external energy demands.

This work chooses a scenario where TES starts to discharge by closing the TES bypass valves. Since TES discharges less power than electrical heaters, a trajectory is selected with decreasing GHX powers with arbitrary magnitudes. In this demonstration, the unit time step is 10 seconds, and the prediction length is 50 seconds. The entire transient lasts 2,000 seconds (200 steps). Figure 6 compares the achieved GHX power against the targets, and the root mean squared errors are 21 kW. Figure 6 also shows the solved setpoints to achieve the target GHX power. The flow rates through the pump are reduced as expected for reduced GHX powers. There are no changes in heater outlet temperatures because all fluids are directed to the TES. The pressure valves are fully opened, and TES alone is providing heat to meet external heat demands.

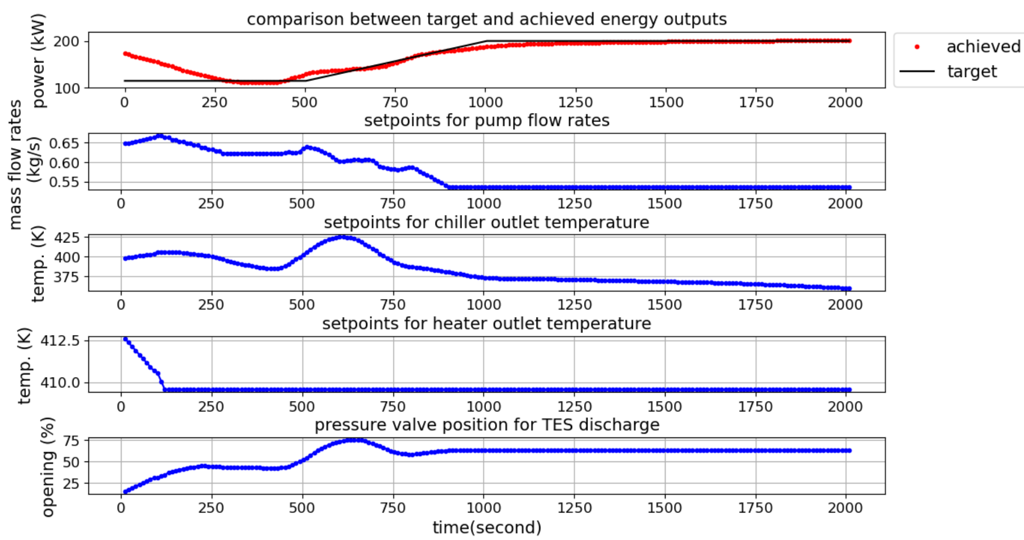

Figure 6: Comparisons of achieved against target GHX power. The average root mean squared error is 21 kW.

5. CONCLUSIONS

This work develops and demonstrates a supervisory control system for TEDS using MPC methods. Two surrogate models are developed for TES and the chiller, respectively. The capabilities of the control system are demonstrated by finding optimal setpoints for pump flow rates, chiller outlet temperatures, heater outlet temperatures, and pressure valve positions such that the target GHX power can be achieved with reasonable errors. Future work will continue improving the performance of this control system, incorporating experimental data for digital twin demonstrations where uncertainty quantification methods will be investigated for real-time state concurrence and diagnosis analysis.

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