Bypass Control of HEN Under Uncertainty in Inlet Temperature of Hot Stream

Authors:

Chaitanya Manchikatla, Zukui Li, Biao Huang

Date Submitted: 2021-10-21

Keywords: Uncertain Optimization, Model Predictive Control, Heat Exchanger Network, Affine Control Policy

Abstract:

The dynamic control of Heat Exchanger Network is significant for developing energy efficient and safe industrial processes. In this project, the hot stream's inlet temperature is considered uncertain because it is common in industries. The cold stream is bypassed around the heat exchanger. This project aims to track the setpoint temperature of the mixed stream by manipulating the bypass fraction of the cold stream around the Heat Exchanger given uncertainty in the inlet temperature of the hot stream. The control is implemented in Nonlinear Model Predictive Control (NMPC) framework. The uncertainty in the optimal control problem (OCP)is dealt by using scenario tree based approximation as well as affine policy based method. The model of the system considered is based on the first principles model, i.e. dynamic model of shell and tube heat exchanger. The Orthogonal collocation technique is used to discretize the first principles model into the system of algebraic equations. The results show that for the possible scenarios of uncertainty, the control variable efficiently tracks setpoint using input from uncertain optimization. The performance of the proposed control method is also demonstrated using step-change in set-point. In comparison, considering the same scenarios of uncertainty used, the graph of the control variable simulated using input obtained from deterministic optimization shows the control variable deviates from the setpoint as time passes.

CSChE Systems & Control Transactions

Open Access | Original Research

Conference Proceedings
Canadian Chemical Engineering Conference 2021
October 24-27, Montréal, Québec, Canada

PSEcommunity.org/LAPSE:2021.0794

PSE PRESS

Bypass Control of HEN Under Uncertainty in Inlet Temperature of Hot Stream

Chaitanya Manchikatla, Zukui Li*, and Biao Huang

University of Alberta, Department of Chemical and Materials Engineering, Edmonton, Alberta, Canada
* Corresponding Author: opti

ABSTRACT

The dynamic control of Heat Exchanger Network is significant for developing energy efficient and safe industrial processes. In this project, the hot stream's inlet temperature is considered uncertain because it is common in industries. The cold stream is bypassed around the heat exchanger. This project aims to track the setpoint temperature of the mixed stream by manipulating the bypass fraction of the cold stream around the Heat Exchanger given uncertainty in the inlet temperature of the hot stream. The control is implemented in Nonlinear Model Predictive Control (NMPC) framework. The uncertainty in the optimal control problem (OCP)is dealt by using scenario tree based approximation as well as affine policy based method. The model of the system considered is based on the first principles model, i.e. dynamic model of shell and tube heat exchanger. The Orthogonal collocation technique is used to discretize the first principles model into the system of algebraic equations. The results show that for the possible scenarios of uncertainty, the control variable efficiently tracks setpoint using input from uncertain optimization. The performance of the proposed control method is also demonstrated using step-change in setpoint. In comparison, considering the same scenarios of uncertainty used, the graph of the control variable simulated using input obtained from deterministic optimization shows the control variable deviates from the setpoint as time passes.

Keywords: Uncertain Optimization, Model Predictive Control, Heat Exchanger Network, Affine Control Policy

Date Record: Original Manuscript received October 18, 2021. Published October 21, 2021.

INTRODUCTION

In industries, nearly 80% of the total energy consumption is related to heat transfer [1]. For efficient heat transfer and energy intensified processes, it is obvious that the design and dynamic control of the Heat Exchanger Network (HEN) play an important role [3]. This saves million dollars to the chemical industries. Generally, the outlet temperatures are controlled by manipulating flow rates. But, when the flow rates are set by process requirements in HEN, bypass control is adopted widely [6]. Bypass control provides very tight temperature control since the dynamics of blending a hot stream (stream through the heat exchanger) and a cold stream (bypassed stream) is very fast.

In literature, the bypass control of HEN was formulated using deterministic approaches like LQR [7]. For HENs, the optimal bypass location was selected by calculating the non-square Relative Gain Array [1]. But, the control problem of the Heat Exchanger Network is considerably challenging because of the highly nonlinear dynamics, disturbances in inlet temperatures of streams [5].

This project aims to track the setpoint temperature of the mixed stream by manipulating the bypass fraction of the cold stream around the Heat Exchanger given uncertainty in the inlet temperature of the hot stream. The control is implemented in Nonlinear Model Predictive Control (NMPC) framework. At each sampling instant the uncertain Optimal Control Problem (OCP) is solved for the entire Prediction horizon (tp). The Prediction horizon is divided into N control horizon intervals of uniform length, and the bypass fraction is assumed to be constant in an interval [2]. For bound constraints on input (bypass fraction), the uncertainty is handled by deriving robust counterparts using the Affine Control Policy approach i.e. the input is assumed to be an affine function of uncertainty. The uncertainty in algebraic equations of the model is handled by assuming scenarios of possible uncertainty [4]. The Receding horizon implementation of MPC is implemented using MATLAB and the optimization is done using GAMS.

PROBLEM STATEMENT

The system considered in this research work is Heat Exchanger Network. Generally, for efficient heat integration process streams are used for heat exchange along with utilities in industries. The desired out temperatures of the streams are controlled by using bypasses, and manipulated these bypass fractions around the heat exchanger. The simple Heat

Exchanger Network with single heat exchanger, a hot stream, and bypassed cold stream is given by **Figure 1**. The **Figure 1** also shows the objective of the current research work.

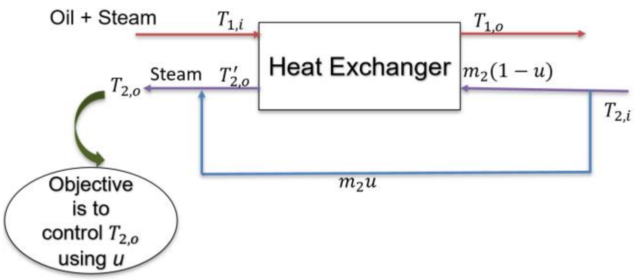

Figure 1. Simple HEN showing bypassed cold stream and objective.

It's common that the inlet temperatures of process streams are corrupted by the disturbances. So, to ensure safe processes and we achieve target out temperatures of the streams the control problem of HEN is formulating considering these disturbances. In this work, we aim to track the setpoint temperature of the mixed stream by manipulating the bypass fraction of the cold stream around the Heat Exchanger given uncertainty in the inlet temperature of the hot stream.

DYNAMIC MODEL OF HEN

The shell and tube dynamic model of the Heat Exchanger i.e., the system considered in this research work is given in this section. Hot stream flows through shell side, and cold through tube side. Counter current flow is assumed. m_1 is the flow rate of hot fluid. If F_2 is the total flow rate of cold fluid, its flow rate through Heat exchanger is given by,

$$m_2 = F_2(1-u) \tag{1}$$

Here u is the bypass fraction. M_1 and M_2 are the flow rates per unit area of hot fluid and cold fluid respectively in Heat exchanger. The model is given by following system of PDEs, and these PDEs denote energy conservation in unit element.

Shell side:

$$\frac{\partial T_1(x,t)}{\partial t} = \frac{m_1}{M_1}\frac{\partial T_1(x,t)}{\partial x} + \frac{\pi d_o K_o}{M_1 C_{P_1}}[T^{wo}(x,t) - T_1(x,t)] \tag{2}$$

Tube outer wall:

$$\frac{\partial T^{wo}(x,t)}{\partial t} = \frac{2\lambda\pi}{M_w C_{P_w} ln(r_2/r_1)}\left[T^{wi}(x,t) - T^{wo}(x,t)\right] + \frac{\pi d_o K_o}{M_w C_{P_w}}[T_1(x,t) - T^{wo}(x,t)] \tag{3}$$

Tube inner wall:

$$\frac{\partial T^{wi}(x,t)}{\partial t} = \frac{2\lambda\pi}{M_w C_{P_w} ln(r_2/r_1)}\left[T^{wo}(x,t) - T^{wi}(x,t)\right] + \frac{\pi d_i K_i}{M_w C_{P_w}}\left[T_2(x,t) - T^{wi}(x,t)\right] \tag{4}$$

Tube side:

$$\frac{\partial T_2(x,t)}{\partial t} = \frac{m_2}{M_2}\frac{\partial T_2(x,t)}{\partial x} 1 + \frac{\pi d_i K_i}{M_2 C_{P_2}}[T^{wi}(x,t) - T_2(x,t)] \tag{5}$$

heat transfer coefficient at outer wall:

$$1/K_O = \frac{1}{K_1 m_1} + R_o \tag{6}$$

heat transfer coefficient at inner wall:

$$1/K_i = \frac{1}{K_2 m_2} + R_i \tag{7}$$

In the current work, the above system of PDE is first discretized into system of ODE, and then the system of ODE is discretized into system of nonlinear equations using Orthogonal collocation technique. The Orthogonal collocation technique is given section 0

METHODOLOGY

The methods used to address bypass control of HEN under uncertainty are described in this section. The problem is solved under nonlinear model predictive control framework using multistage uncertain optimization techniques. The Optimal Control Problem is given by ,

$$\min_{\Delta \boldsymbol{u}} \int_{t=0}^{t\_P} \left(T_{2,o}(t,\zeta) - T_{st}(t)\right)^2 + \sum_{n=1}^{N} \alpha(\Delta u\,(n,\zeta))^2 \tag{8}$$

$$s.t.$$

$$\dot{x}(t,\zeta) = f(x(t,\zeta), u(n,\zeta), \theta) \qquad x(0) = x_o \tag{9}$$

The Heat exchanger model is given by $f(x(t), u(t), \theta)$

$$T_{2,o}(t,\zeta) = u(n,\zeta)T_{2,i}(t) - (1-u(n,\zeta))T'_{2,o}(t,\zeta) \tag{10}$$

$$\Delta u_{min} \le \Delta u(n,\zeta) \le \Delta u_{max} \tag{11}$$

$$x_{min} \le x(t,\zeta) \le x_{max} \tag{12}$$

ζ indicates primitive uncertainty in inlet temperature of hot stream. The objective function is given by Equation (8), the first term of objective function indicates setpoint tracking, and second term indicates controller effort term. Here T_{st} is the setpoint of control variable (the mixed stream temperature). Equation (9) represents HEN model, and Equation (10) represents mixed stream temperature constraint. Equation(11) and Equation(12) represent bounds on change in input and states respectively. Here x is vector containing all the states of the model.

The steps involved in converting above intractable (because of the uncertainty considered) optimal control problem to tractable is shown by **Figure 2**.

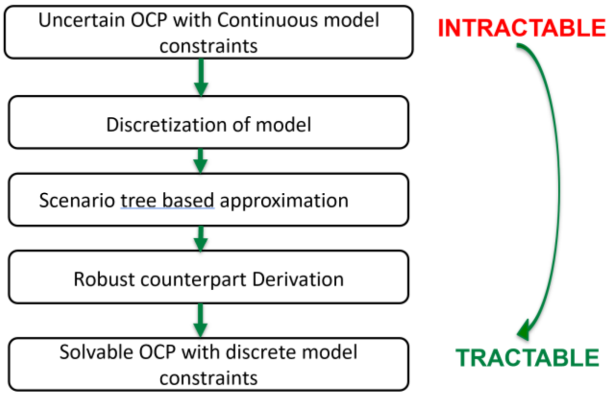

Figure 2. Steps of converting intractable OCP to tractable

Discretization of model

The orthogonal collocation technique is used to discretize the system of ODEs into system of nonlinear equations. The model of the Heat Exchanger Network is represented by this system of nonlinear equations from now on. For demonstration purpose, the Orthogonal collocation technique is applied to single Heat Exchanger model in this section. At each time instant, we assume that the prediction horizon (t_p) is divided into N (control horizon) intervals. The input is assumed to be constant in n^{th} $(n = 1,2,\dots,N)$ interval, and it is denoted by $u(n)$. Each n^{th} interval is divided into $K+1$ intervals using K collocation points. The state vector at $k^{th}(k = 1,2,\dots,K)$ collocation point, $len^{th}(len = 1,2,,,13)$ spatial discretization point, and in n^{th} interval is denoted by $T_{len,n,k}$.

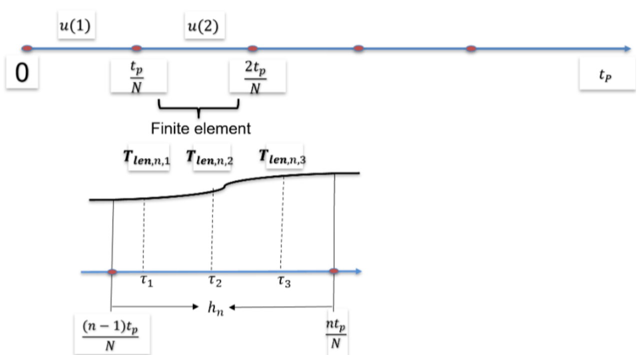

Figure 3. Polynomial approximation of state profile across finite element with 3 collocation points

The states in each finite element are approximated using Lagrange interpolation polynomials. The states are given by,

$$\begin{bmatrix} t = t_{n-1} + h_n\tau \\ T_{len}(t) = \sum_{k=0}^{K} l_k(\tau) T_{len,n,k} \end{bmatrix} \quad \forall t = [t_{n-1}, t_n],\ \tau = [0,1] \qquad (13)$$

$$l_k(\tau) = \prod_{j=0,\, j\neq k}^{K} \frac{(\tau-\tau_j)}{(\tau_k-\tau_j)} \qquad (14)$$

The approximated derivative of states at these collocation points is equated with ODE model, and the HEN model now is given by,

$$\sum_{k=0}^{K} T_{1,len,n,k}\frac{dl_j(\tau_k)}{d\tau} = h_n\left[\frac{m_1}{M_1}\frac{[T_1(len,n,j) - T_1(len-1,n,j)]}{[x_{len} - x_{len-1}]} + \frac{\pi d_o K_o}{M_1 C_{p1}}[T^{wo}_{len,n,j} - T_1(len,n,j)]\right]$$

$$len = 1,2,3,\dots,13.\ \ n = 1,2,3,\dots,N.\ \ j = 1,2,3,\dots,J \qquad (15)$$

$$\sum_{k=0}^{K} T^{wo}_{len,n,k}\frac{dl_j(\tau_k)}{d\tau} = h_n\left[\frac{2\lambda\pi}{M_w Cp_w ln\left(\frac{r2}{r1}\right)}[T^{wi}_{len,n,j} - T^{wo}_{len,n,j}] + \frac{\pi doKo}{M_w Cp_w}[T_{1,len,n,j} - T^{wo}_{len,n,j}]\right]$$

$$len = 1,2,3,\dots,13.\ \ n = 1,2,3,\dots,N.\ \ j = 1,2,3,\dots,J \qquad (16)$$

$$\sum_{k=0}^{K} T^{wi}_{len,n,k}\frac{dl_j(\tau_k)}{d\tau} = h_n\left[\frac{2\lambda\pi}{MwCp_w ln\left(\frac{r2}{r1}\right)}[T^{wo}_{len,n,j} - T^{wi}_{len,n,j}] + \frac{\pi d_i K_i}{M_w Cp_w}[T_{2,len,n,j} - T^{wi}_{len,n,j}]\right]$$

$$len = 1,2,3,\dots,13.\ \ n = 1,2,3,\dots,N.\ \ j = 1,2,3,\dots,J \qquad (17)$$

$$l\sum_{k=0}^{K} T_{2,len,n,k}\frac{dl_j(\tau_k)}{d\tau} = h_n\left[\frac{m_2}{M_2}\frac{[T_2(len,n,j) - T_2(len+1,n,j)]}{[x_{len} - x_{len+1}]} + \frac{\pi doKo}{M_2 Cp_2}[T^{wo}_{len,n,j} - T_2(len,n,j)]\right]$$

$$\boldsymbol{len = 1,2,3,\dots,13.\ n = 1,2,3,\dots,N. j = 1,2,\dots,J} \qquad (18)$$

For all the case studies given in the paper, the discretized models as above are used as constraints after applying for all scenarios of possible uncertainty in solving uncertain Optimal Control Problem (OCP).

Scenario tree based approximation

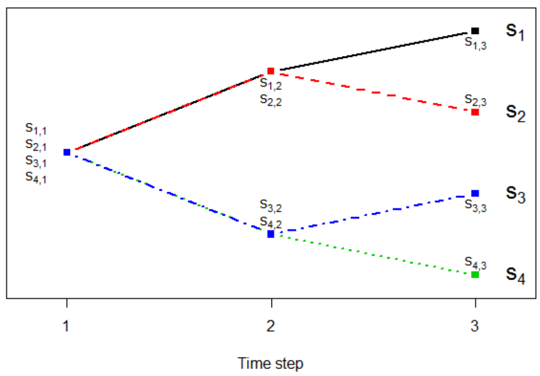

Figure 4. Simple Scenario tree structure

To convert the intractable OCP given by Equations (8)-(12) to tractable, finite number of possible scenarios of uncertainty are considered. For control horizon of N, if S is the possible number of values ζ can take in each interval, total number of scenarios over the entire horizon = S^N.

The constraints of the OCP after applying scenario based approximation are given by,

$$\sum_{j=0}^{K} x_{i,j,s} \frac{d l_j(\tau_k)}{d\tau} \; = \; h_i f\left(x_{i,k,s}, t_{ik}\right) \tag{19}$$

$$k = 1,2,..,K \quad i = 1,2,..,N \;\; \forall s \;\; \forall x \in x$$

$$T_{2,o,s} \; = u_s\left(T_{2,i}\right) - \; (1-u_s)\, T'_{2,o,s} \tag{20}$$

$$x_{min} \le x_{i,k,s} \; \le x_{max} \;\; \forall x \in x \tag{21}$$

Robust Counterpart derivation

The constraints given by Equation (11) are modified by deriving robust counterpart after applying affine control policy. The derivation proceeds as following,

The uncertainty in $T_{1,in}$ is modeled as a function of a primitive uncertainty ζ. A and B are bounds of $T_{1,in}$.

$$T_{1,in,i} = \; A\zeta_i + (1 - \; \zeta_i)B \quad\; \forall i \tag{22}$$

$$\zeta_i \,\epsilon\, [0,1] \;\forall i \tag{23}$$

$$\zeta_i \in \Xi = \{\zeta : W \cdot \xi \; \ge h^u\} \tag{24}$$

Consider the constraint,

$$\Delta u\,(i,s) \;\le \Delta u_{max} \qquad\quad i = 1,2,..,N \;\; \forall s \tag{25}$$

Apply Linear Decision rule,

$$\Delta u_i^T \cdot \xi_{i-1} \le \Delta u_{max} \qquad i = 1,2,..,N \tag{26}$$

Here, $\xi_{i-1} = [1; \zeta_1\,; \zeta_2\,; \ldots..; \zeta_{i-1}]$
Δu_i^T contains affine rule parameters
To avoid change in dimension of $\boldsymbol{\xi}_{i-1}$ as i changes, the truncate operator is introduced.

$$(\Delta u_i^T \cdot P_i^{\xi}) \cdot \xi \;\le \Delta u_{max} \tag{27}$$

Robust counterpart and Apply constraint on $\boldsymbol{\xi}$:

$$\left\{ \begin{matrix} \max \\ \xi \\ -W \cdot \xi \; \le h^u \end{matrix} \;\; \left(\Delta u_i^T \cdot P_i^{\xi}\right) \cdot \xi \right\} \le \Delta u_{max} \tag{28}$$

$$i = 1,2,..,N$$

Introduce a dual variable $\boldsymbol{\Lambda}_i$ and apply duality to inner LP problem:

$$\left\{ \begin{matrix} \min \\ \Lambda_i, \Lambda_i \ge 0 \\ -W \cdot \Lambda \; = \left(\Delta u_i^T \cdot P_i^{\xi}\right)^T \end{matrix} \;\; ((-h^u)^T \Lambda_i) \right\} \le \Delta u_{max} \tag{29}$$

$$i = 1,2,..,N$$

Drop the minimization operator

$$\left. \begin{cases} ((-h^u)^T \Lambda_i) \le \Delta u_{max} \\ \Lambda_i \ge 0 \\ -W \cdot \Lambda \; = \left(\Delta u_i^T \cdot P_i^{\xi}\right)^T \end{cases} \right\} i = 1,2,..,N \tag{30}$$

Equation (30) is used as constraint in tractable OCP.

Tractable Optimal Control Problem

The final form of Optimal Control Problem, which is tractable is given by,

$$\min_{\boldsymbol{u}} \sum_{i=1}^{N} \; \sum_{k=0}^{K} \left(T_{2,o,i,k}(\zeta^*) - T_{st}\right)^2 + \sum_{i=1}^{N} \alpha\left(\Delta u\,(\zeta^*, i)\right)^2 \tag{31}$$

s.t.

$$T_{1,in,i} = \; A\zeta_i + (1 - \; \zeta_i)B \tag{32}$$

$$u(i,s) = \left(u_i^T \cdot P_i^{\xi}\right) \cdot \; \xi_s^{\;T} \tag{33}$$

$$\sum_{j=0}^{K} x_{i,j,s} \frac{d l_j(\tau_k)}{d\tau} \; = \; h_i f\left(x_{i,k,s}, t_{ik}\right) \qquad k = 1,2,..,K$$

$$i = 1,2,..,N \;\; \forall s \;\; \forall x \in \boldsymbol{x} \tag{34}$$

$$T_{2,o,s} \; = u_s\, T_{2,in} - \; (1-u_s)\, T'_{2,o,s} \tag{35}$$

$$x(0) = x_o \tag{36}$$

$$x_{min} \le x_{i,k,s} \; \le x_{max} \;\; \forall x \in x \tag{37}$$

$$\left. \begin{cases} ((-\boldsymbol{h}^u)^T \boldsymbol{\Lambda}_i^1) \le \Delta u_{max} \\ \boldsymbol{\Lambda}_i^1 \ge \boldsymbol{0} \\ -W \cdot \boldsymbol{\Lambda}^1 \le \left(\Delta \boldsymbol{u}_i^T \cdot P_i^{\xi}\right)^T \end{cases} \right\} i = 1,2,..,N \tag{38}$$

$$\left. \begin{cases} ((-\boldsymbol{h}^u)^T \boldsymbol{\Lambda}_i^2) \le -\,\Delta u_{min} \\ \boldsymbol{\Lambda}_i^2 \ge \boldsymbol{0} \\ -W \cdot \boldsymbol{\Lambda}^2 \le \left(-\Delta \boldsymbol{u}_i^T \cdot P_i^{\xi}\right)^T \end{cases} \right\} i = 1,2,..,N \tag{39}$$

The decision variables are Affine rule coefficients. This Optimal Control Problem in solved in receding horizon approach to implement uncertain Model Predictive Control of HEN.

CASE STUDIES

The performance of the proposed control method is demonstrated using two case studies. First is simple Heat Exchanger, and second is a Heat Exchanger Network. The optimization is done in GAMS 25.1.1, and overall MPC is implemented using MATLAB 2020a. The parameters of the Heat Exchanger and the streams are given in

Single Heat Exchanger

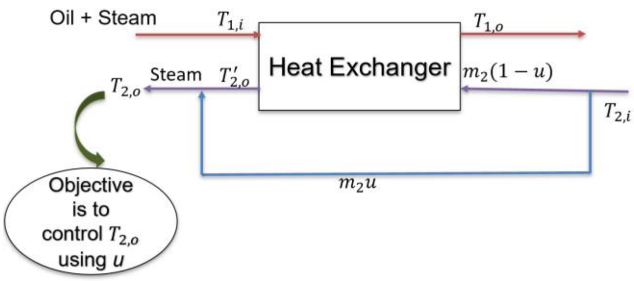

Figure 5. Single Heat Exchanger system

The decision variable (bypass fraction of cold stream) is obtained by optimizing the uncertain OCP given in section 0. Four scenarios of possible uncertainty are used in optimization to obtain the value od decision variable. The prediction-horizon of 20 is divided into 2 finite elements. The scenarios used in optimization i.e. possible scenarios of inlet temperature profiles of hot stream is given by **Figure 6.** Hot stream temperature profiles for the scenarios used in optimization**Figure 6**. The corresponding bypass fraction profiles (decision variables) is given by **Figure 7**. The control variable profiles for the scenarios used in optimization is given by **Figure 8**. It shows that for the scenarios used in optimization, the control variable simulated using optimum input tracks the setpoint efficiently.

To test the performance of the decision variables obtained four random testing scenario profiles of the inlet temperature of the hot stream are considered. These profiles are given by **Figure 9**. The control variable profiles obtained for the testing scenarios simulated using input from uncertain optimization is given by **Figure 10**. As expected, the control variable deviates little from the setpoint because these scenarios are not used in optimization. To compare the performance of the uncertain MPC, the control variable profiles are generated using deterministic input for the testing scenarios. The corresponding graph is given by **Figure 11**. The **Figure 11** shows the control variable deviates from the setpoint as time passes using deterministic input. So the uncertain MPC has advantage over deterministic MPC.

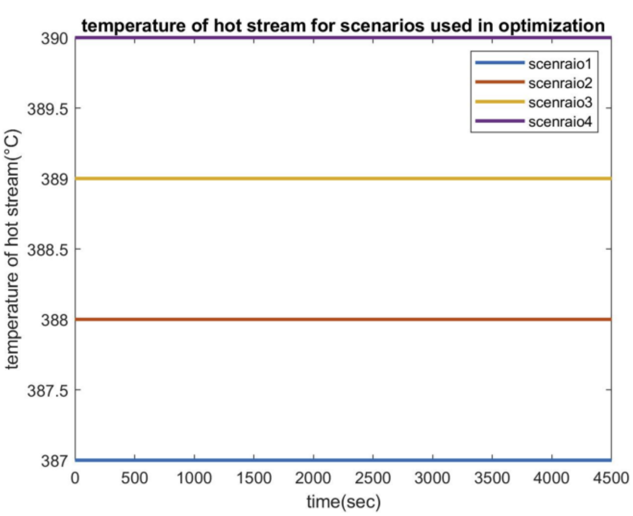

Figure 6. Hot stream temperature profiles for the scenarios used in optimization

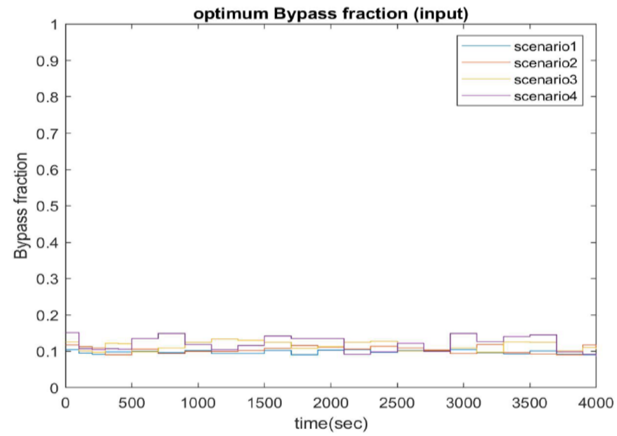

Figure 7. Optimum bypass fraction profiles for the scenarios used in optimization

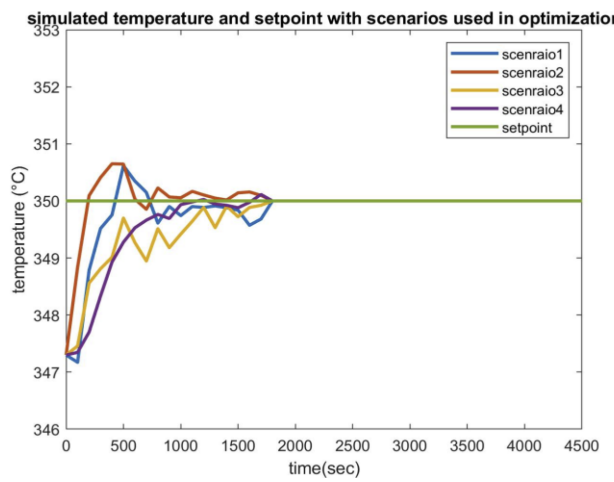

Figure 8. Control variable Profile for the scenarios used in optimization and input of uncertain optimization.

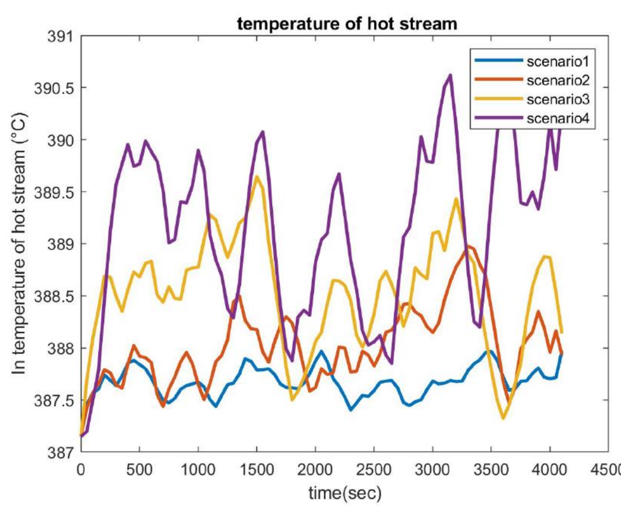

Figure 9. Scenarios used for testing of proposed control method

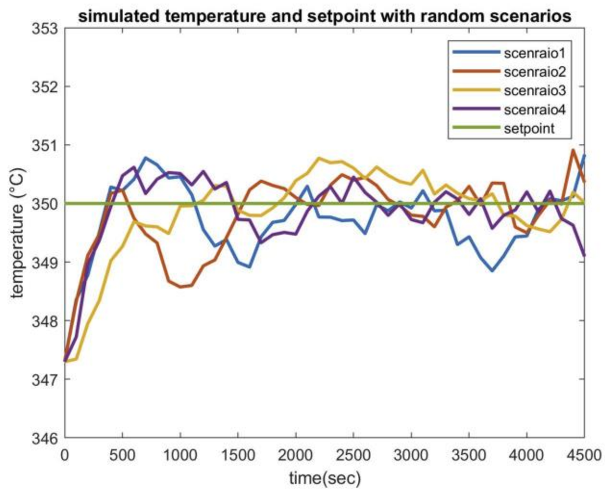

Figure 10. Control variable profiles obtained using testing scenarios and input of uncertain optimization

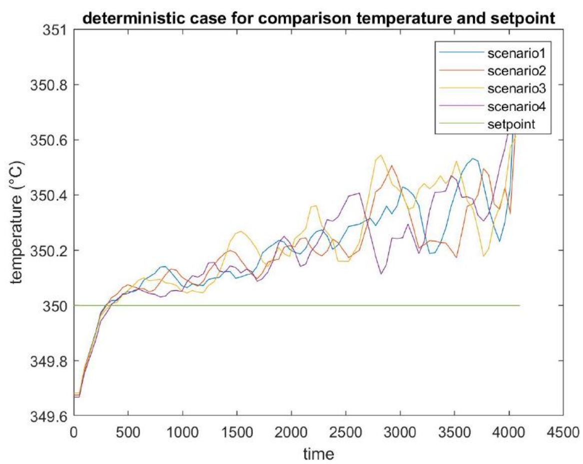

Figure 11. Control variable profiles obtained using testing scenarios and input of deterministic optimization

Heat Exchanger Network

The HEN considered for second case study of the current research work is given by **Figure 12**. This HEN is adopted from [1].

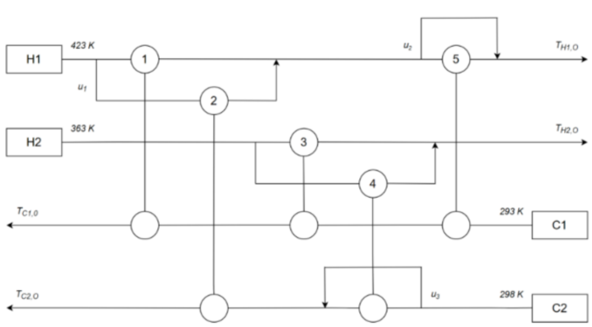

Figure 12. Heat Exchanger Network for the second case study

For the HEN also, four scenarios of possible uncertainty are used in optimization to obtain the value od decision variable. The prediction horizon of 40 is divided into 2 finite elements. For this case study, we consider disturbances in H1 stream, and the control variable is out temperature of C2 stream. The scenarios used in optimization i.e. possible scenarios of inlet temperature profiles of hot stream is given by **Figure 13**. The corresponding bypass fractions profiles are given by **Figure 14**, **Figure 15**, and **Figure 16**. The control variable profiles (the out temperatures of C2 stream) for the scenarios used in optimization is given by **Figure 8**.

To test the performance of the decision variables obtained four random testing scenario profiles are considered, and these profiles are given by **Figure 18**. For a step change in setpoint, the control variable profiles obtained for the testing scenarios simulated using input from uncertain optimization is given by **Figure 19**. For the step change in setpoint, the control variable profiles are generated using deterministic inputs for the testing scenarios. The corresponding graph is given by **Figure 11**, which shows the control variable deviates from the setpoint as time passes using deterministic inputs.

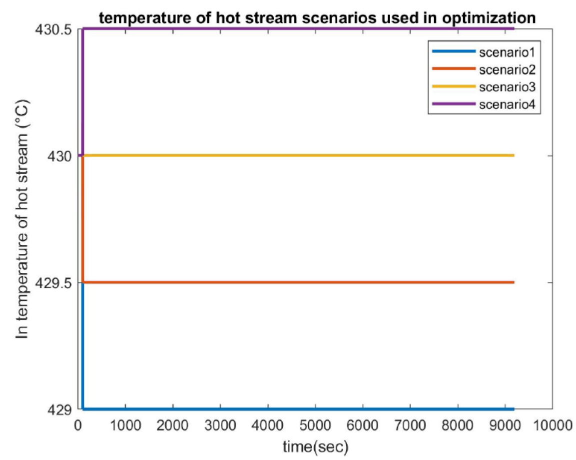

Figure 13. Hot stream (H1) temperature profiles for the scenarios used in optimization

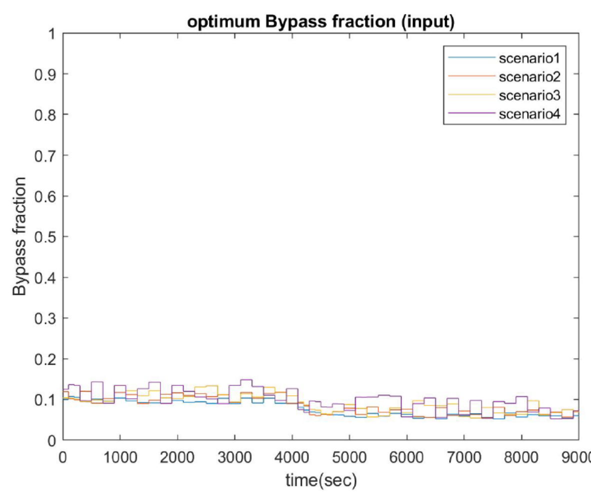

Figure 14. Optimum bypass fraction profiles of u_1 stream for the scenarios used in optimization

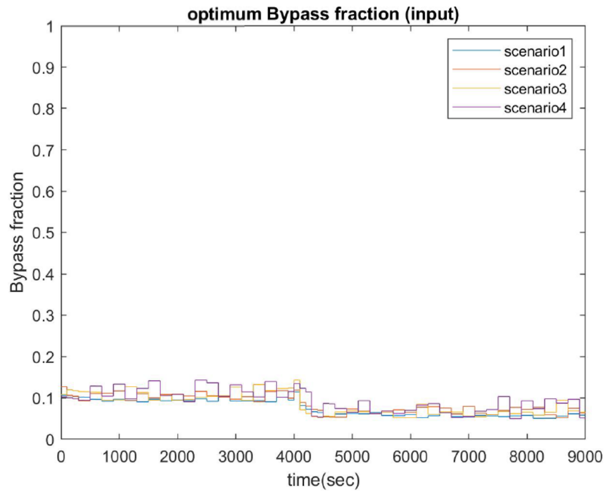

Figure 15. Optimum bypass fraction profiles of u_2 stream for the scenarios used in optimization

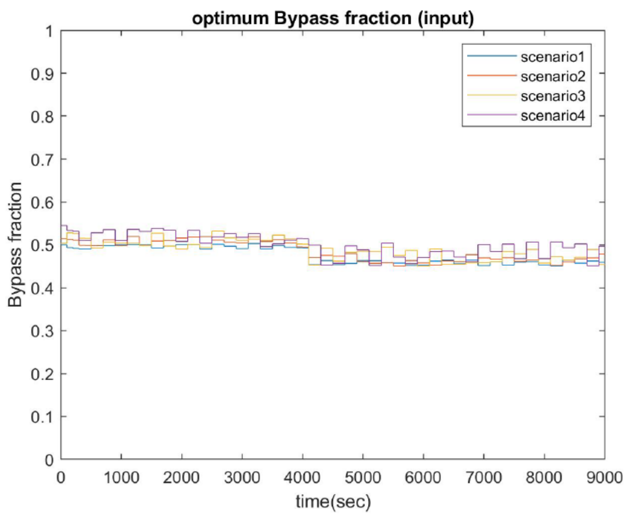

Figure 16. Optimum bypass fraction profiles of u_3 stream for the scenarios used in optimization

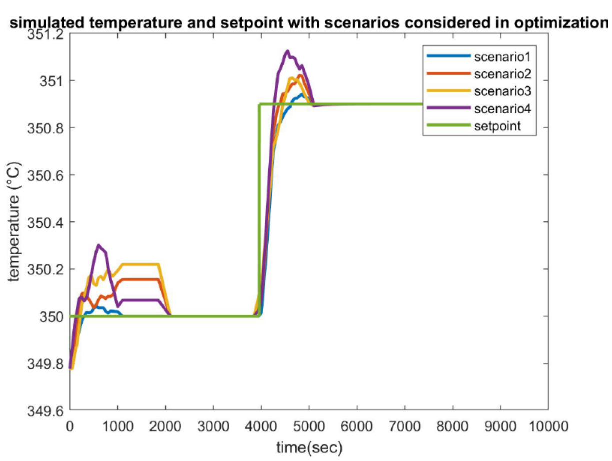

Figure 17. Control variable Profile (C2 out temperature) for the scenarios used in optimization and input of uncertain optimization.

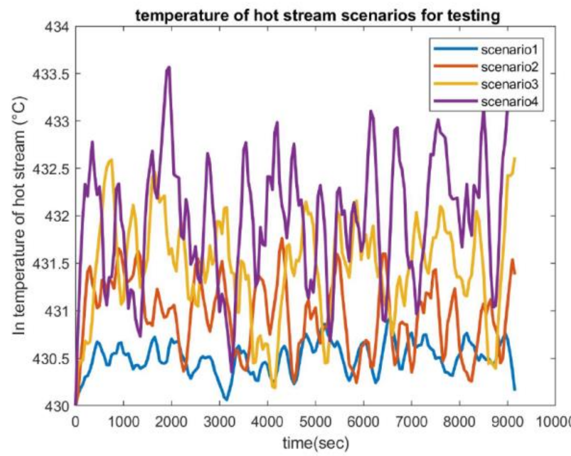

Figure 18. Scenarios used for testing of proposed control method (in temperatures of H1 stream)

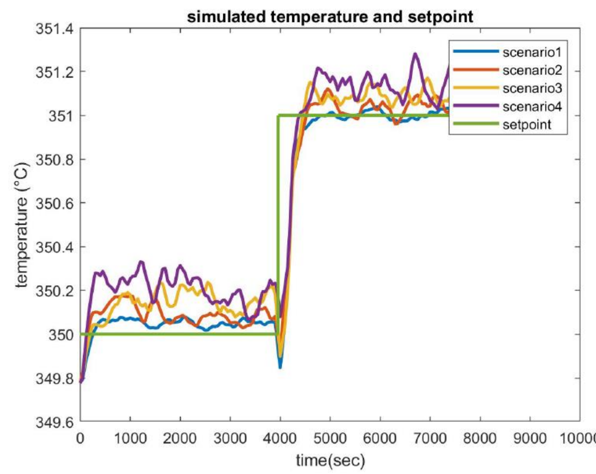

Figure 19. Control variable profiles obtained using testing scenarios and input of uncertain optimization

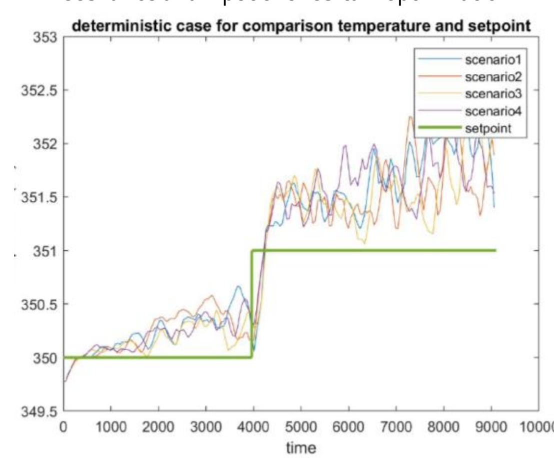

Figure 20. Control variable profiles obtained using testing scenarios and input of deterministic optimization

Table 1: Parameters of the Heat exchanger and the streams.

Parameter	symbol	Value
Hot stream Flowrate	m_1	3.93 (kg/s)
cold stream Flowrate	m_2	30.95 (kg/s)
Specific heat capacity of hot stream	C_{p_1}	4 ((kJ/(kg.K)))
Specific heat capacity of cold stream	C_{p_2}	2.5 (kJ/(kg.K))
heat exchage area	S	230 (m^2)
Outer diameter of tube	d_o	25 (mm)
Inner diameter of tube	d_i	22.5 (mm)

NOMENCLATURE

Name	symbol
heat transfer coefficient at outer wall	k_o
heat transfer coefficient at inner wall	k_i
Overall heat transfer coefficient	K
mass of wall of Heat Exchanger	M_w
Heat transfer rate	Q
fouling resistance of outer wall of Heat Exchanger	R_o
fouling resistance of inner wall of Heat Exchanger	R_i
tube outer radius	r_o
tube inner radius	r_i
temperature of hot stream at inlet of Heat Exchanger	$T_{1,i}$
temperature of hot stream at outlet of Heat Exchanger	$T_{1,o}$
temperature of cold stream at inlet of Heat Exchanger	$T_{2,i}$
temperature of cold stream at outlet of Heat Exchanger	$T'_{2,o}$
temperature of mixed stream	$T_{2,o}$
Temperature of outer wall of Heat Exchanger	T_{wo}
Setpoint of temperature of mixed stream	T_{st}
time coordinate	t
Temperature of inner wall of Heat Exchanger	T_{wi}
Bypass fraction	u
Thermal conductivity of wall	λ
Weighing term for Controller effort	α

ACKNOWLEDGEMENTS

The authors would like to acknowledge the following for sponsoring the research,

- Computer Process Control group, University of Alberta
- Natural Sciences and Engineering Research Council of Canada.

REFERENCES

1. Sun L, Zha X, Luo XL. Coordination between bypass control and economic optimization for heat exchanger network. *Energy* 160:318-329 (2018).
2. Ehlinger V, Mesbah A. Model Predictive Control of Chemical Processes: A Tutorial. In: Coulson and Richardson's Chemical Engineering. Ed: Chhabra Rp, Shankar V. Elsevier. p367-402 (2017)
3. Luo XL, Xia C, Sun L. Margin design, online optimization, and control approach of a heat exchanger network with bypasses. *Computers & Chemical Engineering* 53:102–121 (2013).
4. Mohankumar Y, Li Z, Huang B. Steam allocation and production optimization in SAGD reservoir under steam-to-oil ratio uncertainty. *J Petrol Sci Eng* 183: 106456 (2019)
5. Wang YF, Chen Q. A direct optimal control strategy of variable speed pumps in heat exchanger networks and experimental validations. *Energy* 85: 609-619 (2015)
6. Skorospeshkin MV, Sukhodoev MS, Skorospeshkin VN. An adaptive control system for a shell-and-tube heat exchanger. *J Phys Conference Series* 803:012153 (2016).
7. Delatore F, José J, Fabrizio L, Novazzi L. Multivariable Optimal Control of a Heat Exchanger Network (HEN) With Bypasses. *IASTED Technol Conf* 697-062 (2010)