Dynamic Modeling and Predictive Control of Cardiovascular System Using Vagal Nerve Stimulation

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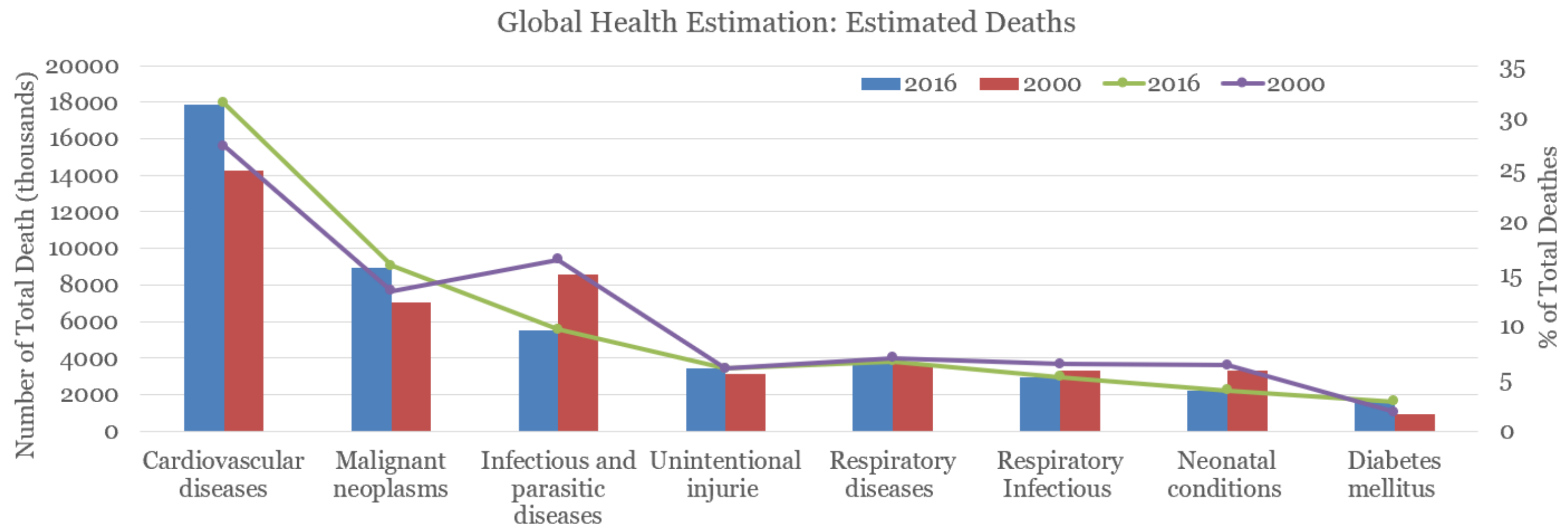
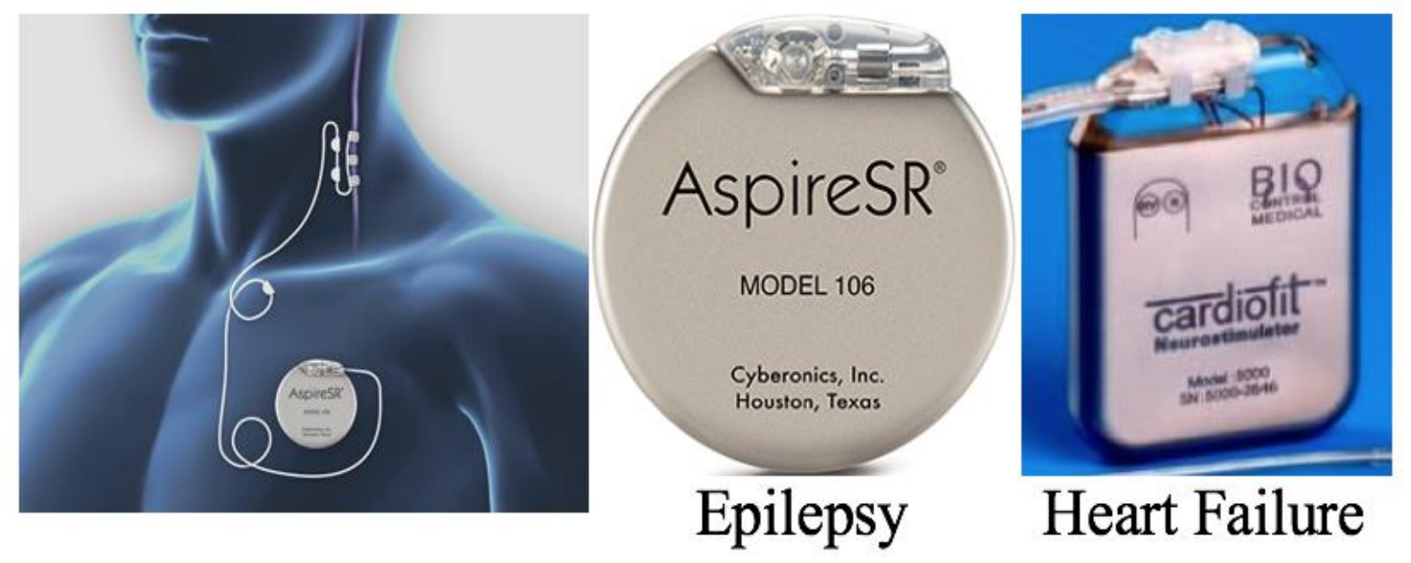
I. Introduction and Motivation

- Cardiovascular disease (CVD) remains the leading cause of death worldwide for the last 15 years and accounts for about 30% of the total deaths.



Data Source: World Health Organization (WHO) Global Health Observatory Database

- Vagal nerve stimulation (VNS) is an alternative therapy to CVD between surgery and medication by delivering electric stimulus to the vagal nerve.
- Various applications of VNS devices are delivered in an open-loop approach or a SISO closed loop control, requiring the MIMO design to increase efficiency.



Epilepsy

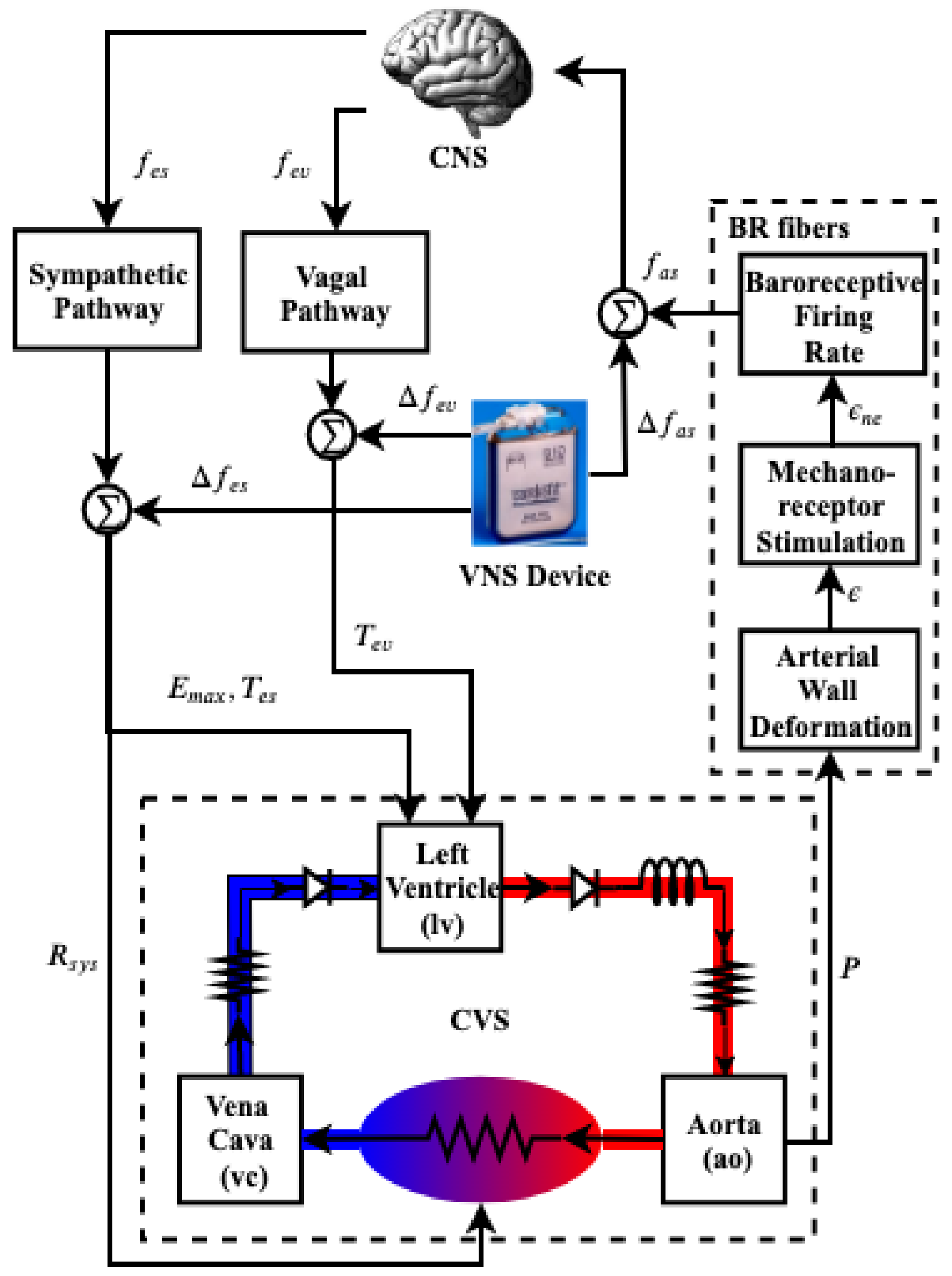
Heart Failure

- Model Predictive Control (MPC) can control multiple hemodynamic variables by simultaneously manipulating stimulation locations and configurations.

This work details the implementation and evaluation of the nonlinear MPC algorithm for the Cardiovascular system by using VNS therapy.

II. Proposed Plant Model

- Model components: cardiovascular system (CVS), baroreflex system and VNS device.
- CVS is modeled using lumped-parameter approach:
    - Capacitance: the left ventricle, the artery, and the vein
    - Resistance: arterioles, venules, and capillaries
    - Newtonian flow
    - Inertial effect by the inductor
    - Valves by diodes
- The firing rate based baroreflex system has three components:
    - Baroreceptive (BR) fibers
    - Central nervous system (CNS)
    - Sympathetic and vagal fibers
- The VNS device has three stimulation locations delivering continuous rectangular impulses with changeable frequency and width.

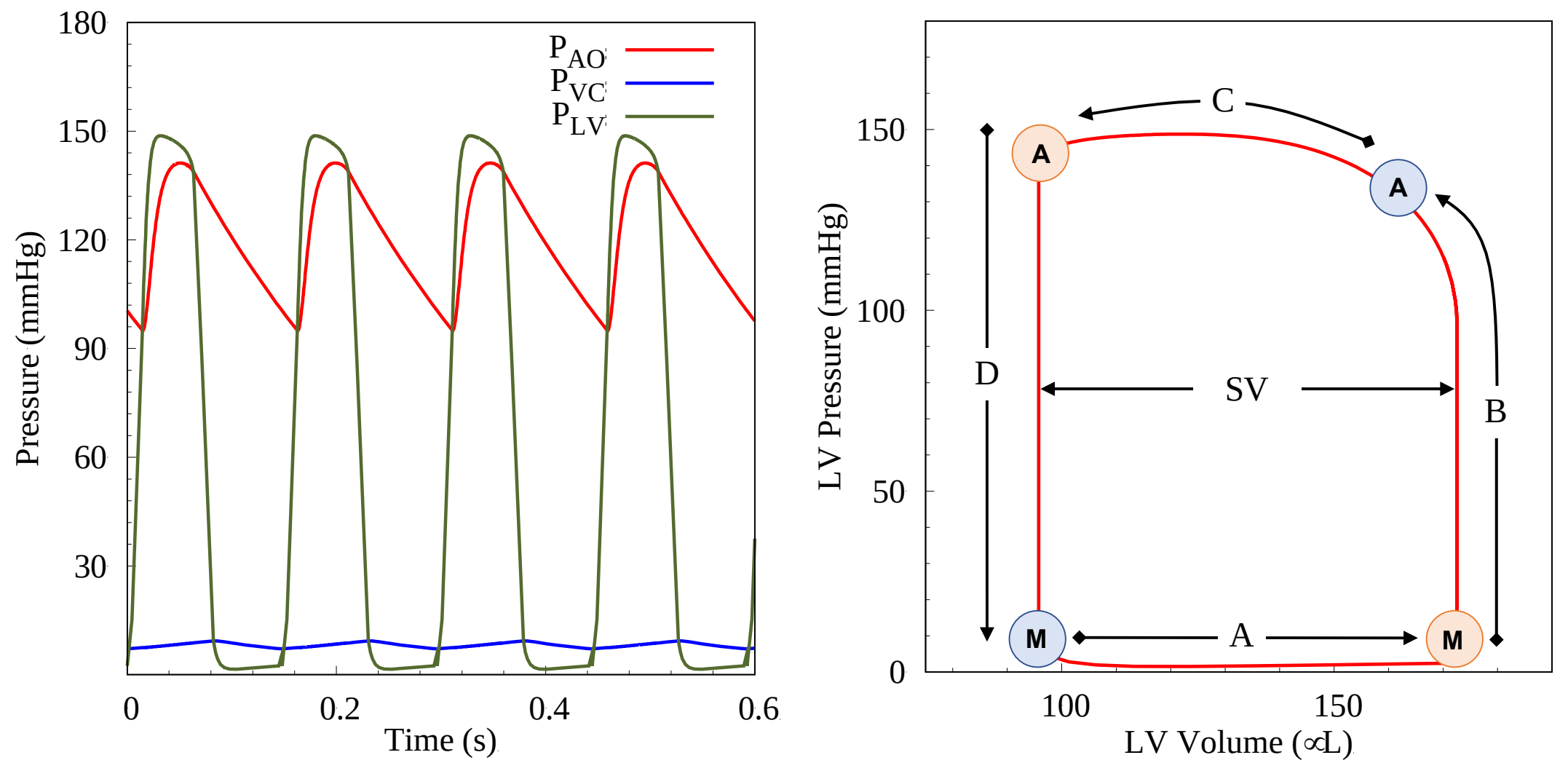


Schematic of Plant Model

The resulting model is hybrid in the form of nonlinear 10th order ordinary differential equations.

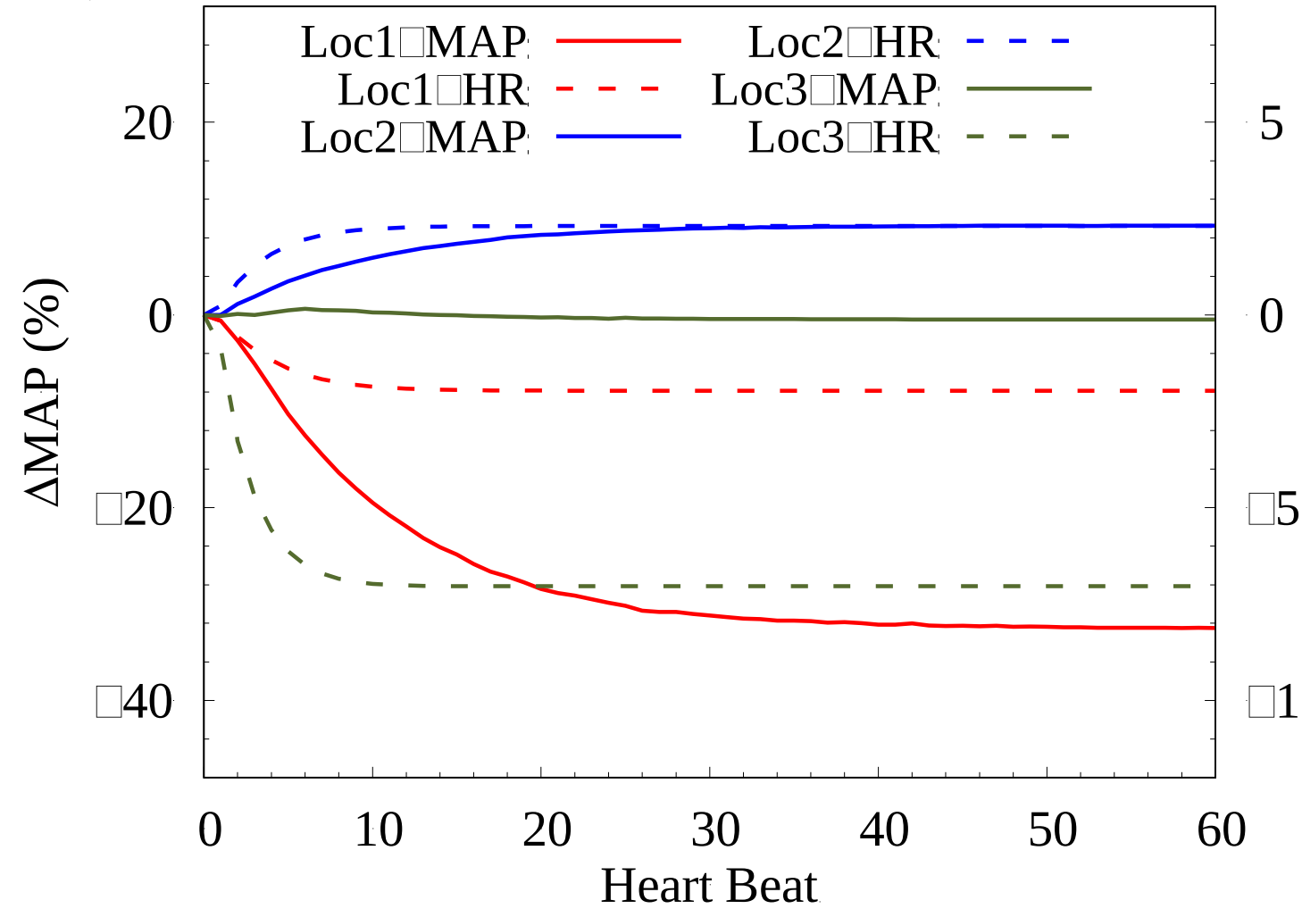
III. Model Evaluation

- The CVS/baroreflex model can reach a cyclic steady state with four consecutive intervals representing filling, contraction, ejection, and relaxation.



A : Filling
M : Mitral valve close
B : Isovolumetric contraction
A : Aortic valve open
C : Ejection
A : aortic valve close
D : Iso volumetric relaxation
M : Mitral valve open

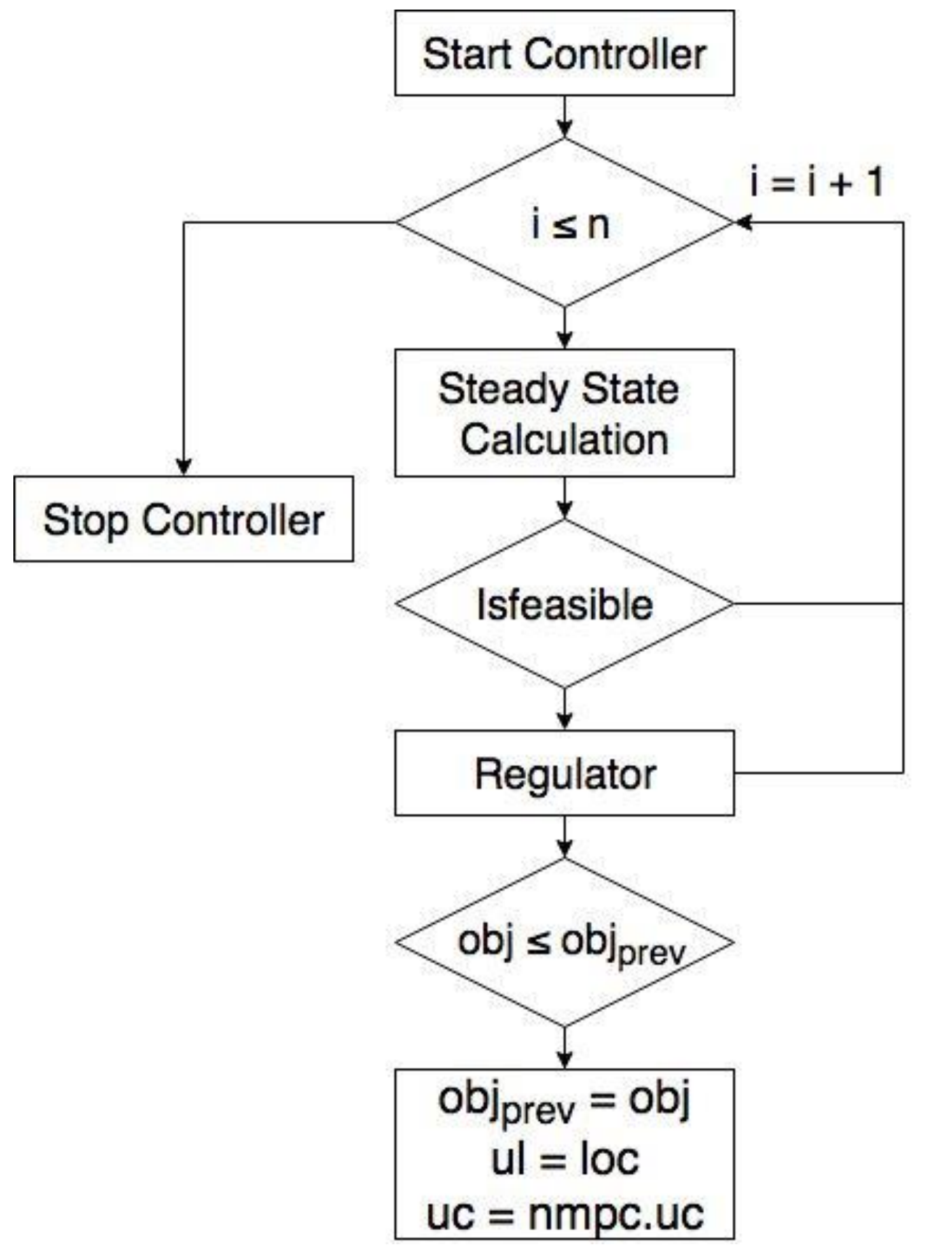
- A complex interaction between mean arterial pressure and heart rate can be modeled by varying composition of different types of nerve fibers.



Loc1 – 100% of baroreceptive fibers
Loc2 – 100% of sympathetic fibers
Loc3 – 100% of vagal fibers

IV. Nonlinear Model Predictive Control Algorithm

- Control objectives: maintain heart rate (HR) and mean arterial blood pressure (MAP) at a constant level by independently manipulating stimulation location and width and frequency of the stimulus.
- The nonlinear MPC uses optimization to find the best control path for a mixed-integer problem:



Regulator:

$$\min_{u} \sum_{i=0}^{N-1} [x(k+i \mid k) - x_s(k+i \mid k)]_Q^2 + \sum_{i=0}^{N-1} [u(k+i \mid k) - u_s(k+i \mid k)]_R^2 + [x(k+N \mid k) - x_s(k+N \mid k)]_P^2$$

s.t.

$$\hat{x}(k+i+1 \mid k) = f(\hat{x}(k+i \mid k), u(k+i \mid k))$$

$$u_{min} \leq u(k+i \mid k) \leq u_{max}, \quad i \in [0, N-1]$$

$$\hat{x}(k \mid k) = x_0$$

Target Calculator:

$$\min_{x_s, u_s} \quad \frac{1}{2}[(y_s - y_{sp})_{Q_s}^2 + (u_s - u_{sp})_{R_s}^2]$$

$$\text{s.t.} \quad f(x_s, u_s) = 0$$

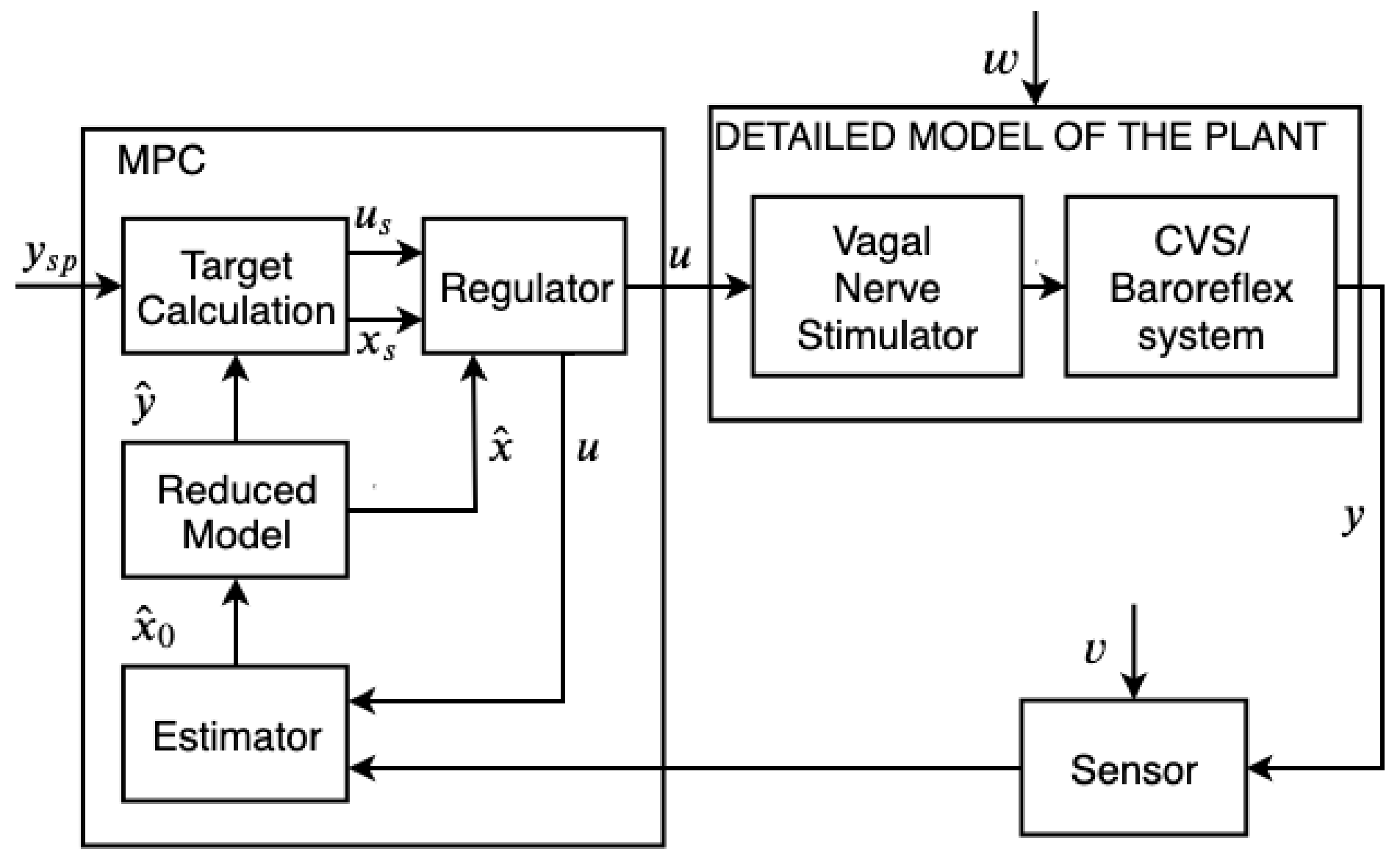
$$y_s = h(x_s, u_s)$$

$$u_{min} \leq u \leq u_{max}$$

- The steady-state target calculation obtains the setpoint value of each input and state variable and filters the feasible combinations of stimulation locations.
- Regulator tracks set points in the infinite horizon with constraints of input variables applied for a prediction horizon.

V. Closed-Loop Nonlinear Model Predictive Controller

- The detailed model, which is computationally expensive and practically infeasible for MPC, is used for evaluating the MPC algorithm.
- The reduced model in MPC retains the nonlinear effects but relates the stimulation location and parameters to HR and MAP on a beat-to-beat basis.

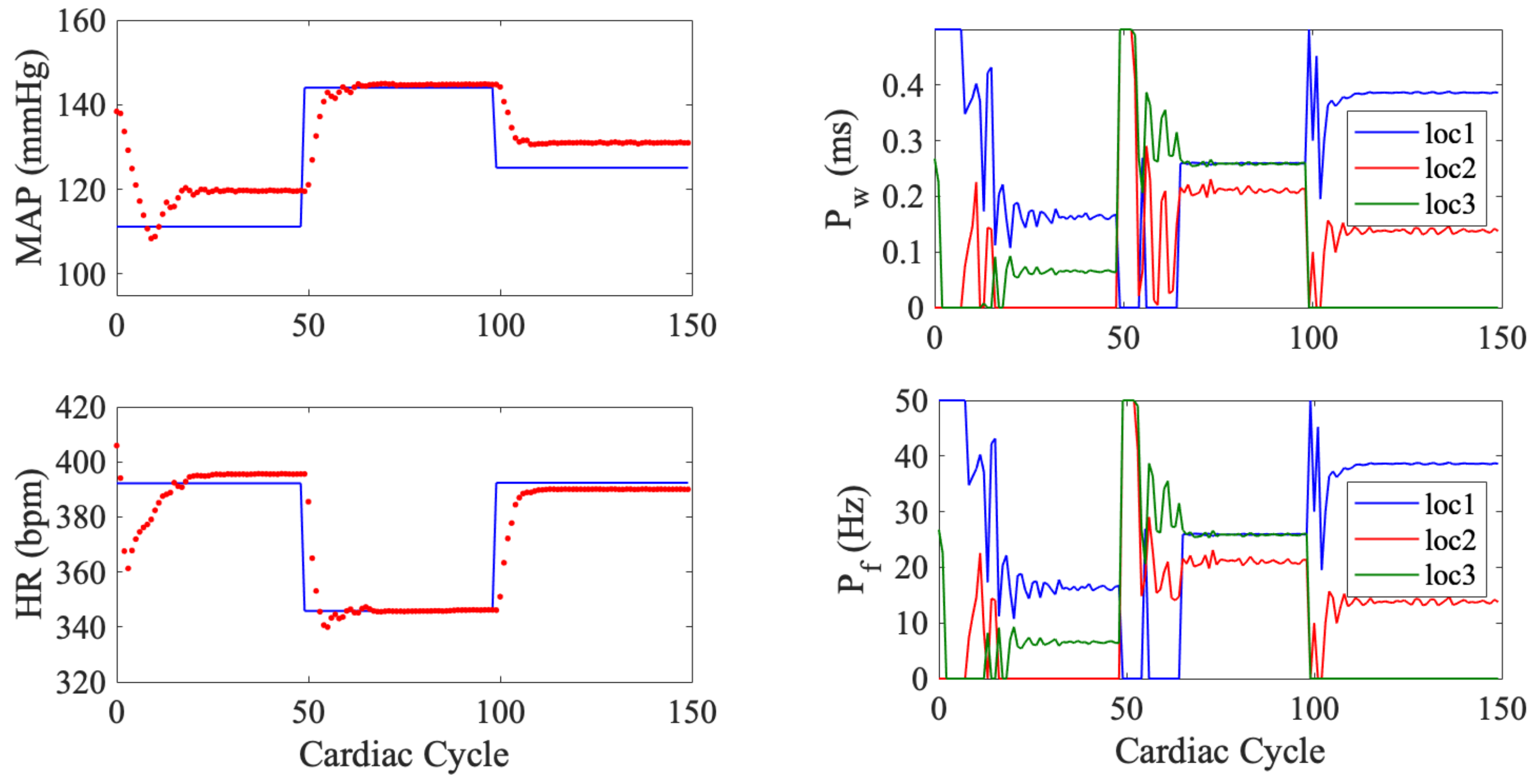


- The parameters of the reduced model are identified based on the input-output data generated by the detailed model.
- The estimator consists of a moving horizon estimator and an extended Kilman filter to optimize the initial state.

VI. Controller Evaluation

Table: Three Possible Cases of Set-Points

Cases	Outputs	Inputs		
		loc1	loc2	loc3
1	MAP = 111	$P_w = 2.5e-4$	\	\
	HR = 392	$P_w = 25$	\	\
2	MAP = 144	\	$P_w = 1e-4$	$P_w = 3e-4$
	HR = 346	\	$P_w = 10$	$P_w = 30$
3	MAP = 125	$P_w = 3e-4$	$P_w = 1e-4$	\
	HR = 393	$P_w = 30$	$P_w = 10$	\



- The NMPC functions to switch stimulation locations.
- More weight is assigned for HR in system identification and controller.
- The offset is produced by the model mismatch.

VII. Conclusions

- The detailed physiological model quantitatively simulates the cardiovascular response to vagal nerve stimulation in real-time.
- Nonlinear MPC manipulating three stimulation locations and two stimulation parameters in each location independently controls a wide range of HR and MAP.
- Implementation of the nonlinear MPC in embedded hardware for real-time control remains an open challenge due to long computational time and high expense.