Fault Recovery for a Class of Unmanned Autonomous Vehicles Using Gaussian Process Regression

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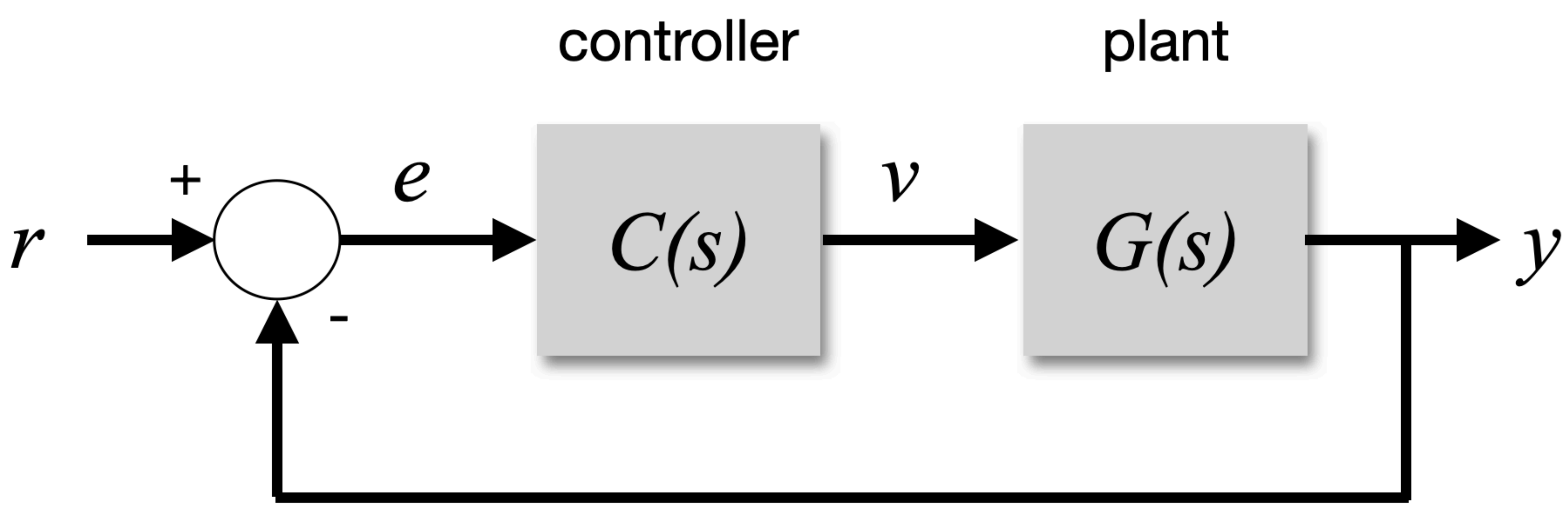
Imagine an **unmanned, autonomous vehicle** (UAV) deployed into a remote area.

The UAV has a robotic arm used to collect soil samples. This arm is positioned via a sequence of unit step inputs applied to a DC servo.

A **proportional-integral-derivative (PID) controller** is used to produce smooth arm movements. The three PID gains (K_p, K_i, K_d) are set prior to deployment.

Communication with a rear area base station is maintained over a radio link.

The goal is to keep the UAV operational for as long as possible.



The controller transfer function is

$$C(s) = \frac{K_\mathrm{d}s^2 + K_\mathrm{p}s + K_\mathrm{i}}{s}$$

and the closed-loop transfer function is

$$G_\mathrm{CL}(s) = \frac{Y(s)}{R(s)} = \frac{C(s)G(s)}{1 + C(s)G(s)}$$

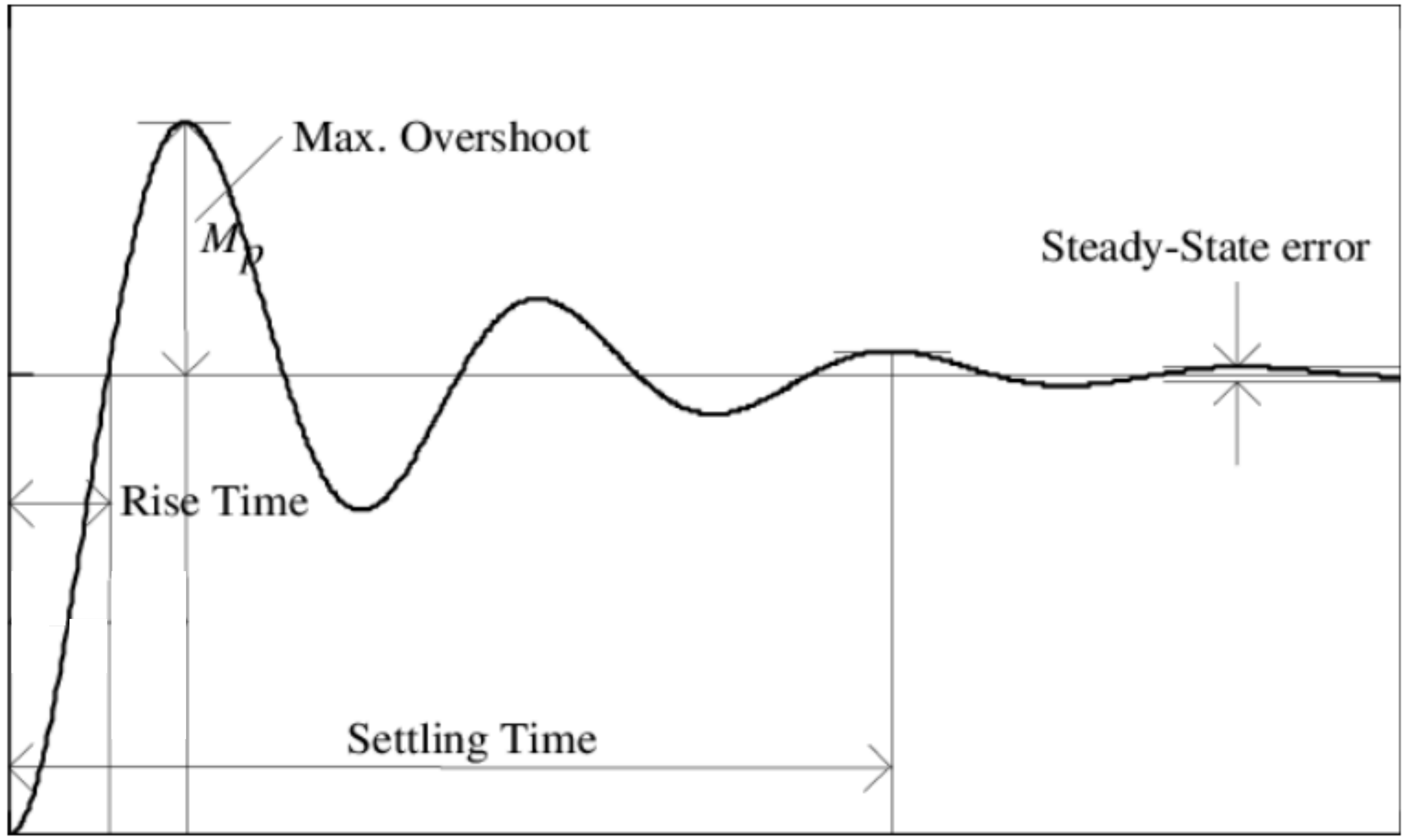


Fig. 2: Unit step response

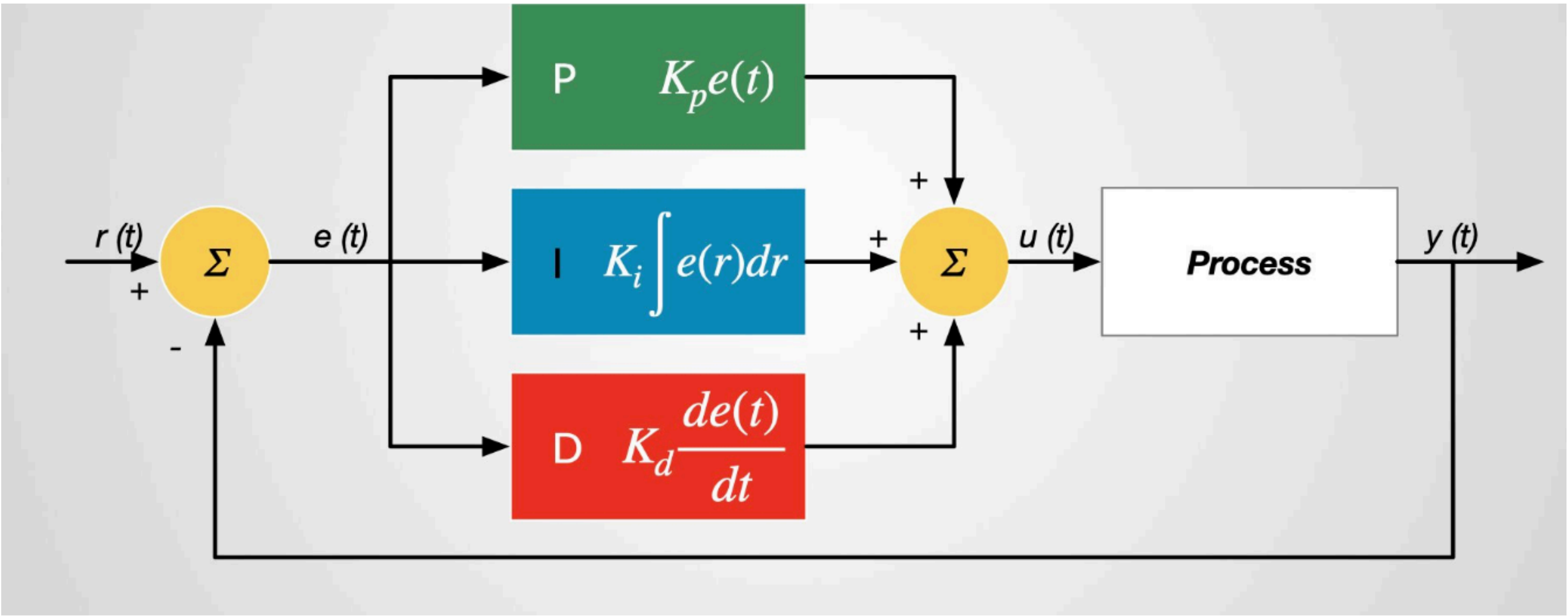


TABLE I: Effects shown for gain increase. '–' indicates small or negligible change

	K_p	K_i	K_d
rise time	↓	↓	–
overshoot	↑	↑	↓
stability	↓	↓	↑
settling time	–	↑	↓
steady-state error	↓	0	–

Now suppose a **fault** occurs in the robot arm. The exact nature of this fault is unknown, but the PID controller no longer produces acceptable arm movements.

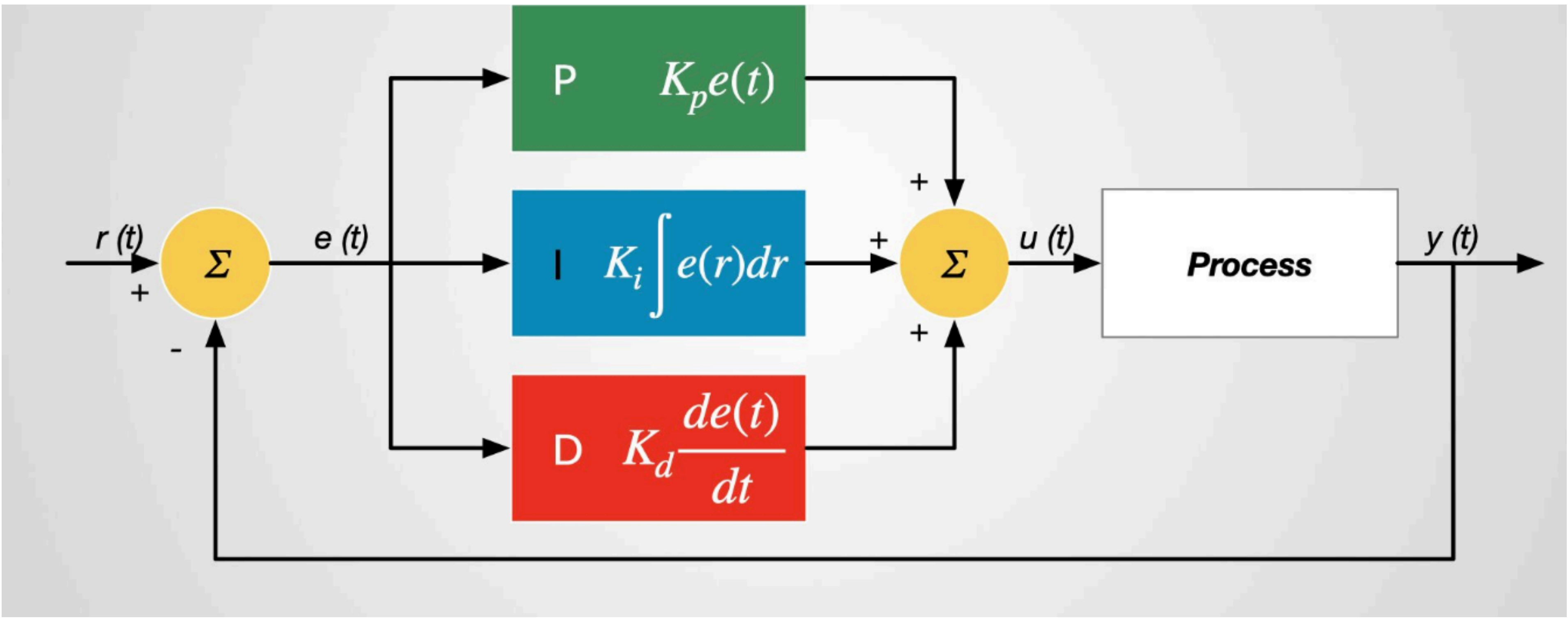
Fault recovery must be initiated to restore, as much as possible, the previous behavior.

Redundant hardware is not available (no space on the UAV).

The only viable recovery method is to readjust the PID controller gains.

The UAV does not have sufficient computing resources to compute new gain values. However, it can set the gains to any value received from the base station over the radio link.

Fault Recovery Overview



In the faulty system some underlying function governs how each PID controller gain influences step response behavior.

For example,

$$\textbf{peak overshoot} = f\left(K_{\mathbf{d}}\right)$$

Regression plays a central role in function approximation. But here the type of regression is important because observed data is severely limited.

Fault Recovery Overview (con't)

So, why is observed data limited???

The UAV lacks the computational power to compute new PID gain values.

It can, however, update the gain values with **new candidate values** received from the base station.

The UAV then applies a step input to the servo and records the response characteristics (rise time, peak overshoot, settling time, etc.)

Each data point acquired requires a physical test on already damaged hardware, which can trigger additional failures if repeated too often.

Fault Recovery Overview (con't)

For this reason the number of data points for regression is limited to typical 3-5 points

Choice of regression type is crucial with sparse data sets

- neural network and random forest can overfit
- support vector requires careful hyper-parameter tuning

Gaussian Process (GP) regression is a good choice

- non-parametric model
- works well with sparse data sets
- effectively models non-linearity
- provides uncertainty measures

The GP is a probability distribution over functions where any finite collection of function values is a multi-variate Gaussian.

Completely described by a mean function $\mu(\mathrm{x})$ and a covariance or kernel function $k(\mathrm{x}, \mathrm{x}')$

$$f(\mathbf{x}) \sim \mathrm{GP}(\mu(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$$

More specifically,

$$\begin{bmatrix} f(\mathbf{x}_1) \\ \vdots \\ f(\mathbf{x}_n) \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu(\mathbf{x}_1) \\ \vdots \\ \mu(\mathbf{x}_n) \end{bmatrix}, \begin{bmatrix} k(\mathbf{x}_1, \mathbf{x}_1) & \cdots & k(\mathbf{x}_1, \mathbf{x}_n) \\ \vdots & & \vdots \\ k(\mathbf{x}_n, \mathbf{x}_1) & \cdots & k(\mathbf{x}_n, \mathbf{x}_n) \end{bmatrix} \right)$$

where $\mathcal{N}(\mu, C)$ is a multi-variate normal distribution of dimension n with mean μ and covariance matrix C.

The squared exponential kernel is frequently used: $k(x, x') = \exp\left(-\frac{(x - x')^2}{2l^2}\right)$

Let X and X_* denote the training set and testing set, respectively, with Y and Y_* the corresponding observation sets.

1. Starting point (the **prior**)
   - $\mu = 0$
   - $k(x_*, x'_*)$ uses the test points $x_* \in X_*$

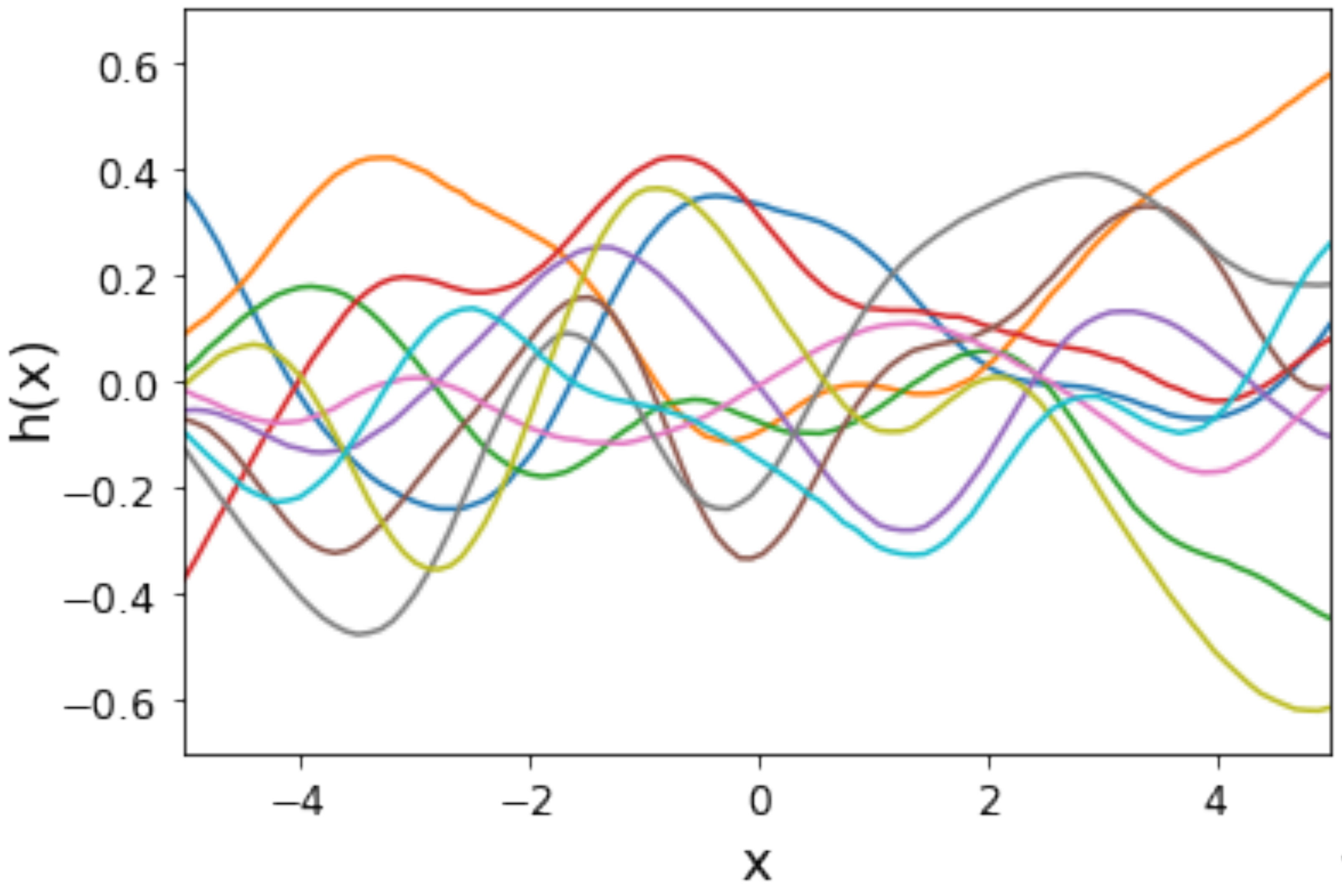
2. Introduce the training set (X,Y) **observations** (e.g., data from sensors)

3. The results (the **posterior**)

   Update mean function (μ) and covariance matrix (C) match training points and testing points.

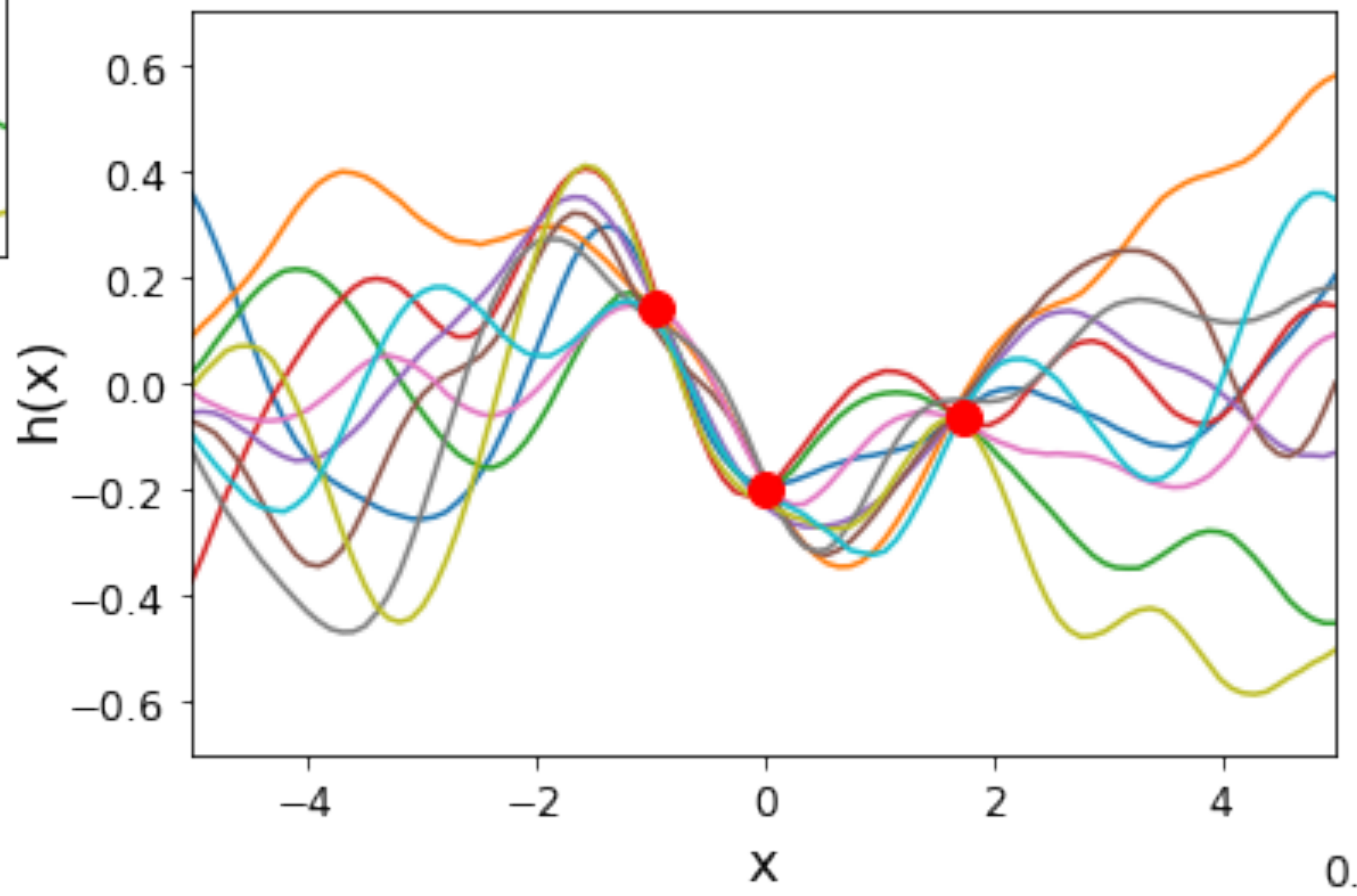
$$f(\mathbf{x}) \mid \mathscr{D} \sim \mathrm{GP}\left(\bar{m}(\mathbf{x}), \bar{k}(\mathbf{x})\right)$$

See paper for update equations

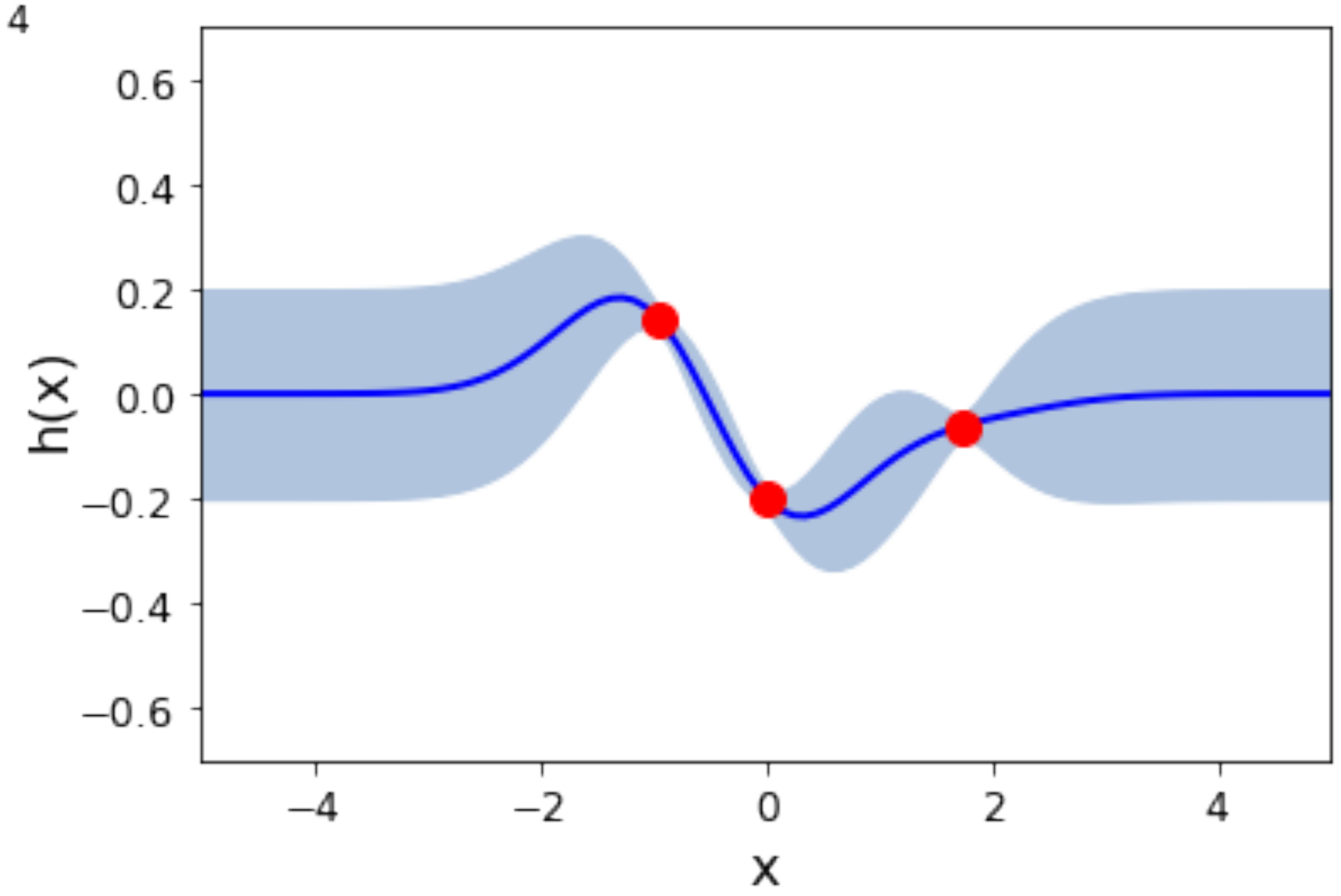


The prior

The posterior



The mean function



Fault Recovery Overview (con't)

Fault recovery is then straightforward:

1. A human operator at the base station transmits a candidate PID gain to the UAV.
2. The UAV updates the gain and applies a step input to the DC servo. The step response characteristics are recorded.
3. The UAV transmits the step response to the base station. This becomes a data point for the GPR.
4. The operator uses the **GP mean function** to select a final PID gain value and transmits it to the UAV, completing the recovery process.

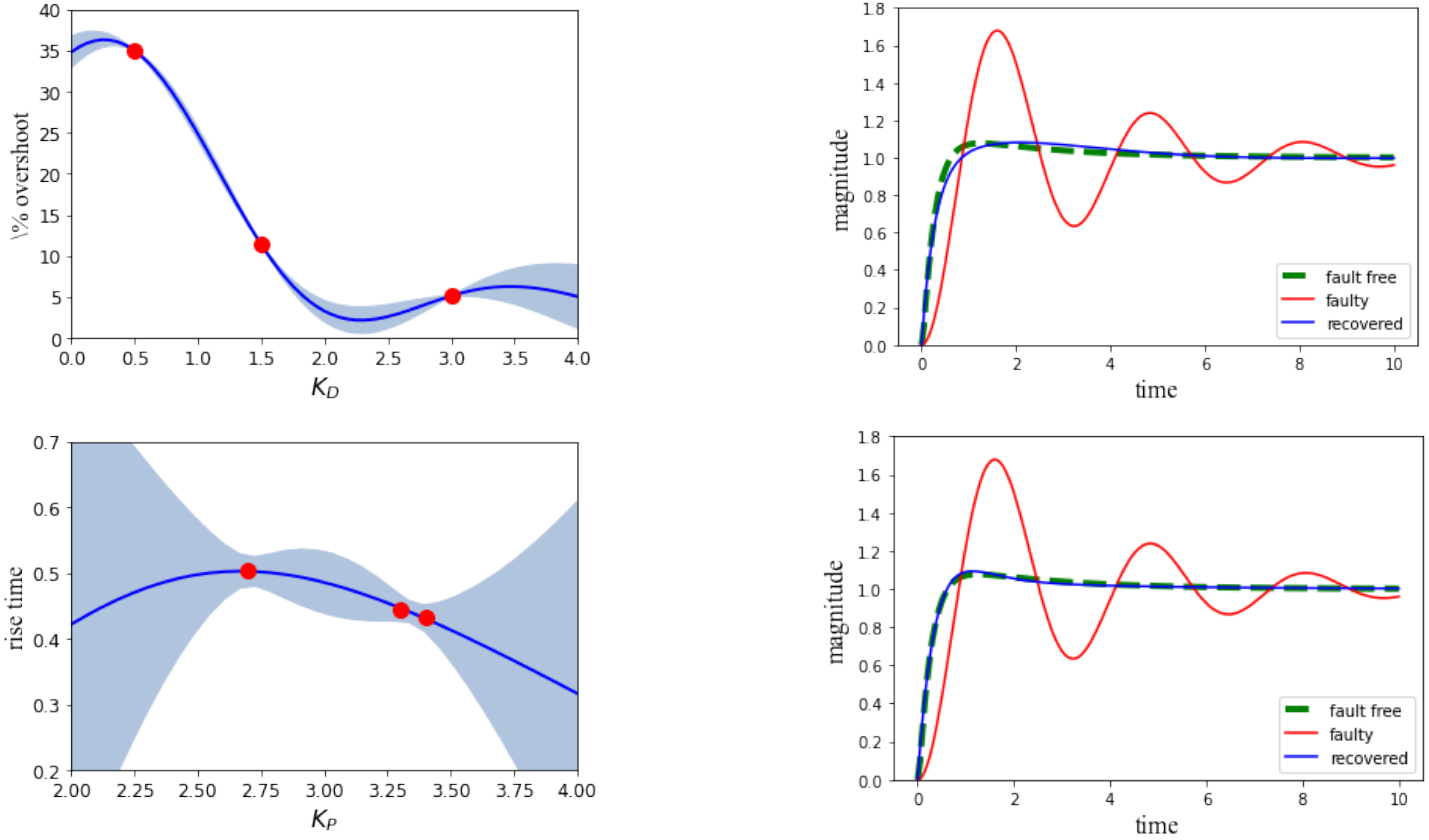
The PID controller gains were initially set to produce a slightly overdamped step response (7%).

Motor parameters from a commercial DC servo were extracted from the data sheet to produce the motor transfer function G(s)

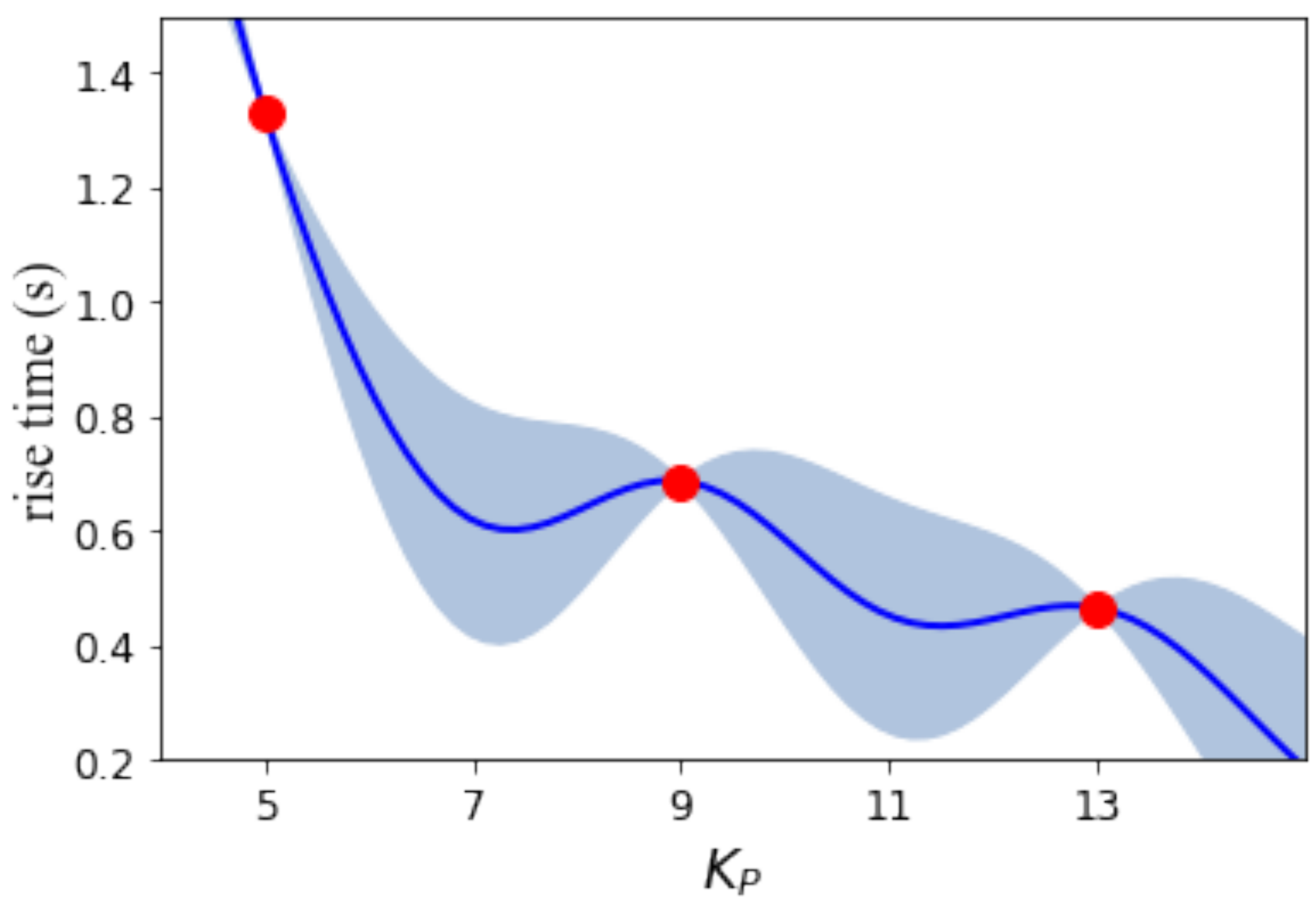
Two test cases were considered

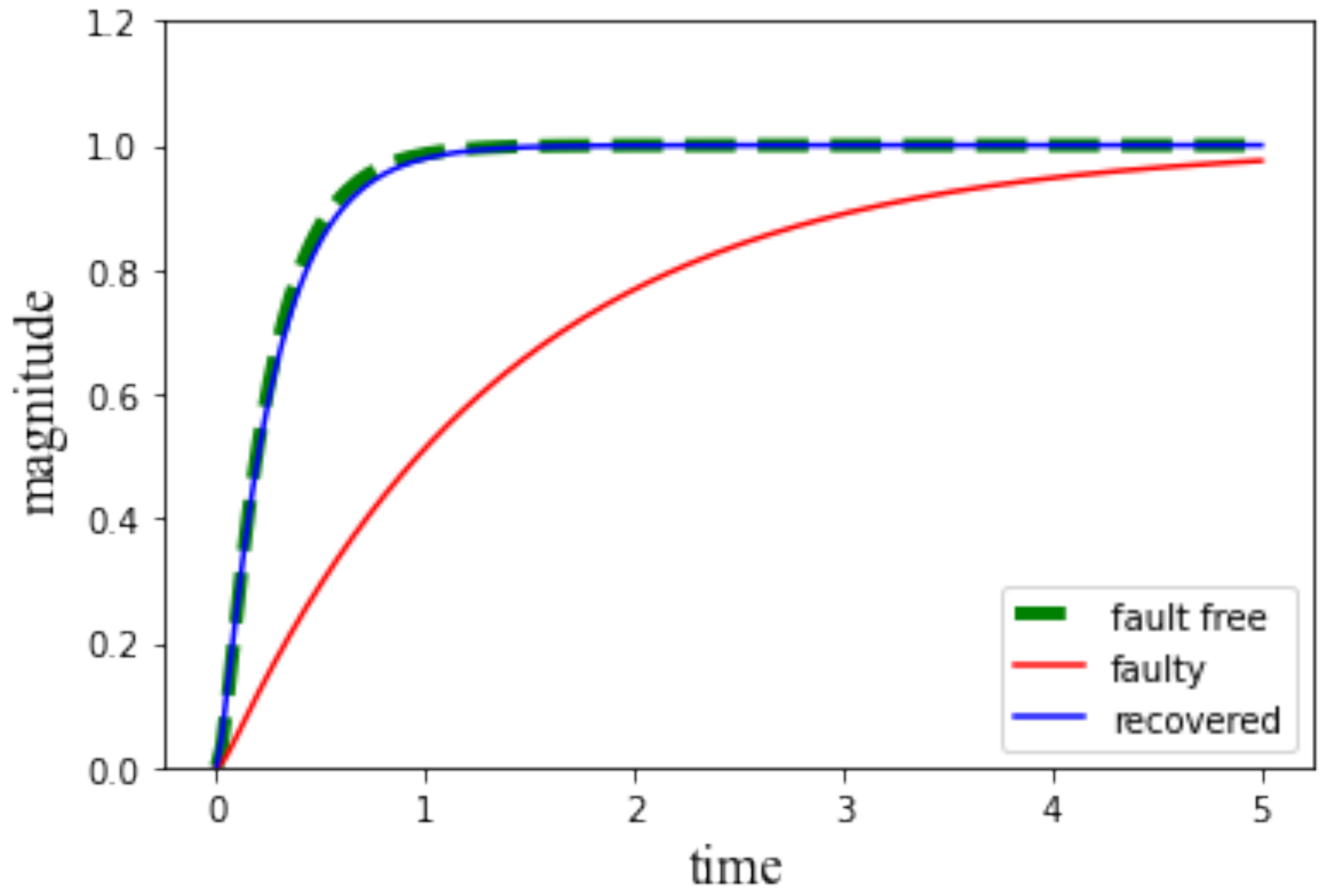
- underdamped
- overdamped

Underdamped



Overdamped


rise time (s)
1.4
1.2
1.0
0.8
0.6
0.4
0.2
5
7
9
11
13
K_P


magnitude
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
1
2
3
4
5
time
fault free
faulty
recovered

A key advantage of GP regression in this application is its **ability to model uncertainty.**

This enables operators to select PID gain values for fault recovery that minimize the risk of instability—an essential consideration in safety-critical systems.

For instance, if a particular K_d value predicts a rise time of 0.8 seconds with a ±0.2 second standard deviation, the operator may opt for an alternative K_d with lower uncertainty (but still acceptable system behavior) or collect additional data in that region to refine the prediction.

Either choice limits the data required to select new gain values for fault recovery, thereby reducing the risk of causing further damage to the faulty system.

Questions