

• Control law: $u_{PI} = Kc \left(E + \frac{1}{T_{T}}\right)$

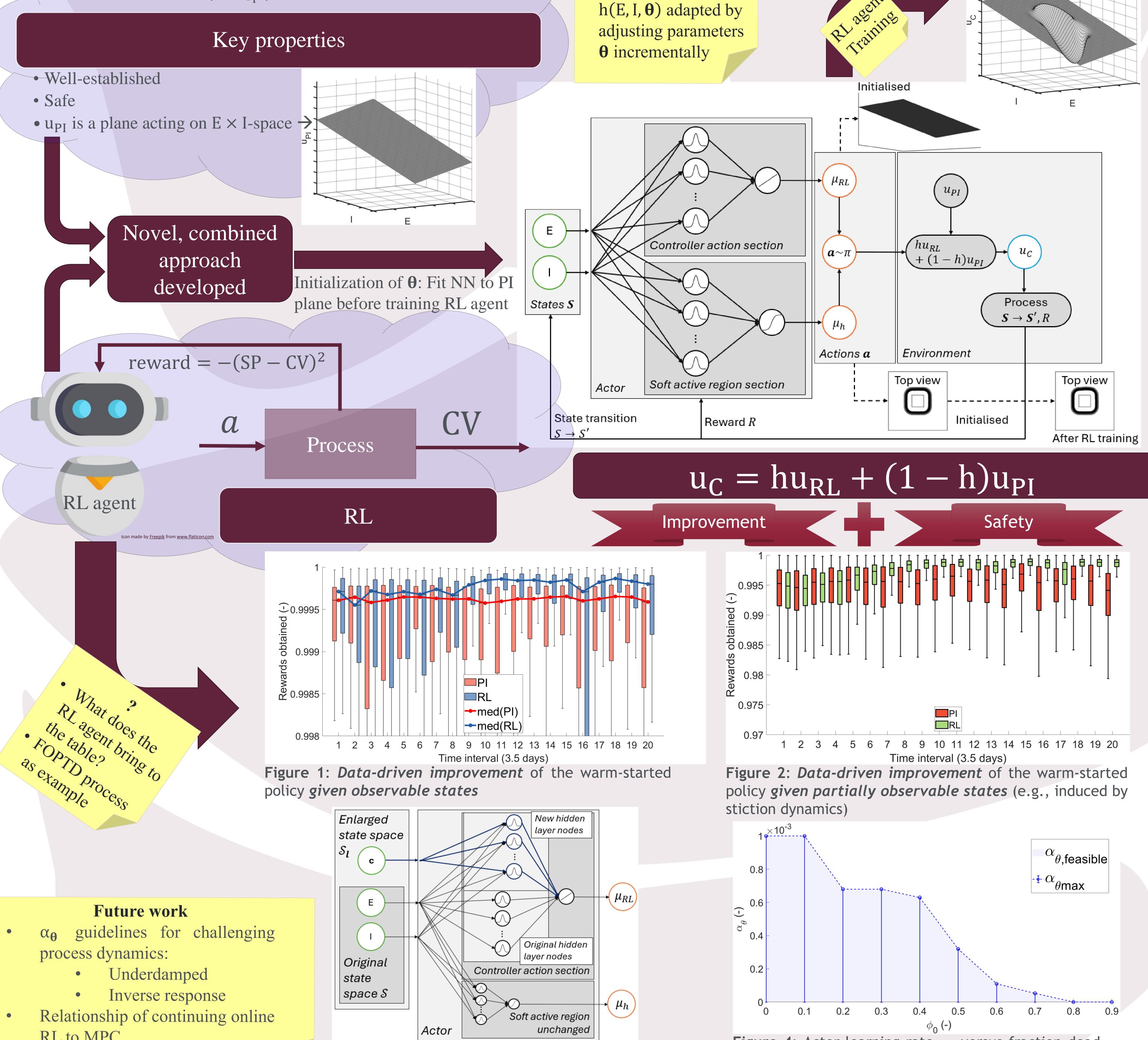
 $+ I_b$

Safe, visualizable reinforcement learning for process control with a warm-started actor network based on PI-control

E.H. Bras, Prof. T.M. Louw, and Prof. S.M. Bradshaw 20068530@sun.ac.za, tmlouw@sun.ac.za, smb@sun.ac.za

| Reinforcement Learning-based process control | Aim and Objectives |
|--|--|
| Data-driven, adaptive control through trial-and-error Roots in optimal control theory Assumptions regarding process dynamics removed Process control requires safety-aware approaches | <i>Aim:</i> To support the adoption of model-free RL by practitioners <i>Objectives:</i> Establish a synergy between RL and classical control Develop generally applicable tuning guidelines for typical process dynamics Extend application to clarify overlap between RL and model predictive control (MPC) |
| PI control | Training? Training yields a non-linear |
| • Control law: $u_{\text{DL}} = \text{Kc}\left(\text{E} + \frac{1}{-}\text{I}\right) + \text{I}_{\text{b}}$ | Training? Infining yields a non-incar • up (F, I, A) and control policy |

• $u_{RL}(E, I, \theta)$ and



- RL to MPC

Figure 3: Opportunity to *leverage feedforward* measurements without assuming knowledge about feedforward dynamics.

Figure 4: Actor learning rate α_{θ} versus fraction dead time ϕ_0 . *RL agent tuning* defined in terms of a set of insensitive hyperparameters which *displays* robustness to a range of process dynamics.

Postgraduate Symposium 2024

Chemical Engineering

forward together \cdot sonke siya phambili \cdot saam vorentoe