Development of Control System Implementation Platform in Advanced Manufacturing

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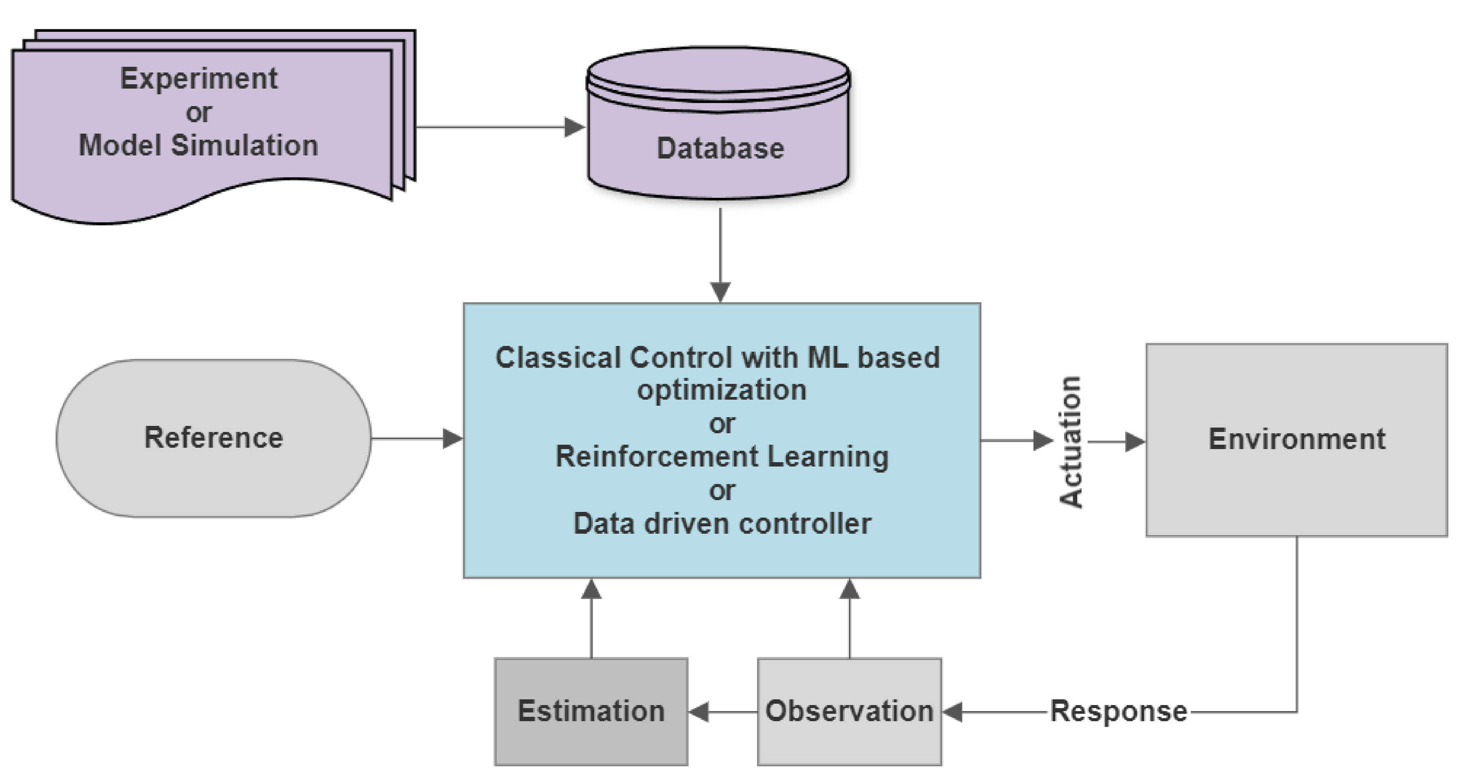
MOTIVATION

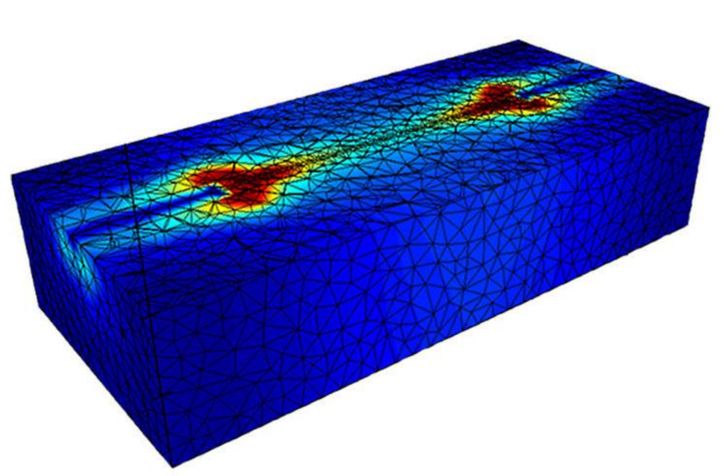
In the field of advanced manufacturing, various complex systems are utilized to achieve advancement in forming complex parts and materials. The systems that are utilized for advanced manufacturing tasks are often difficult to describe using known dynamics. Therefore, the open-loop process is a common practice. Lack of in-situ monitoring and closed loop process limits the control aspect of the systems that costs the quality of the output.

In the realm of classical control loop solutions, the knowledge of the system dynamics is relevant to provide robust and adaptive control mechanisms. However, rapid growth in accessible computational capacity in recent times promoted data-driven robust controller design.



RESEARCH QUESTION

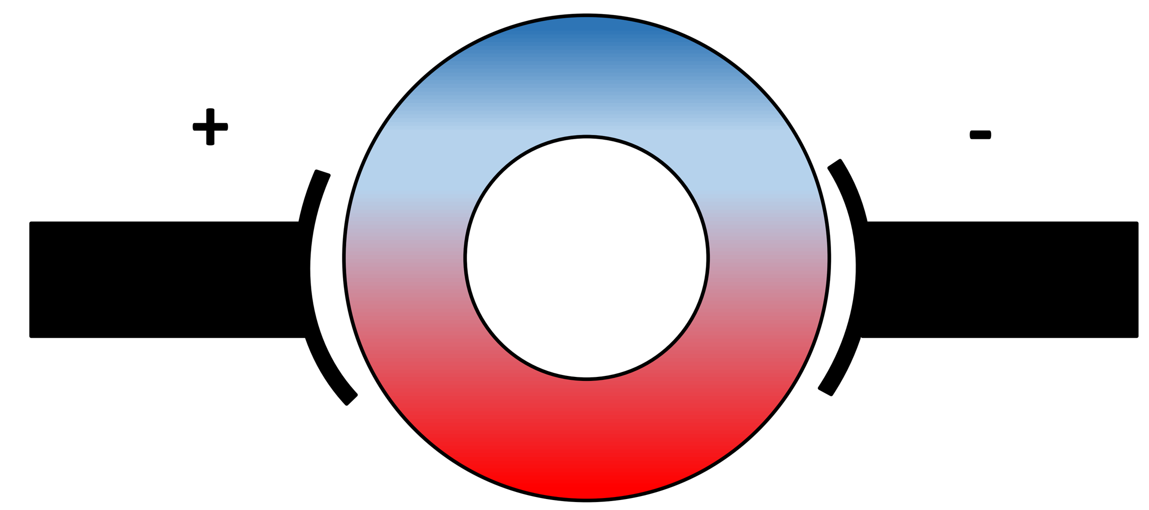
The study explores the controller design approach applied to systems with unknown dynamics. The study is carried out for a specific application commonly appears in the field of advanced manufacturing such as electric field-assisted sintering. The work is designed to develop a data-driven control solution applied to rapid joule heating.



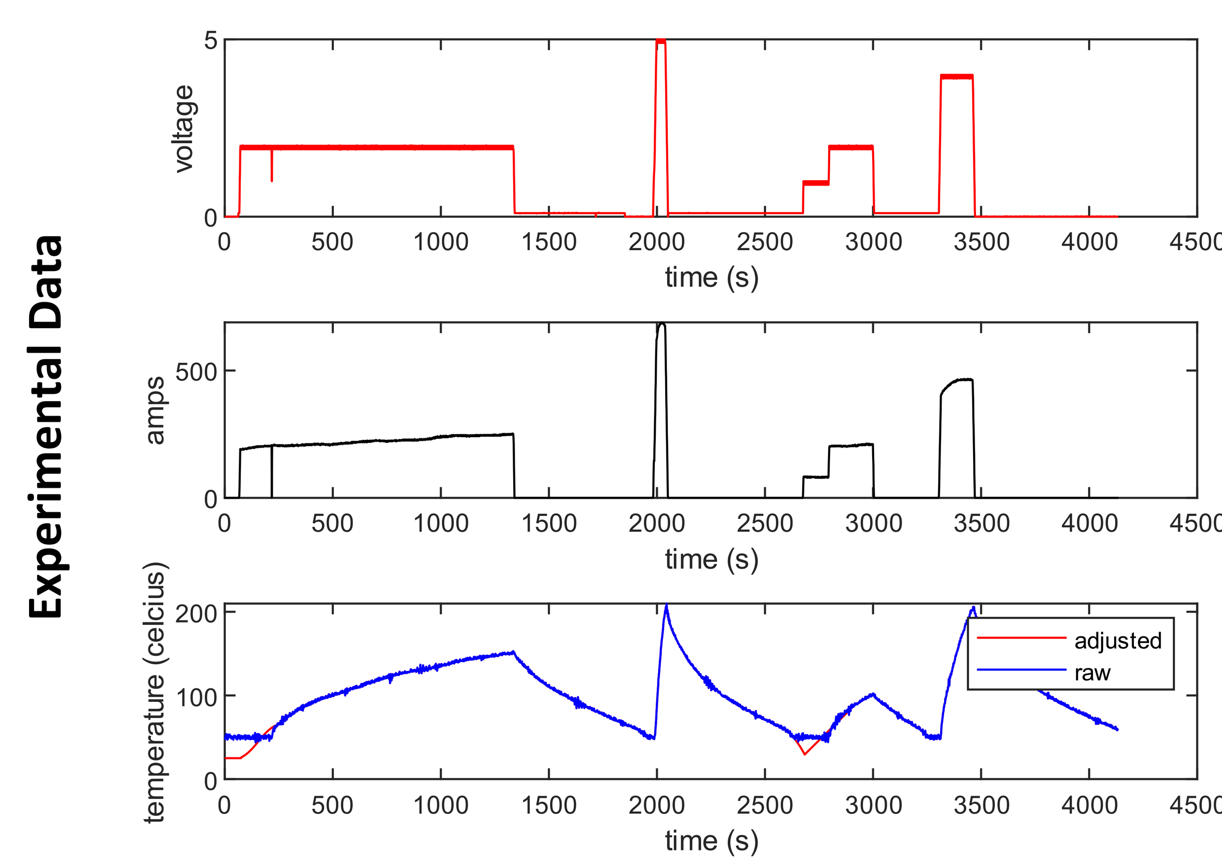
The study addresses the experiment design, data acquisition, system identification, and proposes a model-free reinforcement learning approach utilizing deep deterministic gradient policy (DDGP).

APPROACH

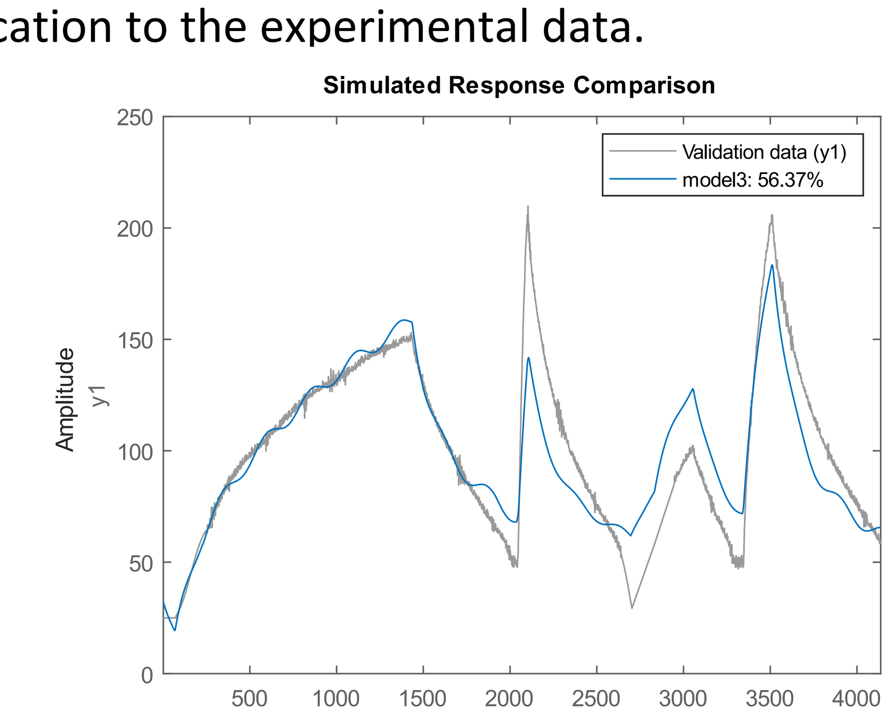
The experiment setup is composed of an electrically conductive roller with a specific material and geometry. A power supply capable of depositing a maximum of 60KW generates a rapid rise in the roller's temperature.



A distributed sensor network is utilized to monitor the system's temperatures in real time. The temperature of the roller is the observed state influenced by the actuating power commands.

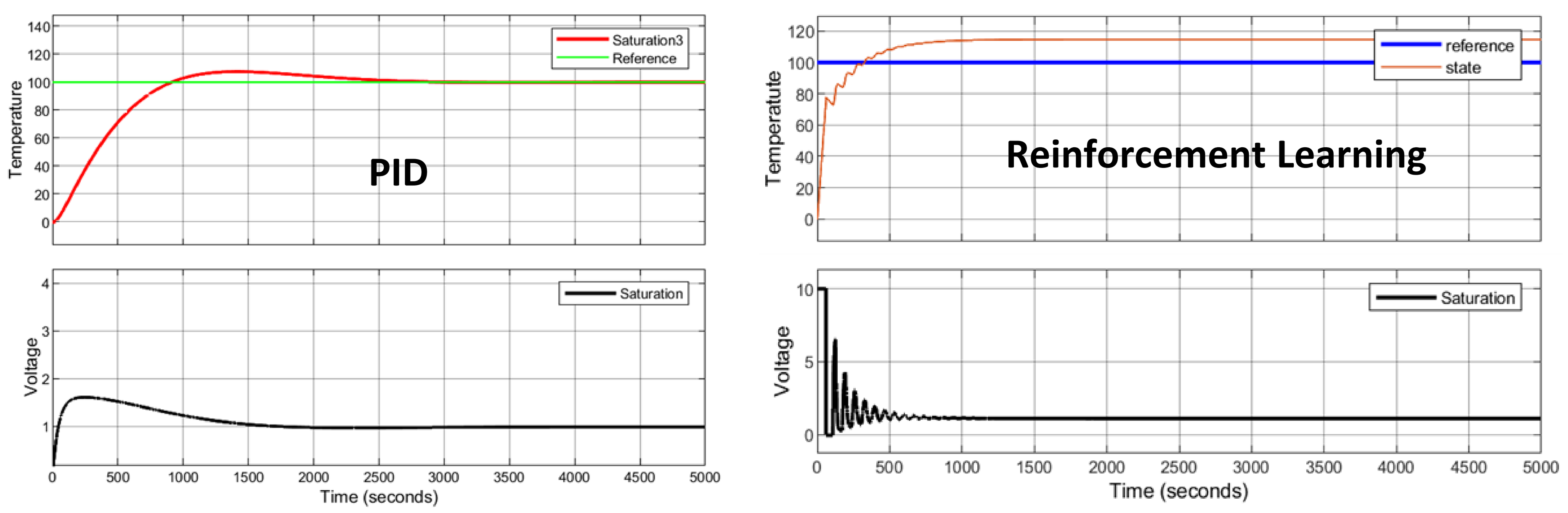


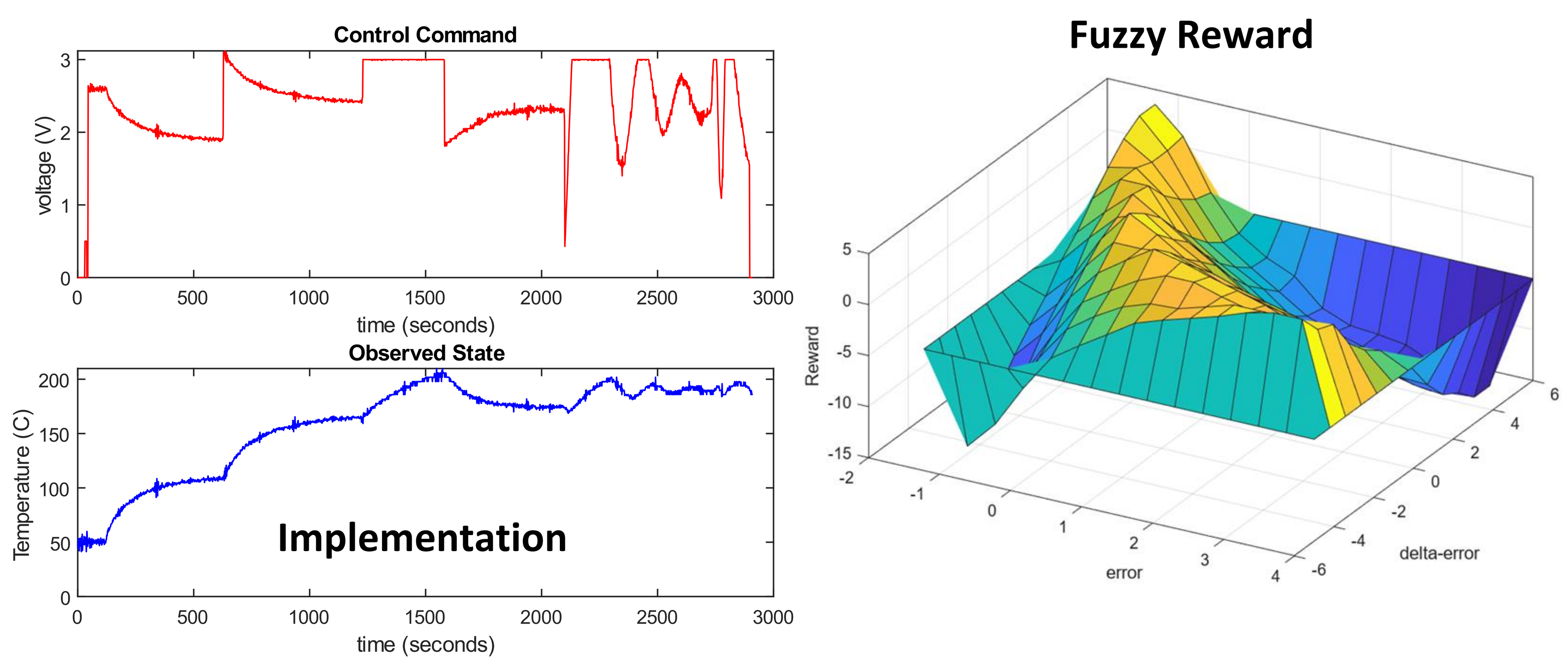
The best-fitted linear transfer function is obtained by applying System Identification to the experimental data.



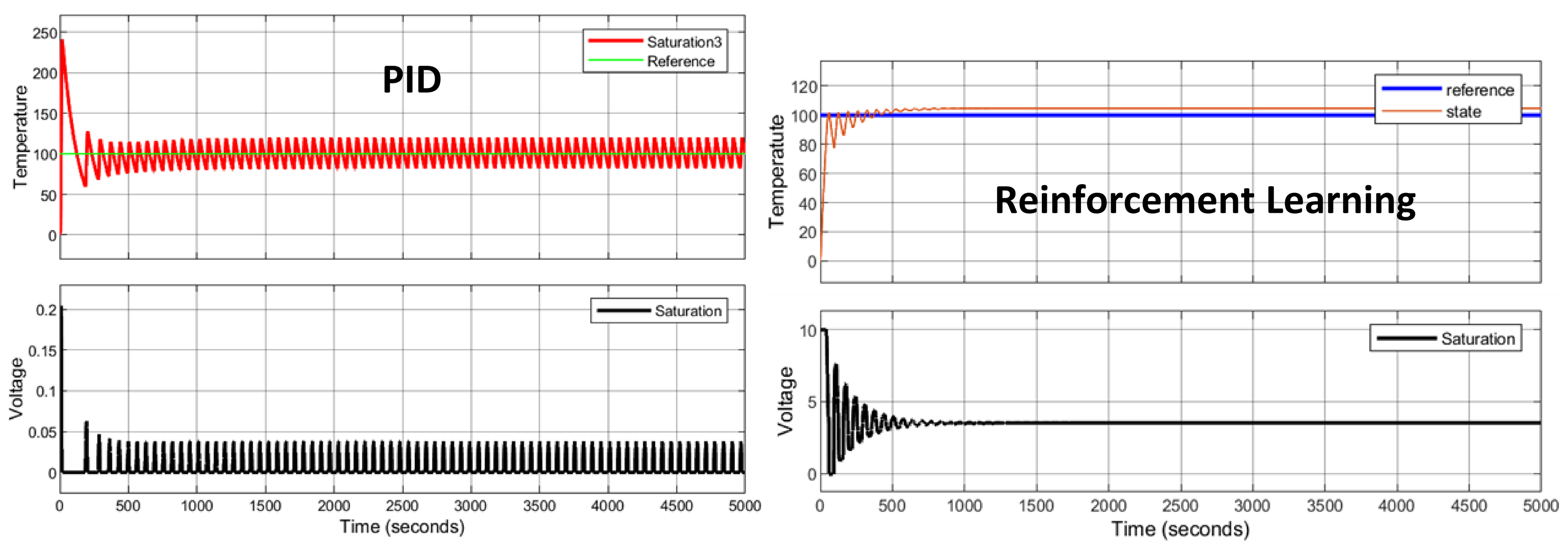
Model-free Reinforcement Learning policy agent is constructed for the partially identified system. The training and validation process is simulated. A PID controller is optimized for the identified system and implemented.

PERFORMANCE MEASURE





Previously optimized controllers are re-tested for robustness by simulation against a new variant of the identified system, derived analytically from a different roller materials.



CONCLUSION

Reinforcement Learning based controllers appear to be robust to the system's variations. The simulation result indicates RL is being a potential generic controller solutions.

The training process could be expensive to implement. A model-based reinforcement learning (MBRL) could be a potential solution.

References

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Model-Based Reinforcement Learning with System Identification and Fuzzy Reward Applied to Advanced Manufacturing

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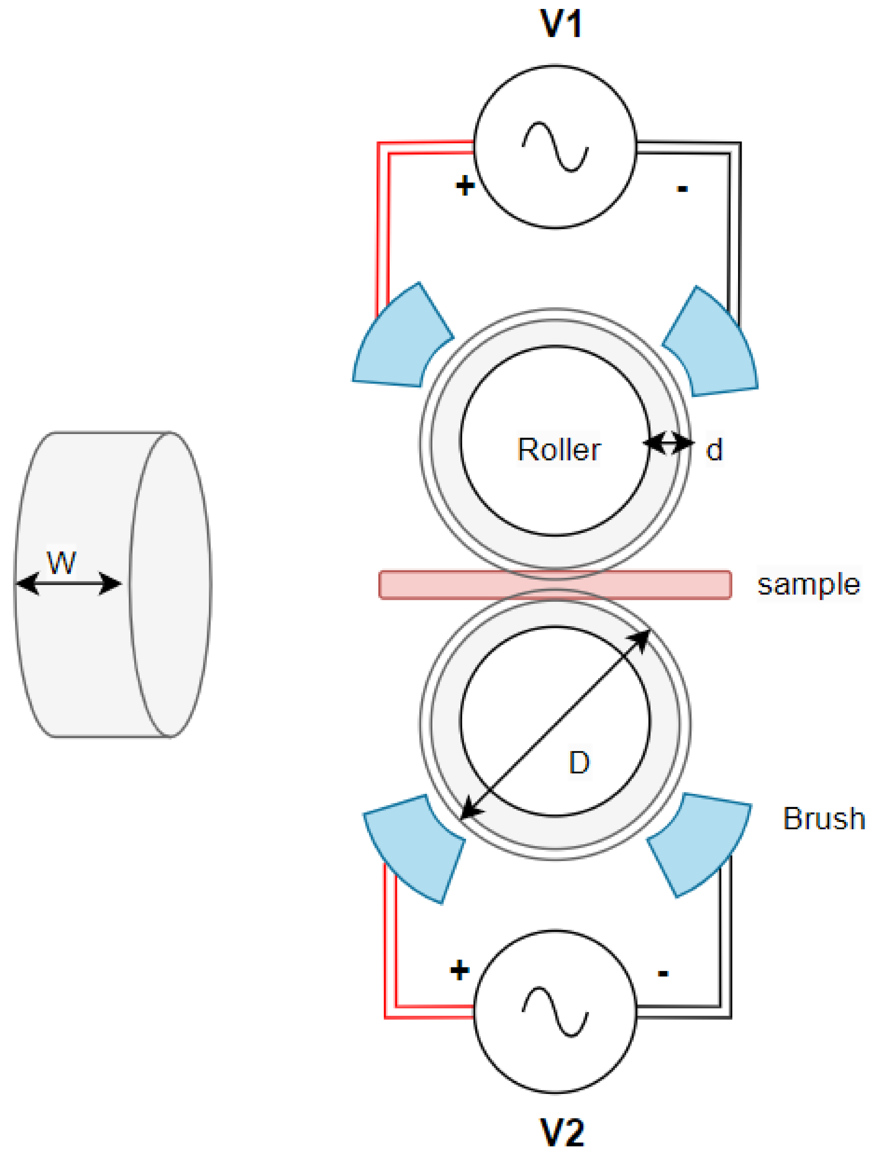
RESEARCH QUESTION

A model-based reinforcement learning (MBRL) allows intelligent control development from series of dynamic experiences without exhaustively interacting with the target plant. This enables wider application of reinforcement learning including Advanced Manufacturing, particularly in the field of Continuous Electric Field Assisted Sintering (CEFAS). The study explores MBRL design for a virtually unknown system dynamics.

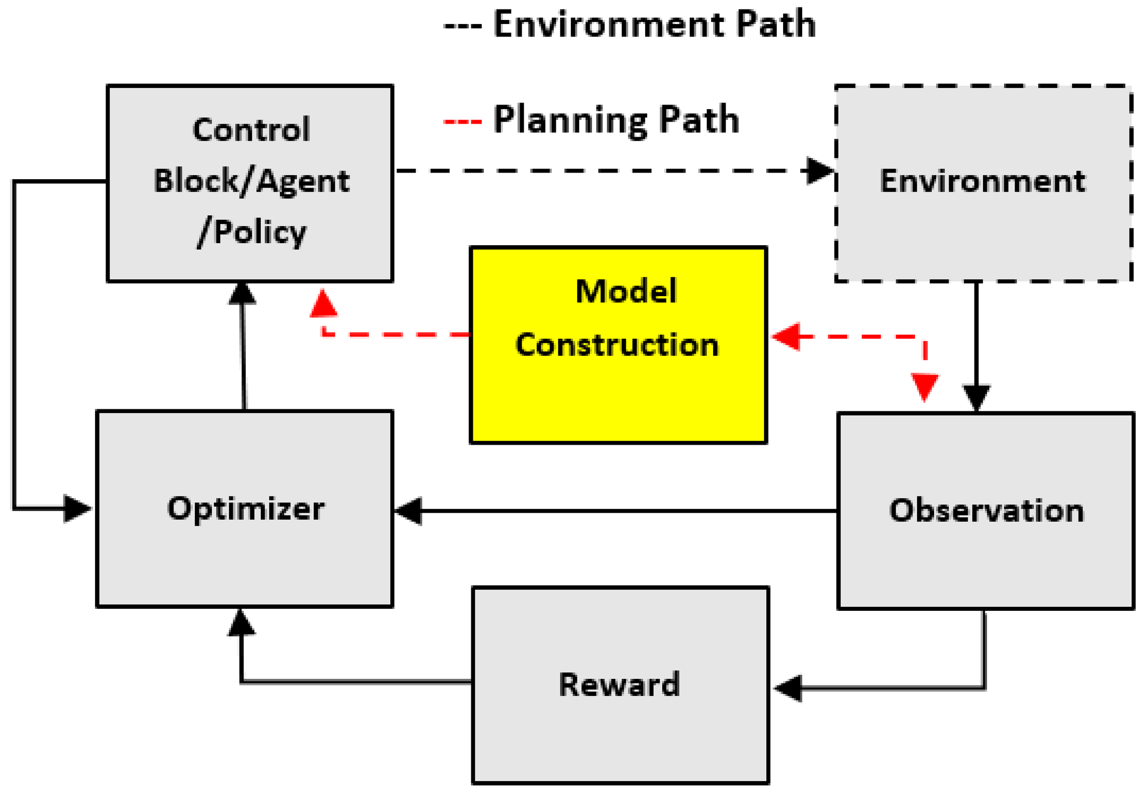


CEFAS

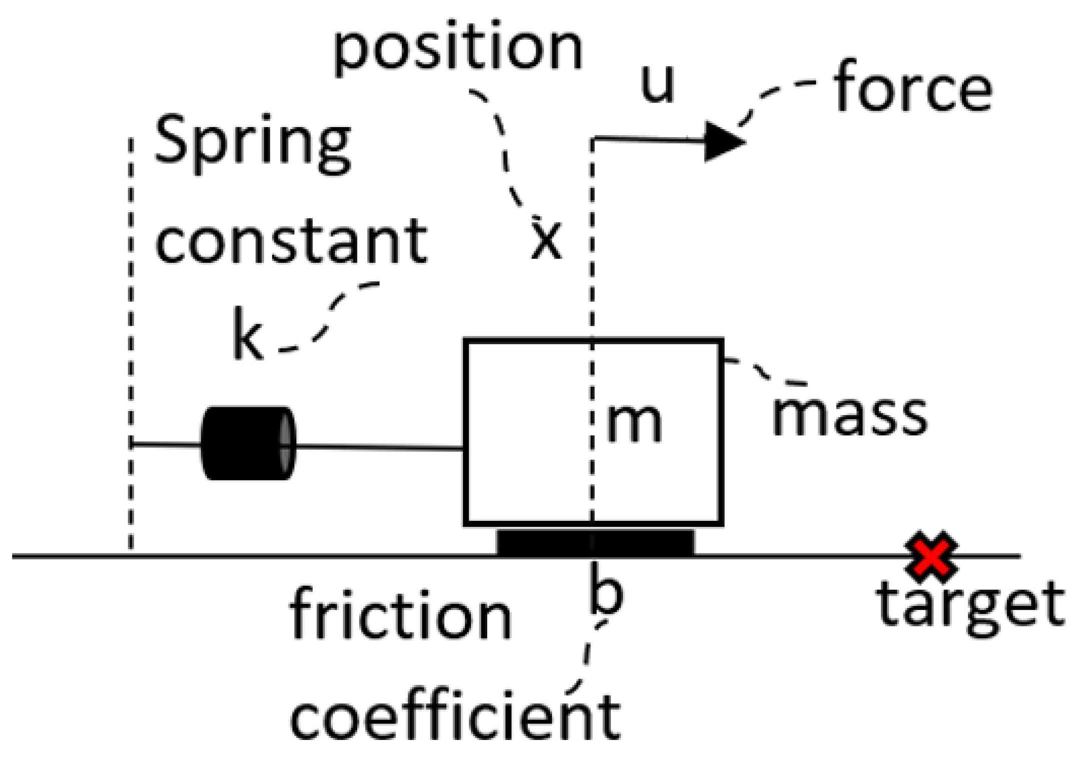
Continuous Electric Field Assisted Sintering

APPROACH

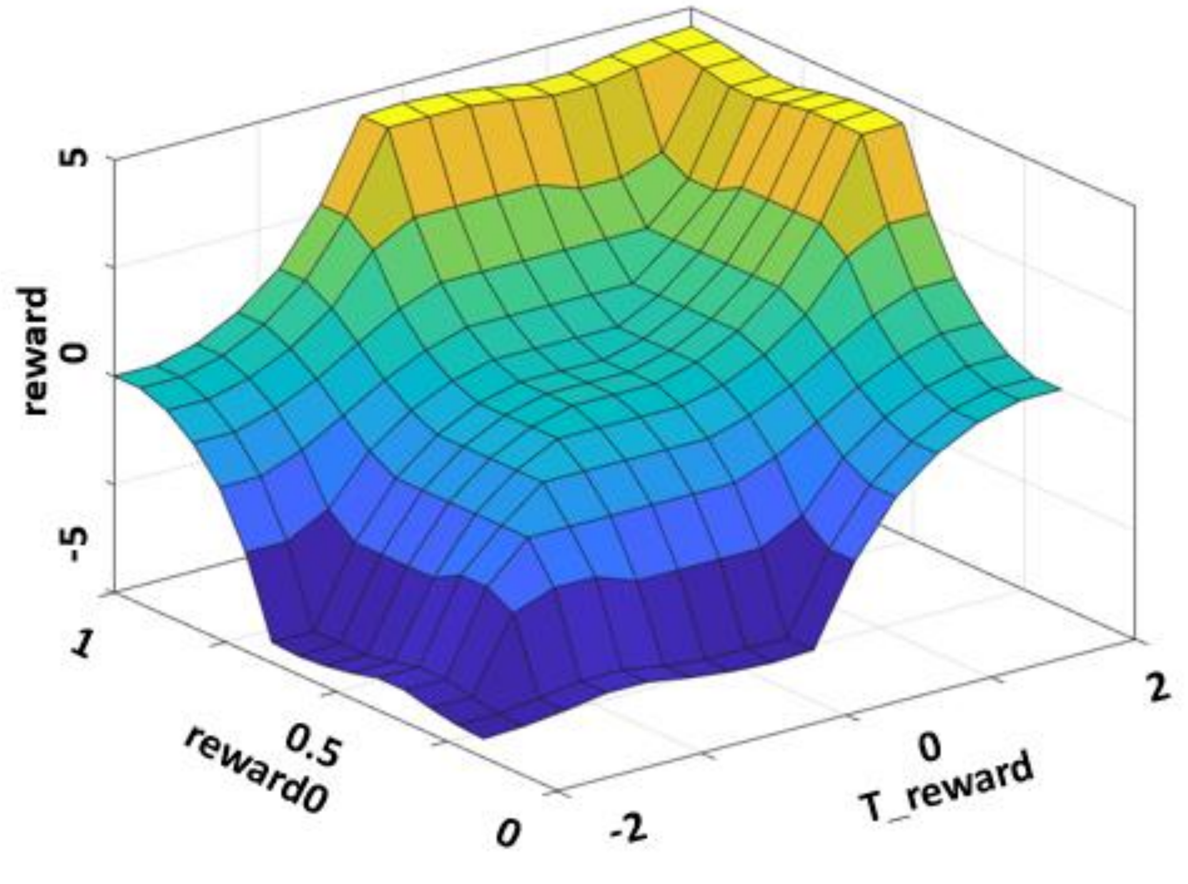
The approach considered in the work for the model-based reinforcement learning (MBRL) utilizes system identification and fuzzy reward formulation. Minimum order estimation gets applied first to determine the system order. This aids transfer function approximation of the linear time-invariant system. A Mamdani fuzzy inference mechanism defines the reward signal. The model obtained integrates into the Q-learning process to simulate experiences bypassing the environment.



Process flow in RL (without the planning path) and MBRL (bypassing the environment with the planning path)

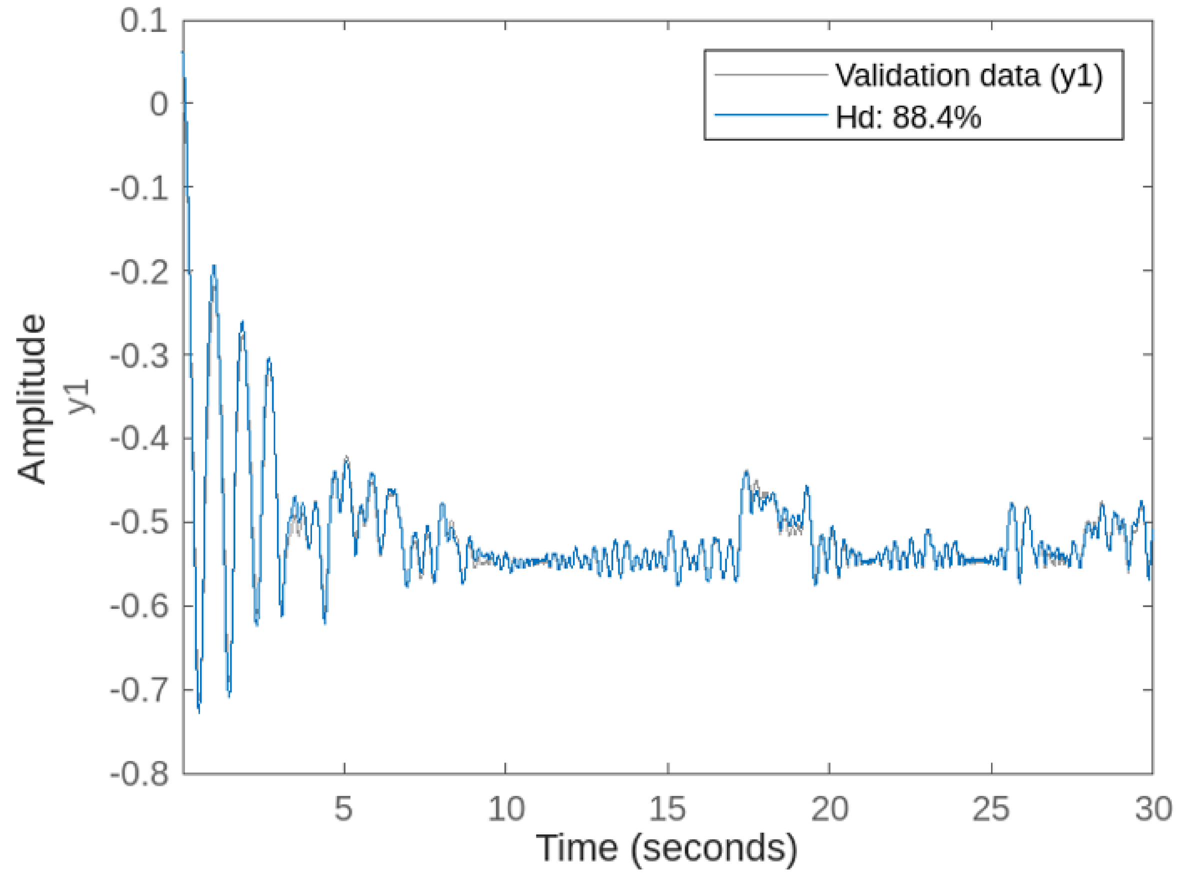


The Mass-Spring-Damper system utilized for the study



The rule surface of the Fuzzy Reward utilized in the study

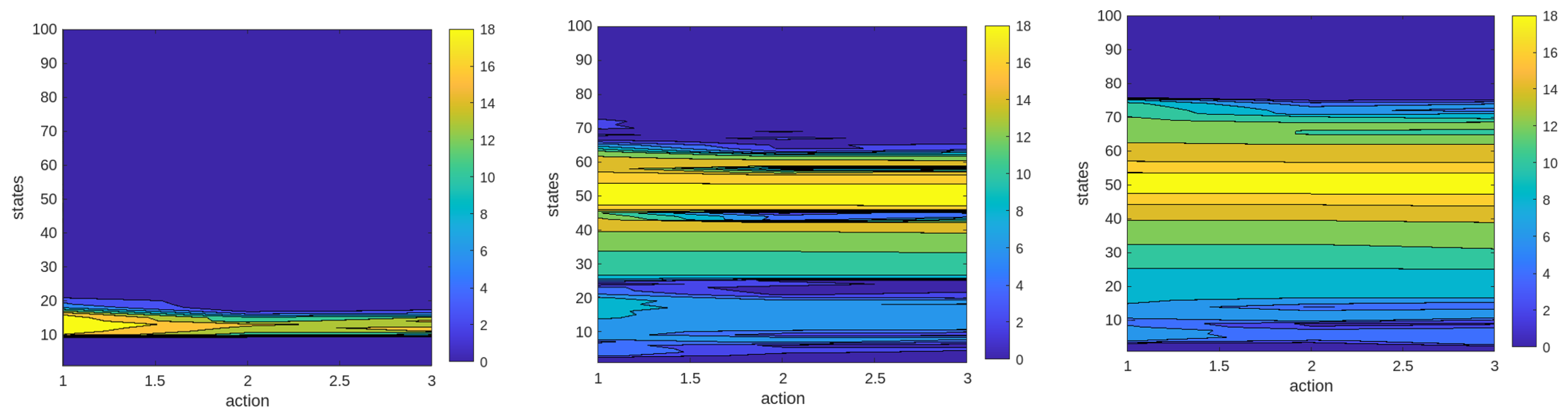
Simulated Response Comparison



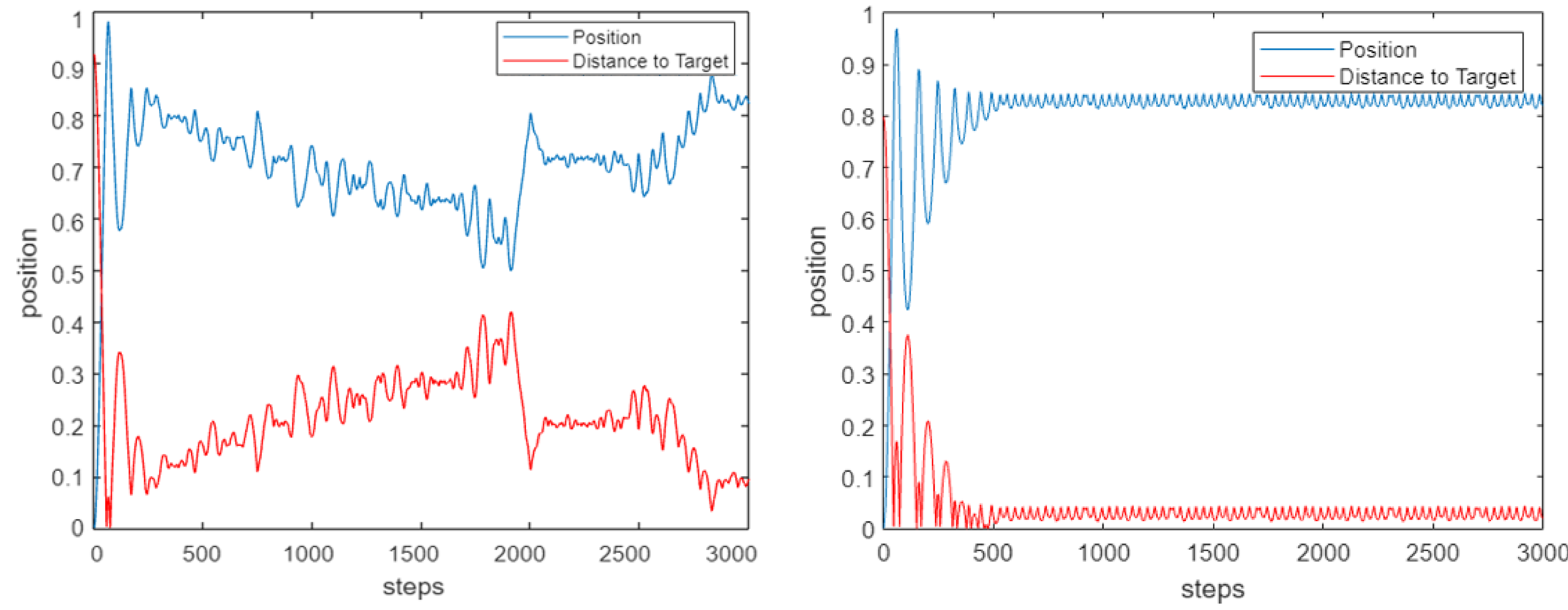
Identified model's simulated response for fitting validation

PERFORMANCE MEASURE

Performance analysis provides evidence of learning improvement without explicitly communicating with the actual plant. A reduction in steady state error and settling time gets achieved.



The colored Q table map illustrates the learning status (left) at the beginning of RL, (middle) before model the construction, and (right) after the model-based learning bypassing the true environment



Response during the validation episode with the (left) a step before the model-based training, and (right) after the completion of the model-based training

CONCLUSION

The proposed framework showcases sample-efficient learning without interacting with the true system. The applicability currently limits to linear systems. Extending the techniques to nonlinear, time-varying dynamics could increase applicability to real-world systems. This study contributes an initial demonstration of MBRL using simple dynamics approximation and fuzzy rewards.

References

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