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AI-Powered Digital Twin and Model Predictive Control for Solar-Powered District Heating Systems

Summary

The use of solar thermal district heating systems contributes to the reduction of fossil fuel consumption in cities. However, the system's performance depends on the variability of solar energy and hot water demand. This research proposes the digital twin-enabled model predictive control (DT-MPC) concept using artificial intelligence (AI) to enhance the optimisation of solar-assisted district heating systems. A Botswana solar and hostel hot water demand dataset of 365 days was employed to evaluate the performance of four control strategies: ON-OFF control, physics-based MPC, digital twin-enabled MPC, and digital twin-enabled MPC using AI. The digital twin-enabled MPC strategy yielded the minimum RMSE of 0.41 °C. On the other hand, the AI-based MPC strategy produced the maximum R^2 of 0.998. Compared to the thermostat control strategy, the proposed strategies improved the thermal tracking and minimised the supply temperature variability. The digital twin-enabled predictive control strategy has great potential for future solar district heating systems, especially in Southern Africa.

Keywords: Artificial Intelligence, Digital Twin, Solar Thermal Systems, Model Predictive Control

Field of application for the findings: Smart energy districts, solar thermal heating, digitalised energy networks

Addressed audience: Energy system researchers, district heating operators, smart city planners

1. Introduction

District heating is increasingly combining with renewable energy sources in order to reduce greenhouse gases and increase energy efficiency in cities. Solar thermal energy has shown promise in terms of high efficiency and high capacity, but it has shown drawbacks in terms of intermittency, and hence careful management is required in order to maintain a stable supply in district heating networks (Lund et al., 2014; Weiss, 2019).

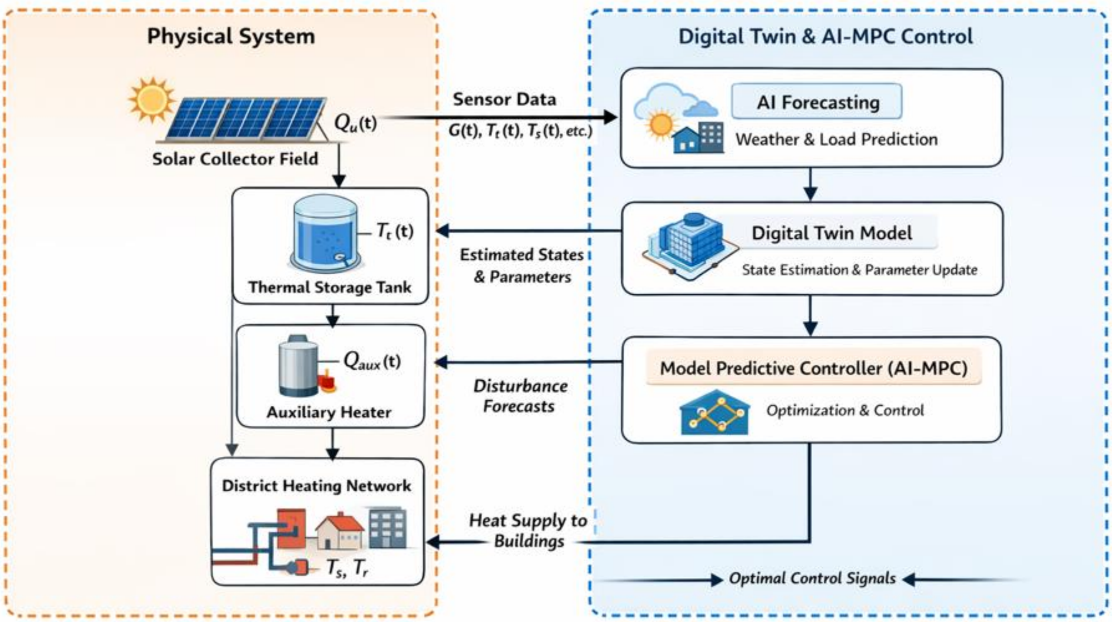

Fig. 1: Architecture of the Digital Twin – AI – MPC Solar District Heating Framework

Model Predictive Control (MPC) is widely applied in solar thermal and district heating systems, owing to its ability to look forward and predict any disturbances in the system, thus optimising over a certain horizon (Killian and Kozek, 2016). However, traditional MPC methods rely on simple models that might not accurately represent the true nature of the physical system.

The concept of digital twin, which is an updated replica of any physical system, has shown promise in improving predictive, monitoring, and controlling capabilities (Tao et al., 2019). AI-based forecasting has also shown promise in improving traditional MPC methods, thus predicting any disturbances in the system, including those due to solar irradiance, weather, and heat demand (Wang et al., 2022).

The combination of digital twin, AI-based forecasting, and MPC in solar district heating is still in its infancy. The architectural framework of this combination is shown in Fig. 1. This study aims at investigating and testing the Digital Twin + AI-MPC method in solar-assisted district heating.

2. Methodology

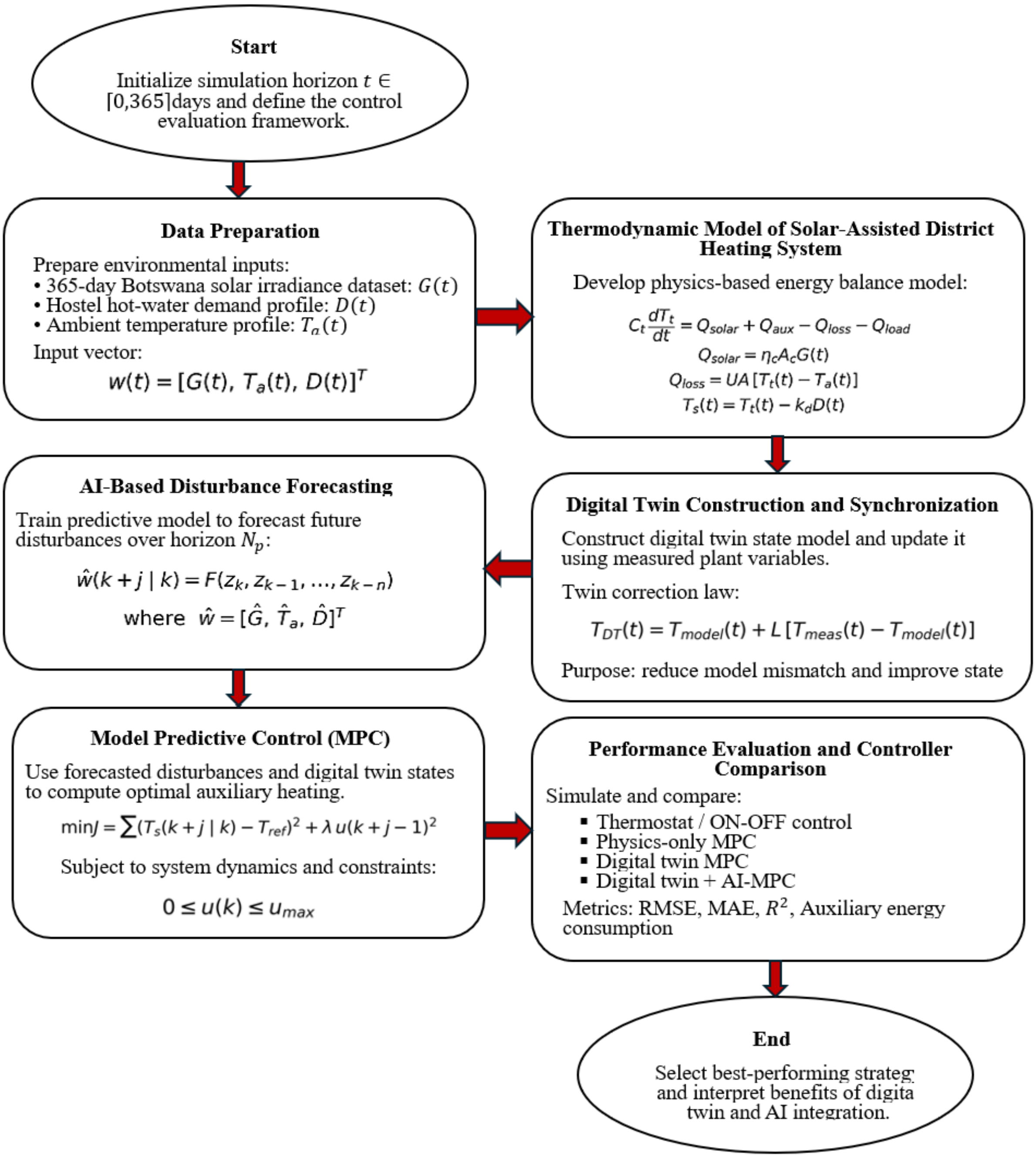

Fig. 2: Architecture of the Digital Twin – AI – MPC Solar District Heating Framework

The paper describes a specific procedure, as shown in Fig. 2. It describes how we develop and test our control strategy based on the concept of a digital twin and AI-MPC for the solar-assisted district heating system. Finally, we evaluate the performance of the control strategies.

3. Results and Discussion

The performances of the four control strategies were compared with a simulation of Botswana's solar conditions over a period of 365 days, as well as real-life hostel hot water usage. The comparison was based on the predictability, tracking, and usage of additional energy. The conventional thermostat control strategy was found to have the highest temperature fluctuations due to its inability to predict future temperature changes based only on the tank temperature. Although it was able to maintain the temperature within a useful range, it was found to have a higher prediction error compared to the others.

Tab. 1: Comparison of the accuracy of the prediction of the four strategies

Control Strategy	RMSE (°C)	MAE (°C)	R^2
Thermostat Control	0.64	0.49	0.995
Physics MPC	0.61	0.46	0.993
Digital Twin MPC	0.41	0.31	0.997
Digital Twin + AI-MPC	0.49	0.35	0.998

The use of a digital twin was found to greatly improve the accuracy of the predictions, as shown in Table 1. The results show that the use of a digital twin technology greatly improves the predictability of the system, and the addition of AI forecasting enables the controller to predict future disturbances. These results are in line with Wang et al. (2015) and Weiss (2019), that discusses the importance of digitalisation and data-driven models for future energy systems. The AI-MPC strategy was found to have the highest correlation, but it was found that it used a little more auxiliary energy due to the need for temperature tracking rather than energy savings, which will be considered in future studies.

The results show that the use of a combination of digital twin technology, artificial intelligence, and model predictive control is a good strategy for solar-powered district heating systems, especially for Southern Africa, where the sun shines brightly throughout the year.

4. Conclusion

The present study proposes a digital twin-based AI-enabled MPC framework for solar district heating systems. Four control strategies are implemented and tested using a simulation of 365 days. The main results are: digital twin MPC has the lowest prediction error, AI MPC has the highest predictive correlation, and model-based controllers offer better temperature stability compared to thermostat control. The study demonstrates that digitalisation and AI can improve solar district heating systems significantly.

5. References

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Appendix: UNITS AND SYMBOLS IN SOLAR ENERGY

Table 1: Nomenclature

Description	Symbol	Unit
Solar collector surface area	A_c	m^2
Heat transfer surface area of storage tank	A_t	m^2
Thermal capacitance of storage tank	C_t	$J\,K^{-1}$
Hot-water demand flow rate	$D(t)$	$kg\,s^{-1}$
Predicted hot-water demand	$\hat{D}$	$kg\,s^{-1}$
Disturbance input matrix	E	–
Solar irradiance incident on collector	$G(t)$	$W\,m^{-2}$
Predicted solar irradiance	$\hat{G}$	$W\,m^{-2}$
MPC objective (cost) function	J	–
Discrete time index	k	–
Load–temperature proportional coefficient	k_D	$K{\cdot}s\,kg^{-1}$
Observer gain	L	–
MPC prediction horizon	N_p	–
Auxiliary heating power input	Q_{aux}	W
Thermal energy extracted by water demand	Q_{load}	W
Thermal loss to ambient environment	Q_{loss}	W
Solar thermal energy gained by collector	Q_{solar}	W
Ambient air temperature	$T_a(t)$	K or $°C$
Predicted ambient temperature	$\hat{T}_a$	K or $°C$
Digital twin corrected temperature	T_{DT}	K or $°C$
Inlet cold water temperature	T_{in}	K or $°C$
Measured system temperature	T_{meas}	K or $°C$
Model-predicted temperature	T_{model}	K or $°C$
Reference supply temperature	T_{ref}	K or $°C$
Hot-water supply temperature	$T_s(t)$	K or $°C$
Storage tank temperature	$T_t(t)$	K or $°C$
Control input (auxiliary heating power)	u_k	W
Maximum auxiliary heater capacity	u_{max}	W
Disturbance vector	$w(t)$	Mixed
Predicted disturbance vector	$\hat{w}$	Mixed
System state vector	$x(t)$	–
Digital twin state estimate	x_{DT}	–
Physics-based model state	x_{model}	–
Measured system output	y_{meas}	K or °C
Model predicted output	y_{model}	K or °C
Solar collector thermal efficiency	η_c	–
MPC control weighting factor	λ	–
Density of water	ρ	$kg\,m^{-3}$
Specific heat capacity of water	c_p	$J\,kg^{-1}\,K^{-1}$