Real-time hybrid modelling to inform smart prediction and management of urban flow regimes

Modélisation hybride en temps réel pour une prévision et une gestion intelligentes des régimes d'écoulement urbains

Lin Zhang[a] , Matthew J. Burns[a] , Kathryn L. Russell[a] , Wei D. Xu[a] , Tim D. Fletcher[a]

a School of Agriculture, Food and Ecosystem Sciences, University of Melbourne - lzzhan6@student.unimelb.edu.au

RÉSUMÉ

Les régimes d'écoulement des cours d'eau sont généralement altérés par l'urbanisation et le changement climatique, ce qui entraîne des crues, une diminution de l'écoulement de base, une dégradation des écosystèmes aquatiques. Les dispositifs de gestion des eaux pluviales sont déployés afin de fournir, entre autres objectifs, des régimes d'écoulement plus proches des conditions naturelles. Le contrôle prédictif par modèle (CPM) en temps réel (GTR) peut déterminer les actions de contrôle optimales pour ces dispositifs, en prévoyant la dynamique des débits sous différents scénarios météorologiques et opérationnels. Cependant, l'exécution de scénarios issus d'un modèle hydrologique et hydraulique dans un cadre d'optimisation CPM est coûteuse en calcul, en particulier lorsque des décisions à pas de temps court sont nécessaires. L'élaboration d'un modèle de prédiction simplifié, à la fois précis et rapide, est donc essentielle pour rendre possible une gestion en temps réel des régimes d'écoulement. Des travaux récents ont montré qu'un modèle hybride combinant des approches physiques et des techniques d'apprentissage profond peut améliorer la précision et l'interprétabilité des prédictions de débit, tout en conservant une vitesse de calcul comparable. Dans une étude de cas menée sur le bassin versant du ruisseau Monbulk Creek, à l'est de Melbourne, un modèle hybride et un modèle d'apprentissage profond produisent des prévisions de débit plus rapides et plus précises qu'un modèle physique. Le modèle hybride sera amélioré par l'intégration de mécanismes physiques supplémentaires, afin de déterminer s'il peut soutenir un contrôle plus adaptatif de dispositifs de gestion des eaux pluviales.

ABSTRACT

Stream flow regimes are typically negatively affected by urbanisation and climate change, causing floods, loss of baseflow, habitat degradation, and thus threatening aquatic ecosystems. Stormwater control measures (SCMs) have been applied to deliver, among other objectives, more natural flow regimes. Model Predictive Control (MPC), a real-time control (RTC) strategy, can be used to find the optimal control actions for SCMs, by predicting flow dynamics under different weather and operating scenarios. However, optimising scenarios from a hydrological and hydraulic model in MPC is computationally intensive, especially where short time-step decisions are required. Constructing a simplified predictive model that can be both accurate and rapid is needed for real-time flow regime management. Recent research has shown that a hybrid model that combines physically-based models and deep learning techniques has potential to improve the accuracy and interpretability of flow predictions, with comparable computational speed to data-driven models. In a case study conducted in the Monbulk Creek catchment in eastern Melbourne, Australia, both the proposed hybrid model and deep learning model generate more accurate and faster flow predictions than a physically-based model (SWMM; stormwater management model). The hybrid model will be further improved by integrating more physical mechanisms, and will then be investigated to see if it can inform more adaptive prediction and control of distributed SCMs.

KEYWORDS

Deep learning, flow regime prediction, hybrid model, stormwater control measures, smart flow management

1 INTRODUCTION

The flow regime describes the characteristic pattern of a waterway's flow quantity, timing and variability. Flow regimes are significantly changed by urbanisation and climate change, causing floods and increased peak flows, loss of baseflow, habitat degradation, ultimately threatening the survival of aquatic plant and animal species (Poff et al., 1997). In recent years, stormwater control measures (SCMs) have been applied to deliver more natural flow regimes. More recently, real-time control technology (RTC), allowing systems to be operated in response to live monitoring data, has been applied to improve the performance of SCMs in regulating flow regimes (Xu et al., 2022). Model Predictive Control (MPC) is often used in the control of RTC systems, but the process is computationally intensive. Real-time operation for multiple flow targets is technically challenging, even more so in the context of changing climate conditions. Meeting such requirements will rely on hydrological-hydraulic models to provide rapid, accurate and adaptive flow predictions.

The hydrological-hydraulic model can not only help provide flow predictions as input for real-time controlled SCMs systems, but also generate dynamic flow processes under control actions, allowing the impact of SCMs on the flow regime to be understood. These models can be mainly divided into physical models and data-driven models. The former are labour-intensive and costly, while the latter show high efficiency in computational speed, but lack transparency and interpretability. Current research has shown that hybrid models integrating deep learning techniques with physical model elements significantly enhance both the accuracy and interpretability of flow process predictions, with comparable computational speed to data-driven models (Zhong et al., 2024). Therefore, hybrid modelling shows potential benefits in informing better flow regime predictions and management in real-time, providing adaptability to respond to climate change and rapid urbanisation.

This study proposes a hybrid structure to model complex urban stormwater networks and predict the flow regime in real-time. The hybrid model is compared with a physical model (SWMM) and a data-driven model (LSTM; long short-term memory network) to verify if the hybrid model shows advantages in model performance.

2 CURRENT RESEARCH PROGRESS ON HYBRID MODELLING FOR URBAN FLOW PREDICTION AND MANAGEMENT

2.1 Method

The hybrid model is constructed by combining an LSTM model with the water balance equation (Fig.1). The water balance equation is embedded in the LSTM loss term as a physical constraint, penalising prediction results that violate the law of continuity in the water balance. Along with the hybrid model, a separate physically-based model (SWMM) and a deep learning model (attention mechanism-based LSTM, ATT-LSTM) are also constructed to verify if the hybrid model can make more accurate and adaptive flow predictions.

Fig 1. The structure of proposed hybrid model

The Monbulk Creek catchment in eastern Melbourne was chosen as the study site. Spatial radar rainfall data was used to calculate the areal rainfall for the whole catchment. The 1-hour resolution input data for LSTM, including rainfall, evaporation, and soil moisture from 2020 to 2024, together with 1-hour resolution flow data, were divided into training samples and testing samples in a ratio of 70–30. Each model was optimised using the NSGA2 method.

2.2 Results

We present here the compared results of the hybrid model, LSTM model and SWMM (Fig.2 and Table 1).

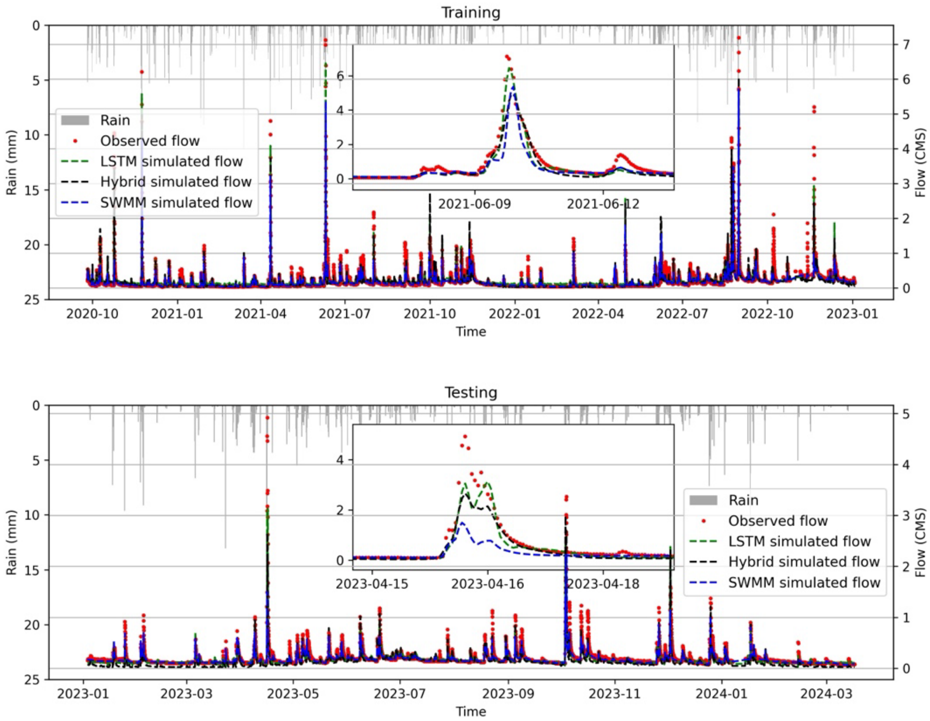

Fig 2. Compared flow predictions of the hybrid model, the LSTM model and the SWMM model

Table 1 Evaluation metrics results for different models

	Training / Calibration			Testing / Validation		
Model type	**R^2**	**Peak error (CMS)**	**Running time**	**R^2**	**Peak error (CMS)**	**Running time**
SWMM	0.76	1.47	33 mins	0.74	2.7	25 mins
ATT-LSTM	0.86	0.73	7 mins	0.79	1.78	0.5 seconds
Hybrid	0.84	1.15	12 mins	0.76	1.93	1.6 seconds

Both the LSTM model and the hybrid model generated more accurate flow predictions, and did so more quickly, than the SWMM model. Specifically, compared with SWMM, the fitting degree of simulated flow from the LSTM model was increased by 13.2% in training and 6.7% in testing, while the peak error was decreased by 50.3% in training and 34.1% in testing. For the hybrid model, compared with SWMM, the fitting degree of simulated flow was increased by 10.5% in training and 2.7% in testing, and the peak error was decreased by 21.8% in training and 28.5% in testing. The run-time is also greatly improved: the LSTM model and the hybrid model ran 3000 and 937 times faster than the SWMM model, respectively.

3 CONCLUSION AND PERSPECTIVES

The preliminary hybrid model performed better than the SWMM model, while showing no obvious advantage compared with the LSTM model. In future work, the structure of the hybrid model will be further improved by integrating more physical mechanisms to see if it shows advantages in interpretability and adaptability under changing weather conditions.

The benefit of conducting hybrid modelling will then be investigated to determine whether the hybrid model can inform real-time adaptive control of distributed SCMs. The MPC method will be used, and the hybrid model in MPC will learn the response relationship between input features (including weather information, control actions and overflow from SCMs) and simulated flow from SWMM under the impact of SCMs. This study hypothesises that the proposed hybrid model will show benefits for flow prediction and management of SCMs, providing in-time, accurate and interpretable predictions of multiple flow targets, adapted to changing weather and operation conditions.

LIST OF REFERENCES

LeRoy Poff, N., David Allan, J., Bain, M. B., Karr, J. R., Prestegaard, K. L., Richter, B. D., Sparks, R. E., & Stromberg, J. C. (1997). *The Natural Flow Regime A paradigm for river conservation and restoration*.

Xu, W. D., Burns, M. J., Cherqui, F., Duchesne, S., Pelletier, G., & Fletcher, T. D. (2022). *Real-time controlled rainwater harvesting systems can improve the performance of stormwater networks*. Journal of Hydrology, 614.

Zhong, L., Lei, H., & Yang, J. (2024). *Development of a Distributed Physics-Informed Deep Learning Hydrological Model for Data-Scarce Regions*. Water Resources Research, 60(6).