Ph.D. in Information Technology
Thesis Defense

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Room Alpha

Wenjin HAO – XXXVI Cycle

FROM FORECASTING TO CONTROL: THE ROLE OF MACHINE LEARNING IN URBAN WATER DEMAND MODELLING AND MANAGEMENT ACROSS SCALES

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Abstract:

Urban water demand management (UWDM) is crucial for fostering sustainable water management, complementing supply-side strategies. Confronted with the challenges of urbanization, population growth, and climate change, the distribution and availability of water resources are undergoing significant transformations. These changes introduce new challenges to demand-side management, necessitating innovative and tailored approaches to sustainably manage water usage across diverse spatial and temporal scales. The design and implementation of these effective demand management strategies are contingent upon an enhanced understanding and accurate forecasting of demand behaviors and patterns across various scales, as well as their interactions with the external environment. Consequently, there is a burgeoning necessity to develop robust and generalized frameworks that can accurately identify key determinants of demand patterns. By harnessing these determinants, it becomes feasible to enhance the forecasting of future urban water demand (UWD) across various spatial scales, from cities to continents, and temporal scales, from sub-daily to monthly. This improved foresight is critical for supporting informed decision-making and strategic actions in demand management, particularly as it adapts to dynamic urban and environmental changes. Furthermore, as a critical component of water distribution networks (WDNs), the dynamics of water demand have significant implications for the operations of the supply network, serving as integral links between demand and supply management in urban water systems. Accurate demand forecasts enable the optimization of resource allocation and enhance the resilience and efficiency of water distribution, thereby ensuring sustainability in urban water management.

Advancement in machine learning (ML) especially deep learning (DL) plays a transformative role in demand modelling, offering the ability to analyze complex data and extract meaningful insights across different scales. Leveraging the enhanced interpretability and predictive capabilities of ML and DL models opens new avenues for refining the precision of demand forecasts. Furthermore, it deepens our understanding of the interactions between external influences and demand patterns. However, the existing research on demand forecasting typically develops models tailored to specific case studies, often neglecting the robustness and generalizability of these models. Moreover, these studies usually focus on a narrow set of external variables, predominantly climatic ones, examining their relationship with water demand. The scope of these models is usually confined to specific urban areas, overlooking the implications for demand forecasting and determinants identification on a larger, more comprehensive spatial scale. Furthermore, despite being recognized as a critical input, the dynamics of demand are seldom examined within real WDNs, limiting our understanding of their influence on network operations.

This thesis addresses these critical gaps by proposing frameworks that enhance forecasting model robustness and expand the range of demand determinants identification on a larger spacial scale. Specifically, the contribution of this thesis is three-fold. First, a robust multi-step forecasting framework for short- to medium-term UWD at the city scale is developed. This framework employs advanced DL techniques and hybrid modeling approaches, testing its predictive robustness against unprecedented changes. Second, a comprehensive framework for identifying determinants and forecasting UWD at a continental scale is introduced. Utilizing deep neural Granger causality, this framework enhances model interpretability and conducts extensive evaluations of demand determinants using diverse public data sources. Finally, the thesis pioneers an optimal control framework that leverages DL-based UWD forecasts within an economic model predictive control (EMPC) strategy for a large-scale WDN. This innovative integration investigates the impact of forecast accuracy on operational control effectiveness, representing a novel exploration in the field. In conclusion, this research underscores the significant enhancements that can be achieved by incorporating advanced ML and DL techniques into UWD modelling and analysis. By adopting these soft computational methods, this thesis not only reveals key insights into demand patterns but also informs the design of more effective and adaptive management strategies. These strategies are crucial for addressing the challenges of water distribution in changing urban environments, ensuring sustainability and efficiency in water management.

PhD Committee

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