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Authors

Bui, Ngoc T
Urban, Jeffrey J

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A Self-Learning Circuit Diagram for Optimal Water and Energy Management

Ngoc T. Bui[1,*] and Jeffrey J. Urban[2,*]

[1] The School of Chemical, Biological and Materials Engineering and the School of Civil Engineering and Environmental Science, the University of Oklahoma, Norman, OK, 73019, USA
[2] The Molecular Foundry, Lawrence Berkeley National Laboratory, Berkeley, CA, 94720, USA
*Contact information: jjurban@lbl.gov, ngoctbui21@ou.edu

Computational methods with real-time forecasting of embedded energy and water networks are critical for resource management and conservation. In this issue of *Energy & Environmental Science*, Liu and Mauter propose a high-resolution computational framework of the embedded energy in water delivery systems to guide efficient management of water resources.

"What gets measured gets managed" - this business aphorism highlights a universal driving principle - and limitation - in resource management. Stewardship of energy and water resources can only be as efficient as the measured data that informs it. In this case, the spatiotemporal resolution of energy and water flows, the links between energy and water, and the accuracy of the forecasting methods employed. Presently, the spatial and temporal resolution of water programs is poor, and relies on inaccurate, generic assumptions of consistent energy and cost returns for all consumers at all times.

The urgency for improving these tools is clear, and a long-term utopian goal would be a fully automated "smart grid" of energy and water supplies that can self-optimize operations and increase efficiency, while having the crosstalk between them priced into the model. This would appropriately recognize the mutualism of these resources – i.e., the so-called "water-energy nexus". Water and energy are intimately intertwined; water and wastewater utilities use up to 6% of regional electricity consumption, and this figure is likely to be larger in water-stressed regions relying on desalination processes to provide potable water. The lack of insight into how energy and water are interacting can result in illogical outcomes premised on noble incentives–e.g. water utilities often offer rebates for water conservation blind to consideration of the energy costs required for conserving that gallon of water. This underscores the necessity for a more holistic consideration of water/energy management. However, calculating these crossover effects (i.e., the energy intensity of water treatment and reuse) has been a challenge to accurately perform due to the involvement of several convolved factors in complex water supply networks under numerous physical, operational, technological, environmental, regulatory, and equity constraints.[1]

On the horizon is a revolution in water management. This is in recognition of two accelerating trends: 1) increased aridity and water scarcity across large swaths of the continental US, and 2) growing energy intensity of the transport, purification, and delivery of water due to the projected increase of water demand. According to the International Energy Agency, by 2035, energy and water consumption will increase by 35% and 85%, respectively, thereby maximizing the stress on our finite water resources and rigid water infrastructure. The inextricable link between water and energy sectors requires us to elasticize their connection with computational dowsing rods to timely inform each other with closed-loop feedback and dynamically shifting instantaneous consumption rate economically. A thorough understanding of the spatiotemporal distribution of the energy and carbon footprint intensity of water supply systems is thus key to build a decision-support platform for managing the water supply practice at low energetic, operational, and environmental costs. Recently, several models have been proposed, some of which integrated price-based and incentive-based demand response (DR), to sustainably utilize and manage resources in the power and water sectors.[2-9]

To pave the way forward, in the current issue of Energy and Environmental Science, Liu and Mauter develop a self-learning forecasting model to optimize delivery and utilization of water in real-world scenarios.[10] Their work ambitiously proposes a new metric for quantifying the embedded energy of the water delivered to consumers - the "marginal energy intensity" (MEI). They develop not only a theoretical description of MEI which accounts for both the water and energy resources, but also apply this framework to a real-world water distribution network (WDN) in Kentucky, US, and follow this through to make policy and pricing recommendations. In essence, they quantified the daily average MEI of the base case water distribution network, and inspected the fluctuation of total MEI values with the hourly water consumption rate at consumer nodes (i.e., demand, D), electricity-price-governed pumping schedule (EP), pipe roughness (R), and target percentage of daily water injection through the furthest injection points (I3). Results show that transmission- and distribution-associated components play a critical role in total MEI, and that daily average MEI values are insensitive to changes in water demand and electricity-price-governed pumping schedule, but are highly sensitive to pipe roughness (R) and the target fraction of daily water supply from individual source (I3) (Fig. 1).

This work is ambitious in scope - it proposes a skeletonized "toy physics" model of water and energy that we analogize to an electrical circuit diagram (Fig. 1A). Complex water distribution networks (WDN) can then be analyzed as sources (external voltage), transmission losses (resistances), injection points (circuit elements), tanks (capacitors), and consumers (work across a load). The elegance of this approach is that it is intrinsically scale-free and it can, in principle, work as well for 334 nodes for a WDS in Kentucky as it can at the county level, or state level - and allow for interoperability and coordinated management for WDS networks across county or state lines. Another appealing aspect of this scale-free approach is that each of the "water circuit elements" can be assigned a time-dependence which captures predicted temporal fluctuations and co-correlations in water/energy use that other models must ignore. This naturally ensures that non-intuitive correlations are captured - e.g. at certain times of the day, electricity prices will be high, and water will be drawn from tanks (capacitors) instead of pumped; and these events can be temporally linked yet spatially distant depending on local transmission loss differences (resistors). This is similar to actively reducing the external voltage in a circuit and having energy be drawn from the capacitors - the water and energy flows are naturally correct within the network for any set of imposed conditions.

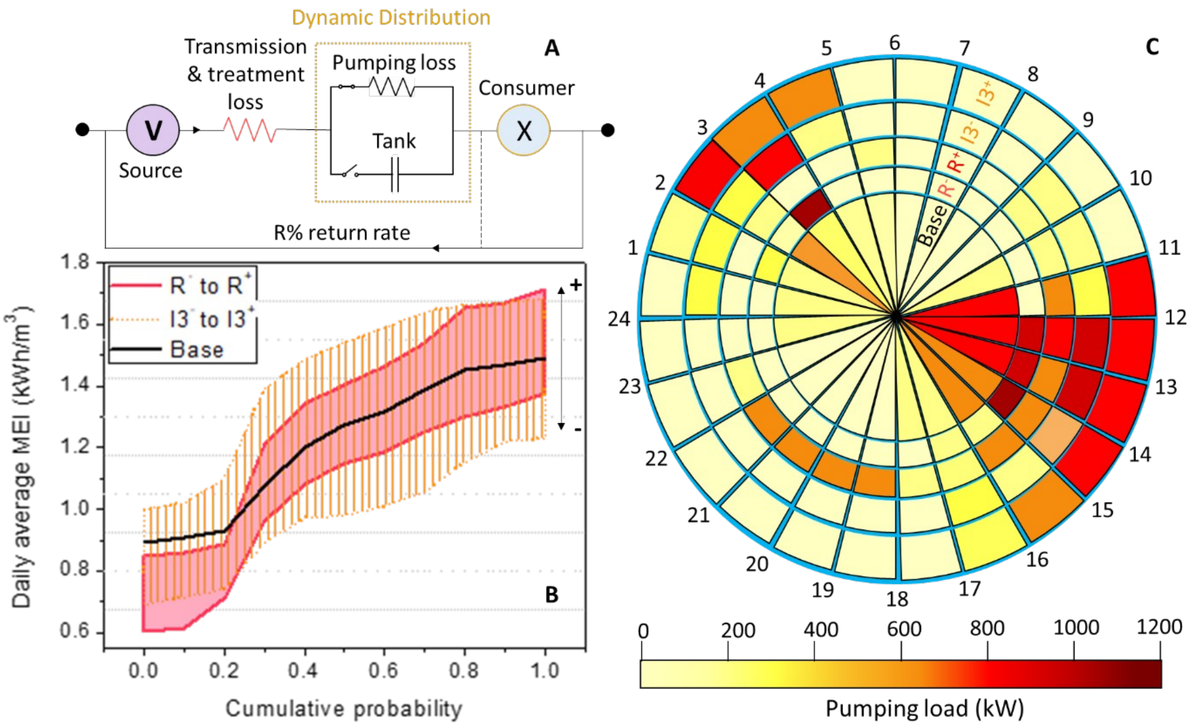

Figure 1- A - An electrical-circuit-analogized concept for the MEI accounted for energy consumed in water transmission, treatment, and distribution; B - Distribution of daily average MEI of consumer nodes in two scenarios in which the MEI values are highly sensitive to (i.e., R^- to R^+ are scenarios where the pipes roughness is decreased or increased by 50%, and $I3^-$ to $I3^+$ are scenarios where the target percentage of daily water injection through I3 is adjusted from 50% in the base case to 30% or 70%; and C – Concentric circle profiles showing clockwise hourly load profiles of the optimal pumping schedules in the base case (the innermost circle) and in the two scenarios (outward circles) – i.e. pipe roughness (R^- to R^+) and water injection capacity through I3 ($I3^-$ to $I3^+$), respectively.

However, much like circuit analysis, the MEI model comes with a set of assumptions that must hold for the framework to prove valuable in real-life applications. One core assumption is that the length- and time-scales for operation are sufficiently fast and discrete compared to the tanks, consumers, injection points, etc. themselves. This recapitulates the fundamental “lumped element” assumption of such circuit diagrams. For example, if the tanks connect to more than one consumer, and the rate of feed to the consumers is different, then it throws the model off. This could be the case if there were significant asymmetric water leakage across the WDS. Further, it is unclear how well the assumptions of linearity (e.g. of mixing) and ideality (e.g. mechanical pumps exhibit load-dependent nonlinearities) will impact networks on larger scales. The authors address several of these concerns in the article by positing intervention of human operators on WDS leakage events, and through clever use of a genetic algorithm which buffers the need to have accurate, time-dependent data on the energy needed to fill the tanks.

The Liu-Mauter model elegantly reveals these embedded water-energy costs, and allows for better stewardship of both resources. For example, their approach could enable water utilities to greatly enhance the energy and carbon impacts of water conservation resources at the same level of financial investment. Further, the theory itself lays a foundation for more advanced models to be built as global/universal platforms for various scenarios. One envisions increasing the potency of the model by further expanding the matrix of parameters under multidimensional constraints (e.g. physical, operational, technological, environmental, regulatory, and equity). The present model is a substantial advance, and can be expanded to more fully represent the full urban water network. Treatment methods, seasonal variability, climatechange-induced weather fluctuations, demographic conditions, consumer behaviors, and non-conventional waters sources, especially streams that tend to clog the pumps and impact pumping efficiency and their life-cycles, are not included in current assessment. Ultimately, for MEI to be relevant, it must provide genuine savings on energy and water consumption - this is yet to be determined for this framework - and be capable of interacting with both centralized and decentralized data networks, and robust to differences in the accuracy of the data provided. Another avenue in which this work can grow and thrive is through the implementation of the tools of machine learning and artificial intelligence. These tools are rapidly evolving and have had great success in making more accurate predictions and decisions in complex, highly ramified and interconnected networks.

The concept of the energy intensity of the water supply is an exciting and comprehensive one, impressively conceived from the tools of physics, but with the potency to inform local water policy. Additionally, this type of approach should inspire other dual-mode types of networked analyses to better inform policy and stewardship decisions - why is there no real-time, self-optimizing carbon intensity of electricity framework model to guide decisions on electricity at the hourly and regional scale while minimizing carbon emissions?

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