Deep learning for pump scheduling

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Keywords : *mixed integer nonlinear programming, deep learning, water networks*

1 The pump scheduling problem

In a water distribution network, the pump scheduling problem is to plan the pumping operations within a discretized horizon $\mathcal{T} = \{0, 1, ..., T - 1\}$ to minimize the electricity cost while meeting the forecast consumption at each demand node and satisfying physical constraints. This optimization problem includes integral decisions (pump on/off status) and nonconvex constraints (pressure-flow nonlinear relations), so it can be modeled as a nonconvex mixed integer nonlinear program (MINLP). At each time step $t \in \mathcal{T}$, the pressure-flow equilibrium through the network is governed by the demand at the service nodes and the levels/pressures of the storage tanks. Then, the decision-making at one time step is propagated through water level in the tanks to the other time steps. In light of these facts, the tank levels can be seen as the bottleneck of the problem. Finding high-quality solutions to the pump scheduling problem, or even any feasible solution, is extremely challenging. Some heuristic approaches were introduced, mainly evolutionary metaheuristics. They usually rely on hydraulic simulation to tackle the nonlinearities accurately, but relax and penalize storage capacity excess. Alternatively, the other end is to take leverage from the MINLP formulation. Mathematical programming approaches usually rely on MILP approximations or relaxations, and look for a best compromise between accuracy and complexity.

In this study, we explore an alternative approach to efficiently handle the intricate dynamics of this problem. As, in practice, pump scheduling is done on a daily basis, it is reasonable to assume that for a given network, operators have access to a significant amount of pre-solved instances, each characterized by demand and tariff profiles and a corresponding (sub-)optimal solution. This collection of data encourages us to devise a data-driven approach to the pump scheduling problem. Recently, machine learning-based optimization algorithms have absorbed lots of attention. Learning models can be employed to directly approximate the optimal solution, an approach categorized as end-to-end learning [1]. For problems with hard constraints, the approximated solution derived from the learning model violates the original constraints of the problem, requiring a post-processing recovery phase to retrieve feasibility. We propose a hybrid approach comprised of machine learning and a decomposition at the post-processing stage to recover feasibility (see *Demassey, Sessa, Tavakoli: Une méthode des directions alternées pour le pilotage des systèmes non-linéaires avec stockage (Roadef 2024)*).

2 Deep learning with diversification and scaling

At the post-processing stage, we apply a variable splitting approach to decompose the problem, by iterating over two subproblems: initially fixing the tank levels and finding the best configuration and at the second subproblem fixing the configuration and then recomputing the levels of the tanks.

Contrarily to end-to-end learning and to match this post-processing algorithm, our deep learning model predicts the (real-valued) tank level profiles instead of the binary scheduling decisions. We first propose to develop a CNN-LSTM architecture, adept at capturing local patterns and temporal dependencies from input data comprising tariff and demand profiles. This model effectively maps these inputs to the corresponding outputs (the tank level profiles), laying the foundation for our solution.

Building upon this, we introduce a second, physics-informed, model, by integrating a continuous surrogate model with the existing CNN-LSTM architecture. This advancement allows for the approximation and incorporation of the integer and nonlinear constraints. It enhances the ability of the data model to conform to physical realities.

Both models utilize Monte Carlo dropout [2] to diversifying the search space and consequently increasing the chance to end up to a feasible solution at the post-processing stage.

Finally, a significant challenge in supervised learning framework is to get a data set to train the model. If no history is available, then it requires getting a solution of the pump scheduling problem for each data input. As the length of the horizon T increases, together with the model accuracy, it becomes impossible to acquire optimal or even feasible solutions. To address this, we develop a novel scaling method. Our learning model is first trained on a lower resolution, and much easier, version of the problem (e.g., $T = 12$). It is then applied to actual higher resolution instances (e.g. with $T = 24$ or 48), simply by interpolating the 12-step predicted solutions. Following this, our decomposition algorithm takes over, refining the interpolated solution to retrieve a feasible solution for the high-resolution scheduling problem.

3 Preliminary results

We have generated instances from 6 years empirical data for the *van Zyl* (VZ) water network. To find the (sub-)optimal solution of each instance with $T = 12$, a branch-and-check algorithm is run with a preprocessing suggested in [3]. For higher resolution instances ($T = 24$ or 48) the tree search can be too time-consuming. 50 instances were selected as the test benchmark each deviates from the other in demand and tariff profile. The performance of the hybrid algorithm (**HA**) (CNN-LSTM+decomposition) with different penalty parameters ($\rho \in \{2, 50\}$) in the decomposition algorithm is compared with branch-and-check with and without preprocessing (BCpre and BC), in finding a first feasible solution.

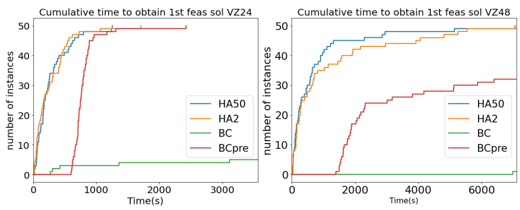

FIG. 1: CPU time to a first feasible solution over 50 test instances for $T = 24$ and $T = 48$

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