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Abstract:

In order to improve the reliability and performance of its hydroelectric fleet, EDF (Électricité De France) seeks to optimize the maintenance scheduling of the components of hydroelectric power plants. In this work, we address an idealized maintenance scheduling optimization problem. We consider components of hydroelectric power plants such as turbines, transformers or generators and we study a system of a given type of components that share a common stock of spare parts. Over time components experience random failures that occur according to known failure distributions. The goal is to find a deterministic preventive maintenance strategy that minimizes the expected cost depending on maintenance and on the occurrences of forced outages of the system. The numerical experiments should involve systems constituted of up to 80 components. For each component and each year on a horizon of 40 years we want to decide whether to perform a preventive maintenance or not. This leads to an optimization problem with 3200 decision variables.

The expected cost of a given maintenance strategy is estimated with a blackbox code. We compare two optimization techniques that are adapted to this framework, namely EGO (*Efficient Global Optimization*) [5] based on kriging techniques and a direct search technique called MADS (*Mesh Adaptive Direct Search*) [1]. These two algorithms are compared on the benchmark COCO (*COmparing Continuous Optimizers*) [4]. MADS turns out to be more efficient than EGO on this benchmark and is applied efficiently on industrial systems with up to 10 components. However, the problem on 80 components is too large for a direct application of blackbox algorithms.

Given the structure of the industrial system, a natural idea is to decompose the global maintenance problem into independent subproblems on individual components. To apply a decomposition scheme, a modelling effort is necessary to express the dynamics and the cost generated by the system. We can write a global maintenance optimization problem:

$$\begin{aligned} \min_{(\boldsymbol{X},\boldsymbol{S},u)\in\mathcal{X}\times\mathcal{S}\times\mathbb{U}} \ & \mathbb{E}\Big(\sum_{i=1}^{n} j_i(\boldsymbol{X}_i, u_i) + j^F(\boldsymbol{X})\Big) \\ \text{s.t. } & \Theta(\boldsymbol{X},\boldsymbol{S},u,\boldsymbol{W}) = 0 \ . \end{aligned} \tag{1}$$

where $\boldsymbol{X}_i = (\boldsymbol{X}_{i,t})_{t\in\mathbb{T}}$ and $\boldsymbol{S} = (\boldsymbol{S}_t)_{t\in\mathbb{T}}$ are random vectors representing respectively the state of component $i \in \mathbb{I} := \{1,\dots,n\}$ and the level of stock through the study period $\mathbb{T} = \{1,\dots,T\}$. The deterministic maintenance strategy for component i is represented by $u_i = (u_{i,t})_{t\in\mathbb{T}}$. The random failures of the components are modelled by the noise $\boldsymbol{W} = (\boldsymbol{W}_{i,t})_{(i,t)\in\mathbb{I}\times\mathbb{T}}$. The term j_i gathers the preventive and corrective maintenance cost for component i and j^F is a non-additive forced outage cost. Finally, Θ is the dynamics of the system and is coupling the components and the stock. The non-additive part of the cost and the coupling in the dynamics prevent from directly splitting the original problem into independent subproblems.

We resort to the Interaction Prediction Principle (IPP) [6] to bring down the resolution of the original problem to the iterative resolution of a decomposable auxiliary problem. At each iteration,

the auxiliary problem breaks down into independent low-dimensional subproblems on a single component, allowing for parallelization. A coordination step is then performed to ensure that the concatenation of local solutions leads to a global solution. The subproblems are solved with the blackbox algorithm MADS which is efficient on low-dimensional instances.

With our modelling, the optimization problem is a mixed-integer problem. As decomposition-coordination methods are based on variational techniques, we provide a continuous relaxation of the system. Relaxation parameters have an important influence on the performance of the decomposition method. To choose these parameters, a sensitivity analysis is performed. The algorithm is executed multiple times on a small system with relaxation parameters drawn using an optimized Latin Hypercube Sampling [3]. A Morris method has also been tested to measure the effect of each individual parameter on the performance of the optimization. However, no clear conclusion could be derived from this analysis. Hence, for the 80-component case, we run the optimization with the parameters that give the best performance on the small system.

On the test case with 80 components, the decomposition algorithm outperforms MADS applied directly on the whole system: the expected cost is improved by 11% compared to MADS. The resulting maintenance strategy performs fewer preventive maintenance than the one found by MADS without degrading the reliability of the system.

The main contributions of this work can be summarized as follows:

- Modelling of an idealized system and formulation of a maintenance optimization problem.
- Implementation of a decomposition-coordination scheme on a relaxed system and coupling with the blackbox algorithm MADS to solve the subproblems. To our knowledge, the Interaction Prediction Principle has not been applied before for a maintenance problem.
- The IPP is a particular case of the Auxiliary Problem Principle (APP) [2]. Theoretical results exist for the convergence of algorithms based on the APP in Hilbert space. A work is on progress to generalize some results on the stochastic APP to the Banach case.

References

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Short biography – I hold a degree in general engineering from Ecole Centrale de Lyon and a Master in Applied Mathematics from the University of Cambridge. My PhD is funded by EDF as part of the AMPH project (Asset Management for Hydraulics) whose goal is to increase the reliability and performance of the hydroelectric fleet. My PhD aims at designing a method for the maintenance optimzation of large systems of components of hydroelectric plants.