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T. Bittar
CERMICS, Ecole des Ponts ParisTech / PRISME Department, EDF R&D

Supervisor(s): J-Ph. Chancelier (Ecole des Ponts ParisTech) and J. Lonchampt (EDF R&D)

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Adress: 6 quai Watier, 78400 Chatou, Batiment S, Bureau S211

Email: thomas.bittar@edf.fr

Abstract:

EDF (*Electricité De France*) is a world leader in electricity generation and manages a large number of industrial assets. An industrial asset can be any physical installation managed by the company (a hydroelectric plant for example). In order to ensure effective and reliable electricity generation, the exploitation of these installations must be optimized. This task falls into the field of industrial asset management. For a given asset, several management strategies can be defined. More precisely, we focus on maintenance strategies that consist in setting up rules for the maintenance of components of a physical system. These strategies represent investments for the company. The goal of asset management is to provide indicators for decision support taking into account all technical and economic dimensions throughout the life of an asset, ensuring that the best investments are done are the right time.

In this work we consider a physical system with components sharing a common stock of spare parts. The performance of a maintenance strategy is quantified with an economic indicator: the NPV (*Net Present Value*). The NPV is the difference between the cost generated by a reference maintenance strategy and the evaluated maintenance strategy. Hence a positive NPV means that the evaluated strategy is better than the reference one. As the costs depend on random failures that can happen during the life of a component, the NPV is itself a random variable. EDF has developed the software VME (*Valorisation Maintenance Exceptionnelle*) that uses Monte-Carlo simulations to estimate the distribution of the NPV. We denote by $j(u, \omega)$ the output of one simulation, which is the NPV for the maintenance strategy u with the realization ω of the random variable W modelling the dates of failure of the components. The performance of a given maintenance strategy can then be quantified by computing an estimation of the risk measure we consider on the NPV (expectation, α-quantile, ...). Here, the risk measure we use is the expectation $\mathbb{E}(j(u, W))$, i.e. the best maintenance strategy is the one which leads to the highest expectation for the NPV.

VME is therefore able to evaluate the performance of a given maintenance strategy, however it is not possible to do optimization with the software in order to find the best maintenance strategy

$$u^\star \in \arg\min_{u \in U} J(u) \text{ where } J(u) = \mathbb{E}(j(u, W)) \tag{1}$$

where U is the set of admissible maintenance strategies. Solving this optimization problem is the goal of this work.

The code VME is considered to be a blackbox: given an input maintenance strategy u it outputs an estimation $\hat{J}(u)$ of $J(u)$ but we have no access to the gradients of J, they are in fact not even necessarily defined. Moreover the evaluation of the objective function J is noisy as the Monte-Carlo method only gives estimations of the expectation. Finally, for large systems, we also need to take into account that one function evaluation, i.e. the computation of $\hat{J}(u)$ for one given $u \in U$ is expensive in computation time. This is due to the fact that we need a large number of Monte-Carlo simulations for one evaluation of J as the variance of the NPV $j(u, W)$ is large.

First, we compare two optimization techniques that are adapted to this framework, namely EGO (*Efficient Global Optimization*) [4] based on kriging techniques and a direct search technique called MADS (*Mesh Adaptive Direct Search*) [1]. At each iteration, EGO uses a metamodel of the code to evaluate the objective function at a promising point for optimization and updates the metamodel accordingly. MADS looks for evaluation points on a mesh which is updated at each iteration depending on the outcome of the evaluation. The rules for updating the mesh and choosing the directions of the search for evaluation points ensure convergence to a local minimum. These two algorithms are compared on the COCO (*COmparing Continuous Optimizers*) platform [3], which is a benchmark designed to assess performance of blackbox optimization algorithms. MADS turns out to be more efficient than EGO on this benchmark.

However, neither MADS nor EGO can tackle directly the optimization of maintenance for large systems as the dimension of the problem becomes too large. A methodology based on a decomposition-coordination method and the more general framework of the auxiliary problem principle [2] is then proposed to split the global optimization problem into subproblems of smaller size. Typically, we want that a subproblem only involves optimization with respect to one component only or the stock. An iterative algorithm consisting of the resolution of the subproblems followed by a coordination step between all local solutions is given. The appeal of this technique is that each subproblem can be solved by any method. Here the low-dimension of the subproblems will make them adapted to the use of MADS. The subproblems can also be solved in parallel as they are independent thus reducing the computation time.

Numerical tests are yet to be performed on a toy system of two components sharing a common stock of spare parts. If successful on this small case, the optimization for the case of a large number of components should also be tractable as it just results in more small subproblems to be solved at each iteration.

References

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Short biography – Before starting my PhD I obtained 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. The main aspects of the project cover the evaluation of the risk of failures of materials and the determination of robust maintenance poclicies. My PhD fits exactly in the latter category as it aims at optimizing maintenance for systems with a large number of components.