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Development of a shape optimisation module for TELEMAC-2D: application to the excavation of a reservoir

Development of a shape optimisation module for TELEMAC-2D: application to the excavation of a reservoir

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Abstract – **Reshaping part of the riverbed is sometimes considered as a solution to prevent issues such as risks of flooding or reservoir capacity decrease. Searching for the best compromise between gains and excavation costs by testing a diversity of scenarios can be time consuming, with no insurance that the optimum solution is found.**

The search for an optimised shape can however be automated using optimisation tools. A shape optimisation python module is here developed to facilitate and strengthen the determination of the best riverbed shape, for TELEMAC-2D studies. It includes the OptimStudy class, which handles the whole shape optimisation process, and offers different optimisation strategies.

The OptimStudy class was used to optimise the excavation in a reservoir. The new shape of the reservoir was defined using 5 parameters: the bank slope, the channel width, and 3 parameters that define the evolution of the bathymetry in the centre of the channel.

An experimental design (by using optimised Latin Hypercube Sample method) was first conducted to explore the parametric field. The analysis of the results allowed to appreciate the relative influence of the parameters and to locate the ranges of the parameters that minimise a cost function. This offered the possibility to reduce the complexity and the extent of the investigation for the optimisation. The results of the experimental design also provided important information about the magnitude and variations of the cost function in the parametric field, which was used to balance their relative importance in the global cost function defined for the optimisation.

An excavation optimisation was then performed using the 3DVAR algorithm of the ADAO module. This work provided a feasible solution to prevent overflow risks while minimising excavation costs.

Keywords: channel shape, optimisation, TELEMAC-2D, PYTHON, ADAO.

I. INTRODUCTION

Sediment deposits in channels and reservoirs often cause water level rise, increasing the risk of flooding and overtopping. Removal of some of the sediments by dredging in the riverbed is sometimes considered, and a trade-off between excavation costs and gains in terms of water elevation and/or reservoir capacity must be decided. Because of the many parameters determining the excavation shape, and the complexity of the cost criteria, searching for the best compromise can be time consuming. The number of excavation scenarios explored is then limited, and the best excavation solution found may be far from the real optimum.

Fortunately, the search for the optimum excavation shape can be automated through shape optimisation algorithms. The field of optimisation has developed significantly over the last decades, thanks to important developments in computational capabilities, data and methods. At EDF R&D, shape optimisation has already been used together with hydraulic models for calibrating a fish passage [1] and for optimising spillways design [2].

A shape optimisation python module was developed to facilitate and strengthen the determination of the best riverbed shape, for TELEMAC-2D studies. The developed scripts include the OptimStudy class, which handles the pre-processing of TELEMAC files, the simulation run, and the cost estimation to be used in an optimisation process.

Section II introduces the developed shape optimisation module. The OptimStudy class was used to optimise the excavation in a dam reservoir. The results of this example are presented in section III. Eventually, section IV highlights future directions of development for the shape optimisation module.

II. SHAPE OPTIMISATION MODULE

A. *Shape optimisation principles*

Shape optimisation consists in determining the shape parameters that minimise a cost function. This automated search implies that the optimised shape can be described by a set of parameters, and that it is possible to associate a cost (flooding risk, economic cost, difference with observations) to any set of parameters.

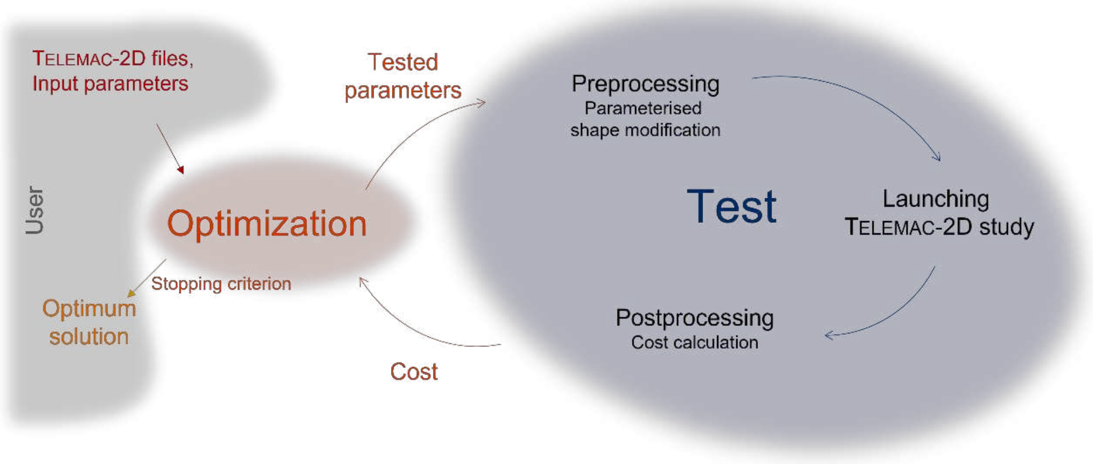

Figure 1. Overview of the organisation of the processes used for shape optimisation.

The optimisation process also relies on the communication between a test procedure (in blue on Figure 1) and an optimisation algorithm (in red on Figure 1). The algorithm prescribes the set of parameters to be tested and analyses its associated cost. From this analysis, a new set of parameters is determined. The test procedure handles pre-processing, model simulation and post-processing, computing a cost for any tested set of parameters.

The user controls the shape optimisation by providing input parameters (the optimisation parameters themselves, their ranges of validity, the files needed to run the TELEMAC-2D study, etc.), including a stopping criterion. When this stopping condition is met, the optimisation process stops and returns the optimum solution to the user.

B. Aims of the developed module

The developed shape optimisation module aims at facilitating the use of shape optimisation for TELEMAC-2D studies. A major part of the development concerned the excavation shape parameterisation and the handling of pre- and post-processing. This was made in a generic way, with the perspective of facilitating their use and adaptation to other shape optimisation problems in TELEMAC-2D studies.

The second axis of development concerned the organisation of the scripts in a tool that, from a limited number of input parameters, manages the whole shape optimisation process. The OptimStudy class was created for this purpose.

Moreover, quality standards (such as Python Pep8) were followed, and the scripts were organised in such a way that future development is facilitated. New test functions, as well as new optimisation methods can be included.

C. Preexisting tools

- Various python modules and scripts already exist for the pre- and post-processing of TELEMAC-2D files. The work presented here relies a lot on these existing tools:

- The pre- and post-processing functions developed for the shape optimisation module use the TelemacFile class from the data-manip module of TELEMAC, and other scripts that enable the modification of TELEMAC variables (bottom friction, bottom, ...) from contour shapefiles.

- The TelemacCas class, from the execution module of TELEMAC, is used to handle the files needed for the TELEMAC-2D simulation.

- A python module has already been developed to study channel erosion [3]. Many of these scripts have been adapted to enable their use in a more general framework, including reservoir excavation.

- Several optimisation tools have been developed by EDF R&D and were integrated to the shape optimisation module [4][5].

D. Overview of the OptimStudy functionalities

The OptimStudy class instantiates an optimisation study object. This object has specific attributes (e.g. TELEMAC-2D steering file, parameters for shape optimisation, optimum solution parameters and cost, name of output files etc.). A diversity of actions (i.e. methods) can be applied to modify these attributes, and are listed below:

(pre-processing)

- Modify the value of a TELEMAC-2D variable (bottom friction, water depth, ...) in a zone defined by a shape contour
- Modify the value of a TELEMAC-2D parameter in a TELEMAC-2D file (steering file, culvert file, ...)
- Modification of the bathymetry

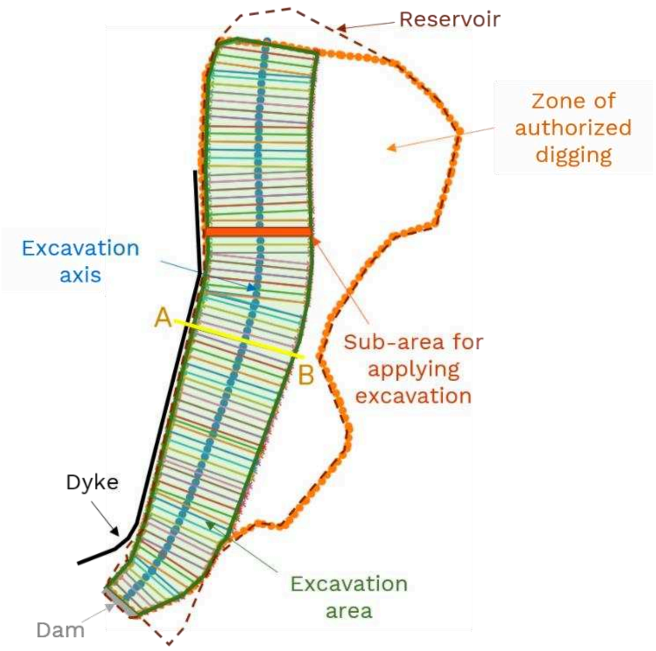

Figure 2. Visualisation of the area where excavation is allowed (orange), hydraulic axis for excavation (blue), and area where excavation is applied (green). The dam and dyke that close the reservoir are also represented here. The parameters taken for this excavation example, also used in Figure 3, 4 and 5, differ from the application optimum solution.

(post-processing)

- Statistical analysis of an experimental design results
- Cost functions (RMSE, volume of excavation, overtopping)
- Data plotting

(optimisation process)

- Running a TELEMAC-2D study
- Test functions, which can be used both for shape optimisation or parameter calibration
- Experimental design build up and run
- Parameter calibration
- Shape optimisation
- Build up and use of a metamodel for optimisation

E. Excavation shape parameterisation

In order to allow its use in a variety of channel shape studies, the excavation shape parameterisation was made generic.

The excavation zone is determined from (1) a polygon (defined in a geographical shapefile), which defines the area where excavation is allowed, (2) the channel hydraulic axis (also defined in a geographical shapefile), and (3) a channel width parameter, that can be varied by the user (Figure 2).

The excavation shape also depends on a banks slope parameter, and the bottom profile at the channel centre is determined from 5 other parameters (Figure 3):

- The bottom value at the most downstream point;
- A series of intermediate points whose distances from downstream determine the locations of slope discontinuities;
- The values of the bottom slope from downstream to the first intermediate point, and then between pairs of successive intermediate points must also be provided;

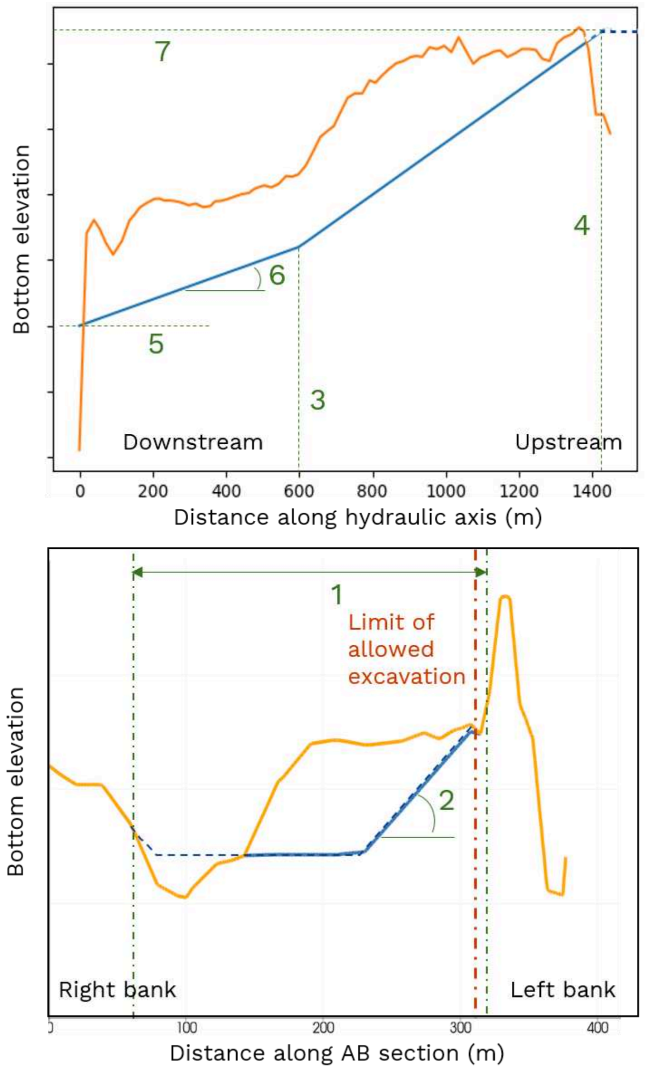

Figure 3. Bottom elevation profiles along the excavation axis (top) and the section AB (see Figure 2) of the reservoir (bottom). The calculated (dashed line) and applied (plain line) excavation are also plotted in blue. Green numbers enable visualisation of the parameters that influence the excavation bottom: (1) channel width, (2) banks slope, (3) Position of an intermediate point, (4) Length of excavation area, (5) downstream bottom elevation, (6) bottom slope in the downstream part of the excavation area (7) upstream bottom elevation.

- The length of the portion of the hydraulic axis where excavation is applied; and
- The bottom elevation value at the most upstream point (optional parameter i.e. default is the actual bottom elevation value at this point);

F. *Shape test-function*

The test function used for shape optimisation follows these successive actions to associate a cost to any set of shape parameters:

- Determine the shape of the excavation from the shape parameters. The excavation zone is divided in several zones (Figure 2);
- Apply excavation to the TELEMAC geometry file (and to the previous computation file), gradually from downstream to upstream. The TELEMAC field *BOTTOM* is modified where the excavation bathymetry is deeper than the actual one (Figure 4);
- Modify the value of the TELEMAC field *BOTTOM FRICTION* where the bathymetry was modified (optional) (Figure 5);
- Run the TELEMAC simulation (includes modifications of the TELEMAC steering file and handling of the TELEMAC files required for the simulation);
- Extract a cost criteria or observation from the results; and
- Combine cost criteria in a global cost value (see an example of global cost-function in section III.A.1).

III. APPLICATION

A. *Presentation of the example case*

As an application, we consider the case of an excavation in a reservoir. The scenario is presented in Figure 2: A reservoir is closed with a dam downstream. On the right bank, a dyke retains water in the reservoir, and is used for flood protection. The value of the flow discharge imposed at the intake of the reservoir is significant enough to cause overtopping on this dyke. The goal of shape optimisation, in this case, is to determine the shape of the excavation in the reservoir that would prevent from risks of overtopping and flooding, while limiting the excavation costs. Two cost criteria are therefore defined: the excavation volume (which is determinant for excavation costs), and the importance of overtopping, estimated as the integral of water depth along the dyke.

For every combination of shape parameters tested during the experimental design and the optimisation process, a TELEMAC-2D simulation is performed, and results are analysed for determining the cost associated with the set of parameters.

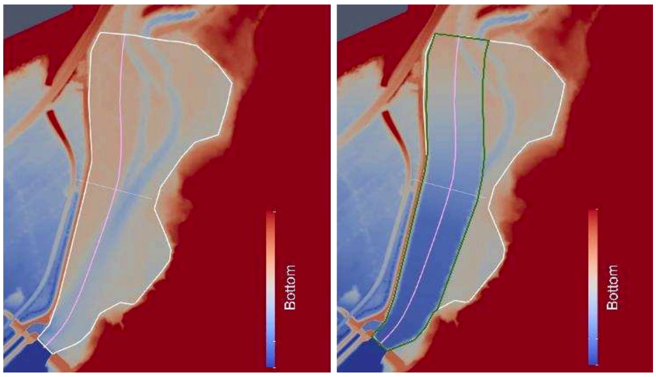

Figure 4. Application of the excavation to the TELEMAC BOTTOM field value. Left: initial bottom elevation, right: bottom elevation after the excavation was applied. The area where excavation is allowed, the excavation axis and the area where excavation is applied are plotted respectively in white, light pink and green.

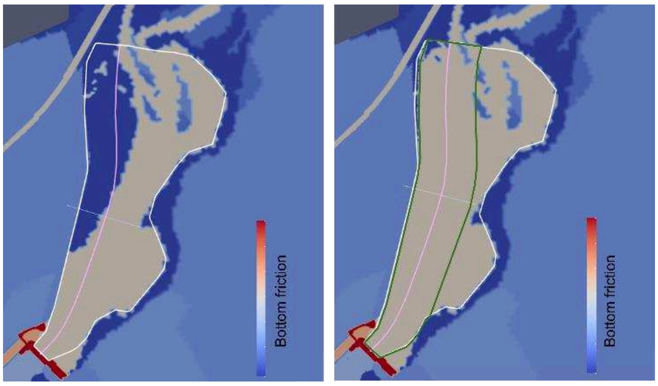

Figure 5. Modification of the TELEMAC BOTTOM FRICTION field value, according to effective excavation. Left: initial bottom friction, right: bottom friction after the excavation was applied. The area where excavation is allowed, the excavation axis and the area where excavation is applied are plotted respectively in white, light pink and green.

The boundary conditions used for these hydraulic simulations are (1) constant discharge flow upstream and (2) constant water elevation downstream. The initial conditions are taken from a previous computation file, which corresponds to the case of a steady state regime within the reservoir, using the original bathymetry (no excavation), with constant flow and constant water elevation set upstream and downstream respectively.

We first chose to use the same entrance flow in this previous computation as in the simulations for testing excavation shapes. However, because of water receding issues on the dyke (see appendix), we preferred to use a low entrance flow for the setup of initial conditions, insuring the absence of non-physical overtopping.

B. *Excavation shape design*

The contour of the zone where dredging is allowed, and the hydraulic axis taken for this study are presented on Figure 2. Among the shape parameters that define the excavation shape (Figure 3), two are set constant: the distance between the most downstream and upstream points (i.e. length of the excavation zone) is maximum, and the bottom elevation value at the most upstream point is set to the maximum of actual bottom values in the upstream reservoir cross section. Using this value for upstream bottom elevation prevents from sharp bottom variations at the edges of the digging area.

The five other parameters are varying over a range of values defined by lower and upper bounds for each parameter: The downstream bottom elevation value is bounded by the geometry of the dam, and by the actual bottom elevation in the reservoir. The channel width ranges from that of the dam to that of the central part of the reservoir. The position of the slope discontinuity is set up inside the middle third of the hydraulic axis, to lower risks of getting torrential conditions in the upstream part of the reservoir. With the same flow regime constraints in mind, the slope in the downstream part of the reservoir ranges from 0 to 2%. The banks slope maximum is set up to respect the stability slope of wet sand and the minimum for banks slope is taken so the defined bottom profile is always reached at the excavation zone centre.

C. Optimisation strategy

We first conduct an experimental design to explore the parametric field. The main goal was to get insights on the variations of the two cost criteria over the set of parameters and on the relative influences of the shape parameters.

A mathematical optimisation is then conducted using the gradient descent algorithm 3DVAR from ADAO (https://pypi.org/project/adao/) [9] to determine an optimal excavation solution.

D. Experimental design

The experimental design (created using optimised Latin Hypercube Sample method [6][7][8]) is composed of 1,000 parameters combinations. Using linux-bash scripts that allow running several TELEMAC-2D simulations on a cluster, the 1,000 experiments were launched in blocks of 20 simulations, with a maximum of 4 blocks launched simultaneously (limitation due to fair use rules of EDF's supercomputers). Each simulation is run on 36 processors in 1h30 (with a mesh containing about 300,000 nodes, and for a simulated time of 3 hours). Running all the experiments took less than one day of computation.

For each experiment, both the excavation volume and the integral of the water depth along the dyke are calculated. The correlation coefficients between shape parameters and these two cost-criteria highlight which parameters have the greatest influence (Table I). The two parameters that have the greatest influence on the magnitude of overtopping are the downstream bottom elevation and the slope in the downstream part of the reservoir. The excavation volume is also greatly influenced by these two parameters, and by the channel width.

Table I Correlation coefficients[9] of shape parameters with cost criteria.

		Cost criteria	
		Excavation volume	***Integral of water depth along the dyke***
Shape parameters	***Channel width***	**0.134**	-0.01
	Banks slope	0.032	-0.074
	Position of slope discontinuity	-0.007	0.035
	Downstream bottom elevation	**-0.384**	**0.945**
	Downstream bottom slope	**-0.712**	**0.254**

[1] [9] The correlation coefficient of two variables is the ratio between their covariance and the product of their mean values

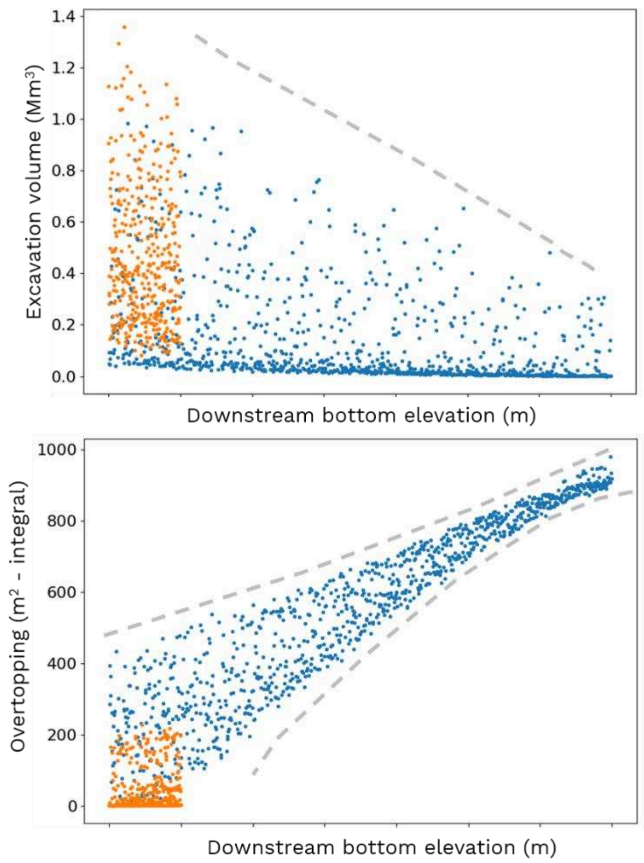

Figure 6. Volume of excavation (top) and Integral of water depth along the dyke (bottom) cost criteria as functions of the downstream bottom elevation. Blue points: initial experimental design, orange points: complementary experimental design. Dashed grey line: possible emplacement of the limit of the area where solutions exist.

On Figure 7 both cost criteria are plotted as functions of the downstream bottom elevation, for the 1,000 experiments. The range of excavation volume values obtained is restricted as the downstream bottom elevation increases, which is consistent with the way the excavation shape is determined. The results also show the strong correlation between downstream elevation and overtopping. The field of solutions seems to be framed by two limits (grey dashed lines) beyond which no solution exists under the given conditions. Besides, the range of downstream bottom elevation values associated with solutions with little or no overtopping is very limited. This parameter is therefore highly constrained by the objective of limiting overtopping.

Results on cost-criteria evolution as a function of the 4 other parameters allowed to constrain the downstream slope parameter values to the 0 – 1% range. The lesser influence of the three other parameters is also confirmed. The ranges of values to be used for optimisation can also be slightly constrained for these parameters.

A second experimental design in the restrained parametric field was launched and complements the results of the first experimental design (orange dots in Figure 6).

Figure 7 shows the excavation volume for each experiment as a function of the overtopping integral. Results point out that there exist excavation solutions that greatly limit overtopping and are associated with excavation volumes of less than 400,000m^3.

E. Optimisation

1) Cost-function

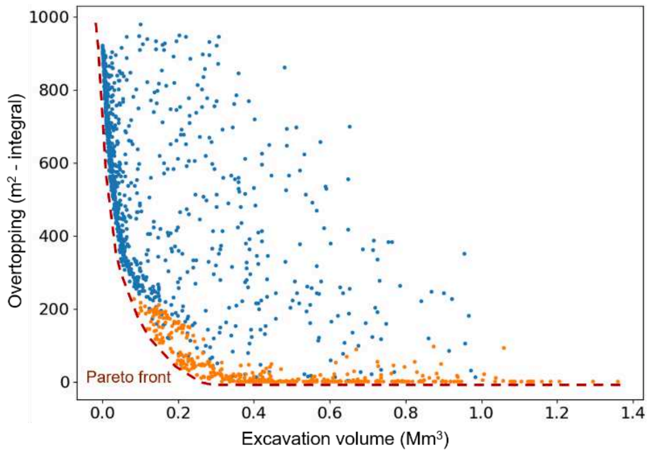

Figure 7. Overtopping cost criteria vs Excavation volume for every experiments of the initial (blue) and complementary (orange) experimental designs. The red line indicates the possible emplacement of the Pareto front of the best compromises.

Figure 7 shows that the overtopping criterion ranges from 0 to about 1,000m^2, while the excavation volume ranges up to 1.4Mm^3.

For this application example, we assume that limiting overtopping is a priority over the cost, and that a value of 1m^2 for overtopping is equivalent in terms of (theoretical) cost to an excavation volume of 1Mm^3. Using such a balance of the cost criteria to design the global cost function (1) favours solutions with limited overtopping. Among those solutions, those with limited excavation volumes are then preferred.

$$Cost = \frac{S_{overtopping}}{c_1} + \frac{V_{excavation}}{c_2} \quad (1)$$

with $c_1 = 1\text{m}^2$, $c_2 = 10^6\,\text{m}^3$

The global cost function defined in (1), is used to calculate the costs associated with the experimental plan solutions. The best solution from the experimental plan is associated with a cost of 0.38 (Table II). We expect to improve these results by using shape optimisation to find an excavation solution associated with an even lower cost.

Table II Best excavation solutions given by the different optimisation strategies.

Optimisation strategy	**Cost (1)**	**Excavation volume (m^3)**	**Overtopping (m^2)**
Experimental design	0.378	~378000	(0)10^{-7}
3DVAR (case 1)	0.498	~484000	1.37 10^{-2}
3DVAR (case 2)	0.357	~357000	(0)10^{-3}
GENOP + Metamodel	0.584	~410	1.73 10^{-1}

The overtopping cost criteria corresponds to the integral of water depth along the dyke.

2) Optimisation method

We use the optimisation algorithm 3DVAR, from the ADAO module [9]. This algorithm minimises a variational function J, which depends on (1) an initial guess on the parameters, (2) an observation (or target), and (3) two error matrices that represent the trust in the initial guess and in the observation. These parameters, and a stopping criterion, are provided by the user.

The 3DVAR algorithm conducts minimisation by a gradient descent process. The variations of the cost function in the proximity of the current set of parameters are evaluated. From this information, the parametric evolution that would minimise the cost function is estimated, and a new set of parameters is selected. The process goes iteratively, until the cost function variations in the proximity of the new set of parameters are negligible, or a maximum number of iterations was reached. This optimisation process usually converges rapidly to an optimum. However, this optimum may not be global, but local.

3) Scenarios

This algorithm was applied to the example case using two different initial guesses. The first initial set of parameters was taken within the parametric area for which overtopping is minimum, using the experimental plan results on parameters influence. The optimisation process is expected to minimise the excavation volume, starting from this initial parametric combination. The second initial set of parameters was taken in the very proximity of the best solution of the experimental plan. The optimisation parameters used for these two optimisation scenarios are given in Table III.

Table III Parameters used for optimisation with 3DVAR (ADAO).

Parameter	Value
Observation (target)	0
Error on observation	1e-4
Error on initial guess	1e3
Increment for gradient calculation	1e-2
Stopping criteria	Cost increment tolerance = 1e-3 Maximum number of iterations = 20

4) Results

Figure 8 presents the evolution of the cost function and of one of the parameters along with the optimisation process (scenario 1). The optimisation process converges rapidly to the solution (in about 10 iterations).

The optimum solutions obtained for both scenarios are presented in Table II. The cost obtained for the scenario 2 optimum solution is 0.36, which is better than the cost of the experimental plan best solution.

The optimum sets of parameters, although corresponding to minima of the cost function, are different. This highlights the presence of several local optima in the cost function. Because of the complexity of the cost function, there is no insurance that the optimum solution obtained for scenario 2 is a global optimum.

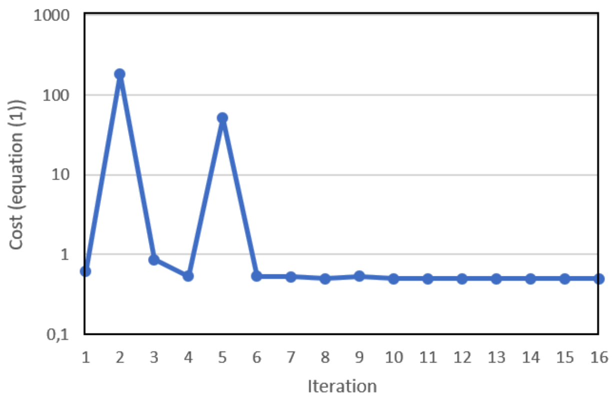

Figure 8. Cost (1) evolution along the optimisation process.

5) Optimum solution

The optimum solution obtained for this study is presented in Figure 9. Overtopping is almost absent, and only concerns the upstream extremity of the dyke. The flow in the reservoir concentrates in the channel that was created by the excavation. At the dam downstream, the flow was increased by 1,000 m^3/s due to the excavation.

The excavation volume associated with this solution nears 360,000 m^3. This information can be used to estimate the economic cost associated with this solution, and compare the dredging scenario with other solutions (e.g. dyke elevation increase).

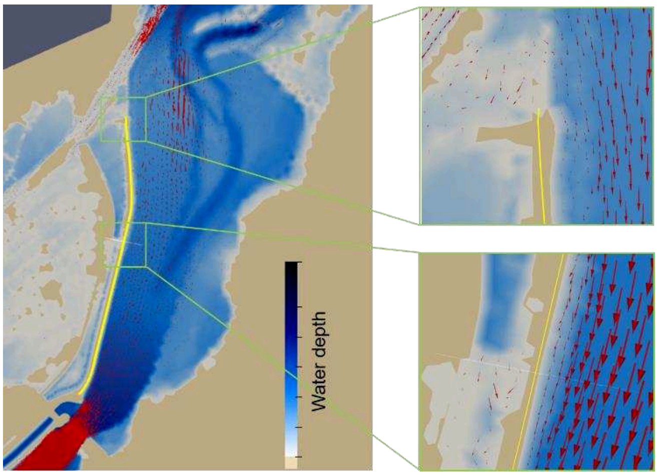

Figure 9. Map of the water depth (blue color scale) and of the velocity (red arrows) for the optimum excavation scenario. The dyke location is indicated with the yellow line.

IV. DISCUSSION

A. Other optimisation strategies

1) Genetic algorithm coupled with a metamodel

The complexity of the cost-function, with several local optima, limits the efficiency of using a gradient descent algorithm (such as 3DVAR) to find the optimum solution. Other optimisation methods exist, including methods that follow the evolution of a population and do not require any information on the cost-function variations, such as genetic algorithms [10].

The advantage of the population-based optimisation methods is its strong efficiency in finding the global optimum of a cost-function. However, they require important computation resources.

A genetic optimisation algorithm (GENOP, developed by EDF-R&D and taken from the Scilab optim_ga module) is included in the OptimStudy class.

To limit the needs in terms of computational resources, the test function, which here includes a TELEMAC-2D simulation, can be replaced by a model of its outputs, i.e. a metamodel. This metamodel is built from a series of experiments for which both the shape parameters and the associated cost are known. It gives an approximation of the cost for any set of parameters in the parametric field, and requires negligible resources.

A metamodel for the application case was built by Kriging from part of the results of the experimental design [11][12]. The remaining experiments were used to test and validate the metamodel. This metamodel was then used together with a genetic algorithm for the search of the optimum solution.

For the application case presented here, we however did not get a better solution using this optimisation strategy. The efficiency of this method was indeed limited here by the complexity of the cost-function variations, that the metamodel did not entirely captured. In particular, the locations of the optima according to the metamodel did not match those of the real cost-function.

These results could be improved by using other cost-functions, and by improving the metamodel build up technique.

2) Multi-objective optimisation

In this article, we applied shape optimisation using a global cost-function that combines the two cost-criteria. On Figure 7, a limit beyond which no solution seems to exist is visible (highlighted by the dashed red line on Figure 7). This limit is the Pareto front of the two cost criteria, i.e. the line regrouping the optimum compromises, according to the importance given to each criterion (e.g. [5]). Obtaining more details on this front would make it easier to arbitrate the choice of the solution that should be implemented to limit overtopping.

Multi-objective optimisation techniques exist and enable the search for the best compromises taking into account several cost-criteria separately (e.g. [5][13]). The Pareto front of the best solutions could be determined using such techniques, and will be included in future developments of the shape optimisation module.

B. Shape optimisation interest for Telemac-2D studies

1) Performances

The experimental design and the shape optimisation using the 3DVAR algorithm both gave very good compromises for the application case. The best solution from the experimental design is close to that obtained from shape optimisation. The fact that shape optimisation only slightly improved the compromise obtained with the experimental plan is linked with two observations:

- A high number of experiments was used for the experimental plan. Moreover, a second experimental design was conducted on a restricted area of the parametric field, where cost optima were expected. The parametric field was therefore well represented, making it possible to find a very good compromise even without using optimisation algorithm.
- Results highlighted that the cost-function variations are complex, and that several local minima exist. In these conditions, the efficiency of gradient descent algorithms in searching for the optimum solution is limited. The best solution obtained here may therefore not be the real optimum scenario.

For the application presented here, shape optimisation initiated from the area where optimum solutions were expected, gave worse results than the experimental plan. This is again tightly linked with the complex behaviour of the cost function and the good precision of the experimental plan. In this case, using a high precision experimental design would have been an adequate strategy for searching for the best excavation scenario. For other shape optimisation problems, the best optimisation strategy could be different, especially if time and computational resources are constrained.

2) Time and computational resources

For the application presented here, only one day was necessary to run the 1,000 experiments of the experimental design (first set of experiments). This was possible due to substantial computational resources available at EDF. With limited resources, the time needed would have been much more important. Contrarily, the shape optimisation process using the 3DVAR algorithm from ADAO, which required the sequential run of 120 simulations in several days but used much reduced computational resources.

For future applications, the choice between shape optimisation and automated experimental design should depend on several criterion:

- Expected precision on the optimal solution
- Available time and computational resources
- A priori knowledge on the cost-criteria variations and amplitude over the parametric field

VI. PERSPECTIVES

Future development will concern the following directions:

- Improvement of the metamodel building method and use.
- Extension of the current tool to enable multi-objective optimisation studies
- Adaptations for TELEMAC models calibration
- Adaptation to other shape optimisation problems.
- Application of the optimisation techniques to other modelling tools.

Last but not least, it should be noted that there are no plans to share this module with the community. Nevertheless, it would be possible to use this work to propose a generic Python Class in TELEMAC to set up this kind of numerical study.

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APPENDIX

TELEMAC receding procedure issue

The initial conditions used for hydraulic simulations were at first taken from an equivalent hydraulic simulation with the actual bottom elevation, at steady state. In these initial conditions, overtopping was present all along the dyke. During hydraulic simulations with a modified bottom elevation, the water levels decreased in the reservoir and above the dyke. For some of the experiments, water levels in the reservoir at steady state were lower than the dyke elevation, even close to the dyke (Figure 10). Water elevation however never reached zero over the dyke (the remaining water depth was a few mm).

In order to get rid of the remaining (non-physical) water at the top of the dyke, the threshold depth for receding procedure was increased from 3 cm to 10 cm, with no success. The solution adopted afterwards was to initiate the hydraulic simulations with much lower water level conditions (corresponding to steady state with a much lower entrance flow).

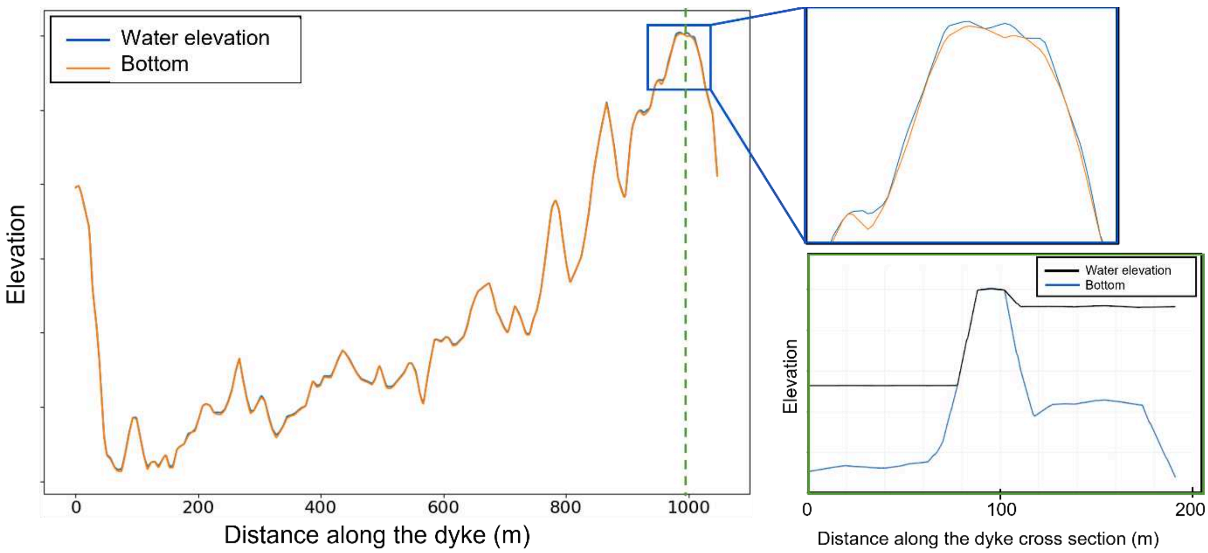

Figure 10. Bottom and water elevation along the dyke (left). Top right: zoom on part of the dyke. Bottom right: bottom and water elevations along a cross section orthogonal to the dyke. The emplacement of the cross section is indicated in the left panel with the dashed green line.