Solving Economic and Environmental Optimal Control in Dumping of Sewage with a Flexible and Parallel Evoluationary Computation

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We solve a state constrained optimal control problem with parallel implementations of an intelligent optimization system based on evolutionary self-learning named Flexible Evolution Agent. The target of the problem to solve is to find the optimal locations of liquid waste dumping sites in offshore waters, so the concentration of a considered pollutant must not exceed a pre-established value, either at a specific distance from the shore or in different protected areas, as can be fish hatcheries. Simultaneously, we also minimize the investment costs such as hydraulic infrastructures. We propose a 3D finite volumes Taylor-Galerkin version for the pollutant concentration simulation. Numerical results with evaluation of performances of the parallel computations carried out are shown.

Economic and Environmental Optimal Control in dumping of sewage

The demand for models capable of predicting the effects of wastewater discharge in coastal areas has increased due to the high rate of coastal population increase, high demand for industrial sites along the coasts and ever increasing beach and harbour activities. The global model integrates the marine environmental quality assessment through waste dispersion and decay model, on the other hand the consideration of multiple outfalls operating simultaneously, and also the cost of waste disposal. A pipeline starts off from each sewage farm or accumulation site, at the end of the pipeline and through one or several diffusers, the sewage is dumped and dispersed in the environment. We try to place physically these outfalls so that the concentration of the pollutant in question does not exceed a pre-established level, either at a specific distance from a boundary or in a subdomain and; simultaneously to minimize the cost of placing in situ the pipelines with theirs respective diffusers.

The problem is a state constrained optimal control, where the position of the outfalls is the control and the state is the pollutant concentration in each point of a 3D domain under study. Moreover, the cost function is non-linear because of the geometric distances involved. In our study the pollutant is taken to be coliforms. The resolution of this problem or similar ones is very difficult using the usual determinist methods, basically because of the complexity of the mathematical analysis due to the state equation modelled with Dirac deltas, and non-convex constraints on the state. Therefore, we consider Evolutionary Computation.

We consider a finite volume implementation proposed by González and Winter (2000) and González (2001), where the governing equation for the pollutant transport have been transformed using a method based on combining a high order temporary development of the pollutant concentration, using Taylor series development, and finite volume method.

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A numerical scheme assessment and a study of the unsteady problem accuracy were developed González (2001). Results from validation test conclude that the numerical solution obtained with this model for the pollutant concentration calculation is very close to the analytical solution. The model does not suffer from false diffusion in multi-dimensional flows, although the velocity vector is not parallel to one of the coordinate directions, as it occurs with many numerical schemas

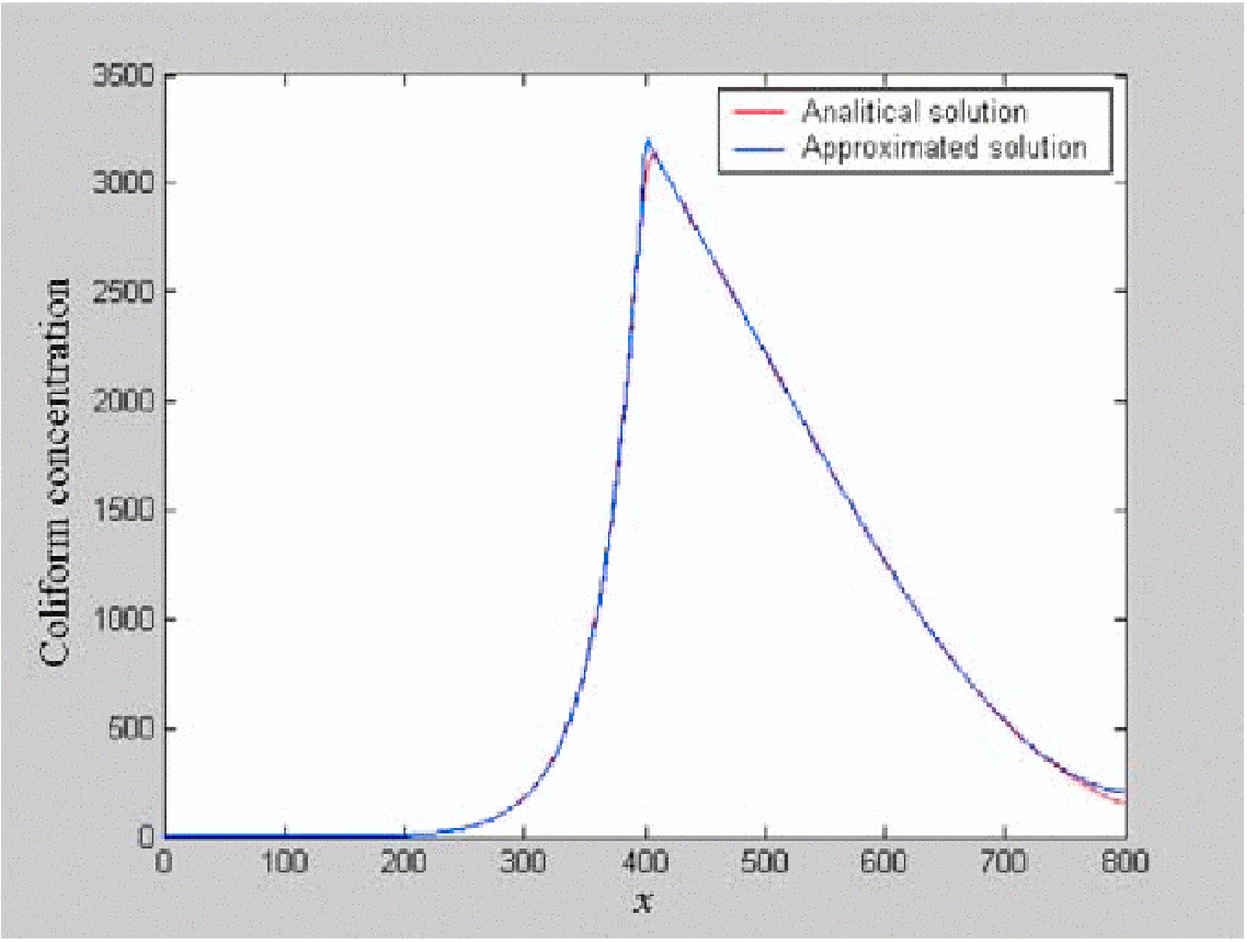

Figure 1. Coliform concentration for 1D test case, t = 15 min

Parallel Computation with Evolutionary Flexible Agent for optimization

The problem of finding economical locations of liquid waste dumping sites, satisfying the water quality requirements for activities and water uses, can be expressed as:

Minimize

$$F_{\cos t} = \sum_{j=1}^{nsf} \left[\sum_{k=1}^{nstretch} G_{jk} + \sum_{i=1}^{ndif} L_{di}^{j} \; C_{dif} + \sum_{k=1}^{nstretch} \delta_k \frac{L_k^j}{d_k} \; C_{anchorage} \right]$$

subject to

$$\sum_{i=1}^{ntotdif} C_{Ai}\left(x^*, y^*, z^*\right) \leq C_A \;, \; \forall \left(x^*, y^*, z^*\right) \in \Gamma^*$$

where

$$G_{jk} = Lz_{jk} Az_{jk} \;\; Hz_{jk} \;\; Cz_k + L_k^j \;\; Ct_k + \left(Lz_{jk} \;\; Az_{jk} \;\; Hz_{jk} - L_k^j \;\; At \;\; Ht\right) \;\; Cc_k$$

Γ^* is a vertical surface parallel to the coast where the pollutant concentration must not exceed a predetermined value, nsf is the maximum number of sewage farms considered, ndif is the maximum number of diffusers per sewage farm, ntotdif is the total number of diffusers and, for each sewage farm j; Lz_{jk}, Az_{jk}, Hz_{jk} are, respectively, length, width and height of the trench in the k-th stretch, d_k is that distance in metres for the k-th stretch, and δ_k is a indicator of this necessity: $\delta_k = 1 \Rightarrow$ it is necessary , $\delta_k = 0 \Rightarrow$ it is not necessary.

Cz_k is the cost/m^3 of digging the trench in the k-th stretch, Ct_k is the cost/m of the pipeline used in the k-th stretch, Cc_k is the cost/m^3 of covering the trench, in the k-th stretch.

C_{dif} is the cost/m of the diffusers and $C_{anchorage}$ is the cost of each anchorage.

$C_{Ai}\left(x^*, y^*, z^*\right)$ is the A pollutant concentration from i-th diffuser at coordinates $\left(x^*, y^*, z^*\right)$

C_A is the A pollutant upper limit specified for the desired water quality.

The cost function F_{cost} is non linear because of the geometric distances involved.

Evolutionary algorithms (EAs) are efficient heuristic search methods with powerful characteristics of robustness and flexibility to solve complex optimization problems (Bäck and Winter, 2001), even as numerical simulation method (Jimenez et al 2001,Winter et al, 2003/4). They have the ability to escape from local minima where deterministic optimization methods may fail or are not applicable. For computational cost, the merit of EAs is that they grow only linearly with problem size if they are well designed, while other methods usually grow exponentially. EAs are easy to be parallelized because they are population-based search methods. Despite their operational simplicity Parallel Evolutionary Algorithms (PEAs) are complex non-linear algorithms with many control parameters affecting both the quality of the search process and their efficacy.

However, the computational performance and efficiency of the EAs are closely related with the introduction of parameters and/or operators adaptation, which are specific for the problem to be solved. They are advanced methods (i.e. see Kee et al, 2001), but normally they only are valid to solve efficiently the problem for which they were designed. Recently, a new, efficient and robust procedure for the optimization of complex problems, is the named by us as Flexible Evolution Agent (FEA), it has been developed in the CEANI Division of IUSIANI (Winter et al, 2001, 2002, 2003), and applied to solve the application treated here, with serial computation (Gonzalez 2001 and Gonzalez et al 2001)

The target of FEA is to get the biggest benefit from the explotation of the stored information, and in addition, to incorporate new procedures to facilitate the internal decision-making to be automatically made in the own optimization process. This Agent has a Dynamic Structure of Operators (DSO), Enlargement of the Genetic Code (EGC) of candidate solutions and uses a Central Control Mechanism (CCM). The DSO enables the use of any of the sampling operators at each step along every optimization run depending on operator's previous contribution to the common task (to get the optimum). EGC includes useful information for the process control included in the CCM. After several implementations, the identification of the sampling operator used to obtain each variable of the candidate solutions has proved to be the most useful information, but only when a simple Probabilistic Control Mechanism (PCM) based on rules IF-THEN-ELSE is used as a CCM. The joint use of the DSO, the EGC and the CCM has permitted the elimination of the crossover and mutation probabilities. The PCM is responsible for reaching a trade-off between the exploration and the exploitation of the search space, which is equivalent to achieving a competitive and cooperative balance among the sampling operators.

For an effective reduction of computation time are demanded PEAs, especially on asynchronous grid computing environments. For a review of PEAs see the book of Erick Cantu-Paz (2000), and solving CFD applications, see B. Galván et al (2003)

In this paper, firstly a Parallel Master-Slaves with asynchronous implementation is considered, where fitness evaluations are distributed among several processors, and as soon as a slave evaluates a candidate solution, it is inserted into the population. When the evaluation of fitness has a very high computational cost, like is our case, it is an efficient method. Also we consider a Coarse-grained Parallel or Distributed EAs model, thus each processor handles a subpopulation by itself, the subpopulations or demes communicate through certain migrant individuals from one deme to another and it controlled by the topology that defines the connectivity between the subpopulations, according to the migration structure chosen. With a good emigration strategy, it can be obtained a fast convergence and it can sometimes be explained as superlineal speedups. We propose a dynamic migrate rate controlling the number of candidate solutions to migrate, and a dynamic migration interval that affects the frequency of the migrations, all under a flexible and intelligent procedure, running a FEA in each sub-population. Also experiences with non-static topologies will carry out.

For both proposed parallel implementations the Parallel Virtual Machine (PVM) message-passing model is used to remote solvers, receive results and to transfer candidates according the kind of implementation.

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