Application of Evolutionary Algorithms for Model Calibration

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ABSTRACT

Calibration of plant specific parameters of a process-based plant model can represent a considerable challenge when observed data are available from multiple environments. Calibration of model parameters can be considered as a search for the optimal set of parameters in a high-dimensional parameter space. An evolutionary algorithm with self-adaptation has been developed and applied to calibrate parameters of the Sirius simulation model for modern wheat cultivars and common ragweed in Europe.

Categories and Subject Descriptors

I. Computing Methodologies::2 ARTIFICIAL INTELLIGENCE:: I.2.8 Problem Solving, Control Methods, and Search::Heuristic methods

General Terms

Algorithms, Performance.

Keywords

Evolutionary optimization, self-adaptation, Sirius, ragweed, EA-SA.

1. INTRODUCTION

Calibration of plant specific parameters for a simulation model of inter-plant competition can represent a considerable challenge when observed data are available for multiple environments because of the problems with genotype × environment × management interactions. Calibration can be considered as a search of the optimal set of model parameters in a high-dimensional parameter space with a complex and computationally expensive function as a criterion for optimization. We demonstrate how an evolutionary algorithm with self-adaptation (EA-SA) can be used to solve this highly complex problem [1-3].

2. METHODS AND RESULTS

EA-SA includes two sets of parameters: fitness parameters, which belong to the domain of the optimization function, and control parameters which control the variation of fitness parameters.

EA-SA {
Initialise $(x, v, \sigma_v, \sigma_l)$(t=0)
Iterate (StoppingRule)
{
$\{(x, v, \sigma_v, \sigma_l)^{i,j}(t), i < k_v\ j < k_l\}$ = CreateOfsprings $\left((x, v, \sigma_v, \sigma_l)(t)\right)$
$(x, v, \sigma_v, \sigma_l)(t+1)$ = Select$\{(x, v, \sigma_v, \sigma_l)(t), (x, v, \sigma_v, \sigma_l)^{i,j}(t)\}$
}
}
CreateOfsprings $\left((x, v, \sigma_l, \sigma_v)(t)\right)$ **{**
for(i<k_v){
$\sigma_v^i = \mathrm{mutate}(\sigma_v)$
$v^i = \mathrm{mutate}(v, \sigma_v^i)$
for(j<k_l){
$\sigma_l^{i,j} = \mathrm{mutate}(\sigma_l)$
$x^{i,j} = x + (\sigma_l^{i,j}\ \xi^{i,j})v^i$ where $\xi^{i,j}$ =rand(C^1)
$(x, v, \sigma_l, \sigma_v)^{i,j}(t) = \left(x^{i,j}, v^i, \sigma_v^i, \sigma_l^{i,j}\right)$
}
}
}

Select {
if($F(x) \le F(x^{i,j})$
{
$(x, v, \sigma_v, \sigma_l)(t+1) = \left(x, v^l, \sigma_v^l, \sigma_l^{l,m}\right)$, where $F\left(x^{l,m}\right) = \min\{F(x^{i,j})\}$
}else{
$(x, v, \sigma_v, \sigma_l)(t+1) = \left(x^{l,m}, v^l, \sigma_v^l, \sigma_l^{l,m}\right)$, where $F\left(x^{l,m}\right) = \min\{F(x^{i,j})\}$
}
}

Mutate(σ) { return $\left(\sigma\, e^{\mathrm{rand}(C^1)}\right)$}
Mutate$(v, \sigma_v^i,)$ { return $\left(\mathrm{norm}(v + \sigma_v^i \mathrm{rand}(C^n))\right)$ }

Figure 1. A schematic representation of a variant of EA-SA used for model calibration.

Although both parameters are changed randomly every step of the search, they converge to the optimum state due to direct selection pressure for fitness parameters and indirect selection for control parameters. Evolutionary algorithms with self-adaptation do not require fine tuning of control parameters during the search in complex spaces, where predefined heuristic rules are unavailable or difficult to formulate [4].

Given experimental data for a single plant at multiple environments, we are looking for a set of plant parameters which gives the best agreement between observed and simulated data. We used the following implementation of EA-SA (Fig 1). The evolving state is described as $(x, v, \sigma_v, \sigma_l)$, where $x \in C^n, v \in$

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$S^n, \sigma_v \in [0,1], \sigma_l \in [0,1]$ $C^n = [-1,1]^n$ and $S^n = \{v \in C^n, |v| =$; x represents a state in a parameter space, v represents a mutation vector for x with scaling parameters σ_v and σ_l. A fitness function F was calculated as weighted differences between observed and simulated values of selected output variables. EA-SA has been successfully tested for many tests functions, e.g. a test function presented on Fig. 2.

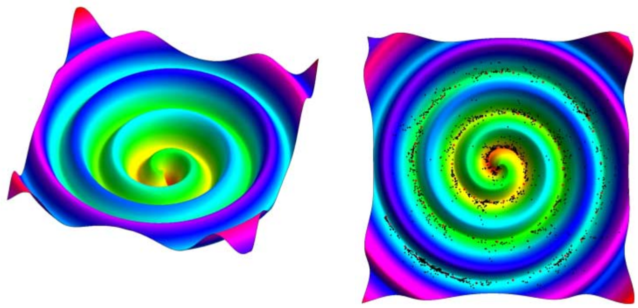

Figure 2. An example of convergence of EA-SA on a test function with minimum at {0,0}.

Sirius is a process-based model for inter-plant competition, which contains approximately 44 plant specific parameters [5]. Some of these parameters can be measured in experiment or their values can be obtained from the literature; the others need to be calibrated. To reduce the dimension of the parameter space for calibration, the cultivar parameters were divided into five independent groups and parameter calibration was performed in several steps. At the beginning, parameters controlling phenology (phylochron, vernalisation and day length responses) have been calibrated; this allowed to predict accurately major phenological events, e.g. flowering.

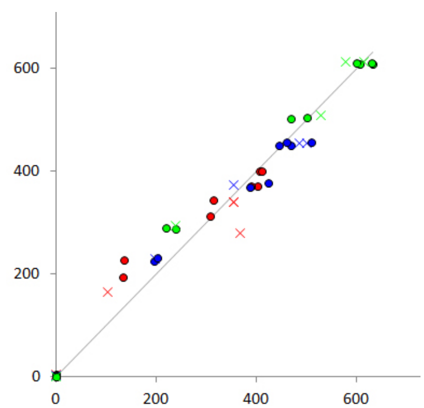

Figure 3. Simulated vs. observed grain yields in in Clermont-Ferrand, France for N experiments in 1994 (crosses are observations used in calibration, circles are observations used for validation; green - high N, blue - middle N, red - low N).

Then, parameters related to canopy and LAI were calibrated, which allowed accurate predictions of intercepted photosynthetic radiation. In the next step, parameters controlling biomass production under non-limited conditions were calibrated. Finally, parameters related to water and N stresses were estimated which allowed predictions of grain yields under variety of managements. The calibration procedure based on EA-SA is incorporated into Sirius automating parameter calibration for different plant species.

EA-SA was tested to calibrate cultivar parameters for modern wheat varieties using several experimental datasets, including a dataset for the nitrogen-use experiment at Clermont-Ferrand, France (1 site × 1 year × 9 N levels, Fig. 3), a dataset from the rain-shelter experiment at Lincoln, NZ (1 site × 1 year × 7 water treatments), and the BBSRC-INRA nitrogen-use experiment dataset (16 cultivars × 4 sites × 3 years × 2 nitrogen levels).

Sirius was also used to predict spatial distribution and pollen production of *Ambrosia artemisiifolia* L. (common ragweed) in Europe in response of climate and land use change as a part of the EU-funded ATOPICA project (www.atopica.eu). EA-SA was used to calibrate Sirius for ragweed, including the eco-physiological parameters that determine the response of different weed life stages to the environment.

3. ACKNOWLEDGMENTS

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