Improving Constrained Glider Trajectories for Ocean Eddy Border Sampling within Extended Mission Planning Time

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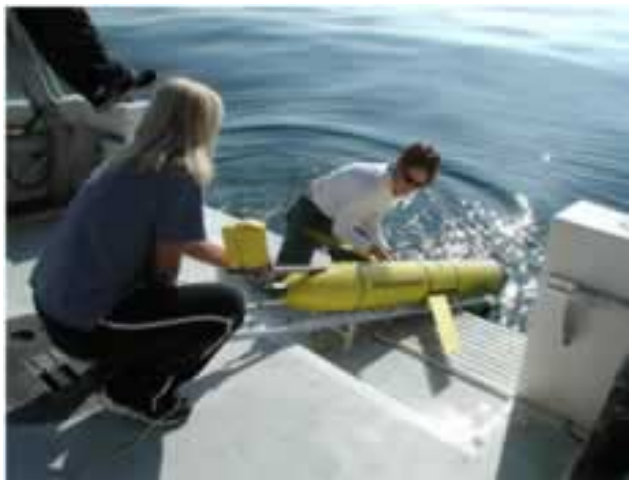
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Underwater Glider: Autonomous, Unmanned, Robotic

- **underwater glider** – navigating sea oceans,
- *Autonomous Underwater Vehicle* (**AUV**)
  $\neq$
  Unmanned Aerial Vehicle (**UAV**)
- AUV Slocum model (expertise in domain of ULPGC, work with J. D. Hernández Sosa)





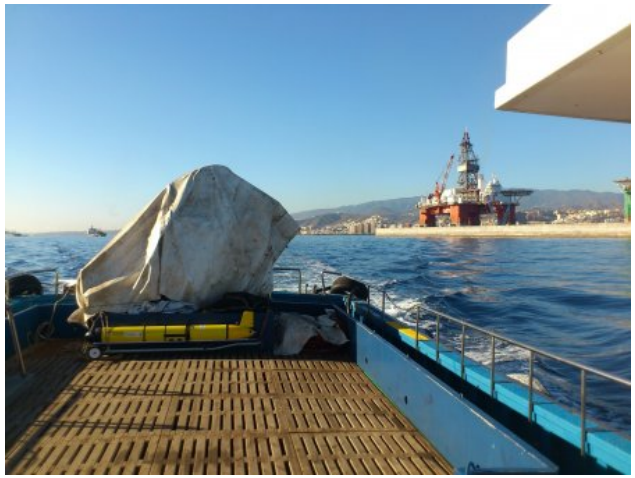


Images:
http://upload.wikimedia.org/wikipedia/commons/e/ed/Black_Hornet_Nano_Helicopter_UAV.jpg
http://upload.wikimedia.org/wikipedia/commons/0/0e/Slocum-Glider-Auvpicture_5.jpg
http://upload.wikimedia.org/wikipedia/commons/d/d2/MiniU.jpg

Robotic Unmanned Sea Glider Slocum G2

- High durability: 25 to 365 days,
- long range 600–1500 km (alk. batt.), 4000–6000 km (Li^+)
  - buoyancy-driven: horizontal 0.35m/s (0.68 knots),
  - 2 knots using propeller.
- Dive to depth 1000 meters, long range, modular,
- integrates sensors of physical and bio/chemical parameters[2]
  - temperature, salinity, dissolved oxygen, turbidity, chlorophyl and sea currents - possible rapid replacement of sensors.







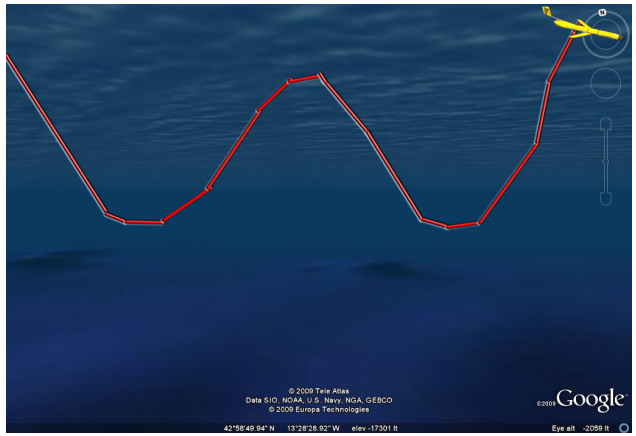
[1] lh6.googleusercontent.com/-Mq308aI1s2g/UHVf4k3uoiI/AAAAAAAACbw/LeiYHXMQRbs/s640/PA060013.JPG

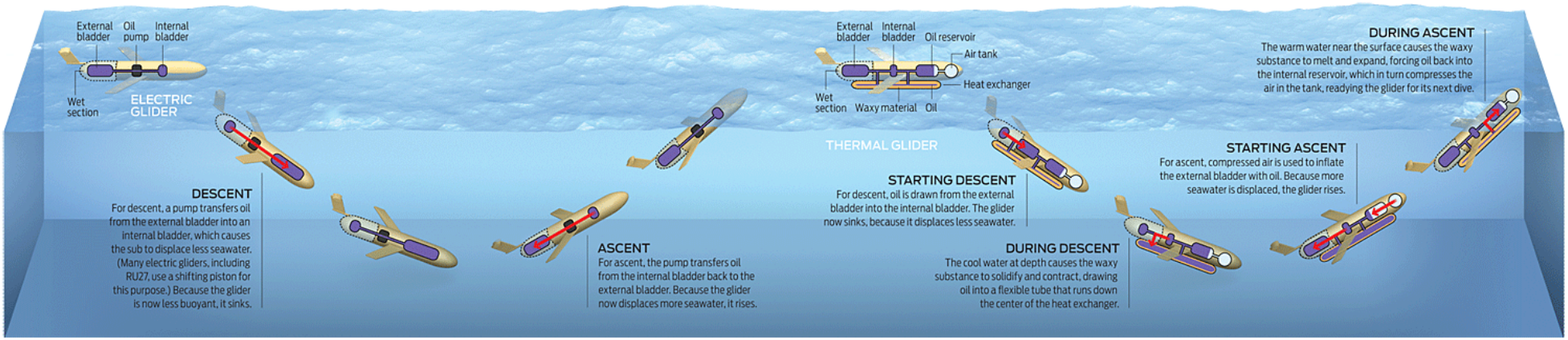
[2] http://www.webbresearch.com/pdf/Slocum_Glider_Data_Sheet.pdf

The Buoyancy Drive and Submarine Probes Usefulness

- Driving "yoyo" uses little energy, most only on descent and rise (pump); also for maintaining direction little power is consumed.

+ Use: improving ocean models with real data,
+ the real data at the point of capture,
+ sampling flow of oil discharges,
+ monitoring cable lines, and
+ real-time monitoring of different sensor data.

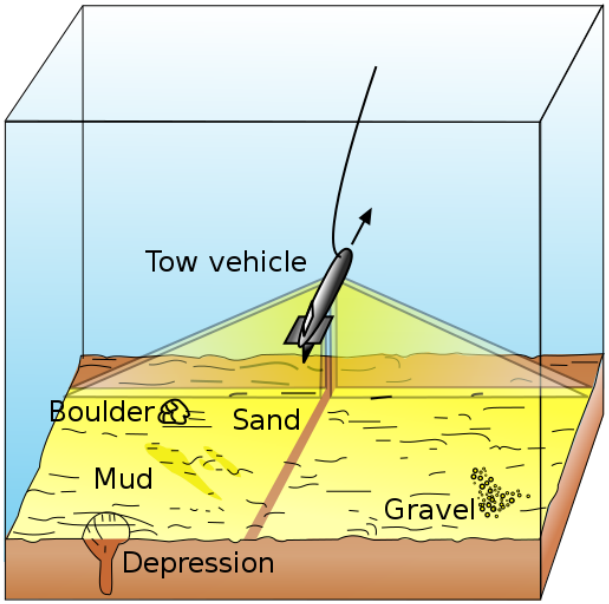


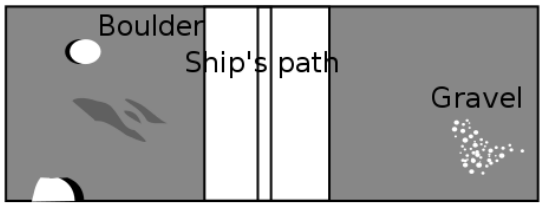


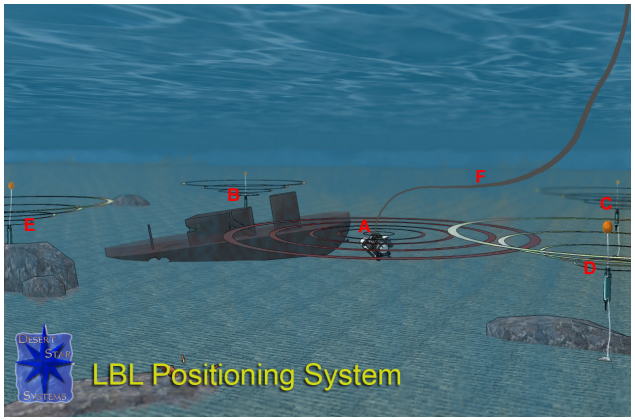
[1] http://www.i-cool.org/wp-content/uploads/2009/11/google-earth-glider-path.jpg
[2] http://spectrum.ieee.org/image/1523708

Satellite Navigation and Autonomy

- Radio waves can not penetrate deep water, GPS signal is cut.
  - During a dive the AUV is autonomous,
  - AUV uses internal sensors for navigation,
    - compass, depth, sonar, relief sonar (mapping seabed[1]), gyroscope, accelerometer, magnetometer, thermistor, conductivity meter.
  - acoustic modem for wireless communication with underwater tied sensors[2].



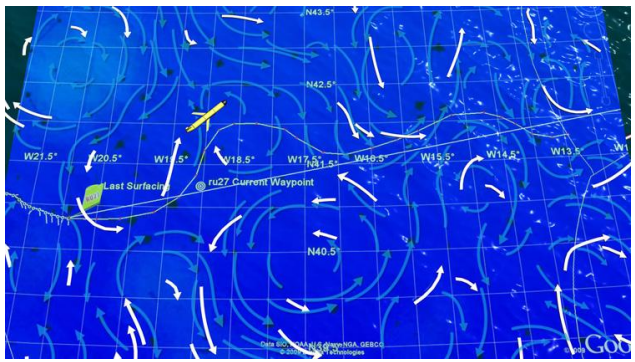


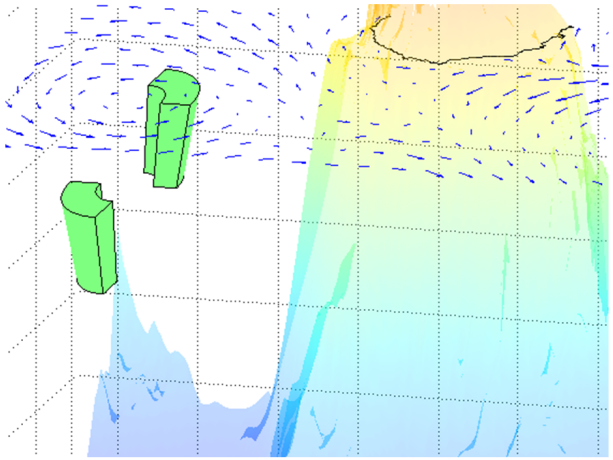


[1] http://upload.wikimedia.org/wikipedia/commons/5/5b/Side-scan_sonar.svg
[2] http://upload.wikimedia.org/wikipedia/commons/a/ad/LBL_Acoustic_Positioning_Aquamap_ROV.jpg
[3] http://www.ego-network.org/dokuwiki/lib/exe/fetch.php?media=img:glider3.gif

Real-time Data Streams about the Environment, Eddies

- **MyOcean IBI** (`http://myodata.puertos.es/`),
- different satellite data about the sea (eg. currents),
- *Regional Ocean Modelling System*: refreshment each 4 hours,
- covers 19° W 5° E / 26° N 56° N, resolution 1/36°, 3 days,
- furthermore: a surrogate currents model in 3D (JD H-S),
  - extrapolation from hourly 2D surface data,
  - computed using 3D interpolation from neighboring points.





[1] `http://ocean.si.edu/sites/default/files/styles/colorbox_full/public/photos/glider_RU27_eddies_extra%20arrows.jpg?itok=pqbU1Vba`

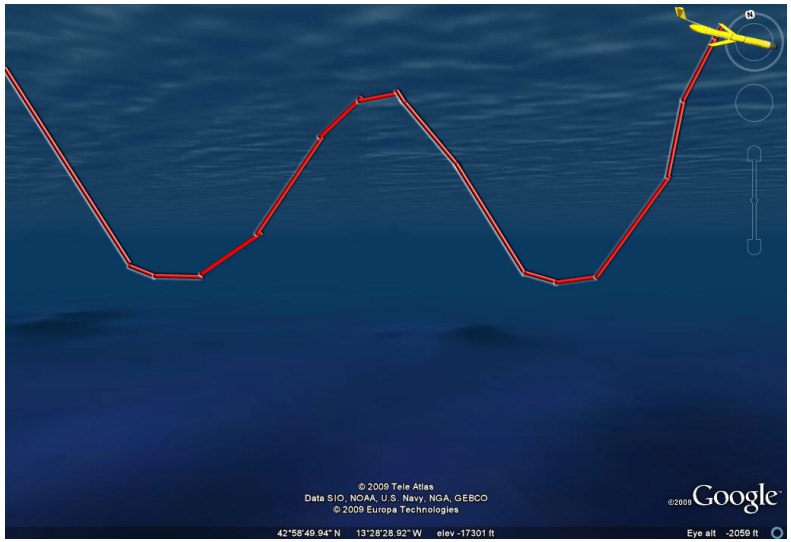
[2] `http://robotics.usc.edu/~ryan/Publications_files/GliderEddyPlan.pdf`

[3] `http://www.myocean.eu/automne_modules_files/pmedia/public/r16_9_201009_gibraltar.flv`

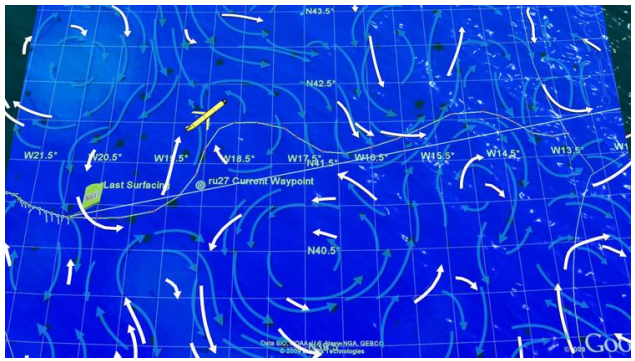
The Optimal Trajectory Task (simplified, unconstrained)

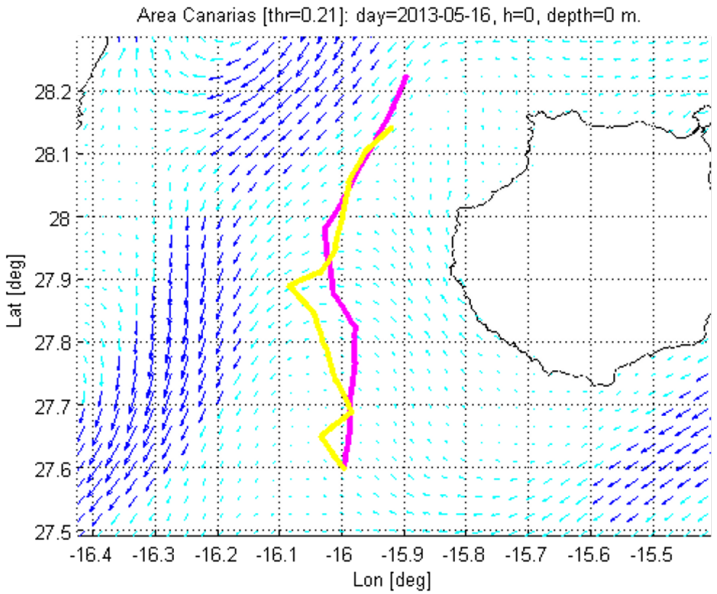
fitness evaluation (UGPP simulation):

$b_0 = \text{bearing}(\mathbf{p}_0, \mathbf{p}_{\text{target}})$;
$b_1 = b_0 + u_{i,1,g+1}$;
$\mathbf{p}_1 = \text{simulate_stint}(\mathbf{p}_0, b_1, \text{map})$;
for $j = \{2, 3, ..., D\}$:
$b_j = b_{j-1} + u_{i,j,g}$;
$\mathbf{p}'_{j-1} = \text{simulate_drift}(\mathbf{p}_{j-1}, \text{map})$;
$\{\mathbf{p}_j\} = \{\mathbf{p}_{j-1}\} \cup \text{simulate_stint}(\mathbf{p}'_{j-1}, b_j, \text{map})$;
end for
$f(\mathbf{u}_{i,g}) = \| \mathbf{p}_D - \mathbf{p}_{\text{target}} \|$;



We are trying to...





Some DE Family of Algorithms at Hand

- Algorithms at CEC – world championships on EAs:
  - SA-DE (CEC 2005: SO) – book chapter JCR,
  - MOjDE (CEC 2007: MO) – vs. DEMO 40/57 I_R, 39/57 I_H,
  - DEMOwSA (CEC 2007: MO) – rank #3, 53 citations,
  - DEwSAcc (CEC 2008: LSGO) – 63 citations,
  - DEMOwSA-SQP (CEC 2009: CMO) – rank #2, 47 citations,
  - DECMOSA-SQP (CEC 2009: CMO) – rank #3 at 2 functions,
  - $\text{jDE}_{\text{NP,MM}}$ (CEC 2011: RWIC) – LNCS SIDE 2012,
  - SPSRDEMMS (CEC 2013: RPSOO).
  - Performance assessment of the algorithms at world EA championships: several times best on some criteria
- Performance assessment on several industry challenges
  - RWIC (*Real World Industry Challenges*) - CEC 2011,
  - procedural tree models reconstruction (ASOC 2011, IS 2013),
  - hydro-thermal energy scheduling (APEN 2015), ...
- More on evolutionary algorithms introduction: A. Zamuda. **Differential Evolution and Large-Scale Optimization Applications**. *IGI Global, InfoSci-Videos*, April 2016.



Differential Evolution (DE)

- A floating point encoding EA for global optimization over continuous spaces,
  - through **generations**,
    the evolution process improves **population of vectors**,
  - iteratively by combining a parent individual and several other individuals of the same population, using **evolutionary operators**.
- We choose the **strategy** *jDE/rand/1/bin*
  - **mutation**: $\mathbf{v}_{i,G+1} = \mathbf{x}_{r_1,G} + F \times (\mathbf{x}_{r_2,G} - \mathbf{x}_{r_3,G})$,
  - **crossover**:

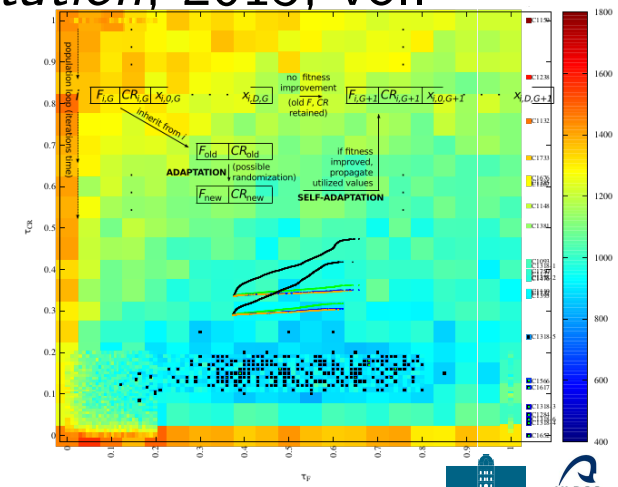
$$u_{i,j,G+1} = \begin{cases} v_{i,j,G+1} & \text{if } \text{rand}(0,1) \leq CR \text{ or } j = j_{rand} \\ x_{i,j,G} & \text{otherwise} \end{cases},$$

  - **selection**: $\mathbf{x}_{i,G+1} = \begin{cases} \mathbf{u}_{i,G+1} & \text{if } f(\mathbf{u}_{i,G+1}) < f(\mathbf{x}_{i,G}) \\ \mathbf{x}_{i,G} & \text{otherwise} \end{cases},$

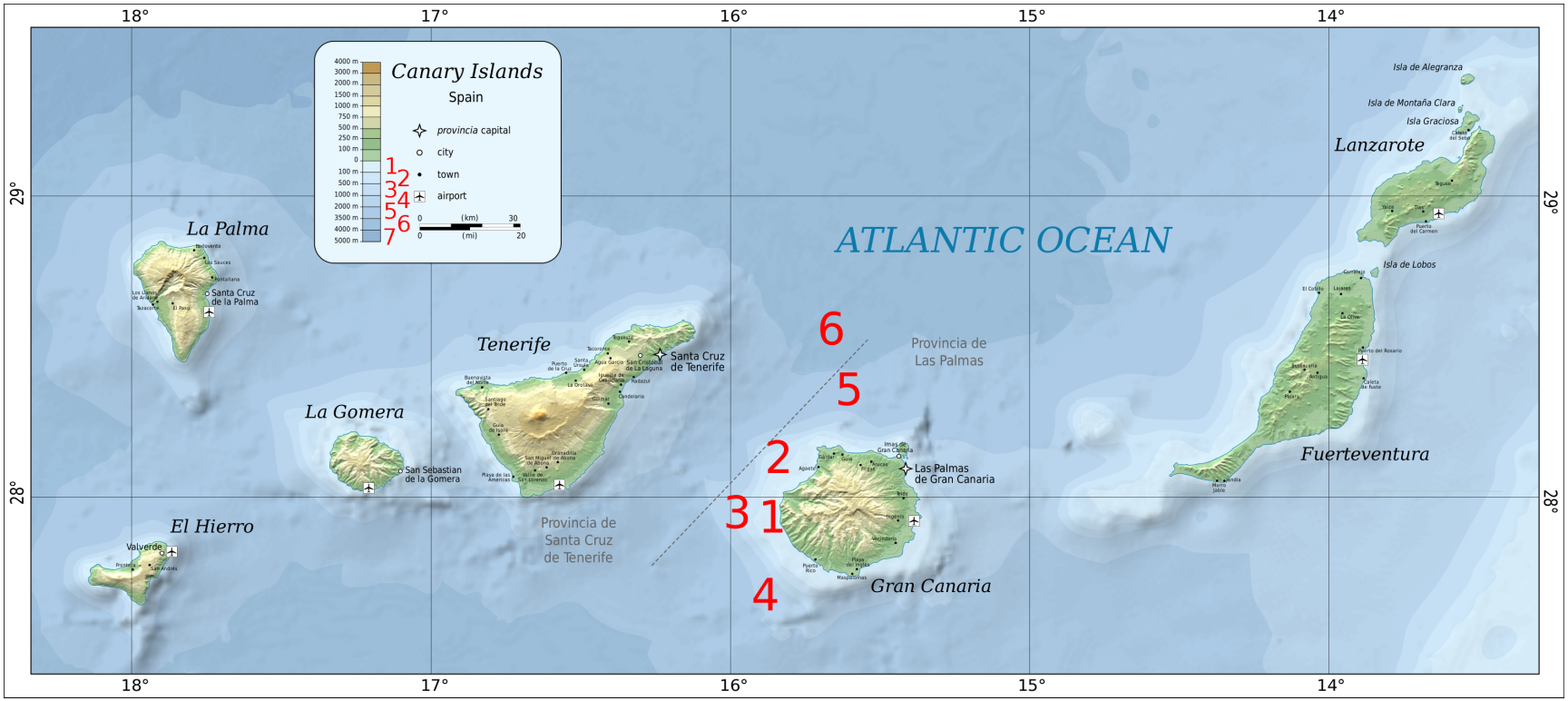


Control Parameters Self-Adaptation: based on SWEVO RAMONA Study

- Through more suitable values of control parameters the search process exhibits a better convergence,
- therefore the search converges faster to better solutions, which survive with greater probability and they create more offspring and propagate their control parameters
- Recent study with cca. 10 million runs of SPSRDEMMS: A. Zamuda, J. Brest. **Self-adaptive control parameters' randomization frequency and propagations in differential evolution**. *Swarm and Evolutionary Computation*, 2015, vol. 25C, pp. 72-99. DOI 10.1016/j.swevo.2015.10.007. – **SWEVO 2015 RAMONA**



Preparations – *Ocean, Mesoscale Eddies, Vulcanic Islands*

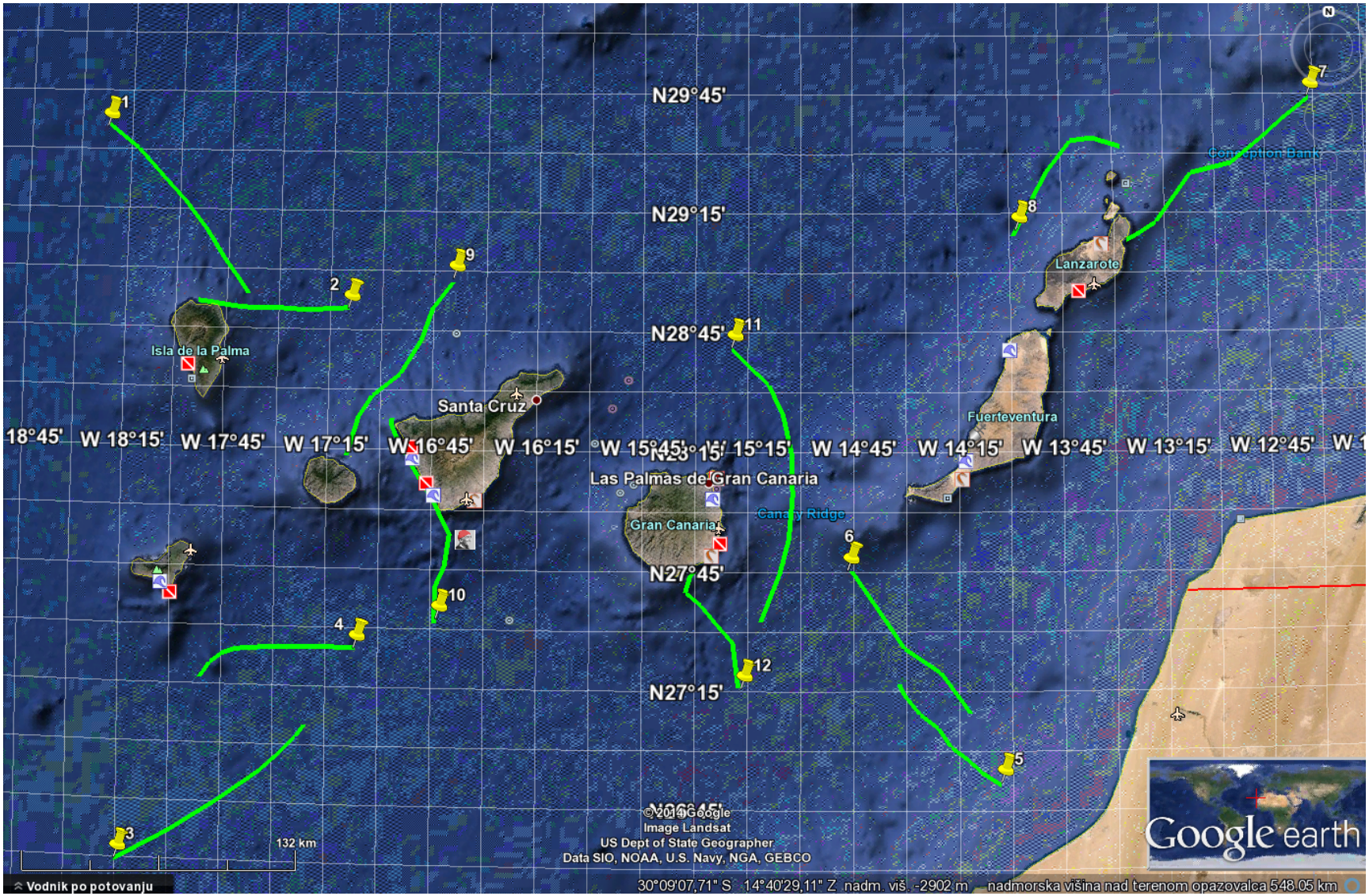






Viri: Wikipedija, Google Earth

Previously (Unconstrained): *Scenarios & Trajectories*



https://www.google.si/maps/@28.059806,-15.998355,650054m/data=!3m1!1e3

Constrained UGPP: Importance & Aims

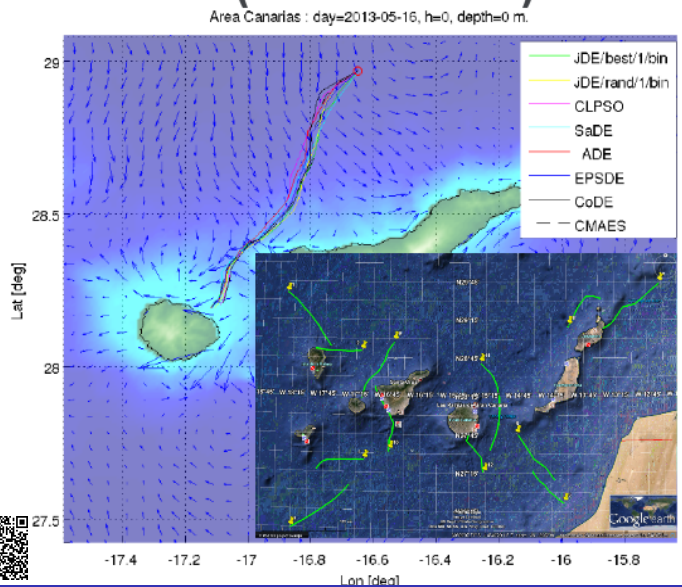
Ocean eddy border: main interest zone (eddy characterization)

- reactive navigation is not always valid for the sampling of rapid evolving structures (like in characterizing the eddy structure)
- pre-computing optimized paths constitutes then an alternative: promoting underwater glider autonomy and extending it's operational capabilities

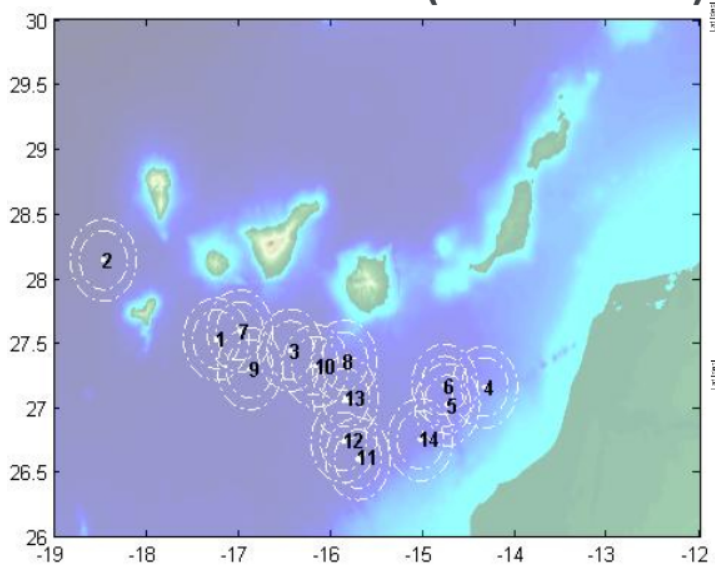
Selecting DE mechanisms configuration in constrained UGPP

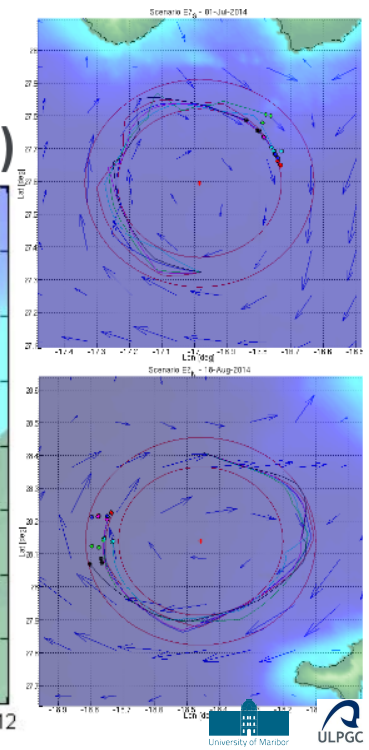
- violation of the constraint: quantified by integrating out-bounded trajectory path parts

BEFORE (base article)

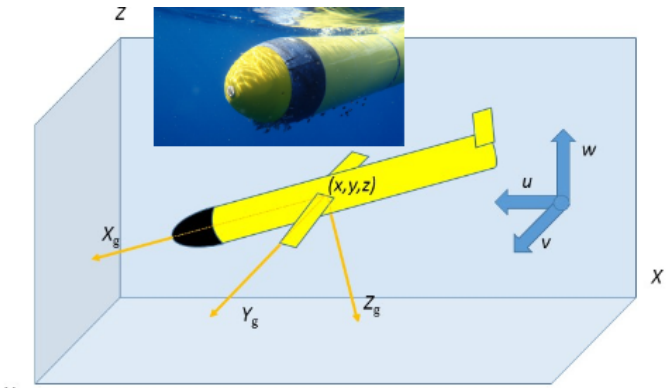


AFTER (new article)





Fitness & constraints



Step 3 Fitness computation: compute the fitness as the unsampled angular sector around the eddy center, that is, the remaining angle to cover a full 2π turn:

Step 3.1 Compute the angle increments of the path around the eddy center, $\Delta\gamma$:

$$\Delta\gamma_k = \gamma_{k+1} - \gamma_k, \quad \forall k = 1, 2, \ldots, K-1. \tag{27}$$

Step 3.2 Compute the cumulative angle (around the eddy center, zero angle at $\mathbf{p}_0$).

$$\alpha_k^{\text{cum}} = \begin{cases} 0, & k = 1, \\ \alpha_{k-1}^{\text{cum}} + \Delta\gamma_{k-1}, & \forall k = 2, 3, \ldots, K. \end{cases} \tag{28}$$

Step 3.3 Compute the fitness value as the difference between the angular extent and a full turn:

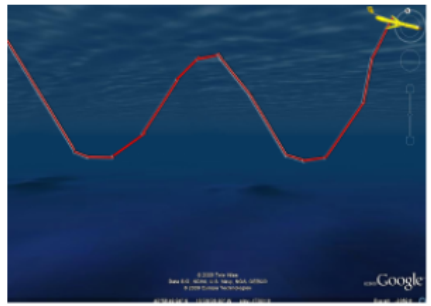
$$\alpha_{\text{ext}} = \max_{K=1}^{K}\left(\alpha_k^{\text{cum}}\right) - \min_{K=1}^{K}\left(\alpha_k^{\text{cum}}\right), \tag{29}$$

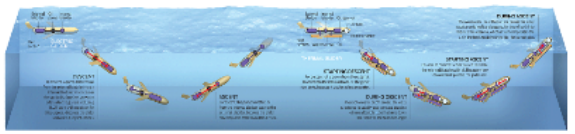
$$f(\mathbf{u}_{i,g+1}) = 2\pi - \alpha_{\text{ext}}. \tag{30}$$

Step 4 Constraints evaluation

For a circular corridor defined by $r_{\min}$ and $r_{\max}$, the constraint violations of all D trajectory segments points $\mathbf{t}_k$, $\forall k = 1, \ldots, K$, transformed by Eqs. (24) and (26) are defined using the relative polar transformed coordinates as a tangent perpendicular distance $d_{\text{outside}}(\mathbf{t}_k)$ of these points from a corridor border as:

$$v_k = d_{\text{outside}}(\mathbf{t}_k) = \begin{cases} 0 & r_k > r_{\min} \wedge r_k < r_{\max} \\ \max(r_{\min} - r_k, r_k - r_{\max}) & \text{otherwise} \end{cases} \tag{31}$$



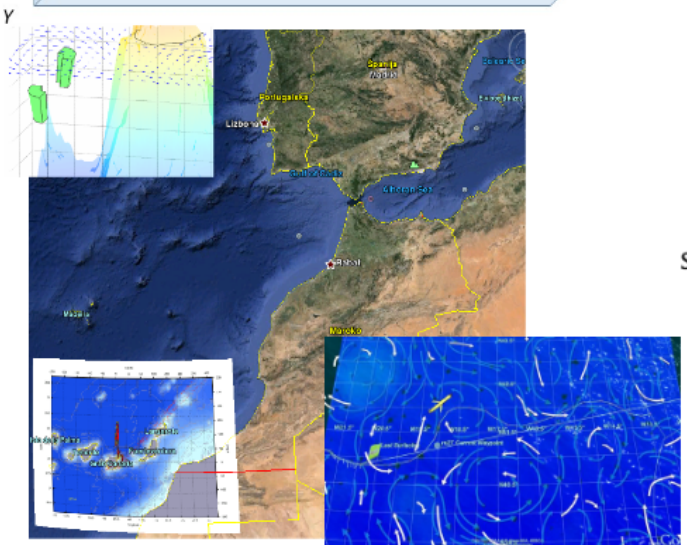


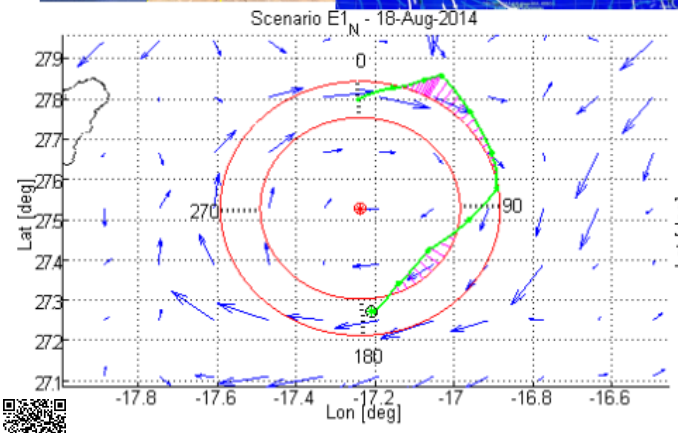
[1] http://www.i-cool.org/wp-content/uploads/2009/11/google-earth-glider-path.jpg
[2] http://spectrum.ieee.org/images/1023708

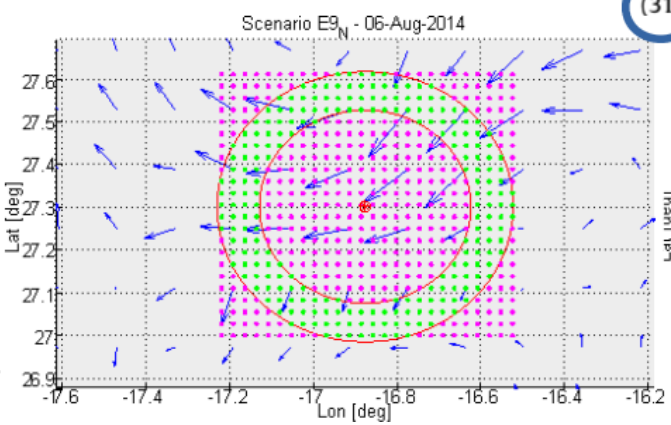
Underwater glider path optimization algorithms

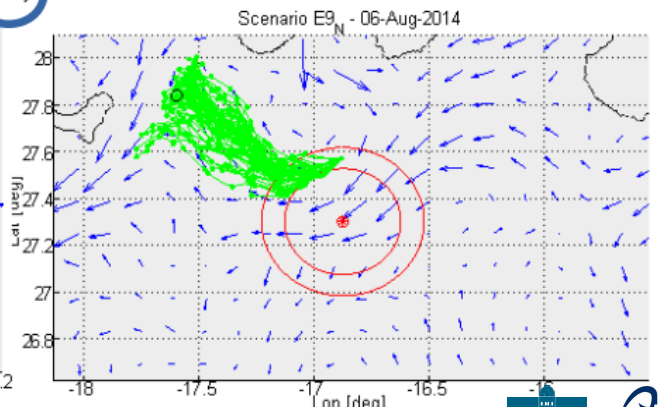
The optimization algorithm instances utilized for constrained UGPP.

Algorithm	Origin	Modifications tested
A_c,B_c,C_c,D_c,E_c,F_c	Ad hoc (Table 2)	6 new variants (all c = sum)
SaDE	[26]	1 new variant (SaDE-C)
JADE	[27]	1 new variant (JADE-C)
EPSDE	[32]	1 new variant (EPSDE-C)
CoDE	[116]	1 new variant (CoDE-C)
CLPSO	[117]	1 new variant (CLPSO-C)
CMAES	[118]	1 new variant (CMAES-C)
ECHT-DE	[119]	1 original
DMS-PSO	[120]	1 original
ABC	[121]	1 new variant (ABC-C)
MABC	[122]	1 original, 1 new variant (MABCe)









New UGPP DE algorithm: adding constraints handling

Algorithm 1 Constrained Differential Evolution for Underwater Glider Path Planning (with `sum` aggregation method).

procedure $\text{NP}_{\text{dyn}}\epsilon_{\texttt{sum}}\text{jDE/best/1/bin@cUGPP}(\mathbf{x})$

Require: $\mathbf{p}_0$ (current glider location), map (MyOcean IBI), $\mathbf{p}_{\text{eddy center}}$ (eddy center as a virtual mission target point), L (number of trajectory points per stint), L' (number of trajectory points per drift), MAX_FES (maximum number of FES allocated), NP_{init} (initial DE population size), $NP_{\min}$ (minimum DE population size), $p_{\max}$ (number of population size reductions), F_l, F_u, τ_1, and τ_2 (jDE constants, $\tau_1 = \tau_2 = \tau$ ad hoc), $\eta_{\%}$, g_c (constraint handling parameters), $r_{\min}$, $r_{\max}$ (corridor borders radii).

Ensure: $\mathbf{x}$ – list of instructions (D incremental bearings) on how to navigate glider; also, for possible further mission plan assessment, some auxiliary outputs are generated based on the evolutionary run, such as 1) computation date and time, 2) fitness and constraint violation of the best obtained $\mathbf{x}$, 3) per-generation convergence of the: a) best fitness or fitness for minimum constraint w.r.t. Eq. (11), b) minimum constraint value, c) mean fitness value for the population, and d) standard violation of fitness values for the population.

uniform randomly generate DE initial population $\mathbf{x}_{i,0}$, $\forall i \in \{1, 2, ..., NP_{\text{init}}\}$;
initialize ϵ-constrant handling method using Eq. (36);
for DE generation loop g (while FES $< MAX_FES$) **do**
  for DE iteration loop i (for all individuals $\mathbf{x}_{i,g}$ of a population) **do**
    if population is to be reduced as of Eq. (5) **then**
      reduce population to half using Eq. (11) for index-wise propagation (see [16]);
    end if
    DE individual $\mathbf{x}_{i,g}$ computation (adaptation, mutation, crossover):

$$F_{i,g+1} = \begin{cases} F_l + rand_1 \times F_u & \text{if } rand_2 < \tau_1, \\ F_{i,g} & \text{otherwise} \end{cases};$$

$$CR_{i,g+1} = \begin{cases} rand_3 & \text{if } rand_4 < \tau_2, \\ CR_{i,g} & \text{otherwise} \end{cases};$$

$$\mathbf{v}_{i,g+1} = \mathbf{x}_{r_{\text{best},g}} + F_{i,g+1}(\mathbf{x}_{r1,g} - \mathbf{x}_{r2,g});$$

$$u_{i,j,g+1} = \begin{cases} v_{i,j,g+1} & \text{if } rand(0,1) \leq CR_{i,g+1} \text{ or } j = j_{rand} \\ x_{i,j,g} & \text{otherwise} \end{cases}, \forall j \in \{1, .., D\};$$

    DE fitness evaluation and constraint violation estimation (UGPP simulation):
      $b_0 = \text{bearing}(\mathbf{p}_0, \mathbf{p}_{\text{eddy center}})$;
      for $j = \{1, 2, ..., D\}$:
        $b_j = b_{j-1} + u_{i,j,g+1}$;
        $\{\mathbf{t}_l^j; \forall l = 1, 2, ..., L\} = \text{simulate_stint}(\mathbf{t}_{L+L'}^{j-1}, b_j, \text{map})$, where $\mathbf{p}_0$ is used as $\mathbf{t}_{L+L'}^0$;
        $\{\mathbf{t}_l^j; \forall l = L+1, L+2, ..., L+L'\} = \text{simulate_drift}(\mathbf{t}_L^j, \text{map})$;
      end for
      for $k = \{1, 2, ..., K\}$ where $K = D(L + L')$ and $\forall \mathbf{t}_k \in \{\mathbf{t}_l^j\}, \forall j = 1, 2, ..., D, \forall l = 1, 2, ..., L + L'$:
        ${}^{\text{R}}\mathbf{t}_k = \texttt{deg2utmCan}(\mathbf{t}_k) - \texttt{deg2utmCan}(\mathbf{p}_{\text{eddy center}})$;
        $\gamma_k = \text{atan2}({}^{\text{R}}t_{k,y}, {}^{\text{R}}t_{k,x}), r_k = \sqrt{{}^{\text{R}}t_{k,x}^2 + {}^{\text{R}}t_{k,y}^2}$;

$$\alpha_k^{\text{cum}} = \begin{cases} 0, & k = 1, \\ \alpha_{k-1}^{\text{cum}} + (\gamma_k - \gamma_{k-1}) & \forall k = 2, 3, ..., K \end{cases};$$

$$\nu_k = \begin{cases} 0, & r_k > r_{\min} \wedge r_k < r_{\max} \\ \max(r_{\min} - r_k, r_k - r_{\max}), & \text{otherwise} \end{cases};$$

      end for
      $f(\mathbf{u}_{i,g+1}) = 2\pi - \left(\max_{k=1}^{K}(\alpha_k^{\text{cum}}) - \min_{k=1}^{K}(\alpha_k^{\text{cum}})\right)$;
      $\overline{\nu}_{u,g+1} = \sum_{k=1}^{K} \nu_k$;
    DE selection: use Eq. (35) if $g < g_c$, otherwise Eq. (11);
  end for
  adjust ϵ-constraint handling method parameters by recomputing η using Eq. (36);
end for
return the best individual obtained among $\mathbf{x}_{i,G}$;

Methods

New approach, based on methods:

A. Zamuda, J. D. Hernández Sosa, L. Adler. Constrained Differential Evolution Optimization for Underwater Glider Path Planning in Sub-mesoscaleEddy Sampling. Applied Soft Computing, 2016, vol. 42, pp. 93-118. (constr. UGPP)

A. Zamuda, J. D. Hernández Sosa. Differential Evolution and Underwater Glider Path Planning Applied to the Short-Term Opportunistic Sampling of Dynamic Mesoscale Ocean Structures. Applied Soft Computing, November 2014, vol. 24, pp. 95–108. (UGPP & DE)

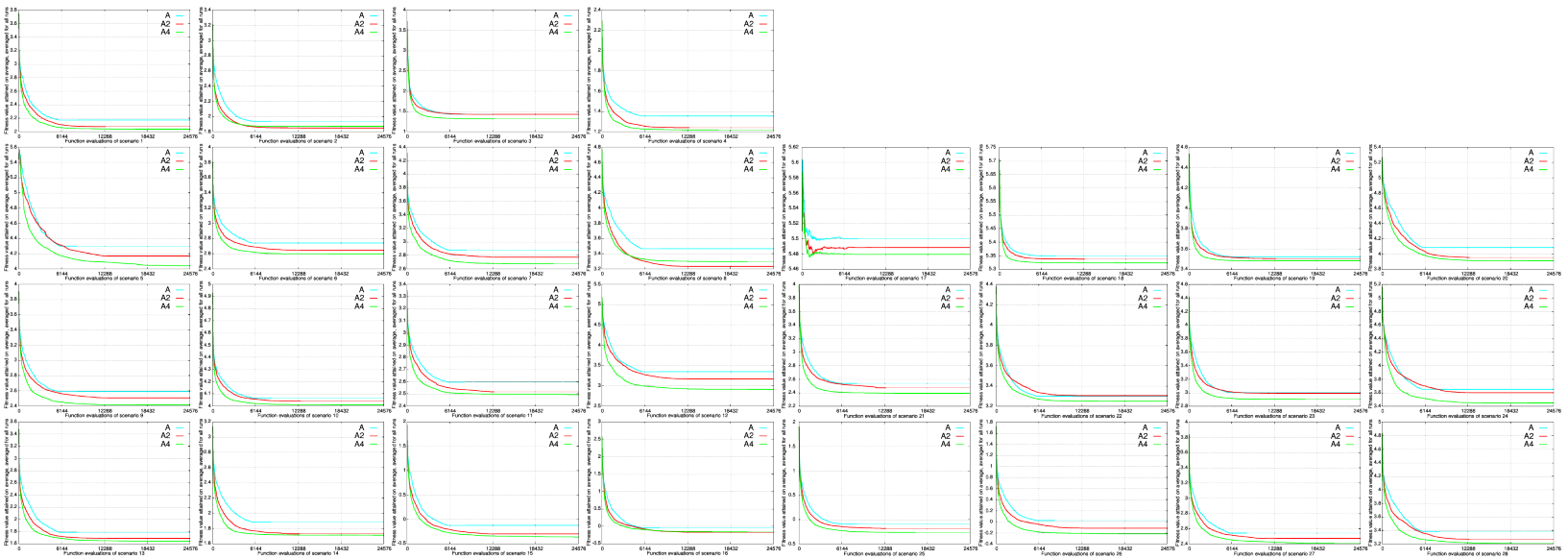
A. Glotić, A. Zamuda. Short-term combined economic and emission hydrothermal optimization by surrogate differential evolution. Applied Energy, 1 March 2015, vol. 141, pp. 42-56. **(CONSTRAINTS HANDLING)**

A. Zamuda, J. Brest. Self-adaptive control parameters' randomization frequency and propagations in differential evolution. Swarm and Evolutionary Computation, 2015, vol. 25, pp. 72-99. **(DE & SELF ADAPTATION)**

A. Zamuda, J. D. Hernandez Sosa. Underwater Glider Path Planning and Population Size Reduction in Differential Evolution. Lecture Notes in Computer Science (Computer Aided Systems Theory - EUROCAST 2015), 2015, vol. 9520, pp. 853—860. **(POPULATION SIZE REDUCTION & UGPP DE)**

Constrained UGPP - Convergences

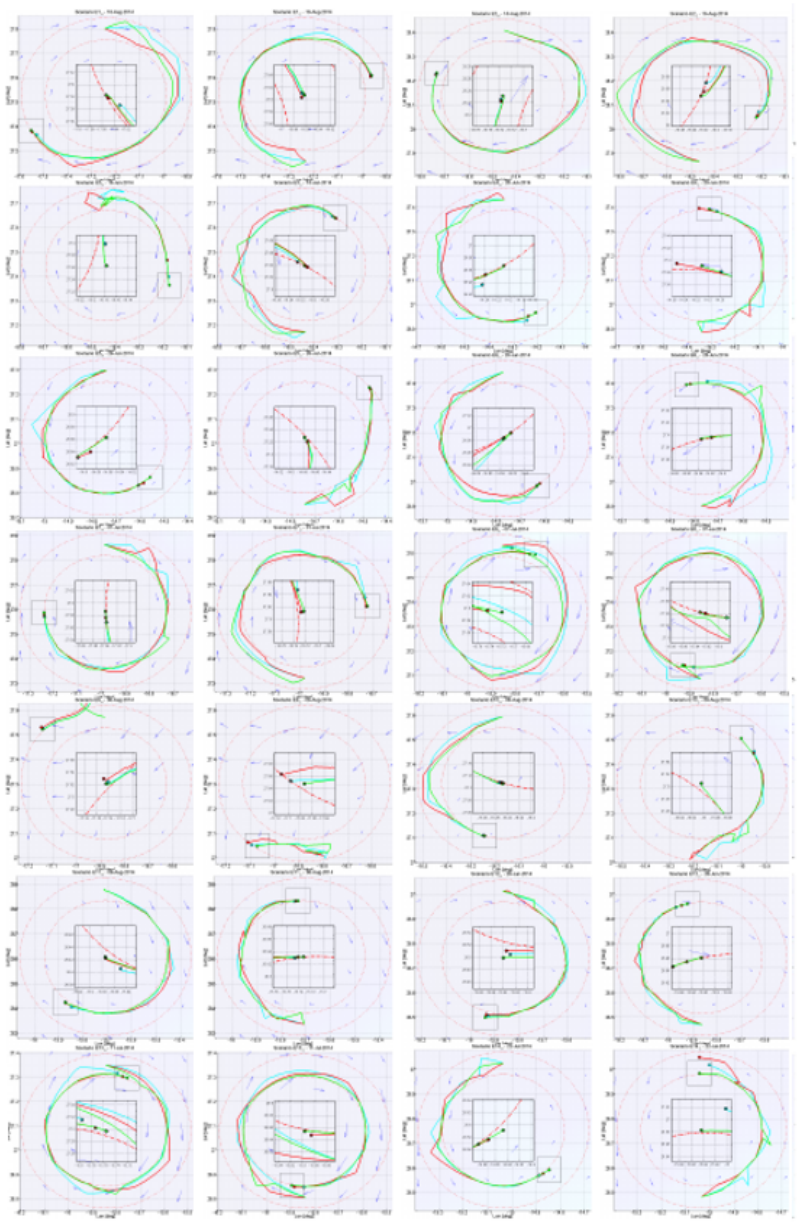
- 28 new scenarios were defined for constrained UGPP,
- optimizer needs to solve the optimum, with various combinations of UGPP properties,
- the time-prolonged algorithm achieves improvement on the original (A: MAXFES=6144) paths qualities, on average:
- with **A2: doubled (MAXFES x 2) time**: +2.57%,
- with **A4: quadrupled (MAXFES x 4) time**: +4.41%,
- fitness convergence graphs seen below:



Constrained UGPP – Comparisons

The best configured DE significantly outperformed some other configurations.

Keeping a trajectory within the limits with 100% success rate in all physically feasible scenarios.



Alg.	Traj.	Best	Median	Worst	Average	Std. dev.
A4	T1	1.7310e+00	2.0423e+00	2.7773e+00	**2.0394e+00**†	2.7032e-01
A4	T2	1.6173e+00	1.8681e+00	2.3670e+00	**1.8699e+00**†	1.8713e-01
A4	T3	8.7239e-01	1.2334e+00	2.4284e+00	**1.3194e+00**†	3.9730e-01
A4	T4	6.7767e-01	1.2217e+00	2.1737e+00	**1.2174e+00**†	3.1223e-01
A4	T5	1.6675e+00	4.3395e+00	5.4486e+00	**4.0394e+00**†	9.6190e-01
A4	T6	2.1139e+00	2.6156e+00	3.1311e+00	**2.5966e+00**†	2.2792e-01
A4	T7	2.1710e+00	2.6060e+00	3.4012e+00	**2.6745e+00**†	3.1907e-01
A4	T8	2.4354e+00	3.2803e+00	4.3233e+00	**3.2948e+00**†	6.3141e-01
A4	T9	2.0639e+00	2.3877e+00	3.0314e+00	**2.4154e+00**†	2.5229e-01
A4	T10	3.8205e+00	4.0318e+00	4.2297e+00	**4.0100e+00**†	1.0496e-01
A4	T11	2.1555e+00	2.5206e+00	2.9411e+00	**2.4924e+00**†	1.9522e-01
A4	T12	2.0162e+00	2.9085e+00	4.6841e+00	**2.9092e+00**†	6.4217e-01
A4	T13	1.0141e+00	1.6191e+00	2.9224e+00	**1.6374e+00**†	4.9358e-01
A4	T14	1.2460e+00	1.6533e+00	2.6466e+00	**1.7101e+00**†	3.5561e-01
A4	T15	-1.1337e+00	-4.7556e-01	8.6688e-01	**-3.6538e-01**†	5.3256e-01
A4	T16	-9.4381e-01	-1.6001e-01	1.1149e+00	-1.6405e-01	5.4784e-01
A4	T17	4.7905e+00	5.4849e+00	5.6613e+00	**5.4792e+00**†	1.0577e-01
A4	T18	5.2439e+00	5.3050e+00	5.5326e+00	**5.3231e+00**†	6.1733e-02
A4	T19	3.4134e+00	3.4637e+00	3.7021e+00	**3.4821e+00**†	6.4535e-02
A4	T20	2.7527e+00	3.8928e+00	4.7468e+00	**3.9105e+00**†	5.3432e-01
A4	T21	1.9886e+00	2.4408e+00	3.2405e+00	**2.3902e+00**†	3.2714e-01
A4	T22	2.8851e+00	3.2290e+00	3.6638e+00	**3.2491e+00**†	1.9568e-01
A4	T23	2.5774e+00	2.8920e+00	3.7203e+00	**2.9018e+00**†	2.7435e-01
A4	T24	3.2961e+00	3.3741e+00	4.2029e+00	**3.4463e+00**†	1.8641e-01
A4	T25	-1.0123e+00	-2.2315e-01	5.2119e-01	**-2.6716e-01**†	4.5015e-01
A4	T26	-8.4029e-01	-2.1112e-01	7.5723e-01	**-2.2001e-01**†	3.1235e-01
A4	T27	1.9533e+00	2.3502e+00	3.0452e+00	**2.4074e+00**†	2.9217e-01
A4	T28	2.5537e+00	3.1605e+00	4.3231e+00	**3.2041e+00**†	3.5716e-01
A2	T1	1.7240e+00	2.0883e+00	2.8101e+00	**2.0746e+00**†	2.5967e-01
A2	T2	1.6113e+00	1.8639e+00	2.3582e+00	**1.8501e+00**†	2.0046e-01
A2	T3	8.7560e-01	1.2964e+00	2.7944e+00	1.4246e+00	5.1383e-01
A2	T4	7.1934e-01	1.2548e+00	2.1388e+00	**1.2392e+00**†	2.9541e-01
A2	T5	1.8283e+00	4.5851e+00	5.4388e+00	4.1684e+00	9.9225e-01
A2	T6	2.1863e+00	2.6546e+00	3.5933e+00	**2.6403e+00**†	2.6789e-01
A2	T7	2.1276e+00	2.7383e+00	3.6176e+00	**2.7726e+00**†	3.4683e-01
A2	T8	2.4218e+00	3.1197e+00	4.3547e+00	**3.2303e+00**†	6.3215e-01
A2	T9	2.0665e+00	2.5128e+00	3.0972e+00	**2.5065e+00**†	2.4603e-01
A2	T10	3.8128e+00	4.0446e+00	4.3388e+00	4.0406e+00	1.1347e-01
A2	T11	2.1098e+00	2.5469e+00	3.0257e+00	**2.5154e+00**†	2.0579e-01
A2	T12	2.0627e+00	2.9905e+00	5.1881e+00	**3.1609e+00**†	7.4347e-01
A2	T13	1.0182e+00	1.6387e+00	2.6710e+00	1.6851e+00	4.9441e-01
A2	T14	1.2311e+00	1.6693e+00	2.7283e+00	**1.7303e+00**†	3.7422e-01
A2	T15	-1.0722e+00	-3.6948e-01	1.9535e+00	**-3.0253e-01**†	5.1522e-01
A2	T16	-9.8626e-01	-2.5268e-01	1.7986e+00	-1.7669e-01	6.3734e-01
A2	T17	4.7974e+00	5.4961e+00	5.6835e+00	5.4883e+00	1.3265e-01
A2	T18	5.2495e+00	5.3261e+00	5.4963e+00	5.3368e+00	6.1141e-02
A2	T19	3.4121e+00	3.4760e+00	4.0201e+00	3.5037e+00	1.0997e-01
A2	T20	2.7896e+00	4.0211e+00	5.0333e+00	**3.9535e+00**†	5.5707e-01
A2	T21	1.9797e+00	2.4480e+00	3.6514e+00	2.4703e+00	3.9068e-01
A2	T22	2.8835e+00	3.2735e+00	3.9395e+00	3.3050e+00	2.2993e-01
A2	T23	2.5730e+00	2.9022e+00	4.2148e+00	2.9898e+00	3.8438e-01
A2	T24	3.2994e+00	3.4699e+00	4.2141e+00	3.5990e+00	2.8439e-01
A2	T25	-1.0104e+00	-2.5751e-01	1.0816e+00	-1.8373e-01	4.8233e-01
A2	T26	-7.6970e-01	-1.4825e-01	7.9006e-01	**-1.1556e-01**†	3.4661e-01
A2	T27	1.9678e+00	2.4676e+00	2.9974e+00	**2.4698e+00**†	2.7013e-01
A2	T28	2.5094e+00	3.1596e+00	4.5422e+00	**3.2688e+00**†	4.7348e-01
A	T1	1.7674e+00	2.1261e+00	2.7025e+00	2.1720e+00	2.2618e-01
A	T2	1.6244e+00	1.9029e+00	2.5204e+00	1.9357e+00	2.0154e-01
A	T3	8.7040e-01	1.2661e+00	3.2448e+00	1.4334e+00	5.4547e-01
A	T4	7.6096e-01	1.3169e+00	2.1555e+00	1.3544e+00	2.8607e-01
A	T5	1.8334e+00	4.4143e+00	5.5626e+00	4.2990e+00	8.7211e-01
A	T6	2.2994e+00	2.7011e+00	3.5593e+00	2.7372e+00	2.4504e-01
A	T7	2.1728e+00	2.8470e+00	4.2371e+00	2.8762e+00	3.8242e-01
A	T8	2.4986e+00	3.5445e+00	4.5309e+00	3.4625e+00	5.9638e-01
A	T9	2.0603e+00	2.5971e+00	3.4156e+00	2.5869e+00	3.0648e-01
A	T10	3.8490e+00	4.0427e+00	4.4186e+00	4.0637e+00	1.3508e-01
A	T11	2.2573e+00	2.5725e+00	3.1102e+00	2.5945e+00	2.0809e-01
A	T12	2.0341e+00	3.3748e+00	5.4085e+00	3.3425e+00	7.6138e-01
A	T13	1.0342e+00	1.6717e+00	2.8566e+00	1.7831e+00	4.4453e-01
A	T14	1.3470e+00	1.8350e+00	2.6524e+00	1.8817e+00	3.4718e-01
A	T15	-9.9174e-01	-1.2333e-01	1.1312e+00	-1.2713e-01	4.4563e-01
A	T16	-9.5301e-01	-1.0059e-01	1.2718e+00	-4.9759e-02	5.0626e-01
A	T17	5.4327e+00	5.4979e+00	5.6372e+00	5.5000e+00	3.2532e-02
A	T18	5.2436e+00	5.3339e+00	5.4936e+00	5.3491e+00	6.4232e-02
A	T19	3.4227e+00	3.4893e+00	4.0338e+00	3.5218e+00	1.0592e-01
A	T20	2.9836e+00	4.1957e+00	4.8505e+00	4.0834e+00	4.8735e-01
A	T21	2.0046e+00	2.5730e+00	3.3584e+00	2.5370e+00	3.7704e-01
A	T22	2.8986e+00	3.2932e+00	3.7677e+00	3.2986e+00	2.0007e-01
A	T23	2.5925e+00	2.9183e+00	3.9335e+00	3.0016e+00	3.0719e-01
A	T24	3.3187e+00	3.5745e+00	4.5536e+00	3.6497e+00	2.8390e-01
A	T25	-8.1672e-01	-1.3410e-01	7.6318e-01	-9.1121e-02	3.7906e-01
A	T26	-8.0083e-01	-1.0429e-02	1.3713e+00	2.3025e-02	3.7411e-01
A	T27	2.0053e+00	2.5412e+00	3.3050e+00	2.5418e+00	3.0787e-01
A	T28	2.7872e+00	3.2677e+00	4.4462e+00	3.3826e+00	3.9488e-01

OBTAINED FITNESS WITH 3 $NP_{DYN}\epsilon_{SUM}$JDE ALGORITHM VARIANTS ON 28 TEST SCENARIOS IN 51 INDEPENDENT RUNS. THE SYMBOL † SIGNIFIES WHEN USING t-TEST ($\alpha = 0.05$, t-STATISTIC WITH $p = 0.95$ AT N=51 IS 1.6753) THAT AN ALGORITHM PERFORMANCE IS BETTER THAN THE VARIANT A PERFORMANCE ON THE SCENARIO TESTED (THE TEST NEVER SIGNIFIED THE OPPOSITE, I.E., THAT ANY CASE WOULD BE WORSE, RESPECTIVELY).

Constrained UGPP - Rankings

Optimization performance **comparison** with different optimization algorithms

The optimization algorithm instances utilized for constrained UGPP.

Algorithm	Origin, variant	Modifications tested	Total MAXFES
A4 and A2	ad hoc (the $NP_{dyn}\epsilon_{sum}$jDE/best/1/bin, [1])	2 new variant settings of A	$\times 2$ and $\times 4$
A, B, C, D, E, F	[1]	6 variants	$\times 1$
SaDE	[27], [1]	1 variant (SaDE-C)	$\times 1$
JADE	[28], [1]	1 variant (JADE-C)	$\times 1$
EPSDE	[29], [1]	1 variant (EPSDE-C)	$\times 1$
CoDE	[30], [1]	1 variant (CoDE-C)	$\times 1$
CLPSO	[31], [1]	1 variant (CLPSO-C)	$\times 1$
CMAES	[32], [1]	1 variant (CMAES-C)	$\times 1$
ECHT-DE	[33]	1 original	$\times 1$
DMS-PSO	[34]	1 original	$\times 1$
ABC	[35], [1]	1 variant (ABC-C)	$\times 1$
MABC	[36], [1]	1 original, 1 variant (MABCe)	$\times 1$

Population sizing & structuring study for several algorithms

- comparing: different DE, PSO, CMA-ES, and ABC variants.

Comparison with best algorithm: A_{sum}

i	algorithm	$z = (R_0 - R_i)/SE$	p	H/H/H	Holland	Rom	Finner	Li
1	A2	3.57	0.000356	0.05	0.05	0.05	0.05	0.05
2	A	8.42	3.88e-17	0.025	0.0253	0.025	0.0488	0.0526
3	NP=30: DMS-PSO	12.8	1.41e-37	0.0167	0.017	0.0167	0.0476	0.0526
4	NP=30: JADE-C	13.3	4.46e-40	0.0125	0.0127	0.0131	0.0463	0.0526
5	C	14.3	1.12e-46	0.01	0.0102	0.0105	0.0451	0.0526
6	NP=30: SaDE-C	17.2	4.16e-66	0.00833	0.00851	0.00876	0.0439	0.0526
7	NP=50: DMS-PSO	18.1	4.33e-73	0.00714	0.0073	0.00751	0.0427	0.0526
8	NP=30: MABCe	20.6	7.64e-94	0.00625	0.00639	0.00657	0.0414	0.0526
9	NP=30: MABC	20.7	3.44e-95	0.00556	0.00568	0.00584	0.0402	0.0526
10	NP=100: DMS-PSO	21.4	8.07e-102	0.005	0.00512	0.00526	0.039	0.0526
11	NP=50: MABCe	21.4	5.39e-102	0.00455	0.00465	0.00478	0.0377	0.0526
12	NP=50: MABC	21.7	2.88e-104	0.00417	0.00427	0.00438	0.0365	0.0526
13	NP=50: JADE-C	23.1	1.73e-118	0.00385	0.00394	0.00405	0.0353	0.0526
14	D	23.3	1.77e-120	0.00357	0.00366	0.00376	0.034	0.0526
15	E	25.3	2.3e-141	0.00333	0.00341	0.00351	0.0328	0.0526
16	NP=50: SaDE-C	25.3	1.1e-141	0.00313	0.0032	0.00329	0.0315	0.0526
17	NP=100: MABCe	26	4.71e-149	0.00294	0.00301	0.00309	0.0303	0.0526
18	NP=100: MABC	26.1	2.22e-150	0.00278	0.00285	0.00292	0.0291	0.0526
19	NP=30: ECHT-DE	27.2	2.77e-163	0.00263	0.0027	0.00277	0.0278	0.0526
20	NP=100: CMAES-C	27.2	2.66e-163	0.0025	0.00256	0.00263	0.0266	0.0526
21	NP=50: CMAES-C	28.1	1.99e-173	0.00238	0.00244	0.0025	0.0253	0.0526
22	NP=30: CMAES-C	28.1	1.99e-173	0.00227	0.00233	0.00239	0.0241	0.0526
23	NP=30: CoDE-C	32.8	9.61e-236	0.00217	0.00223	0.00229	0.0228	0.0526
24	NP=30: CLPSO-C	32.9	2.78e-237	0.00208	0.00213	0.00219	0.0216	0.0526
25	NP=100: JADE-C	32.9	8.96e-238	0.002	0.00205	0.0021	0.0203	0.0526
26	NP=100: SaDE-C	33.5	1.58e-245	0.00192	0.00197	0.00202	0.0191	0.0526
27	NP=30: ABC-C	33.7	1.56e-249	0.00185	0.0019	0.00195	0.0178	0.0526
28	NP=50: ABC-C	34.5	8.87e-261	0.00179	0.00183	0.00188	0.0165	0.0526
29	NP=50: ECHT-DE	35.9	5.24e-283	0.00172	0.00177	0.00181	0.0153	0.0526
30	NP=50: CLPSO-C	38.1	0	0.00167	0.00171	0.00175	0.014	0.0526
31	NP=50: CoDE-C	38.3	0	0.00161	0.00165	0.0017	0.0127	0.0526
32	NP=30: EPSDE-C	38.3	0	0.00156	0.0016	0.00164	0.0115	0.0526
33	NP=100: ABC-C	39.1	0	0.00152	0.00155	0.00159	0.0102	0.0526
34	F	41.3	0	0.00147	0.00151	0.00155	0.00894	0.0526
35	B	41.4	0	0.00143	0.00146	0.0015	0.00766	0.0526
36	NP=100: CLPSO-C	41.6	0	0.00139	0.00142	0.00146	0.00639	0.0526
37	NP=100: CoDE-C	41.9	0	0.00135	0.00139	0.00142	0.00512	0.0526
38	NP=100: ECHT-DE	43	0	0.00132	0.00135	0.00138	0.00384	0.0526
39	NP=50: EPSDE-C	45.5	0	0.00128	0.00131	0.00135	0.00256	0.0526
40	NP=100: EPSDE-C	50.5	0	0.00125	0.00128	0.00132	0.00128	0.0526

ON FRIEDMAN STATISTIC AT $\alpha = 0.05$, THE POST-HOC PROCEDURES REJECT HYPOTHESES OF SAME PERFORMANCE, I.E. THE BASE ALGORITHM A IS OUTPERFORMED (REVERSED RANKS) BY EACH ENHANCED ALGORITHM: BONFERRONI-DUNN'S AT p-VALUE ≤ 0.025, HOLM/HOCHBERG'S (H/H), ROM'S, AND LI'S AT p-VALUE ≤ 0.05, AND HOMMEL'S REJECTS ALL.

i	algorithm	$z = (R_0 - R_i)/SE$	p	H/H/H	Holland	Rom	Finner	Li
2	A4	16.9	8.93e-64	0.025	0.0253	0.025	0.0253	0.0526
1	A2	10	1.13e-23	0.05	0.05	0.05	0.05	0.05

Constrained UGPP - Conclusions

Constraints violation & fitness convergences

Constraint handling definition strategies, different DE mutation strategies' configurations, and population sizing parameterizations

Population sizing & structuring study for several algorithms

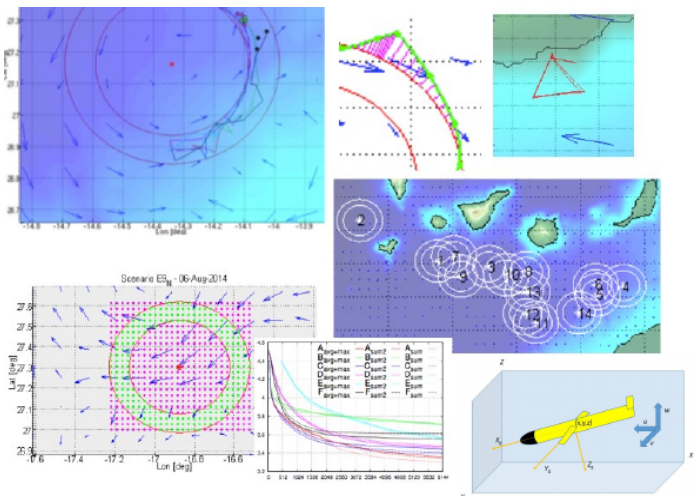
- comparing: different DE, PSO, CMA-ES, and ABC variants

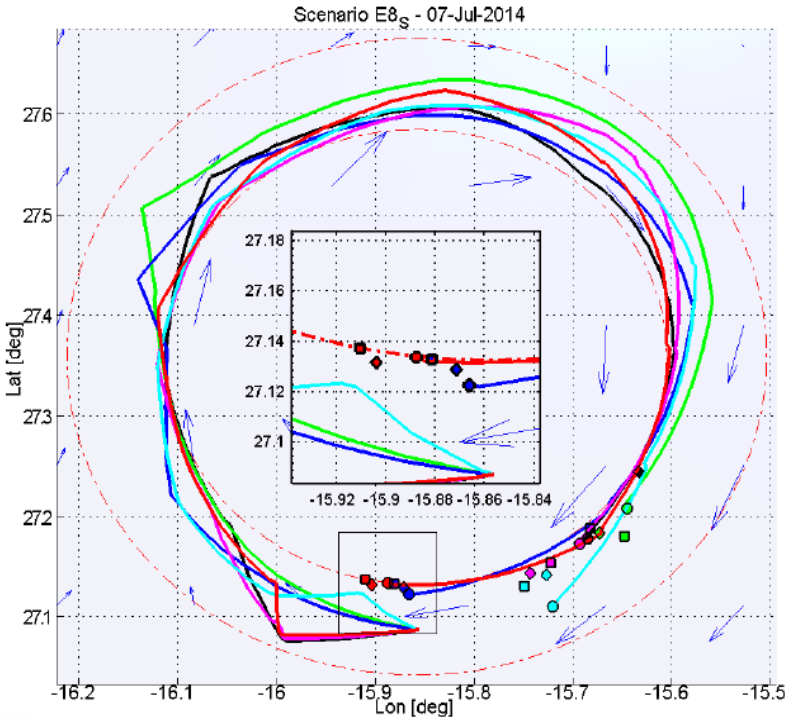
Our proposed solution outranked all other compared algorithms

- keeping a trajectory within the limits with 100% success rate in all physically feasible scenarios,
- on average, it improved the randomly initialized trajectories fitness by roughly 50%,
- even reaching perfect fitness (all-around, 360-degree eddy corridor sampling) in some scenarios.

Improving Constrained Glider Trajectories for Ocean Eddy Border Sampling within Extended Mission Planning Time: CONCLUSIONS

- Corridor-constrained optimization: eddy border region sampling
  - new challenge for UGPP & DE
- Feasible path area is constrained
  - trajectory in corridor around the border of an ocean eddy

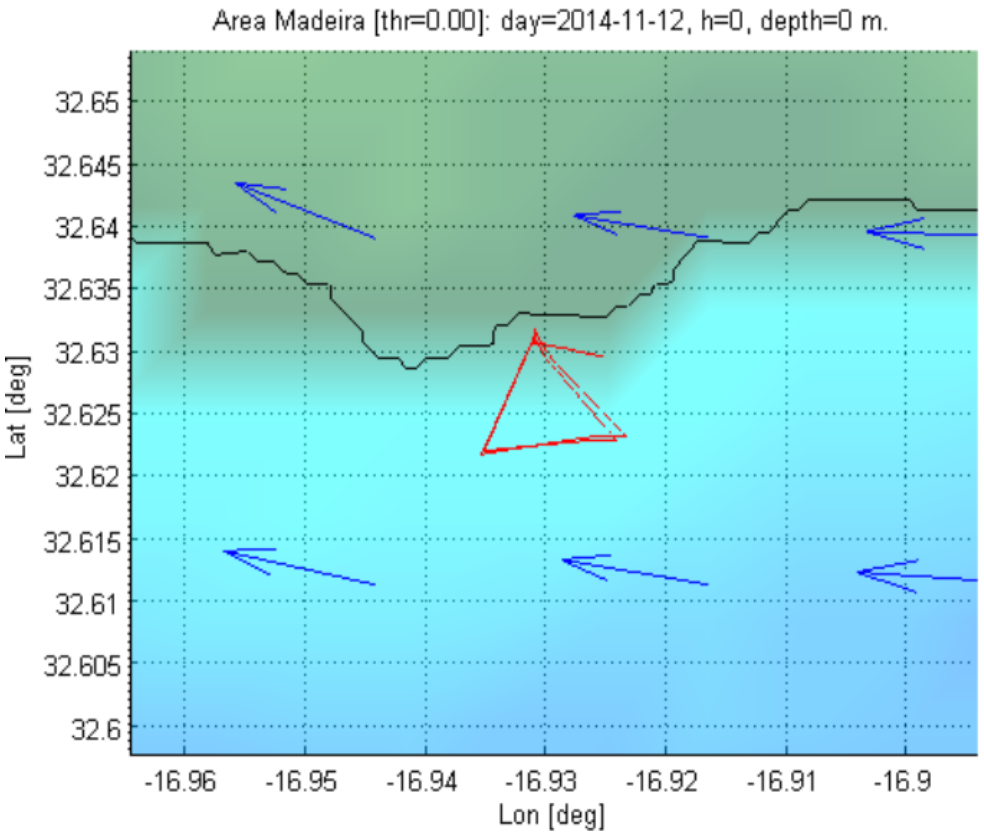




The objective of the glider here is to sample the oceanographic variables more efficiently,
while keeping a bounded trajectory.

Extending time improved trajectories significantly and robustly.

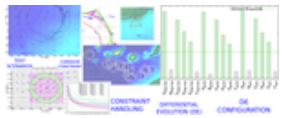
Constrained UGPP: Next Steps & Future Work



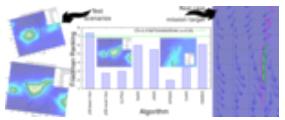
- Variable number of bearings,
- extended parameters study,
- more corridor sampling types,
- multi-objective optimization,
- runtime parallelization,
- swarm robotics controllers in cloud,
- real mission validation tests:
  - budget-bound opportunities,
  - real vehicles at the ULPGC marine technology SITMA unit.

Some More Publications

- A. Zamuda, J. D. Hernández Sosa, L. Adler. **Constrained Differential Evolution Optimization for Underwater Glider Path Planning in Sub-mesoscale Eddy Sampling**. Applied Soft Computing, 2016, vol. 42, pp. 93-118. DOI 10.1016/j.asoc.2016.01.038.



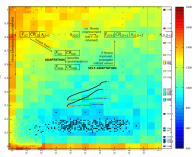
- A. Zamuda, J. D. Hernández Sosa. **Differential Evolution and Underwater Glider Path Planning Applied to the Short-Term Opportunistic Sampling of Dynamic Mesoscale Ocean Structures**. Applied Soft Computing, vol. 24, November 2014, pp. 95-108. DOI 10.1016/j.asoc.2014.06.048.



- H. Hamann, Y. Khaluf, J. Botev, M. Divband Soorati, E. Ferrante, O. Kosak, J.-M. Montanier, S. Mostaghim, R. Redpath, J. Timmis, F. Veenstra, M. Wahby and A. Zamuda. **Hybrid Societies: Challenges and Perspectives in the Design of Collective Behavior in Self-organizing Systems**. Frontiers in Robotics and AI, 2016, vol. 3, no. 14. DOI 10.3389/frobt.2016.00014.



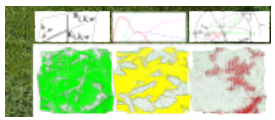
- A. Zamuda, J. Brest. **Self-adaptive control parameters' randomization frequency and propagations in differential evolution**. Swarm and Evolutionary Computation, 2015, vol. 25C, pp. 72-99. DOI 10.1016/j.swevo.2015.10.007.



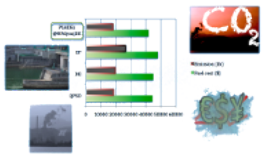
- A. Zamuda, J. Brest. **Vectorized Procedural Models for Animated Trees Reconstruction using Differential Evolution**. Information Sciences, vol. 278, pp. 1-21, 2014. DOI 10.1016/j.ins.2014.04.037.



- A. Zamuda, J. Brest. **Environmental Framework to Visualize Emergent Artificial Forest Ecosystems**. Information Sciences, vol. 220, pp. 522-540, 2013. DOI 10.1016/j.ins.2012.07.031.

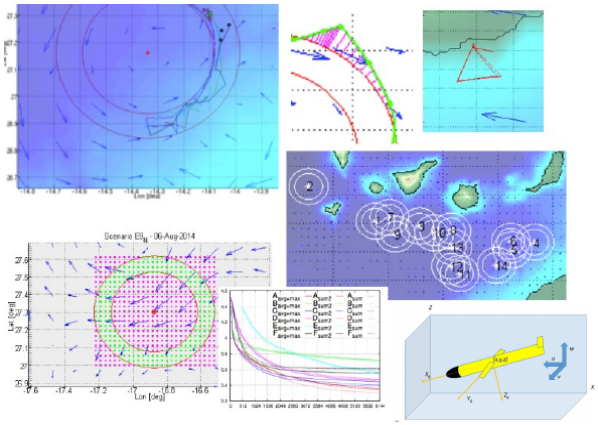


- A. Glotić, A. Zamuda. **Short-term combined economic and emission hydrothermal optimization by surrogate differential evolution**. Applied Energy, 1 March 2015, vol. 141, pp. 42-56. DOI 10.1016/j.apenergy.2014.12.020.



Thank you very much for listening!





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Questions and suggestions?