Addressing uncertainty, multiple objectives, and adaptation in DICE: Can dynamic planning shed new light on the decision-making process?

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[1] ABSTRACT

Traditionally, integrated assessment models of climate change optimize a **single economic objective** using a **deterministic set of equations** to describe socioeconomic and physical processes, as well as their dependencies. This work aims to remove these two assumptions introducing another **objective on the physical climate system**, as well as introducing a **stochastic disturbance** on the **atmospheric temperature process**. This results in the formulation of a **multi-objective stochastic optimal control** problem whose solution is the set of the **Pareto-optimal** policies with respect to the two objectives. These outperform the traditional static optimization solution as they are **adaptive** with respect to uncertainty and give a full representation of the different **tradeoffs among the objectives**.

[2] RESEARCH OBJECTIVE

Evaluate the improvements obtained by adopting a multi-objective optimal control perspective in integrated assessment modelling of climate change under stochasticity.

[3] METHODOLOGY

We adopt our methodology on the well known **DICE** model which is simple and compact enough to be used in such a preliminary analysis.

[3.1] INTRODUCING STOCHASTIC DISTURBANCE IN ATMOSPHERIC TEMPERATURE

After **simulating the DICE temperature model under historical forcing** we obtain the **residuals with respect to the HadCRUT4** temperature observations. Since residuals are **satisfying the normality hypothesis**, we describe the temperature process as follows:

$$\mathbf{T}_{t+1} = \mathbf{\Phi}^{\mathbf{T}} * \mathbf{T}_t + [\xi_1 F_t \ \ 0]^T + \left[\varepsilon_{t+1}^{TA} \ \ 0\right]^T$$

$$\varepsilon_{t+1}^{TA} \sim N(0, \sigma_{T^A}^2)$$

[3.2] MULTI-OBJECTIVE STOCHASTIC OPTIMAL CONTROL PROBLEM

$$\min_{p} \mathop{E}_{\{\varepsilon_t\}_{t=1,\dots,H}} |-J^e \quad J^c|$$

$$\boldsymbol{x}_{t+1} = \boldsymbol{f}(\boldsymbol{x}_t, \boldsymbol{u}_t, \boldsymbol{w}_t, \varepsilon_t)$$

$$\boldsymbol{u}_t = p(t, \boldsymbol{x}_t)$$

$$\boldsymbol{x}_t = [M_t^{AT} \ M_t^{UP} \ M_t^{LO} \ T_t^A \ T_t^O \ K_t] \in \boldsymbol{X}$$

$$\boldsymbol{u}_t = [\mu_t \ s_t] \in \boldsymbol{U}$$

$$\boldsymbol{w}_t = [A_t \ L_t \ \sigma_t \ \theta_t^1 \ F_t^{EX} \ E_t^{land}] \in \boldsymbol{W}$$

We want to minimize **two objectives: economic utility** (to be maximized) and the **sum of atmospheric temperature** over the whole horizon. **Decisions** are **taken using a control policy**, i.e. a function which maps the states of the system into decision variables.

[3.3] EMODPS (EVOLUTIONARY MULTI-OBJECTIVE DIRECT POLICY SEARCH)

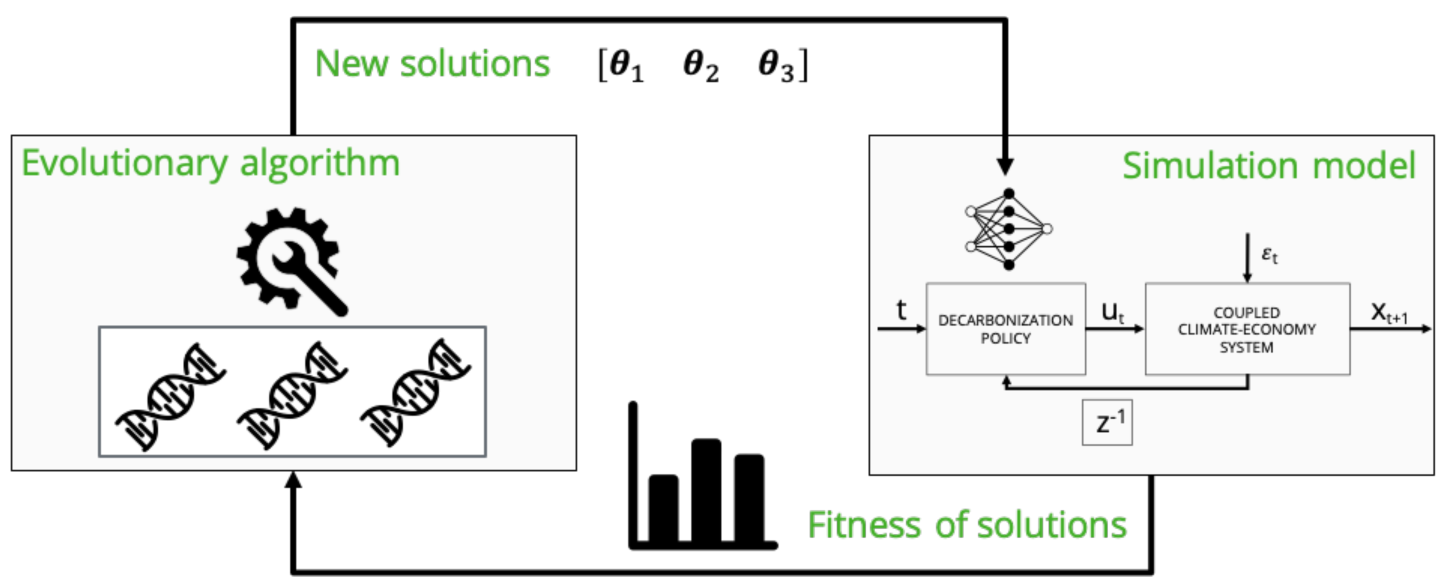
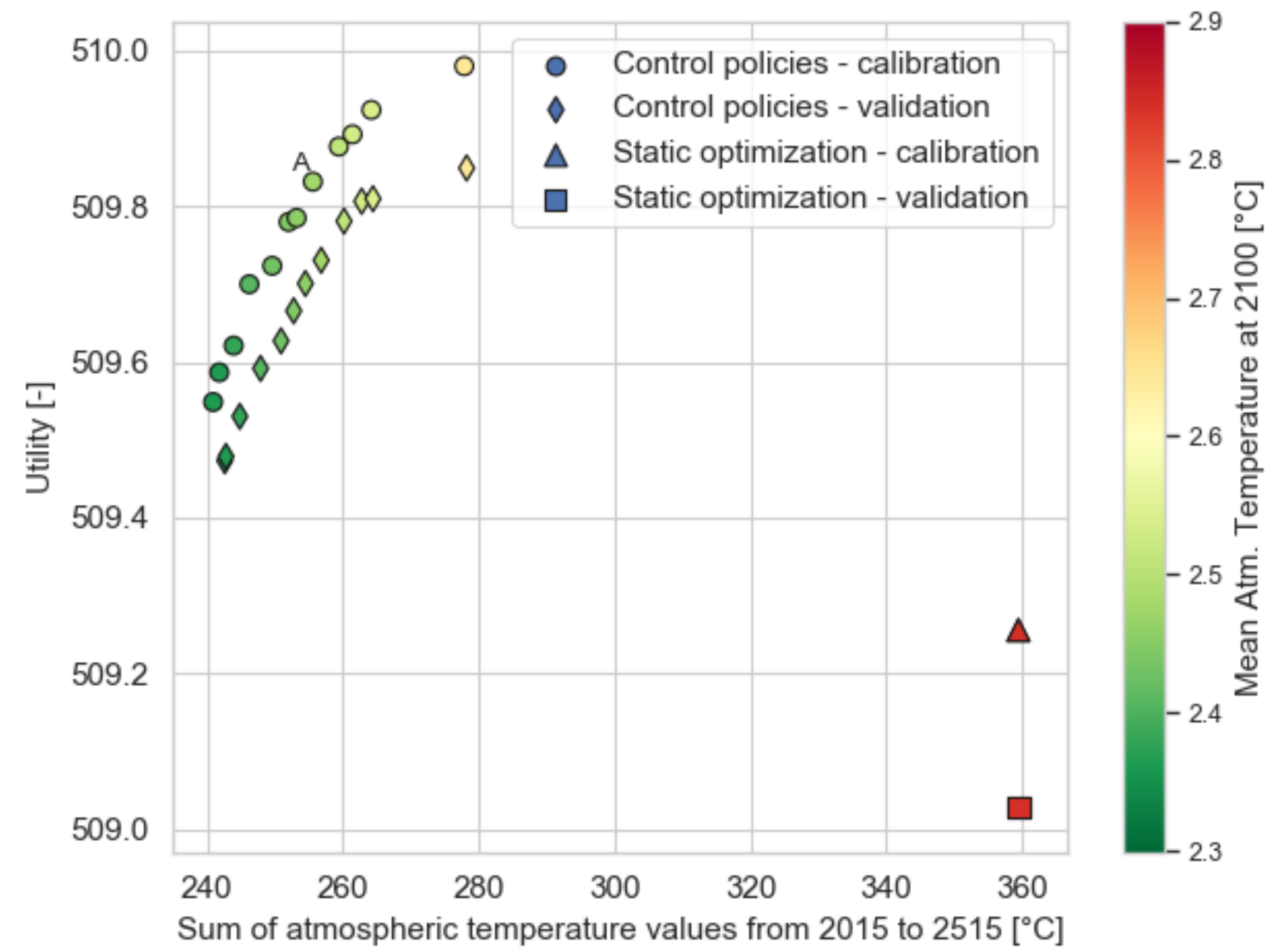


Figure 1
We solve the problem using **EMODPS**, a **simulation-based optimization algorithm** which iteratively evolves the pareto-optimal solutions.

We **compare solutions** obtained via the **proposed methodology** and using **the traditional static optimization approach**, i.e. directly fixing the decision variables.

[5] RESULTS

Figure 2
The whole set of solutions obtained is reported in the space of the objectives under calibration (over 1000 simulations) and validation (simulation of found solutions over 10000 new simulations). **The solution found via static optimization** is not able to adjust to the stochasticity and therefore **yields a lower utility with respect to any control policy**. In addition to that, the performance of the static optimization solution **produces a high value of atmospheric temperature. Optimal control policies** as they can hedge against fluctuations, are able to **improve the utility while reducing the value of atmospheric temperature**. The trade-off is more pronounced the more we move towards low temperatures. Finally, the **objectives loss in validation of the control policies is smaller** than in the static optimization one.



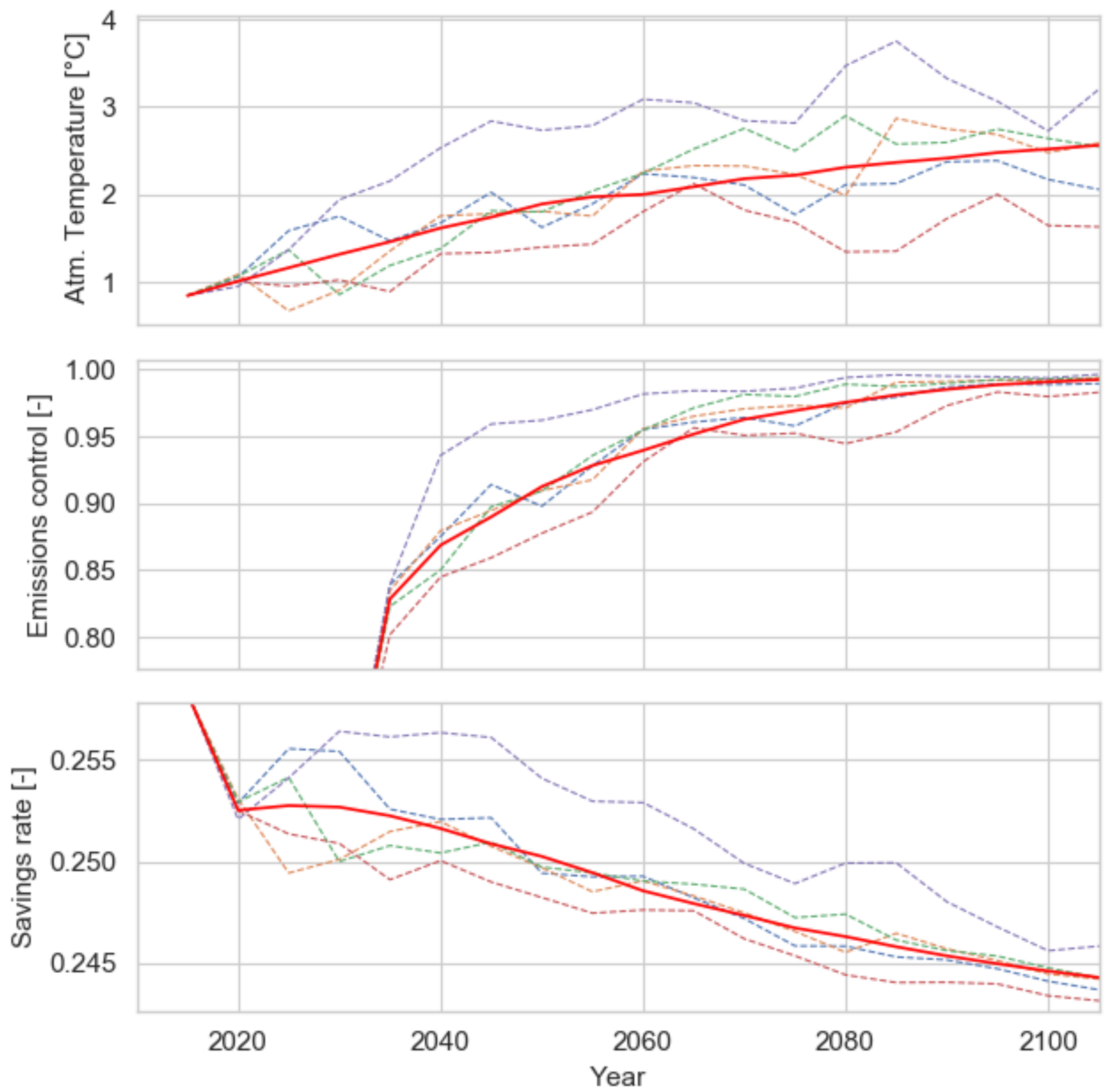


Figure 3
We report here some **sample trajectories from the solution marked with an A** in figure 1 (above). This control policy is at the elbow of the pareto front, thus represents a good compromise for both the objectives. The trajectories show how the decision variables (emission control and savings rate - bottom two panels) are influenced by the atmospheric temperature and its associated stochastic disturbance.

As for the **emission control**, it **ramps up until 2035** very fast with minor differences among different trajectories **independently of atmospheric temperature. After 2035**, the **control becomes more stringent as higher temperatures are observed**.

With respect to the **savings rate**, different strategies take place since the first time step. If **temperature increases** faster than expected, **larger investments are needed to maintain a strong economy** providing resources to be spent in emission control , to hedge against the damages and maintain a high utility. **If temperature grows slowly**, less effort is needed and **more resources can be diverted to consumption** resulting in higher utility.

[6] HIGHLIGHTS

Under stochastic disturbance, a **multi-objective optimal control approach outperforms static optimization** method allowing to **improve performance for the multiple objectives** considered and **ensuring adaptiveness with respect to uncertain evolution of the system**.

REFERENCES

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