Impact of Climate Model Parametric Uncertainty in an MPC Implementation of the DICE Integrated Assessment Model

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Abstract: Integrated assessment models (IAMs) are a key tool in studying the interdependence of the global economy and the climate system. For example, the dollar value of carbon dioxide emissions due to anthropogenic climate damages, known as the social cost of carbon dioxide (SC-CO2), can be computed via the widely used DICE (Dynamic Integrated model of Climate and the Economy) IAM by solving an open-loop optimal control problem. The results of such an open-loop decision-making strategy, however, do not fully reflect the impacts of uncertainty in the dynamic response of the global climatic system to radiative forcing. In this paper, we propose an implementation of the DICE IAM based on model predictive control (MPC). This MPC-based approach draws a clear distinction between the climate model used by DICE for mitigation planning purposes, and the “true” global climate herein captured by a low-order emulation of a model drawn from a state-of-the-art climate model ensemble (CMIP5, the fifth phase of the Coupled Model Intercomparison Project). The closed-loop control methodology in this paper thereby quantifies the impact of parametric climate model uncertainty (plant–model mismatch) on estimates of the SC-CO2 obtained from DICE.

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1. INTRODUCTION

Integrated assessment models (IAMs) are a central analytical tool for the design of optimal pathways of anthropogenic carbon dioxide (CO2) emissions pathways. By coupling simplified models of the global climate system with highly stylized models of global macroeconomic behavior, IAMs capture the intrinsically interdependent nature of the climate–economy system: CO2 emissions are a by-product of fossil-fueled economic activity, while global warming due to the enhanced greenhouse effect gives rise to economic damages; see, for example (IPCC (2013)).

The IAM employed in this paper is DICE (Dynamic Integrated model of Climate-Economy), arguably the single most influential and widely studied integrated assessment model (Nordhaus and Sjöre (2013); Nordhaus (1992)), and one of just three IAMs that inform official climate policy evaluations in the United States.

By solving an open-loop control problem, DICE determines economically optimal CO2 emissions pathways. The open-loop use of DICE for decision-making, however, disregards widely acknowledged uncertainties in both geophysical and economic models.

Computed in this open-loop fashion, policies designed by DICE are consequently sensitive to parametric uncertainty in both climate and economy models, as well as unmodeled disturbances and/or measurement noise. One response to this shortcoming is to design policies that are robust to model uncertainties within a certain bound. Such an approach, however, fails to fully maximize the economic objective (Beyer and Sendhoff (2007)).

An alternative approach to dealing with key uncertainties is taken by the U.S. government Interagency Working Group on Social Cost of Carbon (2010), or IAWG. The IAWG assigns probability distributions to each of several uncertain parameters in the climate–economy model, and performs Monte Carlo-style simulations in which values of these parameters are drawn from assumed distributions at each model run.

A critical shortcoming of the IAWG strategy is that it is inherently open-loop. Specifically: the social cost of carbon dioxide (SC-CO2) is computed by the IAWG using a predetermined set of socio-economic reference scenarios ([(Interagency Working Group on Social Cost of Carbon, 2010, pp. 15–25)], (Clarke et al. (2009))). As is well-known in the systems and control community, however, open-loop approaches to planning suffer in the presence of a variety of uncertainties; e.g. noisy measurements, disturbances, and both parametric and non-parametric model uncertainty. The limitations of the IAWG’s open-loop approach to computing the SC-CO2 therefore serve as a central motivation for the present paper.

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The open-loop approach is particularly problematic given the primary usage of IAMs in computing the SC-CO2. The SC-CO2 is defined as the dollar value of the economic damage caused by a one ton increase in CO2 emissions to
the atmosphere. While the U.S. currently uses a value of US$42 per ton of CO₂, other governments, businesses, and international finance organisations use similar estimates of the SC-CO₂ in cost-benefit analyses (Carbon Disclosure Project (2016); The Economist Intelligence Unit (2015)). The SC-CO₂ therefore not only underpins trillions of dollars worth of investment decisions (Hope (2015)), but by definition prices CO₂ emissions at a level consistent with sustainable development (United Nations (1987, 2015)). Appropriately understanding, characterizing, and coping with uncertainty is therefore of paramount importance, as recently highlighted in (National Academies of Sciences, Engineering, and Medicine (2017)).

In this paper, a two-phase procedure based on model predictive control (MPC) is proposed for the design of DICE-based optimal emissions pathways. In the first phase an optimal input (policy) vector for the future is calculated using a model of the real process (the “model”). In the second phase, the first value of the input vector is applied to a proxy reality (the “plant”) and new measurements of the states from the plant are fed back to the model to recompute the next optimal input policy vector. The process repeats in a receding horizon fashion that reflects—in a very natural manner—Article 4(9) of the Paris Agreement in which CO₂ mitigation targets are to be reviewed on rolling 5-year commitment periods; see United Nations Framework Convention on Climate Change (2015).

Since the real climate obviously cannot be used as the plant for the purposes of an IAM, it is necessary to employ a suitable climate proxy. In this paper, we take as this “simulated reality” one of a number of low-order climate models whose structure mirrors that of the DICE planning model, but whose parameters are chosen to emulate key attributes of the steady-state and dynamic response of high-performance climate models appearing in the fifth assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC); see Flato et al. (2013). To illustrate the proposed method, we calculate the range of uncertainty in the projected mean atmospheric temperature.

This paper makes three key contributions. First, by clearly distinguishing between the internal climate model (planning model) used within DICE and the climate proxy (simulated reality), a mechanism is provided for quantifying the impact of parametric climate model uncertainty (plant-model mismatch) within the DICE framework. Second, we present the necessary information to easily replicate within DICE the behavior any one of an ensemble of 23 CMIP5 models and calculate SC-CO₂ values for each model. Third, we quantify the uncertainty range of the atmospheric temperature when the default DICE planning model is employed in conjunction with a simulated reality model drawn from the CMIP5 climate model ensemble.

The rest of the paper is organized as follows. In Section 2, we present a summary of the DICE model, followed by the arguments for solving the finite horizon optimal control problem of DICE as an infinite horizon problem. Next we describe the SC-CO₂ and CMIP5 climate model parameters. Then, we provide the background information on the replication of the behavior of CMIP5 models in DICE. In Section 3, we provide the method for applying the MPC technique to DICE, followed by its extension to the model plant mismatch scenario in Section 4, before concluding in Section 5.

2. BACKGROUND

In this section we provide the background information on the DICE model and the optimal CO₂ mitigation policy relevant terms, namely the SC-CO₂, CMIP5 ensemble, and the climate model parameters. We also provide information for replicating the behavior of any of the CMIP5 climate models in DICE.

2.1 The DICE model

A block diagram of the DICE IAM is shown in Fig.1. Numerous constants and the full definitions of the exogenous inputs are necessarily omitted here due to space limitations. The interested reader is referred to Nordhaus (2014), Nordhaus and Sztorc (2013), or Kellett et al. (2016) for the full definition of the various parameters and exogenously defined quantities, together with other refinements applied in the full DICE model ¹. The description closely follows the information presented in Weller et al. (2015a,b).

DICE is a six state non-linear time-varying discrete-time model that couples a three state \((M_{AT},M_{UP},M_{LO})\) tank type carbon cycle model, a two state \((T_{AT},T_{LO})\) tank type climate model, and a single state \((K)\) economic model in a feedback form. The description about the states can be found in Weller et al. (2015a).

DICE models the increase in the \(T_{AT}\) value as negative growth in the global gross domestic product in order to calculate optimal CO₂ emissions reduction trajectories. These optimal policies are implemented by the two control inputs, the emissions control rate, \(\mu\), and the fraction of the gross domestic product invested back into the economy, \(s\). With non-linear functions representing the CO₂ emissions, \(E(K(t),\mu(t),t)\), radiative forcing, \(F(M_{AT}(t),t)\), and the investment in the economy, \(I(K(t),\mu(t),t)\), taken from Weller et al. (2015a), the DICE model can be written as follows:

¹ DICE was initially introduced in Nordhaus (1992) and has been updated several times. Herein, we use DICE2013R as described in Nordhaus (2014); see also Kellett et al. (2016)
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