

Equilibrium Analysis of MPC-based Climate Change Policy in Dynamic Games between Developed and Developing Regions

Namiki Kato, Yasuaki Wasa and Ken-Ichi Akao

Abstract—This paper analyzes an open-loop Nash equilibrium of climate change policies and long-term mitigation pathways based on Model Predictive Control (MPC) in non-cooperative dynamic games between developed and developing regions. After introducing a globally-used mathematical framework for a well-known integrated assessment model (IAM), the Regional Integrated Climate and Economy (RICE) model, with economic evaluations in multi-regional heterogeneity, this paper presents a dynamic noncooperative game between developed and developing regions based on possible international agreements. In particular, through numerical analysis, we show that an MPC-based iterative decision process, selected from the permissible control range to support a prescribed rising surface temperature since the Industrial Revolution, is effective.

I. INTRODUCTION

Addressing global warming (or “boiling”) is currently one of the most pressing international issues. Within the field of systems control, there is a strong expectation for the provision of scientific knowledge and technologies to solve this problem [1]. The Paris Climate Change Agreement calls for limiting the increase in the global average temperature to below 2.0°C and pursuing efforts to limit it to 1.5°C compared to the pre-industrial level [2]. To implement this agreement, each nation seeks realistic policies that balance economic and environmental aspects to achieve a sustainable, carbon-neutral society by 2050. A numerical analysis based on an integrated assessment model (IAM) is a promising approach to supporting scientific findings on climate change. The parts of IAMs are summarized in the Integrated Assessment Modeling Consortium [3]. Notably, the Dynamic Integrated Climate-Economy (DICE) model [4], [5], proposed by 2018 Nobel Laureate in Economics, William Nordhaus, has been utilized in the reports of the Intergovernmental Panel on Climate Change (IPCC) [6] and has undergone temporal improvements [7]. One development of the DICE model is the Regional Integrated Climate and Economy (RICE) model [8], which extends the economic model to multiple regions.

In systems and control fields, there is very little research on climate change control. The papers [9]–[12] demonstrate the policy design based on the Model Predictive Control (MPC) using the DICE/RICE models. The research group of Weller and Kellett [9], [10] investigates systems and control approaches of the climate-economy assessment based

on MPC with the DICE model. In [9], it is pointed out that distributed implementation based on the game-theoretic framework with the RICE model is one of the future directions. Chen and Shi [11], [12] propose implementing the dynamic game in the RICE model. However, these analyses [11], [12] do not sufficiently address policy and goal achievement discussions from an environmental perspective.

This paper proposes dynamic noncooperative games between developed and developing regions. The RICE model in [11], [12] is composed of the twelve economic regions in the world. Motivated by the so-called “Annex” category based on the principle called “common but differentiated responsibilities (CBDR),” which is established in the Paris Agreement [2], and the actual national development and climate policies to achieve net-zero emissions [13], this paper divides the twelve economic regions into four developed regions and eight developing regions and analyzes the open-loop Nash equilibrium solution in the dynamic game between developed and developing regions. The primary issue of the international agreements is to seek a negotiation-proof equilibrium choice in the context of cooperative or noncooperative game [14], [15]. To overcome the issue [14], [15] and consider the actual process [2], we propose the decision process, which features iteratively deciding the policies of developed and developing regions in a repeated game. In particular, the regions decide their climate change policies based on the investment allocation rate and emission reduction rate during the planning future period while complying with the upper limit of a surface temperature increase required by the Paris Climate Change Agreement and a possible international negotiation process. Through simulation with the parameters specific to each region, estimated by Nordhaus [8], we discuss the feasibility of the policy obtained by the proposed game from political and environmental perspectives regarding decision-making turns, forecast intervals of the MPC, and temperature rise constraints. The paper [16] presents the input constraint under the DICE model to satisfy the feasibility of 2.0°C. However, from the viewpoint of the dynamic game structure, this paper requires different input constraints from the DICE model [16].

The contributions of this paper are summarised as follows:

- 1) a dynamic noncooperative game of climate change policies between developed and developing regions based on the RICE model is presented;
- 2) After we sketch out the optimization property that the globally optimal solution of the RICE model is guaranteed, an MPC-based iterative decision method, selected from the permissible control range to support

N. Kato and Y. Wasa are with the Department of Electrical Engineering and Bioscience, Waseda University, Tokyo 169-8555, JAPAN. wasa@waseda.jp

K.-I. Akao is with the Graduate School of Social Sciences, Waseda University, Tokyo 169-8050, JAPAN.

This work was partially supported by JSPS KAKENHI 21H00717.

a prescribed rising surface temperature since the Industrial Revolution, is proposed; and

- 3) effectiveness and limitations of the proposed method are demonstrated in simulation.

The paper is structured as follows: After introducing the RICE model in Sec. II, a social optimization problem, which is presented by Nordhaus [8], and dynamic noncooperative games between developed and developing regions are formulated in Sec. III. In Sec. IV, an MPC-based iterative decision process is presented between the developed and developing regions. Section V investigates the effectiveness and limitations of the MPC-based open-loop Nash equilibrium obtained by the proposed game through a numerical study. The paper is finally concluded with Sec. VI.

II. INTEGRATED ASSESSMENT MODEL

The DICE model [4] is an economic and climate-integrated assessment model that considers the entire Earth as a single economic agent. Conversely, regional characteristics exist in reality, and the RICE model is a DICE extension that accounts for economic agents across multiple regions. This paper discusses based on the RICE-2011 model [8], similar to [12]. The paper [12] examines a noncooperative game model for twelve regions (US, EU, Japan, Russia, Eurasia, China, India, Mideast, Africa, Latin America, Other High-Income countries (OHI), and Other Asian countries (Oth-Asia)). This paper investigates the dynamic game between developed and developing regions, classifying them into four developed regions (US, EU, Japan, OHI ($i = 1, \dots, 4$)) and eight developing regions ($i = 5, \dots, 12$). Furthermore, we set one unit of time to $\Delta_t = 5$ years, assuming policies are implemented at a constant value per unit of time, and denote the final year of analysis for global warming as T_f .

First, we introduce the economic model. Economic activities occur autonomously in each region i ($= 1, \dots, 12$), applying the standard economic growth model, the Ramsey model, appropriately modified for environmental issues. In this paper, similarly to [8], the effects of goods movement due to international trade between regions are not considered.¹ The gross domestic product (GDP) Y_i at time t is given by a Cobb-Douglas production function

$$Y_i(t) = A_i(t)K_i(t)^{\gamma_i}L_i(t)^{1-\gamma_i}, \quad (1)$$

where γ_i represents the elasticity of output concerning capital, A_i means the total factor productivity of the Hicks-neutral variety, and L_i indicates the population, i.e., the labor force. Particularly, considering the unit period Δ_t , the dynamics of capital K_i are described using the depreciation rate δ_i per unit period and investment I_i as

$$K_i(t+1) = (1 - \delta_i)^{\Delta_t} K_i(t) + \Delta_t I_i(t). \quad (2)$$

¹Though all parameters are intuitively time-dependent, some of the parameters defined in this paper use the same time-independent values as the previous studies [7]–[12]. These predicted values for the future year have the same trend as the current values. See [7] for more details.

The net domestic product (NDP) Q_i is given by considering the impact of global warming as

$$Q_i(t) = \Omega(t)(1 - \Lambda_i(t))Y_i(t). \quad (3)$$

The global economic activity loss Ω common to climate change depends on the surface temperature T_{AT} as

$$\Omega(t) = \frac{D(t)}{1 + D(t)}, \quad (4)$$

$$D(t) = \psi_1 T_{AT}(t) + \psi_2 T_{AT}(t)^2, \quad (5)$$

where D indicates a climate damage factor. The parameters ψ_1 and ψ_2 are universally appropriate coefficients. The economic mitigation rate Λ_i for each region due to emission reduction is given by

$$\Lambda_i(t) = \theta_{1i}(t)\mu_i(t)^{\theta_{2i}}, \quad (6)$$

which depends on the emission reduction rate $\mu_i \in [0, 1]$. The parameters θ_{1i} and θ_{2i} are region-dependent appropriate coefficients. Net production Q_i is allocated for the investment I_i for future use or the consumption C_i at the current time. If the allocation ratio for investment is $s_i \in [0, 1]$, the following equations give the investment I_i and consumption C_i :

$$I_i(t) = s_i(t)Q_i(t), \quad (7)$$

$$C_i(t) = Q_i(t) - I_i(t) = (1 - s_i(t))Q_i(t). \quad (8)$$

Next, we introduce the climate change model on temperature. The emission amount E_i at time t for each region i consists of emissions from economic activities E_i^{ind} and land use change emissions E_i^{land} . Considering the number of years per unit period Δ_t , the emission amount E_i is given by

$$E_i(t) = \Delta_t(E_i^{ind}(t) + E_i^{land}(t)), \quad (9)$$

$$E_i^{ind}(t) = \sigma_i(t)(1 - \mu_i(t))Y_i(t), \quad (10)$$

where σ_i represents the emission intensity, and $\mu_i \in [0, 1]$ is the emission reduction rate. The total emission for the entire Earth is the sum of these emissions

$$E(t) = \sum_{i=1}^{12} E_i(t) \quad (11)$$

Mainly, if we explicitly consider the global fossil fuel-dependent emission cap $CCum(t)$, it imposes the constraint $\sum_{i=1}^{12} E_i^{ind}(t) \leq CCum(t)$. Similar to literature [11], [12], this paper does not consider this constraint in the optimization problem.

The dynamics of carbon concentration interact between the surface M_{AT} , the upper ocean M_{UP} , and the lower ocean M_{LO} , and the total emission E affect the concentration at the surface as

$$\begin{bmatrix} M^{AT}(t+1) \\ M^{UP}(t+1) \\ M^{LO}(t+1) \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{21} & 0 \\ \phi_{12} & \phi_{22} & \phi_{32} \\ 0 & \phi_{23} & \phi_{33} \end{bmatrix} \begin{bmatrix} M^{AT}(t) \\ M^{UP}(t) \\ M^{LO}(t) \end{bmatrix} + \begin{bmatrix} b_M \\ 0 \\ 0 \end{bmatrix} E(t), \quad (12)$$

where the parameters ϕ_{**} and b_M mean appropriate values. The radiative forcing F is given by the sum of the effects of

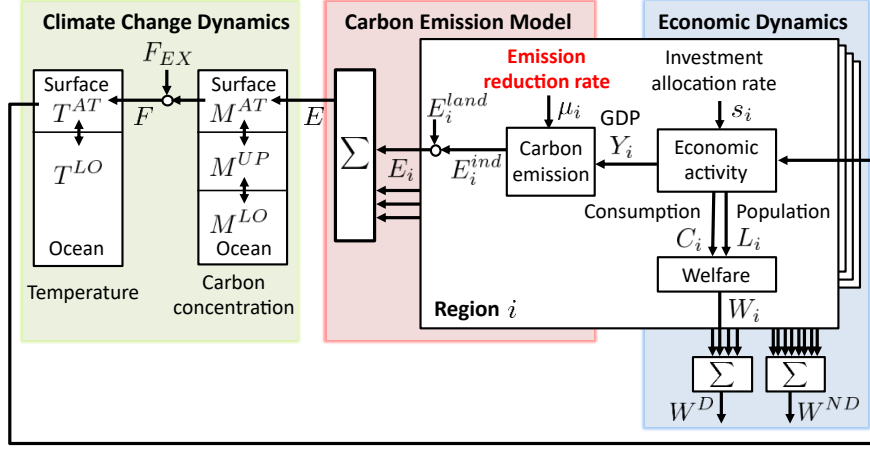


Fig. 1. A block diagram of the RICE model.

accumulated carbon dioxide and other gases such as methane and fluorocarbons F_{EX} as

$$F(t) = \eta \log_2 \left(\frac{M^{AT}(t)}{M_{1750}^{AT}} \right) + F_{EX}(t), \quad (13)$$

where M_{1750}^{AT} indicates the carbon concentration on the surface before the Industrial Revolution, i.e., in 1750, and η is a suitable coefficient. Then, the dynamics of the surface temperature T^{AT} and ocean temperature T^{LO} are represented by the following equation.

$$\begin{bmatrix} T^{AT}(t+1) \\ T^{LO}(t+1) \end{bmatrix} = \begin{bmatrix} \xi_{11} & \xi_{21} \\ \xi_{12} & \xi_{22} \end{bmatrix} \begin{bmatrix} T^{AT}(t) \\ T^{LO}(t) \end{bmatrix} + \begin{bmatrix} b_T \\ 0 \end{bmatrix} F(t), \quad (14)$$

where the parameters ξ_{**} and b_T mean suitable constants. The state is denoted as $x = (M^{AT}, M^{UP}, M^{LO}, T^{AT}, T^{LO}, (K_i)_{i=1, \dots, 12})$. A block diagram summarizing the above is shown in Fig. 1.

III. OPTIMIZATION AND GAME FORMULATION

Motivated by the Annex category based on the principle called CBDR [2] and the actual national development and climate policies to achieve net-zero emissions [13], this section proposes a social optimization problem and the dynamic game between the developed and developing regions based on an economic and climate-integrated assessment model.

First, we introduce a social welfare function corresponding to the above state variables. The social welfare function W_i for each region i ($i = 1, \dots, 12$) from the initial time t_0 to the planning future time $t_0 + T$ is given by

$$W_i(T; t_0) = \sum_{t=t_0+1}^{t_0+T} \theta_i(t) R_i(t) U_i(C_i(t), L_i(t)) \quad (15)$$

where θ_i is called the Negishi weight, which represents an equilibrium price in an international competitive market under budget constraints, and R_i is the discount rate given by

$$R_i(t) = \frac{1}{(1 + \rho_i)^{\Delta_i(t-t_0)}} \quad (16)$$

For the utility function U_i related to consumption, Nordhaus [8] uses $U_i(C_i(t), L_i(t)) = L_i(t)(C_i(t)/L_i(t))^{1-\alpha_i}/(1-\alpha_i)$ under a sufficiently long finite time optimization problem. Literature in the control field [10]–[12] formulates an infinite time optimization problem and performs MPC-based optimization. Assuming the application of MPC, we follow the literature [10]–[12] and give the utility per capita consumption multiplied by the population (labor force) L_i as

$$U_i(C_i(t), L_i(t)) = L_i(t) \frac{(C_i(t)/L_i(t))^{1-\alpha_i} - 1}{1 - \alpha_i}, \quad (17)$$

where α_i indicates a region-dependent coefficient.

Next, we formulate the optimization problem and the game. Since this paper classifies the world into developed and developing regions, the social welfare function of the developed regions W^D is given by

$$W^D(T; t_0) = \sum_{i=1}^4 W_i(T; t_0), \quad (18)$$

and that of the developing regions W^{ND} is given by

$$W^{ND}(T; t_0) = \sum_{i=5}^{12} W_i(T; t_0), \quad (19)$$

respectively. The policy decision variables, i.e., the control input parameters in the control field, are the emission reduction rate $\mu_i \in [0, 1]$ and investment rate $s_i \in [0, 1]$ for each region i . Therefore, at each time t to be solved in the optimization problem or the dynamic noncooperative game, the developed regions decide on eight variables

$$u^D(t) = ((\mu_1(t), s_1(t)), \dots, (\mu_4(t), s_4(t))),$$

and the developing regions decide on sixteen variables

$$u^{ND}(t) = ((\mu_5(t), s_5(t)), \dots, (\mu_{12}(t), s_{12}(t))),$$

respectively. Assume realistic initial state values and exogenous variables other than state and decision variables at the initial time t_0 are given (or appropriately estimated). Then, similarly to the settings by Nordhaus [8] and control

literature [10]–[12], the world’s total social welfare function maximization problem over a finite horizon T is given by

$$\begin{aligned} \max_{u^D, u^{ND}} W(T; t_0, p) \text{ s.t. (1)–(14), } x(t_0) = x_0, \quad (20) \\ W(T; t_0, p) = pW^D(T; t_0) + (1 - p)W^{ND}(T; t_0) \end{aligned}$$

where $p \in [0, 1]$ is a parameter adjusting the degree of evaluation between developed and developing regions. The papers [11], [12] explore the cooperative game compromise point, i.e., Pareto optimal solution, under negotiation from the Pareto Frontier obtained by varying the weight $p \in [0, 1]$, that is, the burden ratio between developed and developing regions.

Conversely, the noncooperative game between developed and developing regions is given by

$$\max_{u^D} W^D(T; t_0, u^D, u^{ND}) \text{ s.t. (1)–(14), } x(t_0) = x_0, \quad (21a)$$

$$\max_{u^{ND}} W^{ND}(T; t_0, u^D, u^{ND}) \text{ s.t. (1)–(14), } x(t_0) = x_0. \quad (21b)$$

In dynamic games (21), prominent solution concepts include open-loop Nash equilibrium and feedback Nash equilibrium [17]. This paper analyzes sequential optimization based on MPC following the open-loop Nash equilibrium, whereas investigating the feedback Nash equilibrium remains an important future task.

IV. POLICY DECISION MECHANISM

In this section, we discuss the implementation methods for the optimization problem (20) and the dynamic game (21) utilized in the simulations of the subsequent section. Solak et al. [18] prove that the DICE model can be reduced to the hidden convex optimization problem, which guarantees the globally optimal solution. From the same procedure as the DICE [18], we can hypothesize the globally optimal solution of the RICE model with region-dependent parameters and constants is straightforwardly guaranteed.

Nordhaus [8] focuses on the analysis of solutions obtained through aggregate optimization up to the final year T_f in the context of maximizing social welfare (20), i.e., $\max W(T_f; t_0, p)$, considering the entire world as a single economic zone. On the other hand, considering the history of international agreements at the Conference of the Parties (COP) under the United Nations Framework Convention on Climate Change, where obligations to reduce emissions and the extent of such obligations are revised approximately every five years, challenges remain in the implementability of open-loop Nash equilibrium solutions for the ultra-long-term setting of T_f .

This paper applies the concept of MPC [11], [12]. We solve the optimization problem (20) for the social welfare function $W(T_{pred}; t_0, p)$ up to the terminal time $T = t_0 + T_{pred}$ from the current time t_0 . The initial state x_0 is the actual value at the current time t_0 . Among the obtained optimal solutions, only the solutions for the time interval $T_\delta (\leq T_{pred})$, $(u^D(t), u^{ND}(t))$, $t = t_0, t_0 + 1, \dots, t_0 + T_\delta$, are implemented. The initial time is updated by T_δ units, i.e., $t_0 \leftarrow t_0 + T_\delta$, and the process is repeated.

Next, we discuss the implementation method for the dynamic noncooperative game (21). As mentioned above, based on MPC, we focus on the optimization problem up to the terminal time $T = t_0 + T_{pred}$ from the current time t_0 . When deriving Nash equilibrium solutions, all participants must share all model information; otherwise, sharing decision variable information and numerical iterative updates among participants is required. Considering this, the computation is performed using the following steps with the iteration number $k (\geq 1)$.

The initial values are given as (u_0^D, u_0^{ND}) . In this paper, the initial values are set as the solutions of maximizing social welfare, i.e., $\arg \max W(T_f; t_0, p)$. The solutions are respectively obtained using the following two methods. The implementation is carried out with $(u^D(t), u^{ND}(t)) = (u_{k_f}^D(t), u_{k_f}^{ND}(t))$, $t = t_0, \dots, t_0 + T_\delta$, after an appropriate number of iterations k_f .

(I) Simultaneous decision: In the literature [11], [12], for the choice of actions at iteration number k , under the assumption that the actions of the other side are identical to their immediate previous actions, the optimal response strategies at iteration $k + 1$ are given as

$$\begin{aligned} u_{k+1}^D &= \arg \max_{u^D} W^D(T_{pred}; t_0, u^D, u_k^{ND}), \\ u_{k+1}^{ND} &= \arg \max_{u^{ND}} W^{ND}(T_{pred}; t_0, u_k^D, u^{ND}), \end{aligned}$$

respectively.

(II) Iterative decision: In reality, decisions are not always made simultaneously, as in **(I)**, and situations may arise where turns are explicitly considered [2], [13]. Specifically, at a particular iteration number $k = 2k_D + \delta$ with a variable $\delta = \{0, 1\}$ determining who moves first, developed regions decide their actions, and in the following iteration number $k + 1$, developing regions assess their actions in response to the updated actions of the developed regions. Thus, the following expressions define a sequential (repeated) game. In the first round $k + 1$, the developed regions decide their action u^D under the previous action u_k^{ND} of the developing regions:

$$\begin{aligned} u_{k+1}^D &= \arg \max_{u^D} W^D(T_{pred}; t_0, u^D, u_k^{ND}), \\ u_{k+1}^{ND} &= u_k^{ND}. \end{aligned}$$

At the second round $k + 2$, the developing regions decide their action u^{ND} under the previous action u_{k+1}^D of the developed regions:

$$\begin{aligned} u_{k+2}^D &= u_{k+1}^D, \\ u_{k+2}^{ND} &= \arg \max_{u^{ND}} W^{ND}(T_{pred}; t_0, u_{k+1}^D, u^{ND}). \end{aligned}$$

Note that the iterative policy decision process shown in **(II)** is our proposed method in this paper. The iterative decision-making process with the best response strategy shown in **(II)** guarantees to achieve the globally optimal solution [17]. Meanwhile, the simultaneous decision process shown in **(I)** does not rigorously guarantee convergence at a locally or globally optimal solution.

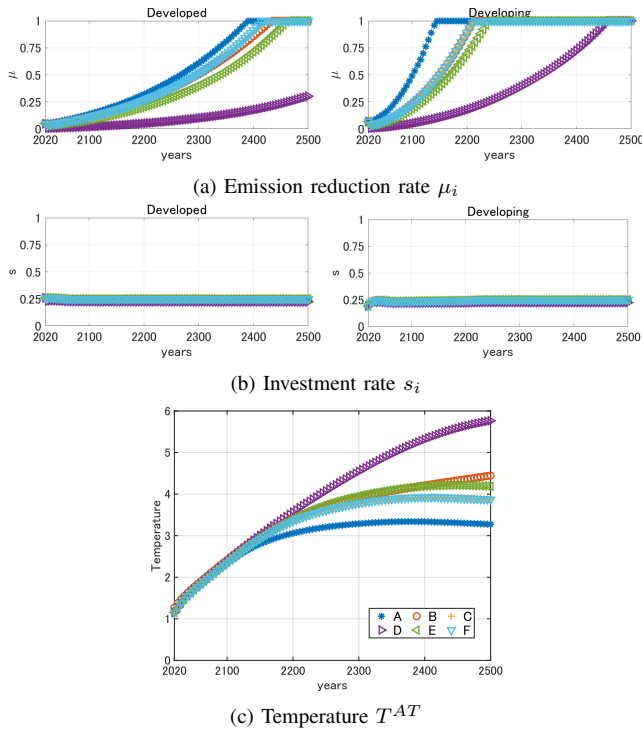


Fig. 2. Results without the temperature constraints.

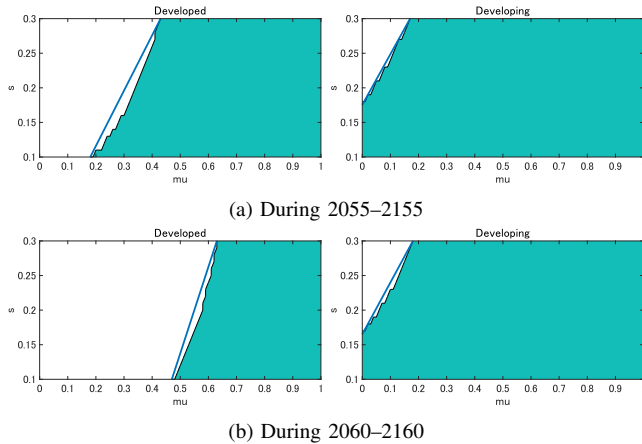


Fig. 3. Admissible control constraints.

V. NUMERICAL STUDY

In this section, through simulation with the parameters specific to each region, estimated by Nordhaus [8], we discuss the feasibility of the long-term mitigation pathways obtained by the proposed game from political and environmental perspectives regarding decision-making turns, forecast intervals of the MPC, and temperature rise constraints. In particular, we conduct a numerical analysis using the MATLAB program integrated with the nonlinear optimization solver based on CasADi, as disclosed in the literature [11]. The initial year is set to 2020, with policy decisions being made every $\Delta_t = 5$ years, following the Paris Agreement [2], and all constants are set according to the values in the RICE model as in [11]. Considering the negotiation process for

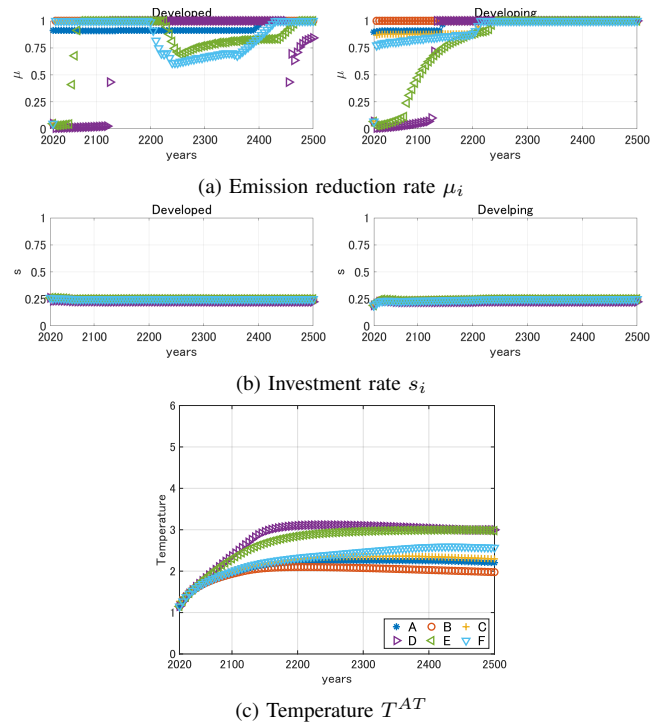


Fig. 4. Results with the temperature constraints.

the international convention on the adoption and amendment of annexes [2], we assume that the policy variables within developed regions and those within developing regions are considered identical, i.e.,

$$u_i \equiv u^n, i = 1, \dots, 4, \quad u_i \equiv u^{nd}, i = 5, \dots, 12$$

In this paper, the following six settings are compared:

- (A) Social welfare maximization (20) with $p = 0.5$, $T = 120$. The setting is similar to [8].
- (B) Dynamic non-cooperative game (21) based on simultaneous decision (I) with $T = 120$. The setting is similar to [11], [12].
- (C) Dynamic non-cooperative game (21) based on iterative decision (II) with $T = 120$.
- (D) MPC-based implementation under dynamic non-cooperative game (21) based on iterative decision (II) with $T_{pred} = 5$ and $T_\delta = 1$.
- (E) MPC-based implementation under dynamic non-cooperative game (21) based on iterative decision (II) with $T_{pred} = 20$ and $T_\delta = 1$.
- (F) MPC-based implementation under dynamic non-cooperative game (21) based on iterative decision (II) with $T_{pred} = 80$ and $T_\delta = 1$.

For the settings (B)–(F), the terminal condition of the iteration process is that sufficient convergence is achieved, and the decision parameters (u_k^D, u_k^{ND}) at the terminal round k are implemented. This paper shows the results for the precedence ($\delta = 0$) of the developed regions in the settings (C)–(F) since there is no significant difference in the results between the precedence ($\delta = 1$) of the developing regions and that of the developed regions ($\delta = 0$).

Then, the results are presented in Fig. 2. From Fig. 2(a) and the regional differences in economic factors, it is evident that under all settings, the requirements of the emission reduction rate μ_i are more stringent for developing regions than for developed regions. Furthermore, as inferred from Fig. 2(b), the investment allocation rate s_i remains around $s_i = 0.25$ for most of the period. The value $s_i = 0.25$ is scientifically reasonable in economics. However, Fig. 2(c) indicates that, regardless of the setting, the surface temperature rise post-Industrial Revolution will exceed 3.0°C by 2200, failing to meet the 2.0°C target required by the IPCC. This paper omits detailed discussions of achieving the 2.0°C target. Still, the authors' analysis of the RICE model handled in this paper revealed that none of the settings could achieve the 2.0°C target. The most effective setting for mitigating surface temperature rise is the cooperative game solution in setting (A), followed by MPC with an iterative decision process over an ultra-long forecast horizon (C) and (F). The worst setting is the simultaneous decision process in the dynamic noncooperative game (B).

In light of these results, we introduce new input constraints in the optimization problem (20) and the game (21) to keep the surface temperature rise below 3.0°C . Specifically, the choices for inputs u^D and u^{ND} are limited to decision values that can achieve the surface temperature rise below 3.0°C in the terminal year 2500. Considering the optimal investment allocation rate s_i to be around 0.25, as shown in Fig.2(b), the range of s_i is limited from 0.1 to 0.3. The range of the emission reduction rate μ_i depends on the parameters specific to each region. From the multi-regional heterogeneity, the range of μ_i is different. For example, the feasible ranges of decision parameters (μ_i, s_i) for the regions in the two durations are shown in Fig. 3. The simulation is recalculated to solve the dynamic game numerically by adding the constraints within the blue line in Fig. 3, approximated as linear constraints.

Then, the results with the feasible range constraints of the decision parameters obeyed by the surface temperature upper limit are displayed in Fig. 4. Compared to the results in Fig. 2 without the constraints, all the settings are urgently required to achieve zero carbon emissions by 2100. Note that the input constraints cause the rapid change of μ_i . Even if the input constraints are added to the RICE model, the hidden convex optimization is guaranteed, and the numerical results are computationally stable. The mathematically rigorous proof will be discussed in a separate paper. Notably, the results from settings (E) and (F) suggest that developed regions may relax emission reduction rates around the year 2200 under long-term forecasting with an iterative decision process in MPC implementation.

Surface temperature rise is mitigated in all settings under the 3.0°C limit. The surface temperature rise of the longer-term MPC prediction is close to that of the social maximization (A). In the settings (A)–(C), the surface temperature rise in 2050 can be reduced to approximately 2.0°C . The above results suggest that the competitive decision process in dynamic noncooperative games, which is based on realistic

international agreements, tends to approach zero carbon emissions and effectively mitigates surface temperature rise and climate change in the long term in the presence of the admissible economic policy constraints.

VI. CONCLUSION

This paper has proposed climate change policies and mitigation pathways based on Model Predictive Control (MPC) and iterative decision processes in noncooperative dynamic games between developed and developing regions, which is motivated by the actual international agreements. In particular, through numerical analysis, we have shown that an iterative decision process based on MPC with 100-year prediction, selected from the permissible control range to support a prescribed rising surface temperature since the Industrial Revolution, can keep the approximate 2.0°C limit. One of the future directions is to explore further technological innovation for carbon reduction in support of the Paris Climate Change Agreement.

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