On game-based control systems and beyond

Renren Zhang[1], Fang Wang[2], Lei Guo[3]*

In the traditional frameworks of both classical and modern control theories, the objects or plants to be controlled or regulated are essentially of "passive" nature, in the sense that they are usually modeled by physical laws and are assumed to have no objectives or payoffs to pursue actively by themselves as in the control of e.g., a car, an aerocraft, and a chemical process, etc. This may not be the situation, however, for many practical regulation problems in, for example, social, economic, and the future "intelligent" engineering systems. Such problems share a common characteristic where the objects to be controlled or regulated usually consist of multiple active agents, whose behaviors are not only driven by physical laws, but also by their own interests or objectives. In general, the agents' interests or objectives may not be the same as those of the global objective of control or regulation, and therefore may result in strategic behaviors of the agents. To regulate such systems, neither the traditional game theory nor the traditional control theory could be applied directly, and it turns out to be necessary to incorporate a game-based structure in the control theoretical framework [1], though there are some known connections between the two theories [2].

This new class of control systems may be referred to as game-based control systems (GBCS) [3, 4]. The GBCS have a hierarchical decision-making structure: one regulator in the macro-level and multiple interacting agents in the micro-level. The regulator can be regarded as a global controller that makes decision first, and then the agents try to optimize their own performances or objectives respectively. We remark that the regulator may contain multiple regulatory variables including either feedforward-feedback control signals or adjustable performance indices or both. Moreover, if the states of the agents can reach a Nash equilibrium as a result of noncooperative dynamic game, then the control of GBCS may be regarded as the control of the Nash equilibrium. On the other hand, if the states of the interacting agents are out of balance due to some reasons, then the regulation of GBCS may help to reach the desired balanced state. We would like to point out that the difference between the GBCS and the Stackelberg game is just as that between control theory and

[1] Key Laboratory of Systems and Control, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, China;

[2] Data Science Institute, Shandong University, China;

[3] Key Laboratory of Systems and Control, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, China. Lguo@amss.ac.cn.

optimization theory. In fact, there are many more problems in GBCS need to be investigated as control systems, for examples, feedback and uncertainty, controllability, observability, stabilizability, system identification, adaptive control, robust control, etc.

It goes without saying that GBCS are ubiquitous, and we just briefly mention two examples here. One example is the regulation of macroeconomics [5], where a government or organization may exert regulations through some policies for various reasons, e.g., the monetary and fiscal policies in the European Union [6], which may be modeled and analyzed by using GBCS. Another example comes from the contact robots which can work with and assist human users, such as rehabilitation robots. It has been shown that humans interact with their environments by minimizing both the performance errors and the costs of their actions [7], and the Nash equilibrium arises naturally in human-robot interactions [8]. Since the Nash equilibrium strategies may lead to system instability, an external regulator is required, which may be modeled as a stabilization problem of GBCS.

Preliminary theoretical studies on GBCS were initiated in [1, 3, 4], and some necessary and sufficient conditions on the controllability of linear GBCS are provided [3, 4]. The study of GBCS is still in its infancy and more in-depth research is needed. Here, we only mention a few interesting problems: whether or not there is a canonical form for GBCS, how to control GBCS under uncertainties in structure and information, how mechanism design methods [9] may be used in GBCS.

Of course, there are many important regulation problems beyond the scope of GBCS. For example, breakthroughs in information technology and artificial intelligence (AI) are rapidly changing the structure of human society, where there are plenty of emerging and challenging regulation problems. The AI has developed from auxiliary tools to good consultations, and may even gradually become a basic social element that is autonomous and should be beneficial to humans. Understanding the behavior of AI systems is essential to our ability to control their actions, reap their benefits and minimize their harms, and thus the study of machine behaviors has been regarded as an emerging field [10]. Furthermore, the objects of social regulation are being upgraded into powerful AI as well as organizations and individuals with capabilities significantly enhanced by AI, and the environment is being transformed into complex systems of man-machine integration. The currently developing intelligent transportation systems, industrial internets, electronic commerce, and smart cities, are a few examples. In the face of various uncertain risks and challenges in the man-machine integration systems (MMIS) , such as the widespread information collection and integration, complex and highly interconnected heterogeneous subjects, technological difficulties of ethical and legal reconstruction, and the task of algorithm regulation [11], it is of great importance to build a social regulatory system that conforms to such value objectives as safety and stability, equity and justice, democracy and freedom, social welfare, and harmonious evolution, etc.

The key to the regulation of MMIS is to regulate the behaviors of humans and machines as well as the emergence behaviors resulted from their interactions and integrations. There are some basic principles that can be followed. For examples, being people oriented,

advantageous complementariness, proportionality, and algorithm regulation, which means insistence that AI systems should support human institutions and fundamental rights to achieve a fair society; reasonable allocation of human and AI functions to give full play to the complementary advantages of human and AI; insistence on the minimum infringement and the balance of legal interests, distinguishing the risk level and determine the regulatory intensity and subjects; regulating the impact of the algorithms from both inside and outside, and promotion of sustainable and harmonious development. Some related issues may be found in various plans, guidelines, and principles for the development of AI, see e.g., [12] and [13] for two recent ones.

A possible path to regulate the MMIS is to combine the control theory for engineering systems with the science of law for social systems, or to expand the scope of the above discussed GBCS to include legal norm as a necessary tool for regulation at different levels. This may likely enable us to secure basic ethical and legal issues, and at the same time to realize the technical objectives of regulation for MMIS. There is no doubt that the regulation of MMIS will be of great importance with grand challenges in the future.

Conflict of interest statement. None declared.

REFERENCES

[1] Y. F. Mu and L. Guo. A new class of control systems based on non-equilibrium games. In: X.M Hu, U. Jonsson, B. Wahlberg and B. K. Ghosh (eds.). *Three Decades of Progress in Control Sciences.* Berlin: Springer-Verlag Berlin Heidelberg, 2010, 313-326.

[2] T. Başar and G. J. Olsder. Dynamic noncooperative game theory(2nd). Philadelphia: Society for Industrial and Applied Mathematics, 1999.

[3] R. R. Zhang and L. Guo. IEEE Transactions on Automatic Control, 64(10):4180-4187, 2019.

[4] R. R. Zhang and L. Guo. SIAM Journal on Control and Optimization, 57(6):3799-3826, 2019.

[5] D. Mahmoudinia, R. B. Dastjerdi and S. Jafari. Quarterly Journal of Applied Theories of Economics, 4(4): 143-174, 2018.

[6] B. Aarle, J. Engwerda, and J. Plasmans. Annals of Operations Research, 109(1-4):229-264, 2002.

[7] N. Jarrasse, T Charalarmbous, and E. Burdet. PLoS ONE, 7(11):e49945, 2012.

[8] D. A. Braun, P. A. Ortega, and D. M. Wolpert. PLoS ONE, 5(8):e1000468, 2009.

[9] T. Borgers. An introduction to the theory of mechanism design. Oxford: Oxford University Press, 2015.

[10] L. Rahwan, M. Cebrian, N. Obradovich, et al. Nature, Volume 568, 477–486, 2019.

[11] L. Andrews, B. Benbouzid, J. Brice, et al, Algorithmic regulation, London: London School of Economics and Political Science, 2017.

[12] Development Planning of New Generation Artificial Intelligence - Developing Responsible Artificial Intelligence, http://most.gov.cn/kjbgz/201906/t20190617_147107.htm. 2019.

[13] White Paper on Artificial Intelligence - A European approach to excellence and trust, https://ec.europa.eu/info/publications/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en, 2020.