

Complexity of regulatory logic and dynamics of Boolean models of biological networks

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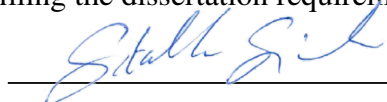


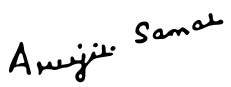
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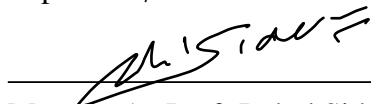
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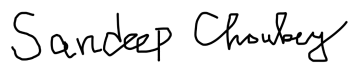
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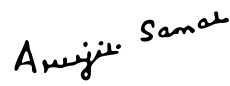

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Declaration

I, hereby declare that the investigation presented in this thesis has been carried out by me.
The work is original and has not been submitted earlier as a whole or in part for a degree or diploma at this or any other Institution or University.



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Oral or Poster presentations

1. Poster presentation titled *Critical assessment of measures to quantify relative stability of states in Boolean models of developmental gene regulatory networks* at the Conference on Nonlinear Systems and Dynamics (CNSD) 2022 held at the Indian Institute of Science Education and Research (IISER) Pune, India, from 15-18 December 2022.
2. Poster presentation titled *Leveraging developmental landscapes for model selection in Boolean gene regulatory networks* at the IMSc60 - Celebrating 60 Years of Creative Science held at the Institute of Mathematical Sciences (IMSc), Chennai, India, from 2-5 January 2023.
3. Poster presentation titled *Leveraging developmental landscapes for model selection in Boolean gene regulatory networks* at the Big Data Algorithms for Biology (BD-Bio) 2023 held at the Indian Institute of Science (IISc), Bengaluru, India, from 2-3 June 2023.
4. Poster presentation titled *Leveraging developmental landscapes for model selection in Boolean gene regulatory networks* at the Network Biology Day held at the Institute of Mathematical Sciences (IMSc), Chennai, India, on 20 July 2023.
5. Poster presentation titled *Biologically meaningful regulatory logic enhances the convergence rate in Boolean networks and bushiness of their state transition graphs* at the Perspectives in Nonlinear Dynamics (PNLD) 2023 held at the Indian Institute of Technology (IIT) Madras, India, from 1-4 August 2023.
6. Oral presentation titled *Adapting concepts from cellular automata to explore bushiness and convergence in Boolean network dynamics* and poster presentation titled *Biologically meaningful regulatory logic enhances the convergence rate in Boolean networks and bushiness of their state transition graph* at the Modelling and Tackling Complex Biological Systems held at the Institute of Mathematical Sciences (IMSc), Chennai, India, from 13-14 October 2023.
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convergence rate in Boolean networks and bushiness of their state transition graphs at the Stochasticity and Plasticity in living Systems held at Sakleshpur, Karnataka, India (organized by National Centre for Biological Sciences (NCBS), Bengaluru), from 14-18 November 2023.

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10. Oral presentation titled *Effect of biologically meaningful functions on the bushiness and convergence of Boolean state transition graphs* at the Symposium on Synthetic and Systems Biology (BioSynSys) 2024 held at the University of Montpellier, Montpellier, France, from 5-7 June 2024.
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