

Machine Learning Centralized Traffic Control System for City Intersections

Patrick Mihalcea

CS4490Z

Project Supervisor: Mike Katchabaw, Dept. of Computer Science

Course Instructor: Laura Reid, Dept. of Computer Science

Introduction

Context:

- Artificial Intelligence should be leveraged.
- AI poses a safety concern without mediation.

Research Gap Addressed:

- Traffic lights may not be needed for autonomous vehicles.
- Numerical simulations lack important analytical factors.

Results Attained:

- Comparison between traffic light performance and machine learning centralized traffic control system (CTCS).

Novelty:

- Visual simulation environment.
- Exploration of an alternative traffic control method.

Impact:

- Innovative research procedure.
- Evidence that modern traffic control methods can be improved.



Background and Related Work

Problems with current traffic control systems

Theorized Solutions



Research Objectives

O1: Compare and contrast traffic control methods based on their throughput of roads, safety, efficiency, and potential when all vehicles are autonomous.

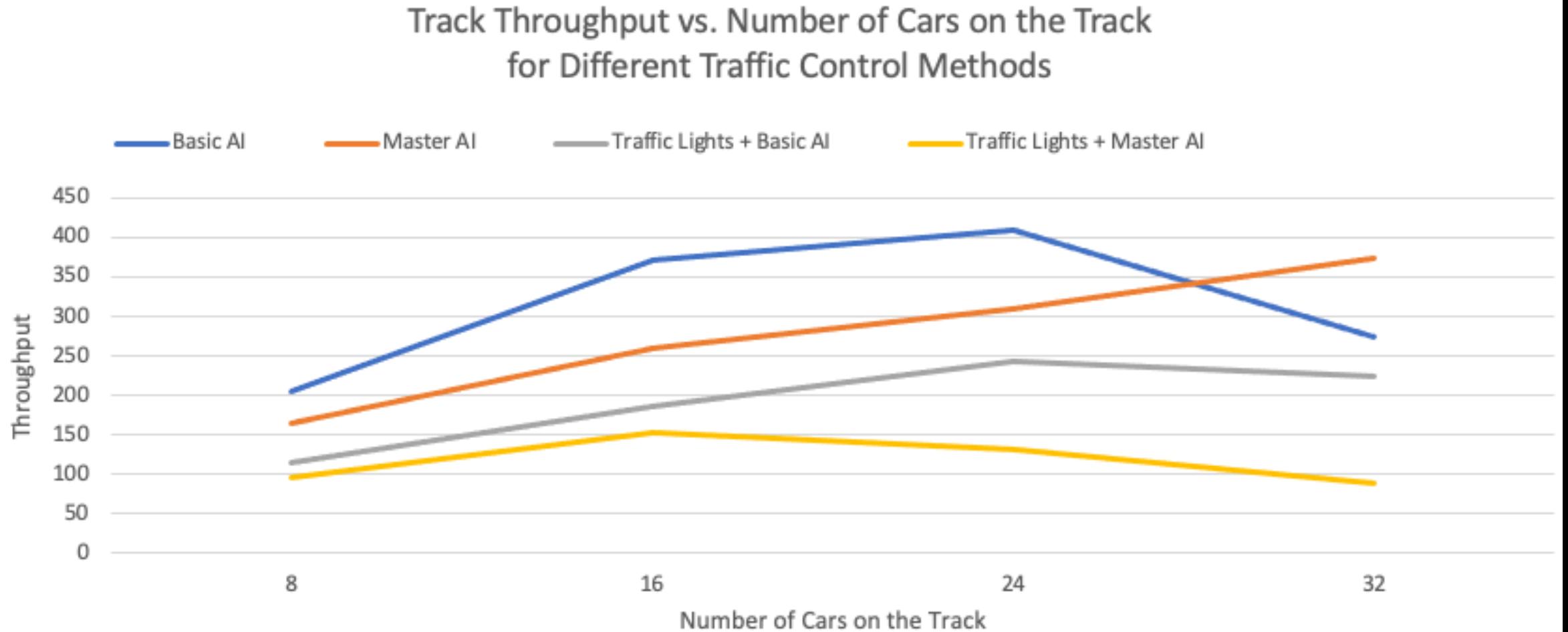
O2: Develop a visual simulation that can assist with introducing realism into traffic control algorithms and provide a means to qualitatively analyze them.



Live Demo of Methodology

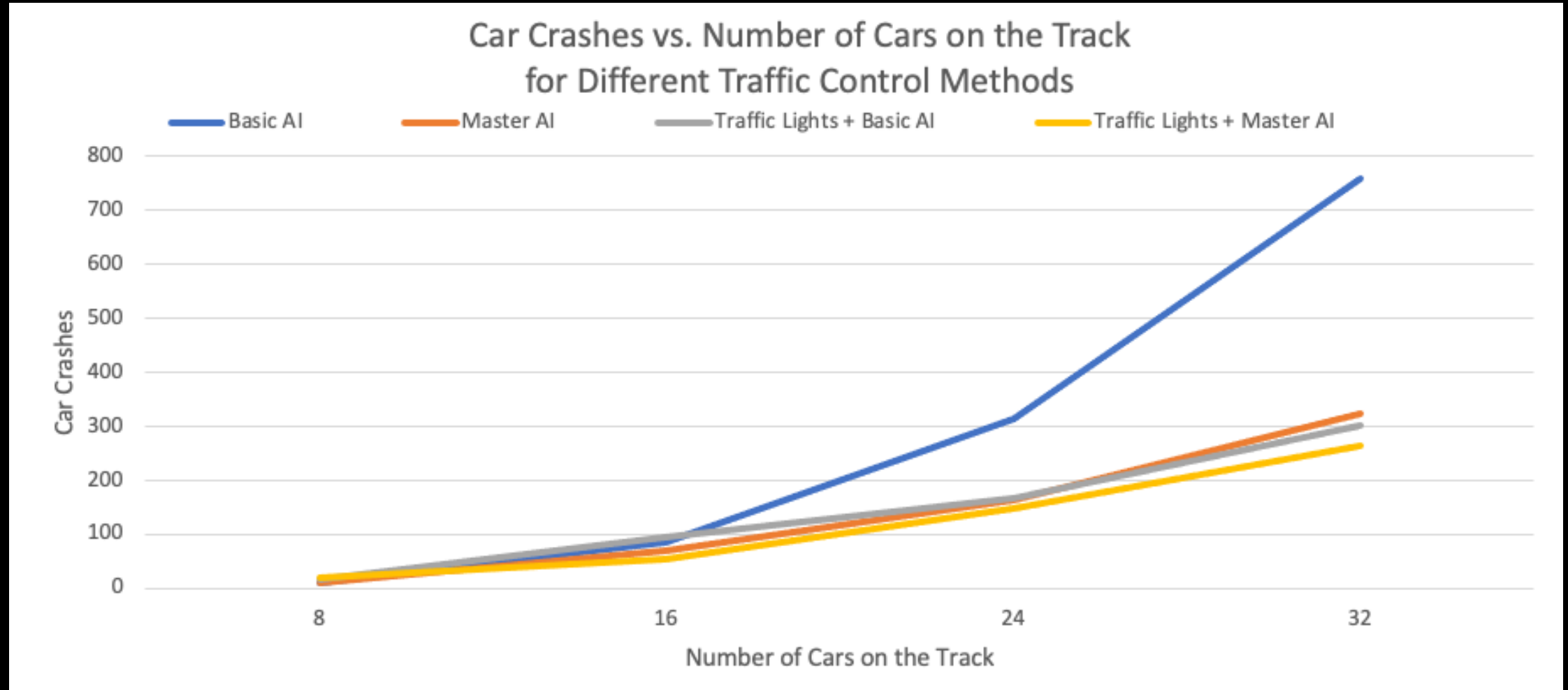
Results

Track Throughput



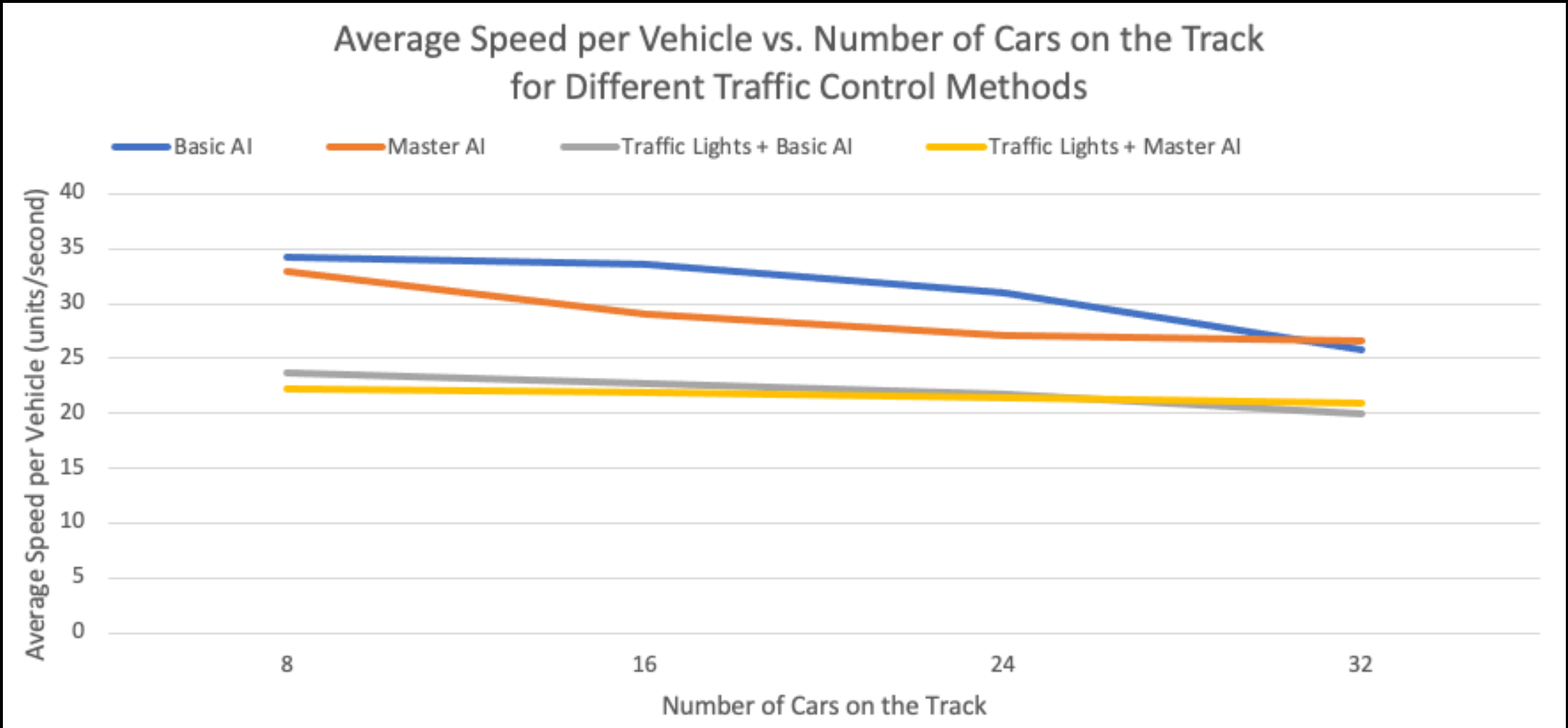
Results

Car Crashes



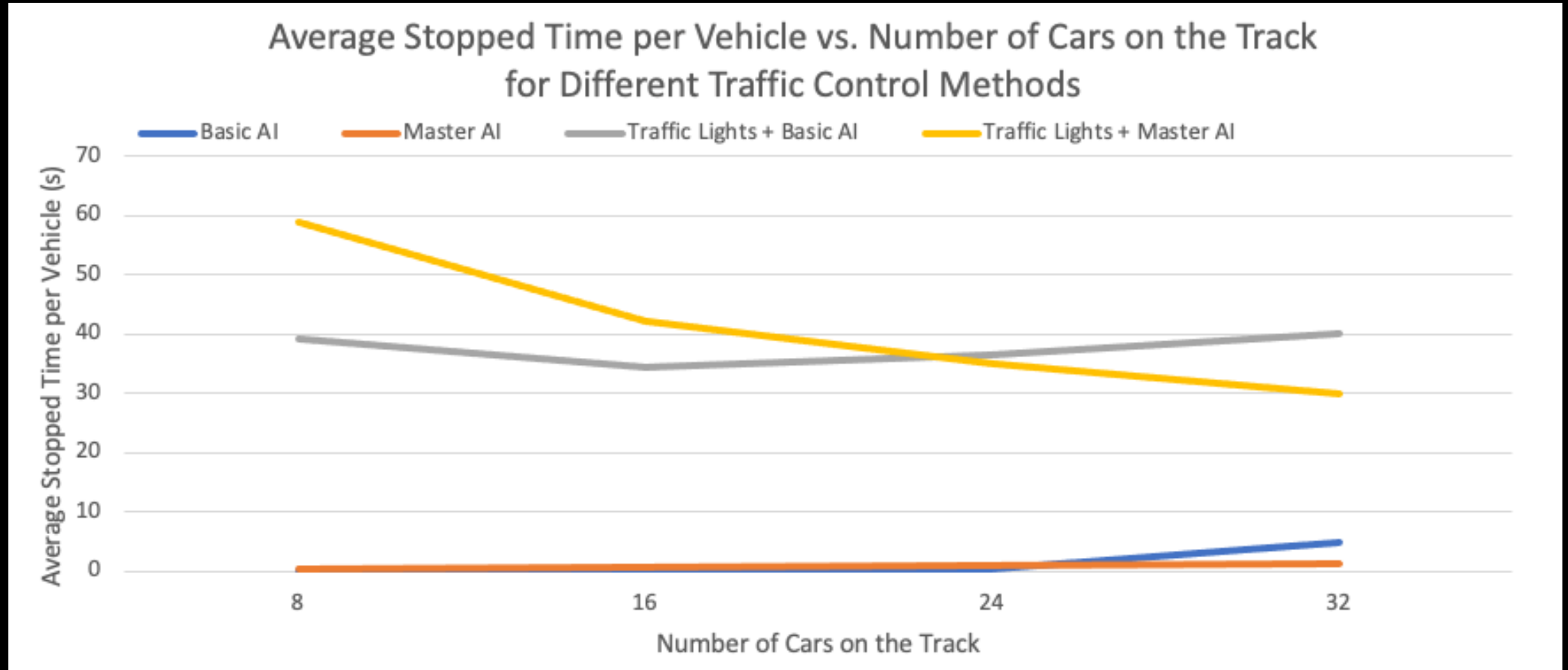
Results

Average Car Speed



Results

Average Stopped Time



Overall Scores

$$\text{SCORE} = (\text{Throughput}) + (\text{CarsOnTheTrack}/2 * \text{AverageCarSpeed}) \\ - (3 * \text{Crashes}) - (\text{CarsOnTheTrack}/2 * \text{AverageStoppedTime})$$

Number of Cars on the Track	Basic AI	Master AI	Traffic Lights + Basic AI	Traffic Lights + Master AI
8	309	268	-2	-108
16	383	278	-195	-169
24	-167	132	-437	-478
32	-1666	-189	-1007	-847
Grand Total	-1141	489	-1641	-1601

Data and Results Analysis

Validity:

- Sufficiently long trials (12 minutes).
- Repeated several times to observe stable patterns.

Limitations:

- Simplified simulation lacking real-world factors.
- Lack of testing for generalizability.

Novelty:

- Visual simulation environment which allows researchers to qualitatively analyze traffic control methods.
- Exploration of an alternative traffic control method (CTCS).

Impact:

- Supportive evidence for innovative traffic control method.
- Influential traffic control simulation that can stimulate future ideation and research.



Conclusions

Need for innovation:

- Autonomous vehicle protocol differences.
- Traffic lights are inefficient.

Support for Centralized Traffic Control Systems:

- Master AI achieved highest overall score and coordination.
- Master AI was more efficient and showed more potential for superior performance in the future.

Simulation:

- Lacks complexity, but serves as reasonable proof of concept.
- Visual aspect is important for interpreting qualitative factors.
- Inspire more complex simulations.



Future Work and Lessons Learned

Future Work:

- More routes and larger city.
- Weather and road conditions.
- Bikers and pedestrians.
- Emergency vehicles.
- SAFETY.

Lessons Learned:

- AI training can be optimized in many ways.
- Hierarchy model of traffic control is more efficient.



References

- [1] T. Bellemans, B. De Schutter, and B. De Moor, "Models for traffic control," *Journal A*, vol. 43, no. 3–4, pp. 13–22, 2002.
- [2] M. Papageorgiou, C. Diakaki, V. Dinopoulou, A. Kotsialos and Yibing Wang, "Review of road traffic control strategies," in *Proceedings of the IEEE*, vol. 91, no. 12, pp. 2043-2067, Dec. 2003, doi: 10.1109/JPROC.2003.819610.
- [3] M. Elsayed and M. Erol-Kantarci, "AI-Enabled Future Wireless Networks: Challenges, Opportunities, and Open Issues," in *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 70-77, Sept. 2019, doi: 10.1109/MVT.2019.2919236.
- [4] M. M. Gandhi, D. S. Solanki, R. S. Daptardar and N. S. Baloorkar, "Smart Control of Traffic Light Using Artificial Intelligence," 2020 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE), Jaipur, India, 2020, pp. 1-6, doi: 10.1109/ICRAIE51050.2020.9358334.
- [5] C. Englund, E. E. Aksoy, F. Alonso-Fernandez, M. D. Cooney, S. Pashami, and B. Åstrand, "AI Perspectives in Smart Cities and Communities to Enable Road Vehicle Automation and Smart Traffic Control," *Smart Cities*, vol. 4, no. 2, pp. 783–802, May 2021, doi: 10.3390/smartcities4020040.
- [6] B. Ghazal, K. ElKhatib, K. Chahine and M. Kherfan, "Smart traffic light control system," *2016 Third International Conference on Electrical, Electronics, Computer Engineering and their Applications (EECEA)*, Beirut, Lebanon, 2016, pp. 140-145, doi: 10.1109/EECEA.2016.7470780.
- [7] Hobbs, F.D. and Jovanis, Paul P.. "traffic control". *Encyclopedia Britannica*, 11 Nov. 2021, <https://www.britannica.com/technology/traffic-control>.
- [8] TSS Customer Service, "4 ways cities are using smart technology to control traffic congestion " traffic safety resource center," *Traffic Safety Resource Center*, 19-Feb-2019. [Online]. Available: <https://www.trafficsafetystore.com/blog/4-ways-cities-are-using-smart-technology-to-control-traffic-congestion/>. [Accessed: 15-Mar-2023].
- [9] K. Grace, J. Salvatier, A. Dafoe, B. Zhang, and O. Evans, "Viewpoint: When will ai exceed human performance? evidence from AI experts," *Journal of Artificial Intelligence Research*, vol. 62, pp. 729–754, 2018.
- [10] M. W. Eysenck and C. Eysenck, *Ai Vs humans*. London: Routledge, Taylor & Francis Group, 2021.
- [11] R. Hult, G. R. Campos, P. Falcone and H. Wymeersch, "An approximate solution to the optimal coordination problem for autonomous vehicles at intersections," *2015 American Control Conference (ACC)*, Chicago, IL, USA, 2015, pp. 763-768, doi: 10.1109/ACC.2015.7170826.
- [12] "About ML-agents package (com.unity.ml-agents): ML Agents: 2.0.1," *ML Agents | 2.0.1*, 08-Nov-2021. [Online]. Available: <https://docs.unity3d.com/Packages/com.unity.ml-agents@2.0/manual/index.html>. [Accessed: 15-Mar-2023].
- [13] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," *arXiv.org*, 28-Aug-2017. [Online]. Available: <https://arxiv.org/abs/1707.06347>. [Accessed: 15-Mar-2023].
- [14] M. Eigen and P. Schuster, "A principle of natural self-organization," *Naturwissenschaften*, vol. 64, no. 11, pp. 541–565, 1977.
- [15] V. Pierre, "Training with Proximal Policy Optimization," GitHub, Oct-2018. [Online]. Available: <https://github.com/gzrjzcx/ML-agents/blob/master/docs/Training-PPO.md>. [Accessed: 16-Mar-2023].

Results Summary (Not part of presentation)

Track Throughput:

- Traffic lights consistently performed worse than trials without traffic lights.
- Master AI achieved increasing throughputs.
- Basic AI had the highest throughput in trials with 8-24 cars.

Car Crashes:

- Basic AI is the most unsafe with very high crash rates as more cars are on the grid.
- Other three traffic control methods achieved similar crash rates.

Efficiency

Average Car Speed:

- Basic AI: 32u/s
- Master AI: 29u/s
- Traffic Lights + Basic AI: 22u/s
- Traffic Lights + Master AI: 22u/s

Average Stopped Time:

- Basic AI: 1s
- Master AI: 0u/s
- Traffic Lights + Basic AI: 38s
- Traffic Lights + Master AI: 45s