Developing an Artificial Neural Network System Through Neuroevolution to Reduce Urban Traffic Congestion

Research Question: How can neuroevolution of artificial neural networks be implemented in traffic control systems to significantly reduce traffic congestion in an urban setting?

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Subject: Information Technology in a Global Society

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I. Introduction

The rapid technological advancements of the past half-century have caused a consistent trend of urbanization: the percentage of the human population living in cities has steadily increased by nearly 20% in the past half century to 55%.[1] Furthermore, this increase is predicted to remain relatively constant for the foreseeable future, with estimates of over two thirds of the global population living in urban areas by 2050. With over half the globe now living in or around metropolitan centres, urban mobility is becoming increasingly limited. Given how dependent society has become on motor vehicles, traffic congestion in metropolitan centres worldwide is subsequently escalating at an alarming rate.[2] Congestion on city streets results in significant economic and productivity losses as city-dwellers spend extra time during their daily commutes. Therefore, a reliable and effective way to reduce traffic congestion is essential to urban infrastructure within metropolitan areas..

Economically speaking, traffic congestion on city streets is extremely costly: a study published by transport data company INRIX discovered that the average driver in dense megacities like New York City or London loses nearly $3,000 and 100 hours of productivity from traffic congestion.[3] Nationally, the same study reports the citizens of Germany, the United Kingdom, and the United States collectively lost 461 billion USD last year, or approximately

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[1] United Nations Population Division (n.d.). *Annual Percentage of Population at Mid-Year Residing in Urban Areas.* Retrieved from https://population.un.org/wup/DataQuery/
[2] Oliveria, M., Neto, A. (2013). *Optimization of Traffic Lights Timing based on Multiple Neural Networks.* Retrieved from 2013 IEEE 25th International Conference on Tools with Artificial Intelligence at https://zapdf.com/optimization-of-traffic-lights-timing-based-on-multiple-neur.html
[3] The Economist (2018, February 28). *The hidden cost of congestion.* Retrieved from https://www.economist.com/graphic-detail/2018/02/28/the-hidden-cost-of-congestion

$975 per person. Additionally, this often-overlooked cost of traffic congestion is projected to increase by nearly 50% in the next decade.[4]

With urban traffic congestion causing a significant economic loss in countries around the world, a reliable solution is urgently needed. The enormous lattices of traffic signals at nearly every major intersection provide an economical and effective way to reduce traffic congestion on city streets.[5] However many systems currently implemented are antiquated and inefficient, unable to process the numerous random variables, prompting the need for advanced systems that minimize delays and maximize efficiency.

As artificial neural network technology and machine learning become more and more prominent in society, they can be implemented to improve urban infrastructure. One possible application of such concepts is within traffic signals around the world, as ANNs are designed to solve such problems. Thus, Information Technology in a Global Society is a fitting subject area.

This essay will investigate how neuroevolution of artificial neural networks can be used to significantly reduce congestion on urban streets by controlling traffic signals by analyzing the benefits and drawbacks of such systems over outdated fixed traffic control systems. Neural networks can handle the complex calculations required to compute optimal signal cycles, making them an ideal backbone for citywide adaptive traffic signal systems. By developing these neural networks using neuroevolution, the calculation systems for signal cycles can be further optimized through algorithms and random mutations to determine the most efficient cycle calculations, reducing urban congestion.

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[4] INRIX (n.d.). *Americans will waste $2.8 trillion on traffic by 2030 if gridlock persists.* Retrieved from http://inrix.com/press-releases/americans-will-waste-2-8-trillion-on-traffic-by-2030-if-gridlock-persists/

[5] Srinivasan, D., Choy, M.C. & Cheu, R. (2006). *Neural networks for real-time traffic signal control. IEEE Transactions on Intelligent Transportation Systems*, 7(3), 261-272. Retrieved from https://www.jhuapl.edu/sPsA/PDF-SPSA/Srinivasan_etal_IEEETITS06.pdf

II. Traffic Control Systems

Since their introduction to American and European streets in the early 20th century, traffic lights have become prominent symbol of urban infrastructure in cities worldwide.[6] Traffic signals are inexpensive to operate and maintain while providing an efficient method of directing traffic, making them the most ideal method of traffic control.

Fixed Signal Control

Currently, the majority of traffic control systems are primitive fixed control systems such as TRANSYT (Traffic Network Study Tool), using optimized predetermined signal cycle times.[7] Cycle times are the duration of each individual phase of the signal cycle, for example, the green times of each roadway, or duration of the left turn signals. Fixed systems, also known as actuated systems, are manually programmed with cycle times for different periods of time, usually rush hour and off-peak, or weekdays and weekends. Timings for fixed control systems are determined by analyzing historical traffic data. However, they need to be retimed often as they become outdated frequently.[8] Actuated systems often result in wasted green time, where one roadway is green with minimal traffic while the other(s) have significant numbers of vehicles waiting. These systems, while functional, are outdated and inefficient due to the random nature of traffic.

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[6] McShane, C. (1999). The origins and globalization of traffic signals. *Journal of Urban History, 25(3),* 379-404. Retrieved from http://sites.tufts.edu/carscultureplace2010/files/2010/09/McShane-traffic-signals-1999.pdf
[7] Oliveria, M., Neto, A. (2013). *Optimization of Traffic Lights Timing based on Multiple Neural Networks.* Retrieved from 2013 IEEE 25th International Conference on Tools with Artificial Intelligence at https://zapdf.com/optimization-of-traffic-lights-timing-based-on-multiple-neur.html
[8] Srinivasan, D., Choy, M.C. & Cheu, R. (2006). *Neural networks for real-time traffic signal control. IEEE Transactions on Intelligent Transportation Systems*, 7(3), 261-272. Retrieved from https://www.jhuapl.edu/sPsA/PDF-SPSA/Srinivasan_etal_IEEETITS06.pdf

Traffic rates on city streets varies drastically on a daily or even hourly basis due to a plethora of events, collisions, or simply more commuters than usual.[9] Larger volumes of traffic than expected often lead to inefficient cycle timing. In addition, subpar weather conditions such as ice and snow require caution, resulting in lower vehicle speeds and more collisions. Evidently, a traffic control system that processes real-time data across an entire city is required to optimize efficiency at all times: adaptive signal control.

Adaptive Signal Control

Adaptive control systems constantly compute optimal cycle times by retrieving real-time traffic volume data.[10] By calculating optimal green time for each roadway and pedestrian crossing in real time, the system eliminates the possibility of wasted green time. In addition, complex adaptive control systems are often programmed to connect more green lights for vehicles along a path, known as a green corridor, eliminating the need to decelerate and accelerate.[11] This alleviates congested road arteries and intersections as much as possible while substantially increasing efficiency and decreasing travel times.

While different adaptive control systems implement different algorithms and weight factor, their fundamental purpose and techniques are the same: retrieve real-time data of traffic entering a specific intersection or section of road to calculate signal times. Many systems

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[9] Srinivasan, D., Choy, M.C. & Cheu, R. (2006). *Neural networks for real-time traffic signal control. IEEE Transactions on Intelligent Transportation Systems*, 7(3), 261-272. Retrieved from https://www.jhuapl.edu/sPsA/PDF-SPSA/Srinivasan_etal_IEEETITS06.pdf
[10] Oliveria, M., Neto, A. (2013). *Optimization of Traffic Lights Timing based on Multiple Neural Networks.* Retrieved from 2013 IEEE 25th International Conference on Tools with Artificial Intelligence at https://zapdf.com/optimization-of-traffic-lights-timing-based-on-multiple-neur.html
[11] Klein, L. A. (n.d.). Sensor Applications in ITS. In *ITS Sensors and Architectures for Traffic Management and Connected Vehicles* (pp. 63-80). CRC Publishing.

currently exist around the world such as Sydney Coordinated Adaptive Traffic System (SCATS), InSync and Split, Cycle and Offset Optimization Technique (SCOOT).[12] SCATS and SCOOT have been proven to be effective in many countries, especially the United States. Meanwhile, other systems such as InSync are rapidly growing in popularity, yet have achieved mixed results at reducing urban congestion and commute times.[13]

Need for Improved Systems

Despite their success, some systems are already being phased out due to deteriorating infrastructure and communication issues. Operating adaptive control systems requires sensors to measure traffic volume on roadways approaching an intersection which are often damaged by weather or construction work if built into the road surface. In addition, some aging systems are not optimized for pedestrian control, or occasionally develop communication problems between the signals and a central monitor/controller.

For example, the SCOOT system implemented along 14 corridors in Toronto, Ontario are being phased out by the government, citing the aforementioned issues in addition to inefficiencies with other types of traffic like pedestrians or cyclists.[14] Replacing them is a pilot project experimenting with InSync and SCATS.[15] However, those systems only partially

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[12] Oliveria, M., Neto, A. (2013). *Optimization of Traffic Lights Timing based on Multiple Neural Networks.* Retrieved from 2013 IEEE 25th International Conference on Tools with Artificial Intelligence at https://zapdf.com/optimization-of-traffic-lights-timing-based-on-multiple-neur.html

[13] Metropolitan Transportation Commission. (n.d.). *Adaptive Traffic Signal Systems Overview and Recent Experience.* Retrieved from https://mtc.ca.gov/sites/default/files/4-Adaptive_Signal_Control_-_How_Does_It_Work.pdf

[14] City of Toronto. (n.d.). *SCOOT System.* Retrieved from https://www.toronto.ca/services-payments/streets-parking-transportation/traffic-management/traffic-signals-street-signs/traffic-signals-in-toronto/scoot-system/

[15] City of Toronto. (n.d.). *Types of Traffic Control Systems*. Retrieved from https://www.toronto.ca/services-payments/streets-parking-transportation/traffic-management/traffic-signals-street-signs/traffic-signals-in-toronto/types-of-traffic-signal-systems/

overcome the challenges faced by SCOOT, prompting the need for a system able to handle numerous variables including weather, pedestrian traffic, cyclists, and transit riders. A system using artificial neural networks provides a substantial improvement over current technologies.[16]

[16] Liang, X., & Du, X. (2018). Deep Reinforcement Learning for Traffic Light Control in Vehicular Networks. *IEEE Transactions on Vehicular Technology*, 20(20).

III. Artificial Neural Networks

Artificial neural networks (ANNs) are complex programs that power artificial intelligence, designed similarly to the biological neural network structure of animal brains containing neurons connected by synapses.[17] These networks are composed of thousands to millions of interconnected nodes that process information, allowing the system to operate dynamically and efficiently to produce intelligent behaviour.[18] Currently, ANN technology is used in pattern recognition, classification, forecasting and analysis, and optimization.[19] In addition, neural networks are commonly programmed to complete video games in record times, such as MarI/O, for the popular platformer Super Mario Bros. With enough development and research, ANNs can potentially accurately replicate actual human or animal brains, however, the computational power and processing required are far beyond the limits of current technologies.[20] Nonetheless, ANNs are an integral part of machine learning and software used today.

Feedforward Neural Networks

The simplest and most popular type of ANN is the feedforward neural network, where layers of networks work methodically, feeding and processing inputs layer through layer to

[17] Van Gerven, M., & Bohte, S. (2018). Artificial Neural Networks as Models of Neural Information Processing. *Frontiers in Computational Neuroscience.* Retrieved from www.frontiersin.org/research-topics/4817/artificial-neural-networks-as-models-of-neural-information-processing.

[18] Marr, B. (2018, September 24). *What Are Artificial Neural Networks - A Simple Explanation For Absolutely Anyone.* Retrieved from https://www.forbes.com/sites/bernardmarr/2018/09/24/what-are-artificial-neural-networks-a-simple-explanation-for-absolutely-anyone/#c3c4fe412457

[19] Ahire, J. B. (2018, April 10). *Real world Applications of Artificial Neural Networks.* Retrieved from https://medium.com/@jayeshbahire/real-world-applications-of-artificial-neural-networks-a6a6bc17ad6a

[20] Sethbling. (2015, June 13) *MarI/O - Machine Learning for Video Games* [Video File]. Retrieved from https://www.youtube.com/watch?v=qv6UVOQ0F44

produce a result.[21] The network receives large quantities of information in the first layer, processes the information using algorithms within the hidden layers, and produces an output.[22] Similarly, when developed for an adaptive traffic control system, inputs are transmitted from various sensors and switches at the intersection or from other networks, while an optimized signal cycle is generated for the traffic signals.[23] The entire process can be thought of as a series of algorithms modifying numbers to produce a final number.[24] However, how can a series of connections and nodes function intelligently, optimizing traffic signal cycles?

How Neural Networks Operate

Figure 1 models a feedforward neural network used to recognize written digits developed by YouTube content creator 3Blue1Brown, which will be used in this paper to explain how ANNs function. The program treats each digit as a combination of parts, for example, 9 contains a circle and a line, 8 is formed with two circles, and so on. Each part is composed of multiple subparts: a couple line segments may form a circle for an 8 or a longer line for a 4. The input layer contains one node for every pixel of the image, which holds a real number value between 0 and 1.[25]

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[21] Maladkar, K. (2018, January 15). *6 Types of Artificial Neural Networks Currently Being Used in Machine Learning.* Retrieved from www.analyticsindiamag.com/6-types-of-artificial-neural-networks-currently-being-used-in-todays-technology/
[22] Mills, T (2018). *Artificial neural networks: how to understand them and why they're important.* Retrieved from https://www.forbes.com/sites/forbestechcouncil/2018/08/13/artificial-neural-networks-how-to-understand-them-and-why-theyre-important/#65b65db05ecd
[23] Liang, X., & Du, X. (2018). Deep Reinforcement Learning for Traffic Light Control in Vehicular Networks. *IEEE Transactions on Vehicular Technology*, 20(20).
[24] 3Blue1Brown. (2017, October 5) *But what *is* a Neural Network? | Deep learning, chapter 1* [Video File]. Retrieved from https://www.youtube.com/watch?v=aircAruvnKk
[25] 3Blue1Brown. *But what *is* a Neural Network? | Deep learning, chapter 1* [Video File].

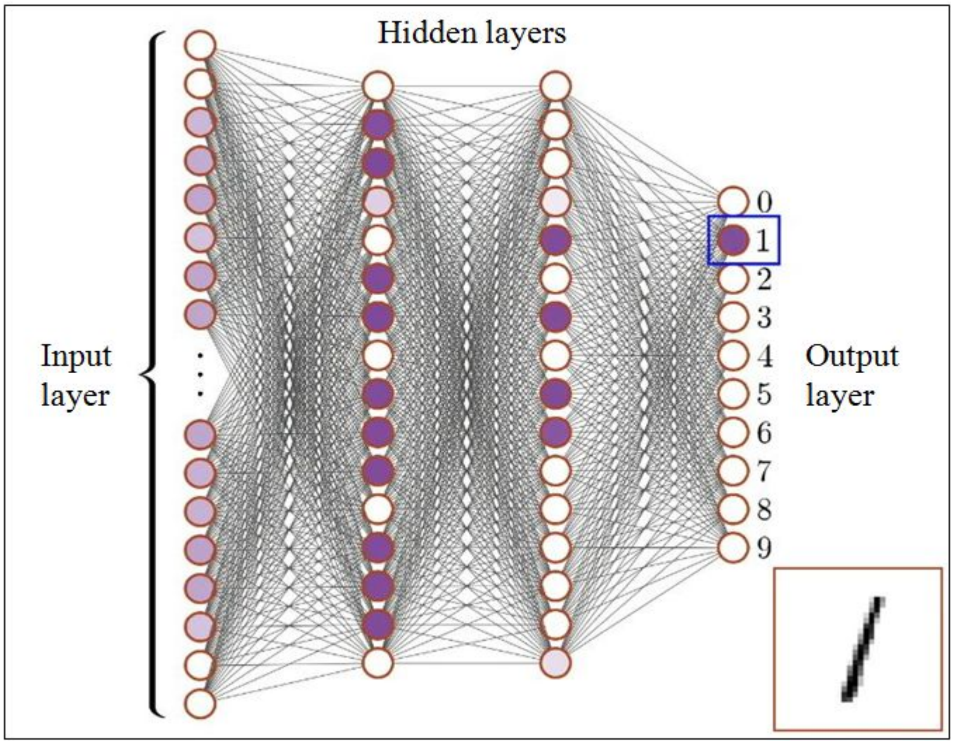

Figure 1: A neural network model for handwritten digit recognition by 3Blue1Brown.[26]

Each node in the input layer is connected to each node of the next layer, and each connection has predetermined weight. The first hidden layer is responsible for detecting subparts, which is done by multiplying each value about pixels from each node by a predetermined weight. These weights essentially indicate which nodes of the previous layer are important or unimportant factors when determining values. The weight of a pixel nearby where the node detects for parts would be weighed a lot more than, say, a pixel in the opposite corner of the image. After weights are factored in, the numbers are added together and inserted into a sigmoid function, returning a value between 0 and 1. This value indicates the likelihood of that specific subpart occuring, with 1 meaning absolute certainty and 0 meaning nonexistent.[27]

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[26] Image source: 3Blue1Brown. (2017, October 5) *But what *is* a Neural Network? | Deep learning, chapter 1* [Video File]. Retrieved from https://www.youtube.com/watch?v=aircAruvnKk
[27] 3Blue1Brown. (2017, October 5) *But what *is* a Neural Network? | Deep learning, chapter 1* [Video File]. Retrieved from https://www.youtube.com/watch?v=aircAruvnKk

The same process is used to turn subparts into parts in the second hidden layer of the ANN. For example, if there are four subparts in a straight line, the node searching for a line in that area will have these subparts weighted heavily, resulting in a higher number from 0 to 1. Then, parts form whole numbers. If there is a top circle and a bottom circle, the node in the output layer representing 8 will likely have an extremely high value, say, 0.923. Meanwhile, other nodes will have lower values. The node with the highest value in the output layer represents the number the neural network believes is written in the image.[28] Using these predetermined weights and algorithms embedded within the hidden layers, the neural network is able to produce a result intelligently.

Extrapolating for Traffic Control Systems

This same concept of dissecting an overall task in an ANN can be applied to a network responsible for traffic signal control at one intersection.[29] Information from sensors mounted on traffic signals, crosswalk buttons, and/or data from another traffic signal are received by the input layer. In addition, constants such as road incline and environmental factors can also be transmitted to nodes in the input layer, factoring into cycle time calculations.[30] Using different weights, nodes in the many hidden layers can calculate values such as average vehicle speeds and congestion rates. Weights would obviously be much higher for variables such as traffic

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[28] 3Blue1Brown. (2017, October 5) *But what *is* a Neural Network? | Deep learning, chapter 1* [Video File]. Retrieved from https://www.youtube.com/watch?v=aircAruvnKk

[29] Srinivasan, D., Choy, M.C. & Cheu, R. (2006). *Neural networks for real-time traffic signal control. IEEE Transactions on Intelligent Transportation Systems*, 7(3), 261-272. Retrieved from https://www.jhuapl.edu/sPsA/PDF-SPSA/Srinivasan_etal_IEEETITS06.pdf

[30] Oliveria, M., Neto, A. (2013). *Optimization of Traffic Lights Timing based on Multiple Neural Networks.* Retrieved from 2013 IEEE 25th International Conference on Tools with Artificial Intelligence at https://zapdf.com/optimization-of-traffic-lights-timing-based-on-multiple-neur.html

volume on a particular roadway or pedestrians pushing the crosswalk button than the weights for relatively minor values such as lane width. Within the hidden layers, the neural network would also analyze parameters to calculate the optimal cycle times for the given intersection with the given data, which is sent to the output layer.

Artificial neural networks are an excellent solution for traffic control systems as more variables and parameters that may affect traffic flow are able to be considered when compared with a traditional actuated system or an outdated adaptive system. All information is also weighted relative to its importance. For example, a major street that is heavily congested would receive the bulk of the green time at an intersection over a minor street, adapting for the randomness of traffic. When the congestion clears, the minor street may receive more green time, especially if pedestrians are crossing. Winter weather would result in slightly longer times as vehicles travel slower. Factoring in all these conditions with traffic flow data from sensors provides the most optimized signal timings for each roadway.

Modular Neural Networks

Modular neural networks are also commonly used to complete complex tasks, as shown in Figure 2. A modular neural network contains hidden layers of other neural networks.[31] Information is retrieved by the modular network's input layer and transferred to the input layers of other independent networks within the system. Each individual neural network then performs a subtask of the problem with its own calculations and processes with the received information.[32]

[31] Maladkar, K. (2018, January 15). *6 Types of Artificial Neural Networks Currently Being Used in Machine Learning.* Retrieved from www.analyticsindiamag.com/6-types-of-artificial-neural-networks-currently-being-used-in-todays-technology/

[32] Azam, Farooq (2000). *Biologically Inspired Modular Neural Networks. PhD Dissertation* (PDF). Virginia Tech. Retrieved from https://vtechworks.lib.vt.edu/handle/10919/27998

The networks then send their outputs to other networks in the system, or to the output layer of the modular neural network. This type of ANN allows for the completion of significantly harder or larger tasks by splitting it into subtasks for individual networks.

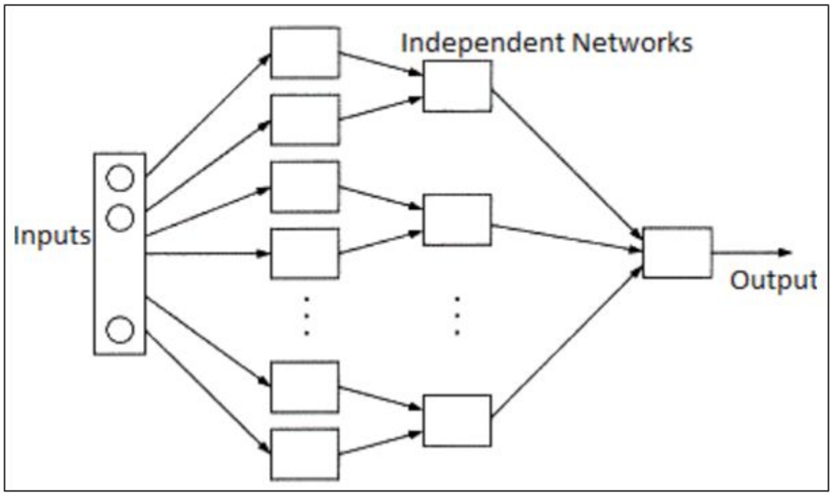

Figure 2: A modular neural network.[33]

Modular neural networks also allow the entire lattice of traffic signals to be linked under a central controller, with each intersection being controlled by a different individual network within the hidden layers. Information constant throughout the metropolitan area such as weather, fog, or icing conditions may be delivered to every controller, while traffic density in specific areas can be retrieved by sensors and transferred only to networks controlling signals in the immediate area. Connecting adjacent systems under a central network also allows for the aforementioned green corridors, where drivers are able to encounter multiple green signals before needing to stop.[34] Overall, the system can be monitored as a whole at a central location, allowing for convenient monitoring and efficient solutions to possible errors.

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[33] Image source: Maladkar, K. (2018, January 15). *6 Types of Artificial Neural Networks Currently Being Used in Machine Learning.* Retrieved from www.analyticsindiamag.com/6-types-of-artificial-neural-networks-currently-being-used-in-todays-technology/

[34] Klein, L. A. (n.d.). Sensor Applications in ITS. In *ITS Sensors and Architectures for Traffic Management and Connected Vehicles* (pp. 63-80). CRC Publishing.

In addition, neural networks also provide additional benefits and flexibility if intersections need to be closed or modified due to construction work, car accidents, investigations, or other events that may significantly disturb traffic flow through a corridor for extended periods of time. Traffic lights may be modified to allow for more vehicles to avoid the affected areas by providing longer left-turn and right-turn phases or other means of redirecting traffic. Adaptive traffic control systems designed with artificial neural networks are therefore extremely versatile and effective compared to typical adaptive signals.[35]

[35] Vital, Allan, et al. *Development of Intelligent Traffic Lights Using Multi-Agent Systems.* Retrieved from www.researchgate.net/publication/51994111_Development_of_intelligent_traffic_lights_using_multi-agent_systems.

IV. Neuroevolution

While ANNs can be programmed by hand, a far more efficient and effective method of developing them is known as neuroevolution, a subfield within artificial intelligence and machine learning. Neuroevolution uses evolutionary algorithms applied to the framework of an artificial neural network to develop more optimized networks, “learning” how to perform tasks and optimize results. This process is comparable to the genetic algorithms that developed single-celled organisms into intelligent humans and other life forms today.[36] Networks that perform the best are used to create the next generation, incrementing the effectiveness of every iteration, similar to Darwinian processes of “survival of the fittest”.[37]

Evolutionary Techniques

There are three different types of neuroevolution techniques, all of which serve different purposes: supervised, unsupervised, and reinforcement learning.[38] In supervised learning, a sequence of inputs are given to the ANN as training data. The optimal outcomes for the given information are already known, so the neural network’s task is to modify its logical processes and algorithms to replicate the set of data. Unsupervised learning is the opposite: neither predetermined data sets nor outcomes are provided to the network. The network is tasked with determining algorithms with random data sets and producing results free of bias, instead

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[36] Sethbling. (2015, June 13) *MarI/O - Machine Learning for Video Games* [Video File]. Retrieved from https://www.youtube.com/watch?v=qv6UVOQ0F44

[37] Stanley, K. O. (2017, July 13). *Neuroevolution: A different kind of deep learning.* Retrieved from https://www.oreilly.com/ideas/neuroevolution-a-different-kind-of-deep-learning

[38] Dev, R. (2018, February 28). *Supervised, unsupervised, reinforcement and continual machine learning models.* Retrieved from https://medium.com/@rahul.dev/supervised-unsupervised-reinforcement-and-continual-machine-learning-models-e76b140c1227

grounded purely on logic systems. Reinforced learning is a relatively recent development using random sets of data where the network is provided feedback based on the outcome and actions during the process. The quality of the result is based on factors such as efficiency, effectiveness, or other parameters.[39]

Neuroevolution of Augmenting Topologies

This essay will explore NeuroEvolution of Augmenting Topologies (NEAT), a reinforcement learning system developed by Kenneth Stanley. The topology of a neural network refers to the overall structure; which nodes share a connection, how many nodes exist and the number of layers. Most neuroevolution techniques are fixed-topology algorithms, meaning the overall structure (e.g. Figure 1's structure) remains constant throughout development; only the weights of each individual connection are modified. Meanwhile, NEAT formulates an expansive neural network in addition to assigning weights from scratch.[40] The task at hand requires optimization of a parameter—traffic flow and reduced congestion—and requires feedback on how successful each network is. As optimal output data for each network is unknown, reinforcement learning is the best option to minimize traffic times. The success of a given network is also extremely simple to measure: simply tally the amount of cars passed that reached their destination through the network over a period of time. Training these networks within a simulation that replicates actual events as closely as possible is the best option.

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[39] Dev, R. (2018, February 28). *Supervised, unsupervised, reinforcement and continual machine learning models.* Retrieved from https://medium.com/@rahul.dev/supervised-unsupervised-reinforcement-and-continual-machine-learning-models-e76b140c1227

[40] Stanley, K., Miikkulainen, R. (2002). *Evolving neural networks through augmenting topologies.* Retrieved from The MIT Press Journals at http://nn.cs.utexas.edu/downloads/papers/stanley.ec02.pdf

The evolutionary process contains generations and species, with the quality of each generated network measured with a value of fitness.[41] The evolutionary process begins with a certain number of networks, usually dozens or hundreds, each known as a species. Information for input layers are sourced from collected data passing through intersections. During the first generation, the species are all slightly different, similar to slightly differing gene composition between animals of the same species. Using the same test values for each species, a simulation is started. Once the simulation ends, or a certain condition is reached (e.g. time elapsed with no activity or fitness progress), the fitness value of each species of the generation is calculated.[42] In this case, the number of cars completing the journey is closely associated with fitness value.

After each generation, the species with the highest fitness scores of the generation are selected to be bred with random mutations. Species within the next generation of neural networks will have a mix of traits from the fittest species. Examples of traits would include nodes to calculate icing conditions of the road based on precipitation and temperature data, or an algorithm used to predict the rate of acceleration of traffic. Mutations add or remove nodes, modify weight values within the neural network, or insert more connections. The evolution continues generation by generation with different sets of data until the neural network has reached an optimal fitness level, providing an extremely optimized solution to reduce traffic congestion on city streets. Eventually, the fitness level would plateau/peak after a lot of successive iterations, indicating the optimal fitness level has likely been reached.

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[41] Stanley, K., Miikkulainen, R. (2002). *Evolving neural networks through augmenting topologies.* Retrieved from The MIT Press Journals at http://nn.cs.utexas.edu/downloads/papers/stanley.ec02.pdf
[42] Stanley, K. *Evolving neural networks through augmenting topologies.*

Examples of NEAT

Figure 3 depicts the neural network structure for MarI/O, a program by YouTube content creator SethBling trained to play Super Mario Bros. previously referenced in Section III of this paper (Artificial Neural Networks). The simple program evolved through NEAT, with generation and species number indicated in the top-left corner of each simulation and maximum fitness reached by that generation of networks is displayed directly below.[43] The diagram placed on the game interface is a model of the fittest species of the given generation. The representation contains an input layer in the square from the left and an output layer with all possible controls at the right. Nodes are indicated by boxes, while connections are lines. Through the evolutionary process, the network builds upon itself, adding and removing connections and nodes, increasing the maximum fitness the networks have reached.[44]

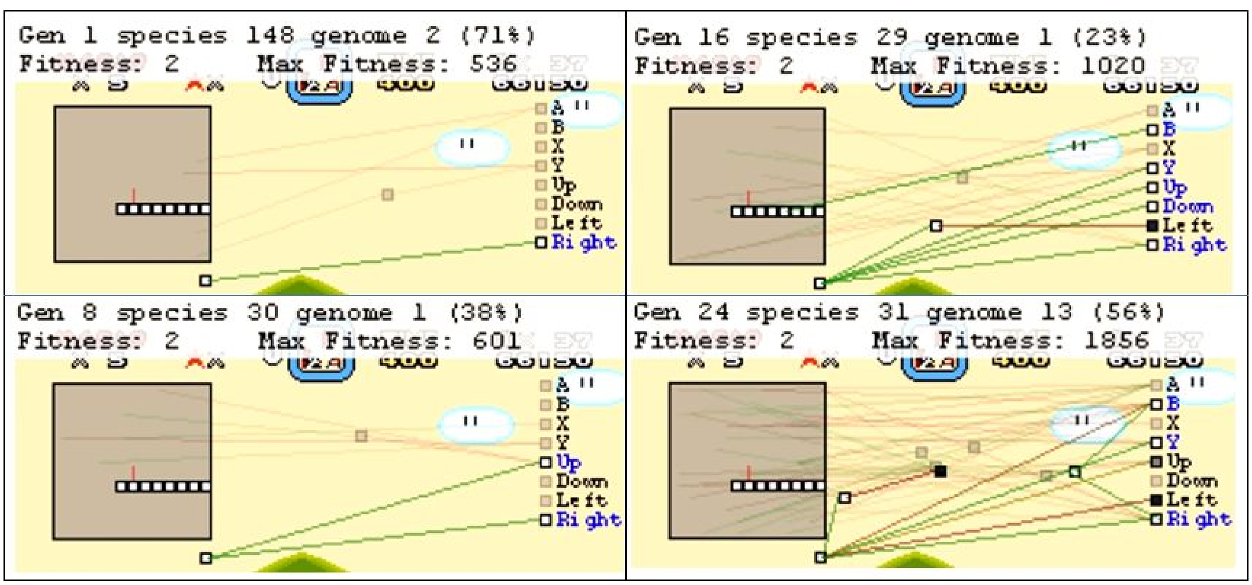

Figure 3: Evolution of MarI/O's structure through generations.[45]

[43] Sethbling. (2015, June 13) *MarI/O - Machine Learning for Video Games* [Video File]. Retrieved from https://www.youtube.com/watch?v=qv6UVOQ0F44
[44] Sethbling. *MarI/O - Machine Learning for Video Games* [Video File].
[45] Image source: Sethbling. *MarI/O - Machine Learning for Video Games* [Video File].

In the beginning of evolution, a network structured to control volumes of traffic in a busy metropolitan area needs to learn that giving one roadway a green light moves traffic, similar to how MarI/O needs to learn how to control the character.[46] While MarI/O evolves in the actual game, a traffic controller requires simulations to evolve to its optimal fitness value before installed on city streets. Through the process of NEAT, the network will learn to control the traffic signal grid far more efficiently than a typical adaptive signal controller. Development will occur similar to the advancement of the neural network shown in Figure 3, however, on a far more complex scale.

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[46] Sethbling. (2015, June 13) *MarI/O - Machine Learning for Video Games* [Video File]. Retrieved from https://www.youtube.com/watch?v=qv6UVOQ0F44

Stalled Growth

Through its evolutionary process, the network may encounter stalled growth over several generations, known as a rut. (Figure 4).[47] Over certain points, the fitness number stalls, indicating the network has hit a rut. However, these issues are easily overcome through the inherent design of NEAT, developing random mutations that alter the topology of the structure, change weights of connections, or create connections.[48]

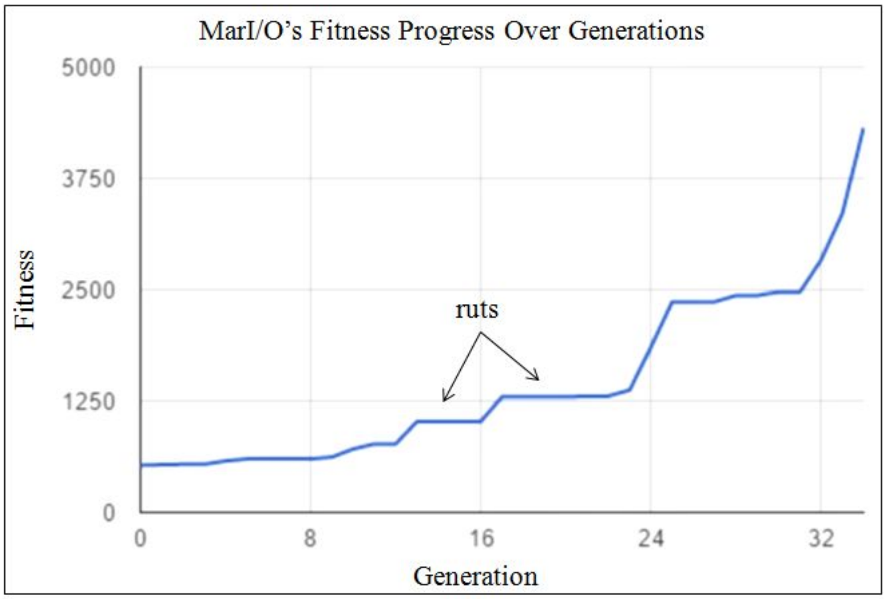

Figure 4: MarI/O's evolutionary progress.[49]

Overall, neuroevolution of augmenting topologies is a suitable method of developing an adaptive signal controller as it ensures the optimization of the network created. While programming such an evolutionary process for a citywide traffic controller is far more complex than programming an ANN that plays Super Mario, its ability to eventually integrate all factors affecting traffic congestion into account makes it an ideal traffic control system.

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[47] Stanley, K., Miikkulainen, R. (2002). *Evolving neural networks through augmenting topologies.* Retrieved from The MIT Press Journals at http://nn.cs.utexas.edu/downloads/papers/stanley.ec02.pdf
[48] Stanley, K. *Evolving neural networks through augmenting topologies.*
[49] Image source: Sethbling. (2015, June 13) *MarI/O - Machine Learning for Video Games* [Video File]. Retrieved from https://www.youtube.com/watch?v=qv6UVOQ0F44

V. Factors Affecting Implementation

Such an expansive system does not come without consequences or drawbacks. The complexity of the network and the need to run countless intensive simulations before implementation makes it elaborate and expensive.[50] As cities are designed very differently, with different volumes of traffic, driving habits of citizens, and varying temperatures, each area the system is applied to requires individual training. In addition, the requirement of a central controller through the use of modular neural networks to generate more green corridors make the entire network susceptible to complete or partial system malfunction (i.e. localized failures at one intersection may result in other intersections not functioning correctly). Future advances in technology can significantly reduce the cost of implementing complex neural networks, while backup traffic control systems and battery power can supplement the primary systems.

Data Input Limitations

Simulations are unable to precisely replicate actual events, especially in a field with so much randomness such as traffic pattern prediction. Humans are fallible and have their own thought processes, causing crashes and unexpected slowdowns in traffic. Therefore, a neural network trained using a simulation will not be completely optimized for real-world applications. [51] Initial training at physical intersections is also not a possibility. Furthermore, retrieving accurate data by observing actual traffic flow through an intersection in order to create accurate

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[50] Srinivasan, D., Choy, M.C. & Cheu, R. (2006). *Neural networks for real-time traffic signal control. IEEE Transactions on Intelligent Transportation Systems*, 7(3), 261-272. Retrieved from https://www.jhuapl.edu/sPsA/PDF-SPSA/Srinivasan_etal_IEEETITS06.pdf

[51] Kareem, E. (2014). *Intelligent Traffic Light Control Using Neural Network with Multi-Connect Architecture*. Retrieved from https://www.researchgate.net/publication/242071252_Intelligent_Traffic_Light_Control_Using_Neural_Network_with_Multi-Connect_Architecture

simulations is costly and time-consuming. However, it is necessary to provide as accurate of a simulation as possible.

Flexibility After Implementation

After the system is in place, cities will expand, creating new streets that must be added to the network. Local governments may also modify existing roads for various reasons. Both these situations would require additions to the current network. In addition, over time, the network developed may no longer be the most efficient system possible, and would require another simulation to further optimize the system.[52] These issues can be resolved with a new composite approach of training neural networks under development known as continual learning.[53] This technique has the ANN continuously learn as real-time data is being processed and the task is completed. The method meets the demands of a dynamically shifting environment like urban streets. While the system is still in its infancy, it would improve the longevity of the ANN.

[52] Klein, L. A. (n.d.). Sensor Applications in ITS. In *ITS Sensors and Architectures for Traffic Management and Connected Vehicles* (pp. 63-80). CRC Publishing.
[53] Dev, R. (2018, February 28). *Supervised, unsupervised, reinforcement and continual machine learning models.* Retrieved from https://medium.com/@rahul.dev/supervised-unsupervised-reinforcement-and-continual-machine-learning-models-e76b140c1227

VI. Conclusion

The drastic economic and social impact of traffic congestion in urban settings is a serious problem that is only expected to grow, requiring an immediate solution. Traffic control systems are an extremely effective way of reducing traffic congestion on city streets, however, current actuated and adaptive systems are unable to keep up with compounding traffic volume. Through the use of feedforward and modular artificial neural networks, an advanced model/algorithm can be created to efficiently control traffic through intersections within the city. All elements that contribute to traffic congestion can be factored accordingly and appropriately, creating an effective algorithm for calculating signal cycle times. This network can be developed through the use of neuroevolution of augmenting topologies to optimize the system, improving travel times throughout the city. Developing networks this way results in logical solutions which far surpass the capabilities of pre-programmed and fallible networks and systems.

While the use of artificial neural network technology in traffic control systems within metropolitan areas is still in its infancy, technological advancements such as improved computational power or continual learning will make the technology a staple for future generations of traffic control systems. Such systems will decrease travel times, reducing the economic losses and environmental impacts caused by traffic congestion.

VII. Works Cited

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