Neuromorphic Computing for Smart Cities

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Abstract

Excessive energy consumption poses a significant threat to the environment. Recognizing that urban areas account for approximately three-quarters of global energy usage (Ge, Friedrich, & Vigna, 2020), our project specifically targets reducing energy consumption in cities.

We demonstrate the feasibility and quantitative impact of neuromorphic computing (NC) for energy-efficient Internet of Things (IoT) applications in urban environments. We find that this approach can significantly lower the energy consumption of infrastructures and processes in these areas while achieving greater performance and accuracy. As a proof of concept, we optimize a network of smart traffic lights using a spiking neural network (SNN), to adaptively change their signaling algorithms within a traffic network based on the amount of congestion at each intersection. We outline how event-based cameras can be effectively coupled with asynchronous neuromorphic processors, and how processors can subsequently relay information within a road network. In turn, this reduces emissions from vehicles by cutting down on the time they spend in traffic. We also propose the architecture of a broad network of neuromorphic devices, to extrapolate our traffic reduction proof of concept to other smart city applications. The applications of NC to reduce the energy consumption of processes in urban environments are endless.

Adaptive algorithms are only the beginning; in this paper, we outline numerous other applications of NC to improve the capabilities of IoT within smart cities. We have chosen to focus on traffic algorithm optimization since it demonstrates core functionality improvements in sensor-processor and processor-network communications and it is easy to generate fake data with which to test our prototypes. The goal of this project isn't to resolve the excessive energy consumption issue in just eight weeks, but to lay the groundwork for future innovations that eventually lead to sustainable, energy-efficient smart cities.

Problem Analysis: The Growing Environmental Impact of Cities

Global Warming and Environmental Degradation

The summer of 2023 was recorded to be Earth's hottest on record, with temperatures rising 0.23 degrees Celsius (0.41 degrees Fahrenheit) above the previous highs (US, 2023). A result of skyrocketing temperatures is the rapid melting of Arctic sea ice, which has decreased in volume by 30% in just the last 50 years (NASA, 2023). This loss of ice not only contributes to rising sea levels but also disrupts the habitats of numerous species. In fact, the world is currently losing species at a rate over a hundred times greater than at any other time in recorded human history (Martin, 2019). Looking forward, the predicted future environmental changes are even more drastic. Notably, one million species are at risk of extinction within the next few decades due to the effects of climate change—a possibility that will impact ecosystems, food security, and even human health (Martin, 2019).

Taking immediate action to address global warming is necessary. The consequences of inaction are predicted to be severe and far-reaching, threatening not only wildlife and ecosystems but also the well-being and survival of the human race.

City Excessive Energy Consumption

Energy consumption is the leading cause of climate change, posing a grave threat to the planet and its inhabitants. It's the largest source of human-caused greenhouse gas emissions, accounting for 75% of the global total (Ge, Friedrich, & Vigna, 2020). Moreover, these emissions, primarily carbon dioxide, are the “main cause of future global warming” (Intergovernmental Panel on Climate Change, 2021). Since energy consumption is a significant contributor to greenhouse gas emissions, reducing our use of it is essential for mitigating the impacts of global warming. In other words, if we don’t significantly cut back on our energy usage, we run the risk of exacerbating climate change and facing the severe consequences that follow.

Some may ask why humanity can’t just entirely rely on renewable sources. Completely shifting to renewable energy isn't feasible due to resource limitations. For example, wind power, one of the most widely used renewable resources today, requires at least 60 acres of land (0.24 square kilometers) per megawatt of energy produced (Landmark Dividend LLC, 2014). To put this into perspective, the United States consumed over 3.5 billion megawatts (3.5 million megawatts) in 2020 alone (GlobalData Plc, 2017). Although wind energy is just one example, it highlights the broader issue: the amount of land, physical resources and time required to meet current energy demands with only renewable sources is near impossible. Thus, to effectively mitigate environmental degradation, we must reduce our energy consumption.

Urban areas play a significant role in this issue, consuming 78% of the world's energy (Nations, 2023). This share is unlikely to decrease due to growing city populations. In fact, by 2050, 70% of the world's population are predicted to live in cities, up from the 56% in 2020 (Institute for Economics & Peace, 2022). As cities become increasingly populated, their already sky-high energy consumption levels will likewise rise. Therefore, we should prioritize reducing energy consumption in cities and make them the focal point of our sustainability efforts. Neuromorphic devices will be significant in this effort due to numerous software and hardware optimizations that will be explained and verified in the following sections of the paper.

The Role of Smart Cities and the Internet of Things

One increasingly popular city-building paradigm is the so-called “smart city.” It attempts to increase the efficiency of actions that a city must perform, like energy generation and traffic management, via data collected from sensors scattered around the city. By making data-informed choices about the operation of each city, smart cities allow urban areas to optimize their behavior to best meet the needs of their residents. For example, a city may use devices embedded within the power grid to track power demand, dynamically storing and releasing energy based on usage throughout the day in order to alleviate network load (Baibakov & Nikolski, 2024).

Critics of smart cities often point to how the implementation and operation of these sensors themselves can be a waste of energy, which, in a fully integrated city, may be a significant portion of its power draw. They also challenge the efficiency and accuracy of these systems, asking about the significance of any optimizations that could be made. Essentially, critics ask city planners to consider whether these devices either waste energy and resources or generate real savings in the long run.

Similarly, the Internet of Things (IoT) refers to the grid of technology and devices that permeates our lives and communicates with each other: smartphones, Internet-enabled appliances, medical devices, and any other networked device. As the core technology in smart cities, the IoT provides significant advantages in efficiency and communication. Nevertheless, like smart cities, it consumes substantial amounts of energy in its operation, thereby exacerbating excessive energy usage.

If implemented correctly, an expanding IoT and future smart cities could reduce our environmental impact, benefiting both the planet and humanity. However, they also carry the risk of further accelerating the deadly consequences of climate change.

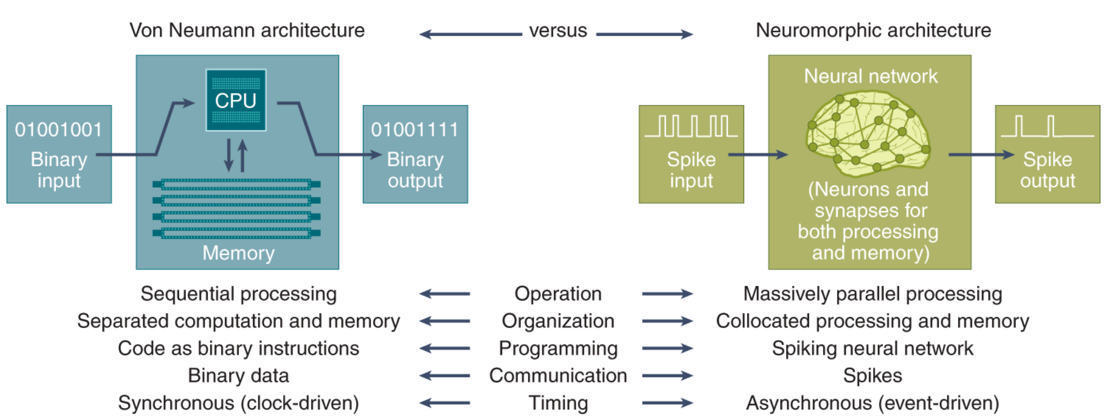
Solution Overview

Neuromorphic computing (NC) is a promising, entirely novel, computing framework that differs dramatically on the hardware level from conventional “von Neumann” chips. Whereas traditional devices operate on hardcoded, system-wide clocks and have discrete memory, processing, and transportation modules, NC imitates the layout of the human brain (Schuman et al., 2024).

The biological brain, made of neurons, is an analog, rather than digital, computing device; power and voltage are handled not by 0s and 1s, but by a continuous spectrum of neuron activity. Like neural networks, each neuron has up to 10,000 connections through its synapses with neighboring neurons and sends them outputs in the form of spikes of electricity. Each neuron also has its own memory and processing power coupled at its core, (the soma).

NC also opens the door to new kinds of neural networks, based on physical hardware rather than digital neurons. The operational principle of Spiking Neural Networks (SNNs) on these chips—where neurons communicate by firing spikes only when necessary—results in sparse and efficient communication that drastically cuts down energy usage compared to continuous data transmissions in conventional systems (IBM, 2024). This spike-based communication is important in reducing latency and power usage, especially beneficial for real-time applications like autonomous navigation systems and image recognition.

Neuromorphic computing has several key optimizations over traditional devices. First, they derive significant energy savings over conventional devices: this is due to the low power consumption of spikes, as well as a reduction in data bus energy costs (as data is stored locally with processing). They are also able to process event-based information more accurately (such as image recognition algorithms) by discarding redundant data, making them more versatile and quicker than traditional computers in handling live information (Baibakov & Nikolski, 2024). By processing data on-device without the need to transmit information back to a central data center, these systems minimize latency, enhance privacy, and reduce bandwidth and energy consumption, and are especially important in scenarios where communications networks are not accessible (eg. deep sea exploration).



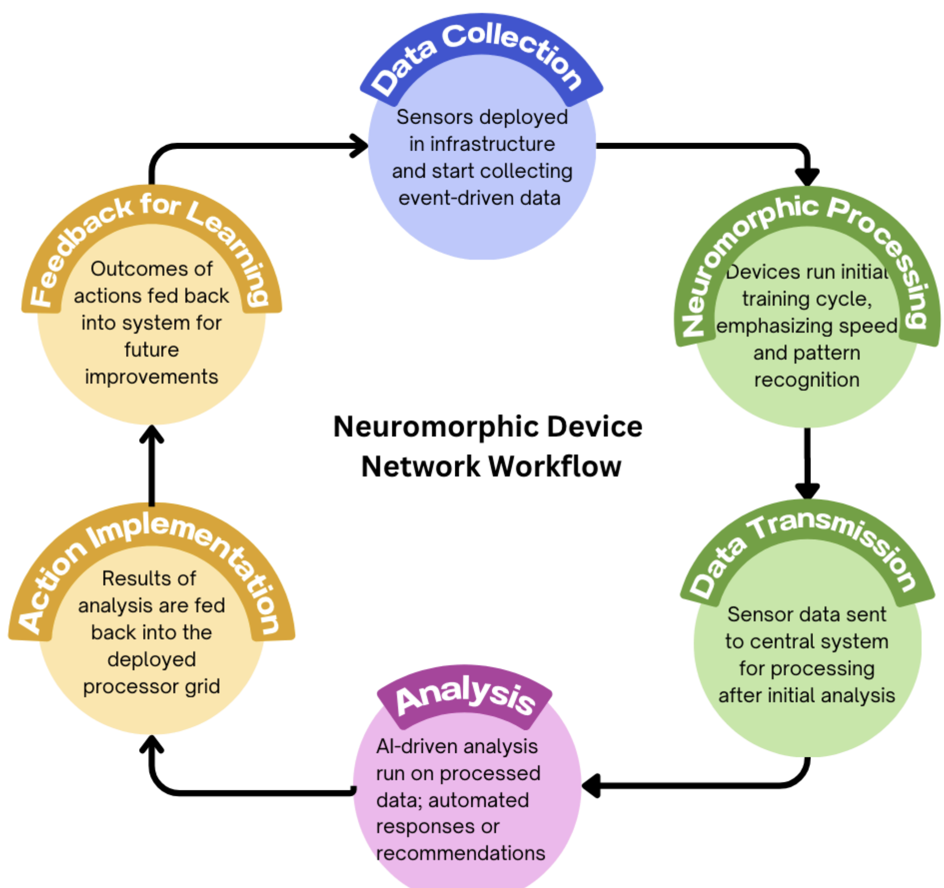
We believe that because of these characteristics of NC, it has great potential to replace a variety of technologies in IoT and smart cities by decreasing their power usage and increasing their efficiency.

The following table summarizes some of our proposed **key use cases** of neuromorphic IoT devices, enabling infrastructure to not only respond to changes in the environment but also holistically predict and adapt to future conditions via energy-efficient means. Note that most of these technologies (minus the NC component) are already prevalent in many world cities, so our proposal aims to integrate them with neuromorphic hardware and increase their usage once initial pilot programs are successful.

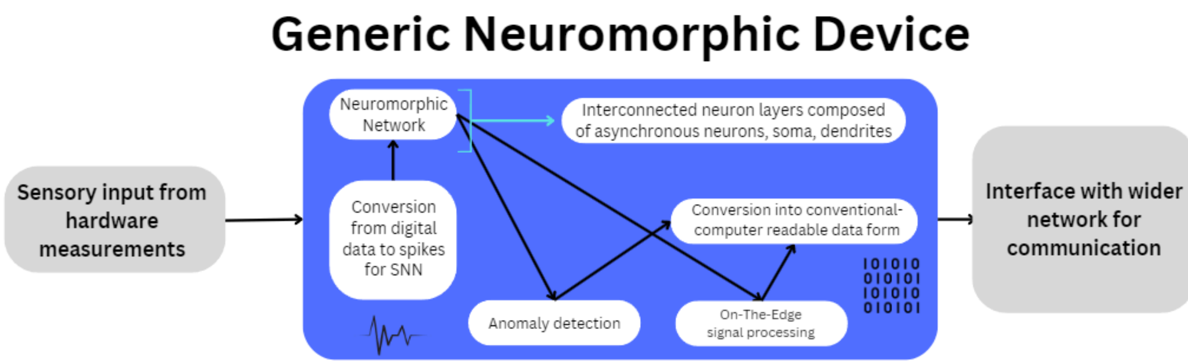
Technology	Use case	Why neuromorphic hardware?
Sensors - strain gauge, accelerometer, fiber optic sensors, acoustic emission sensors	Monitor building structural health for preventative maintenance and immediate response	Easily adjustable disturbance threshold for monitoring large changes without continuous energy use. Detection of deep anomalies such as unusual vibrations, shifts, or stress patterns in real time.
Sensors - temperature, humidity, corrosion, wind, barometric pressure, air quality, seismometers	Integrate environmental measurements into automated predictive modeling and analysis	Distributed monitoring that improves anomaly detection over time, enabling more rapid and accurate responses. Fault tolerance coupled with algorithms that temporally correlate weather events leads to a better understanding of climate phenomena.
Geospatial monitoring - multispectral cameras, radar sensors, LiDAR, thermal sensors, magnetometers, gravimeters	Visualization of geographical data	Can process large and complex datasets in realtime and extrapolate patterns. Durability allows for the monitoring of vast and varied geospatial areas.
Materials with adaptive properties (more durable and fewer maintenance needs)	Self-healing concrete, power lines that reroute around outages to not take out the entire grid, etc.	Energy-efficient processing of complex data streams. For example, neuromorphic devices can learn from the structural behavior of the concrete over time, improving the accuracy of detecting when and where healing is needed. Additionally, these devices can detect where outages occur and decide where to cut off power to prevent cascading outages. Processors can be decentralized, enabling grid scalability and reduced decision latency.

Renewable energy systems	Solar and wind energy farms	Analyze sensor data to optimize energy production, predict issues that may lead to downtime, and do adaptive load balancing to prevent grid instability.
Robotics	Devices to perform inspections and maintenance tasks in challenging environments	Enhance understanding of complex environments, real-time management of robotics actuators, resilience under extreme conditions, and coordination of multiple robots working on the same task.
Wireless communication networks	Rapid coordination among first responders and the public during disasters	Impulse radio communication between neuromorphic devices allows for precise timing and positioning and is ideal for low-power and high-precision applications

The following cycle summarizes how a network of neuromorphic devices communicate and update their local models based on the state of the global network. Once devices are deployed throughout the smart city, they use sensor data to run an initial training cycle. The weights of the SNNs after the initial iteration are transmitted via impulse radio to a central processor that runs analysis on the state of the entire network. Global network weights are used to inform incremental adjustments of local weights until individual devices optimally respond to environmental or infrastructural feedback.



This diagram depicts how an individual neuromorphic device processes input data before relaying it to a central processor. First, sensor input is encoded as spikes with magnitudes proportional to the amount of change in the sensor state from a baseline state (e.g., pressure detected by a pressure sensor relative to 0 psi, intensity of light entering a camera's pixel relative to no photons). Then, the spikes are inputted into an SNN pretrained on simulation data. Depending on how the network is trained, it can decode the spikes into a numerical representation for the current system state.



Results: Evaluating a SNN in an IoT Context

Model Overview

There exists a diverse and varied array of applications of neuromorphic IoT in smart cities. As concrete proof of concept, we have demonstrated an adaptive traffic light algorithm updated through a network of SNNs simulating the behavior and performance of neuromorphic processors. Our model shows how these processors communicate with each other by adapting the weights of their local algorithms based on the traffic distribution within the entire network. It leverages traffic data to dynamically update the city's traffic light signaling algorithm, creating a more efficient transport grid. The end result of this sample model is an increase in the efficiency and speed of city traffic, leading to time, energy, and emissions savings. We argue that the usage of neuromorphic networks in this context generalizes to many other relevant smart city applications, such as infrastructure health monitoring and environmental monitoring, by demonstrating how these devices can communicate and learn from each other.

We began creating our model using a few different libraries to determine which library provided the most accurate NC simulation while remaining feasible to implement within our timeframe. We ultimately decided to pursue Torch NN, as it had the optimal tradeoff between accuracy and ease of integration with our adaptive traffic light algorithm.

Model	Pros	Cons
Brian2	• Easy setup and intuitive syntax • Descriptive training and output visualizations • Dynamic code generation	• No support for deployment on neuromorphic hardware • Not scalable to larger or more complicated models
Lava DL	• Simulation package supports direct deployment onto neuromorphic devices like the *Loihi 2* chip • Scalable to large models and simulations • Supports biologically realistic neural networks	• Development package is low-level and requires custom SNN implementation using package-specific Lava Process Models • Limited development resources and documentation • Relatively new framework, so some features are not yet complete
Torch NN	• Comprehensive documentation • Part of an extensively developed framework with pretrained models and libraries for data loading • Flexibility in developing new layers and loss functions for networks with different use cases	• Performance tuning is required for larger scale applications • Lack of native support for spiking neurons (required custom implementation)

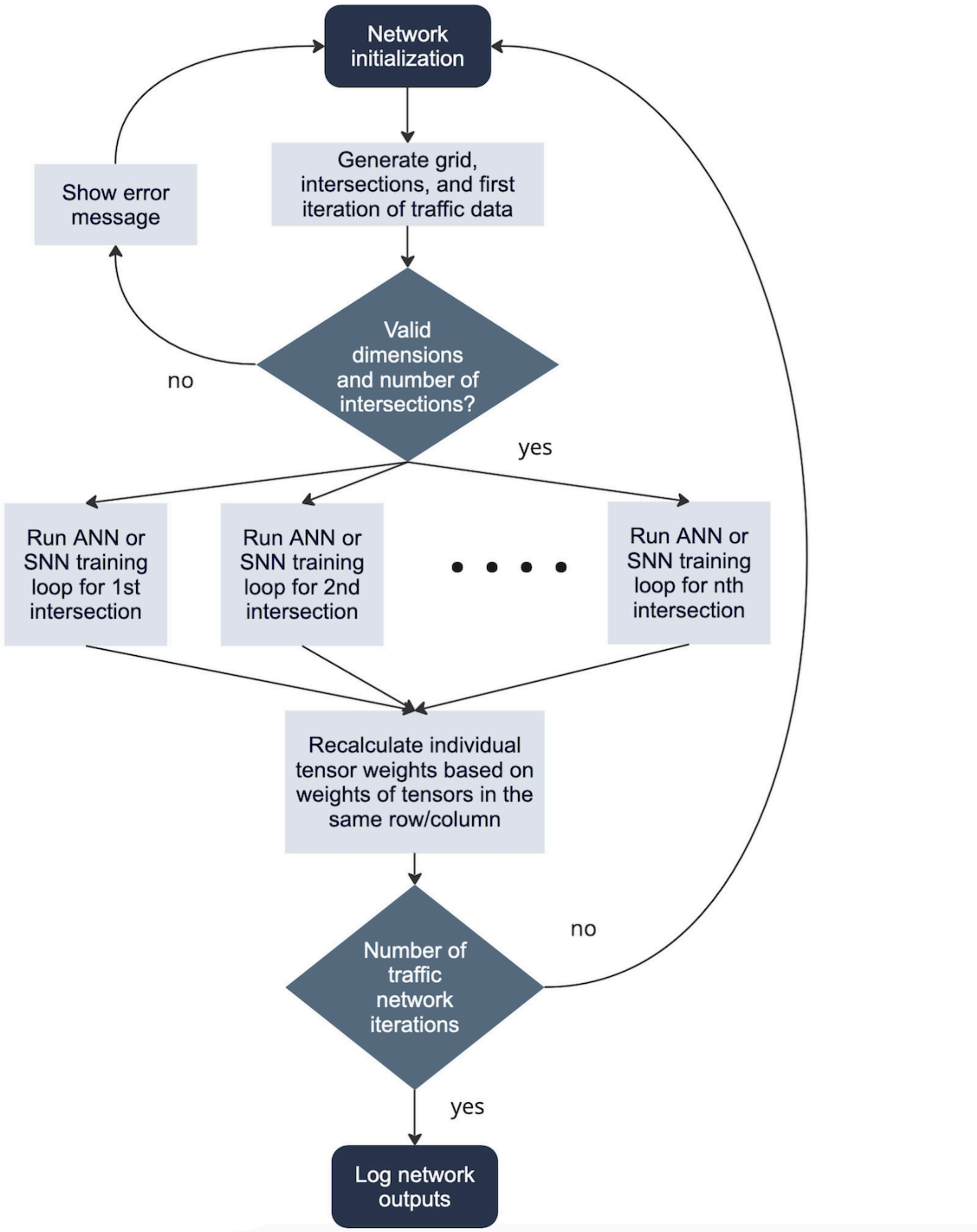
Both an artificial neural network (ANN) and spiking neural network (SNN) model were implemented to compare and contrast the efficiencies and accuracies of neuromorphic computing architectures and of traditional von Neumann architectures when applied to IoT devices. SNNs are inherently more energy efficient than ANNs, due to their event-driven processing, where they only fire when they receive sufficient input.

Both models scale green light duration by traffic density to prevent congestion while allowing the greatest amount of traffic to flow through their intersections. Both use a mean squared error loss function and an Adam optimizer to minimize the loss function. Traffic data is randomly generated using PyTorch's random tensor generation function. Assuming only two-way intersections (with roads crossing each other) for simplicity, our model outputs the duration of time the traffic lights will be green at the NW versus SE intersections.

Traffic model	ANN	SNN
Network	• Feed-forward network with three fully connected dense layers • ReLU activation function • Layer normalization between layers • Dropout layer to help prevent data overfitting	• Feedforward network with two Leaky Integrate and Fire (LIF) neurons and two fully connected linear layers • To better simulate biological neurons, LIF neurons accumulate input over time and emit spikes when a certain threshold is reached, instead of outputting continuous values • Uses a data loader to shuffle data so model results are more generalizable
Training Cycle	1. Reset accumulated gradients 2. Get the next slice of traffic data and update the weights of all network layers 3. Calculate target durations 4. Calculate loss via the loss function between the current network output and the target 5. Update the model's parameters with the optimizer based on the loss function	1. Using the same target calculations as the ANN, the data and target are passed into the model to generate spike activity and membrane potentials 2. Average spiking activity over time is passed into the loss function along with the target, from which the optimizer updates model parameters

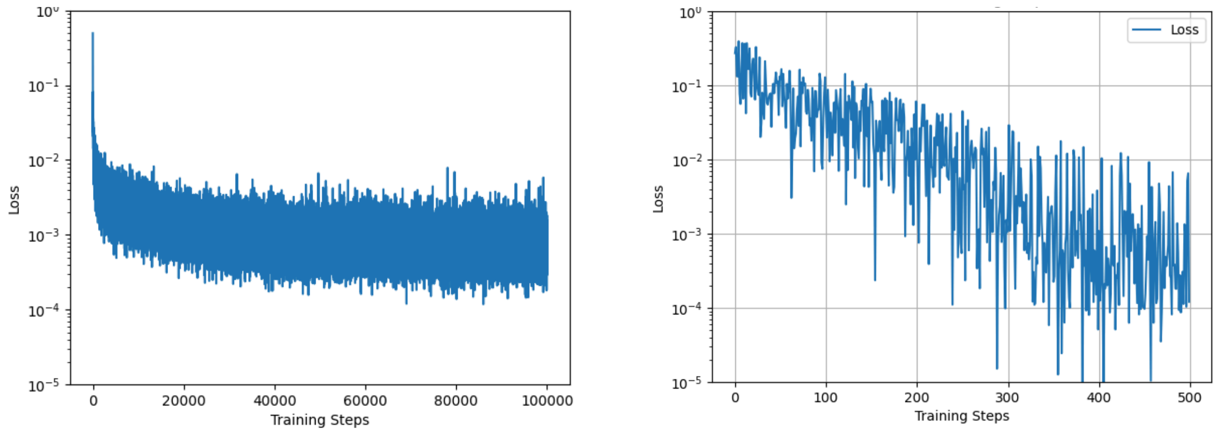
Road Network Implementation

We implemented a virtual road network simulation to assess how well individual models can adjust their weights according to the state of the entire network. We generated an *n-by-m*-dimensional road grid, with an arbitrary number of intersections of interest randomly chosen throughout the grid. Traffic data, representing car density, is randomly generated at each timestamp. Individual traffic light model weights are updated every timestamp. Additionally, the tensors representing green light durations in the NW and the SE direction at each intersection are also updated after individual model weights are updated. To reduce congestion, for every NW and SE street with 2 or more intersections, the relative green light durations are scaled proportionally to the greatest difference among the green light durations in the NW and SE directions. For example, if there are three intersections along a street, and the greatest time delta between the green light in the NW and SE directions is 5 seconds, with the green light in the NW direction being longer, all the other green lights in the NW direction will have 5 seconds added to their duration. Then, the durations of the NW and SE directions are renormalized to fit within the span of a light cycle. The updated tensors are then fed back into the original network, and this cycle of updating individual models, feeding the individual model output into the larger feedback algorithm, and feeding the global algorithm outputs back into the individual models is repeated over each training cycle. To visualize the network workflow:

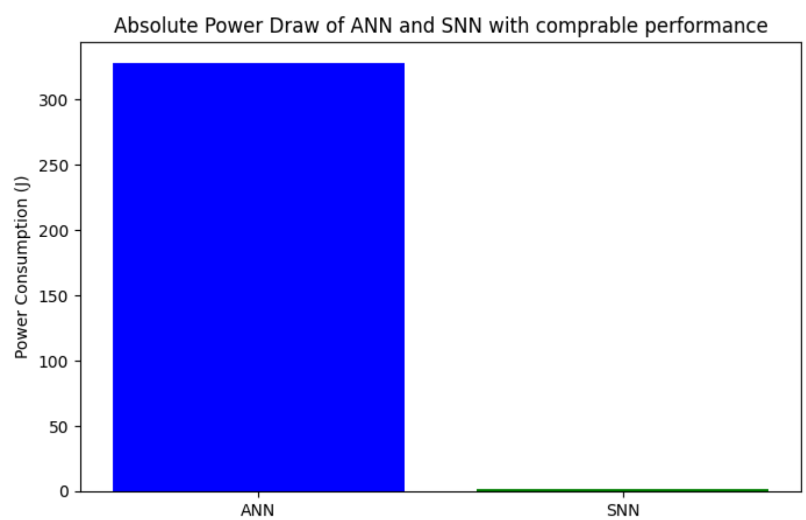


We then quantitatively evaluated both the energy performance and the accuracy of each model.

ANN **SNN**



<u>Fig 1: Comparison of ANN (left) and SNN (right) performance in traffic control scenario.</u> Two models were trained to optimize traffic flow in a hypothetical, arbitrarily defined traffic grid. Despite allowing the ANN to run for 100,000 training epochs, where the SNN was only allowed 500, the SNN showed comparable, if not better performance, with both loss functions approaching 0.001, or 0.1%. If allowed to continue the run, the ANN faces significant diminishing returns, while the SNN is able to push accuracy lower by more than two degrees of magnitude (range of 10^-5).



<u>Fig 2: Power draw of the ANN and CNN network.</u> Power collection was obtained through the ZeusMonitor GPU library to calculate the power consumption of the ANN, approximately 330 Joules. To overcome our lack of access to neuromorphic hardware, we found the number of synaptic events that occurred (51,119,232), and then applied chip-specific power consumption data to the events; for the Intel Loihi chip (23.6 pJ per synaptic event, (Covi et al., 2021)), as a typical device, it would take less than 1 J to run our entire SNN network.

We suggest that these results are indicative of the performance and energy savings that would be derived from applying SNNs and neuromorphic hardware broadly in the IoT.

Significance

Projects like KI4LSA (2022) conducted by the Fraunhofer Institute for Optronics used high-resolution cameras and radar sensors to calculate the number of vehicles and wait times at intersections. They leveraged this data through deep reinforcement learning to train a neural network to calculate the optimum switching behavior for the traffic lights. In simulation, their algorithm (summarized below) reduced traffic congestion by 10-15%.

The traffic light phase transition algorithm LI4LSA proposes can be integrated with our road network algorithm, which generates traffic light phases for simple two-street intersections, once we generalize our implementation to intersections at a junction of an arbitrary number of roads. The scalability issues the LI4LSA study faced can then be mitigated through our proposal of a lightweight network of neuromorphic processors. These processors will be coupled with a camera and an Impulse Radio (IR) receiver and transmitter to communicate with a central processor that updates individual intersection SNNs using the global network weight results. IR transmissions are ideal for low-power and high-precision communications and integrate well with the sparse data transmission of the neuromorphic processors. Therefore, this implementation prevents much of the communication latency introduced by the LI4LSA, including the algorithm's computational complexity and the communication overhead for exchanging information between intersections.

Solution Integration: Neuromorphic IoT for Smart Cities

Next Steps in Integration and Adoption

Each device in the network will include an event-based sensor and a spike-based asynchronous processor implementing Integrate-and-Fire neurons, for effective information storage and recall. The event-based sensors don't process redundant data, leading to reduced power consumption (Caccavella et al., 2023). For example, in image processing, NC devices will only be triggered by changes in brightness; traffic light optimization algorithms will only recalculate network weights when cameras detect significant changes in pixel values that are correlated with changes in congestion.

Example Workflow

Visual data is streamed as the coordinates of each pixel, the timestamp, and the polarity of the event (whether brightness has increased or decreased). To process this data, event-based sensors are combined with asynchronous processors that share the same computational principles as Von Neumann architectures with their clocked circuits (e.g., an event-based vision sensor and an asynchronous neuromorphic processor).

1. Neuromorphic device receives inputs from the embedded sensor featuring a pixel array or off-chip data.
2. Events are queued and sent to processing cores in FIFO order.
3. Each processor core executes a per-event computation sequence of convolution → Integrate-and-Fire (IF) spiking neuron → sum pooling. To synchronize results across neuromorphic processors, the processors can be coupled with external hardware with a FPGA to timestamp outgoing events and do format conversions.

To train the SNNs before deployment onto neuromorphic devices, back-propagation can be used during simulation and the trained model can be deployed onto neuromorphic hardware for the inference phase. Another approach would be to directly train algorithms on the neuromorphic devices through local weight update methods via local plasticity (changing the activation levels of synapses). This can develop adaptive spiking models capable of learning from new data at the edge, since neuromorphic chips often lack support for global learning algorithms, like backpropagation, which rely on differentiable, continuous activation functions.

Addressing Limitations of NCs

Limitation: Strategies such as batch normalization, skip connections, dropout, and pooling are widely utilized to enhance stability and mitigate overfitting, but are designed for continuous-valued networks.

Solution: These issues may be addressed by developing analog techniques for SNNs:

- Batch normalization can be done via spike frequency adaptation to maintain a stable firing range, adaptive thresholding (raising the firing threshold if too much activity), and homeostatic plasticity to self-regulate activity by adjusting synaptic weights or neuron parameters in response to the neuron's average firing rate, membrane potential scaling, and layer-wise normalization.
- Skip connections allow spikes to bypass certain layers, which can facilitate learning in deeper networks by ensuring that spikes can still propagate through the network even if intermediate neurons are not firing.
- Dropout in SNNs translates to randomly silencing neurons or synapses during training. This can be implemented on Loihi by adjusting the probability of spike generation or by dynamically modulating synaptic weights to achieve a similar effect.
- Pooling can be adapted to operate on the temporal patterns of spikes. For example, spike-timing-based pooling could be used to select the earliest spikes or to count spikes

within a time window. This reduces the temporal resolution of the spike trains, similar to how spatial pooling reduces resolution in traditional networks.

Limitation: The divergent behavior of the SNN in simulation and on NC hardware can significantly affect the model's precision.

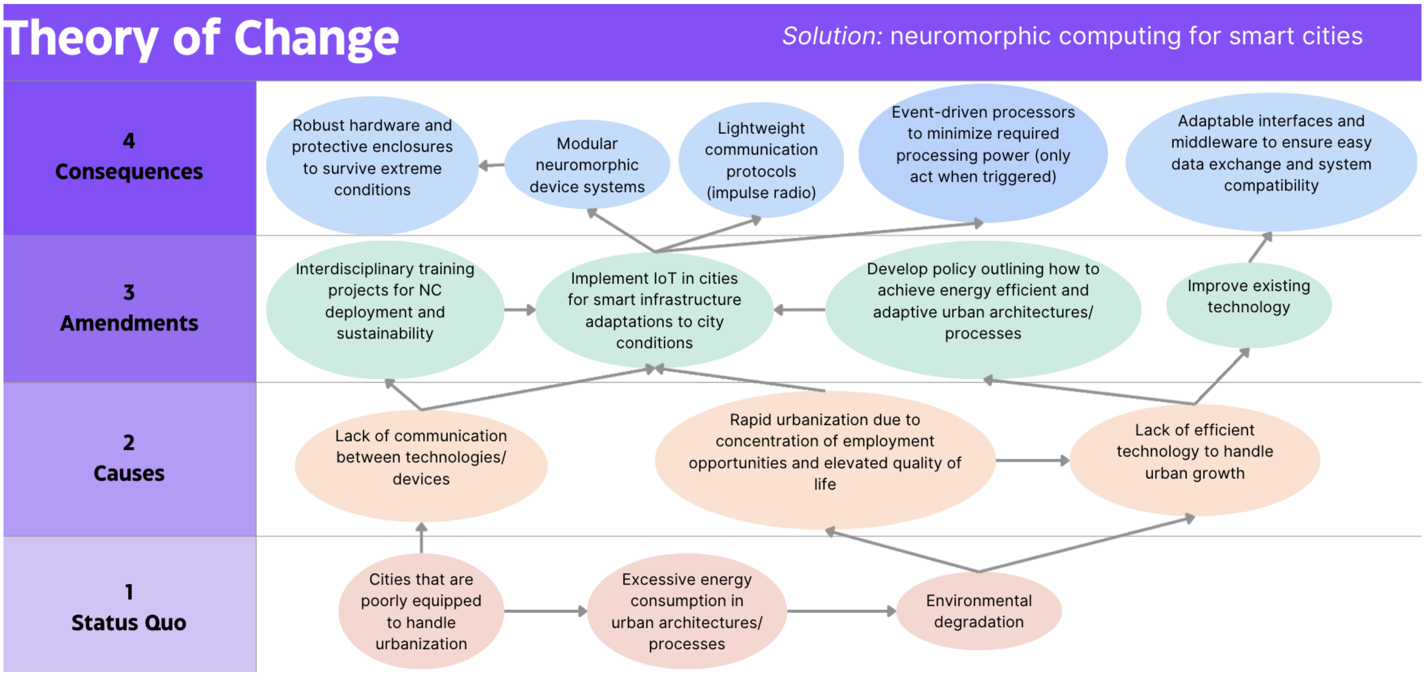
Solution: The need to discretize the stream of input events in temporal bins during simulation leads to a reduction in the number of spikes produced by the neurons compared to the on-chip inference where each event is processed independently. If the time interval for event aggregation used in the simulation is not sufficiently small, the on-chip inference might generate a significantly higher number of spikes than the simulation for the same input, leading to stalling due to limited processing core bandwidth. To adjust for this, the number of spikes generated when the membrane potential exceeds the threshold should be directly proportional to the membrane potential value.

Limitation: The model's training results may not be generalizable beyond the data it was trained on.

Solution: For the model to be able to generalize its results to other datasets, for regression tasks such as object detection, the output spike events need to be converted into continuous values via a linear layer within the SNN, with layer normalization to eliminate batch dependence.

Theory of Change

The following diagram indicates how to resolve various aspects of our problem by developing solutions that target their root causes. Each subproblem under the status quo section has one or more primary causes, which have at least one primary solution and further specifications for those solutions.



Tractability and Neglectedness

Tractability

As with the adoption of any new technology, the rapid development and integration of NC in IoT devices may face challenges with cost, research capability, and production. To begin adoption, we foresee needing government subsidies to encourage adoption up to a critical threshold. However, as the technology matures, we should see rapid increases in both the affordability and the performance of NCs, making them increasingly commercially viable; as precedence, similar events occurred with the adoption of EVs and government-promoted tax benefits to both manufacturers and consumers (EPA, 2024).

Neglectedness

While there is growing interest in energy efficiency and sustainability, current efforts are typically focused on improving specific technologies and not rethinking energy-consuming systems as a whole. Our solution of using neuromorphic computing and IoT aims to address energy consumption at a systemic level, completely revamping the way that the devices around us work: a novel solution.

Next Steps

The following steps must be taken to create a functional framework for integrating neuromorphic IoT into smart cities.

1. Combine our traffic algorithm with the LI4LSA algorithm and generalize it to traffic grids of real cities. Also integrate the algorithm with pedestrian traffic lights.
2. Transfer algorithm implementation to Lava or an equivalent library to be deployed directly to compatible neuromorphic hardware.
3. Use the same neuromorphic device communication scheme to extrapolate our process and algorithm to other applications, such as infrastructure health monitoring and tracking environmental conditions like air quality, humidity, water contamination, etc.
4. Draft public policy to enable the security of the data being transferred by neuromorphic devices. Propose an integration plan for phasing in the new architecture in major cities that doesn't disrupt currently implemented systems via ensuring communication and interoperability between neuromorphic systems and existing digital infrastructure networks. Ensure compatibility by setting international standards and protocols for neuromorphic communication.

References

Baibakov, K., & Nikolski, D. (2024). Chapter 4: Neuromorphic computation and its impact on AI-driven systems. In D. Nikolski (Ed.), Advances in neuromorphic computing (pp. 87-103). Springer. https://link.springer.com/chapter/10.1007/978-3-031-65549-4_4

Caccavella, C., Paredes-Vallés, F., Cannici, M., & Khacef, L. (2023). Low-power event-based face detection with asynchronous neuromorphic hardware. arXiv. https://doi.org/10.48550/arXiv.2312.14261

Chen, J., Skatchkovsky, N., & Simeone, O. (2022). Neuromorphic integrated sensing and communications. IEEE Wireless Communications Letters. https://doi.org/10.48550/arXiv.2209.11891

Climate Change in Data: The Physical Science Basis. https://www.ipcc.ch/. Published 2021. Accessed August 26, 2024. https://www.ipcc.ch/report/ar6/wg1/resources/climate-change-in-data/

Du, Z., Chen, S., & Wang, Y. (2016). Micro-15: Hardware-software co-design of neuromorphic processors. Retrieved from https://courses.cs.washington.edu/courses/cse590g/16wi/du_micro15.pdf

Eshraghian, J. K., Ward, M., Neftci, E., Wang, X., Lenz, G., Dwivedi, G., Bennamoun, M., Jeong, D. S., & Lu, W. D. (2021). Training spiking neural networks using lessons from deep learning (arXiv preprint arXiv:2109.12894). https://arxiv.org/abs/2109.12894

Fraunhofer-Gesellschaft. (2022, February). Traffic lights controlled using artificial intelligence. Fraunhofer-Gesellschaft. https://www.fraunhofer.de/en/press/research-news/2022/february-2022/traffic-lights-controlled-using-artificial-intelligence.html

Schuman, C.D., Kulkarni, S.R., Parsa, M. et al. Opportunities for neuromorphic computing algorithms and applications. Nat Comput Sci 2, 10–19 (2022). https://doi.org/10.1038/s43588-021-00184-y

Ge M, Friedrich J, Vigna L. 4 Charts Explain Greenhouse Gas Emissions by Countries and Sectors. World Resources Institute. Published 2020. Accessed August 26, 2024. https://www.wri.org/insights/4-charts-explain-greenhouse-gas-emissions-countries-and-sectors

Martin, Martin. UN Report: Nature's Dangerous Decline "Unprecedented"; Species Extinction Rates "Accelerating" - United Nations Sustainable Development. United Nations Sustainable Development. Published May 6, 2019. Accessed August 26, 2024.

https://www.un.org/sustainabledevelopment/blog/2019/05/nature-decline-unprecedented-report/

Matsuo, R., Elgaradiny, A., & Corradi, F. (2024). Unsupervised classification of spike patterns with the Loihi Neuromorphic Processor. Electronics, 13(16), 3203. https://doi.org/10.3390/electronics13163203

Müller, A., & Sabatelli, M. (2022). Safe and psychologically pleasant traffic signal control with reinforcement learning using action masking. arXiv. https://arxiv.org/pdf/2206.10122

Royal, M. (2024). Neuromorphic Computing Guide [GitHub repository]. GitHub. https://github.com/mikeroyal/Neuromorphic-Computing-Guide

The Smart City Journal. (n.d.). Smart traffic light technology controlled using artificial intelligence. The Smart City Journal. https://www.thesmartcityjournal.com/en/smart-mobility/smart-traffic-light-technology-controlled-using-artificial-intelligence

United States Government. (n.d.). Tax Incentives for EVs. EPA. https://fueleconomy.gov/feg/taxcenter.shtml

NASA. (2023, October 23). Arctic Sea Ice Minimum | NASA Global Climate Change. Climate Change: Vital Signs of the Planet. https://climate.nasa.gov/vital-signs/arctic-sea-ice/?intent=121

Wind Turbine Lease Rates – How Valuable is Your Wind Farm Lease? | Landmark Dividend - Landmark Dividend LLC. (2014, July 10). Landmark Dividend LLC. https://www.landmarkdividend.com/wind-turbine-lease-rates-2/#:~:text=Quantity%20of%20Land%20Available,turbines%20and%20other%20supporting%20infrastructure.

GlobalData Plc. (2017). The Power consumption in United States of America (2017 - 2020, GWh). Globaldata.com. https://www.globaldata.com/data-insights/power-and-utilities/the-power-consumption-in-united-states-of-america-1083501/

IBM. (2024, June 27). *What is neuromorphic computing?*. IBM. https://www.ibm.com/think/topics/neuromorphic-computing

Covi, E., Donati, E., Liang, X., Kappel, D., Heidari, H., Payvand, M., & Wang, W. (2021). Adaptive extreme edge computing for wearable devices. *Frontiers in Neuroscience*, *15*. https://doi.org/10.3389/fnins.2021.611300