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# Embodied Intelligence in Transportation Systems: Road Network Computing

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**Abstract.** This paper studied the concept of embodied intelligence within transportation systems, focusing on the interactions between purposefully designed physical structures and their dynamic environmental contexts. By drawing inspiration from the intricate complexities inherent in human-designed transportation systems, including the intricate web of road networks and vehicular components, the integration of intelligent elements is examined. Beyond a mere examination, the paper proposes a novel perspective—conceptualizing a transportation system, particularly road networks, as a physical reservoir. This perspective is substantiated through a thorough exploration of the reading mechanism of the traffic states and the echo-state property of road networks. We further dive into the traffic property to explore the inherent computational capabilities, such as fundamental logic operations, within these networks. The illustrative examples of OR, XOR, and AND logic gates within road networks serve as tangible demonstrations of their inherent computational capabilities. These examples not only showcase the computational abilities embedded in road networks but also lay the groundwork for a paradigm shift—a consideration of road networks as a manifestation of embodied intelligence within the broader framework of transportation systems. This paper contributes to the evolving discourse on the transformative potential of road networks as dynamic, intelligent entities, redefining our understanding of transportation systems.

## 1. Introduction

Embodied intelligence frequently manifests through the dynamic interplay between ingeniously designed physical systems and their surrounding environments. An example of such intelligence is the complexity of human-designed transportation systems, including complex road networks, infrastructural elements, and large number of vehicles dispersed across urban landscapes. The continuous enhancement of transportation systems is driven by the urgent need to facilitate the safe and efficient transportation of both individuals and goods in support of diverse human activities. This pursuit has given rise to the integration of intelligent components within transportation systems.

An example of intelligent intervention within transportation is the deployment of intelligent traffic lights. Beyond their conventional role in unidirectional traffic control, these systems demonstrate an adaptive capacity to engage with real-time conditions, thereby facilitating enhanced coordination (Chu, Lam & Li 2022b). Another instance is the sensing capabilities embedded in intelligent vehicles, designed for the purpose of gathering comprehensive information from their surroundings, a crucial aspect of enabling autonomous driving (Van Brummelen, O'Brien, Gruyer & Najjaran 2018). The autonomous vehicle, tasked with the responsibility of safely and efficiently navigating a complex and dynamically evolving physical environment, reflects the complex interaction inherent in embodied intelligence. As these intelligent components become integral to the transportation system, the traditional paradigm is poised to evolve into a truly intelligent transportation system. The synergistic fusion of ingeniously designed physical systems and adaptive, context-aware functionalities is promoting the transportation domain towards a future characterized by heightened intelligence and efficiency.

The human brain has always been acknowledged as the most intelligent processing unit. From the neuroscience point of view, the human brain is comprehended as a composition of nervous tissue forming a biological neural network that facilitates the transmission and reception of chemical and electrical signals throughout the entirety of the body. Drawing inspiration from this intricate biological neural network, computer scientists have devised artificial neural networks (ANNs) that emulate intelligent processes. It is contended that ANNs constitute a pivotal component catalyzing the proliferation of numerous state-of-the-art intelligent applications, including robots learning from demonstrations (Argall, Chernova, Veloso & Browning 2009). Remarkably, certain applications have transcended human capabilities. For instance, the application of ANNs in solving complex challenges such as the Rubik's Cube (Akkaya, Andrychowicz, Chociej, Litwin, McGrew, Petron, Paino, Plappert, Powell, Ribas et al. 2019). Both biological and artificial neural networks hinge upon the complexity inherent in their network structures. If network complexity is posited as a fundamental determinant of intelligence, then it is plausible to assert that a sophisticated road network interwoven with vehicular entities within the transportation system may inherently embody a certain degree of intelligence.

To observe, evaluate, and enhance the intelligence of a physical system, the frameworks of reservoir computing (Jaeger 2001b) (Maass, Natschläger & Markram 2002) and fluidic circuits (Preston, Rothemund, Jiang, Nemitz, Rawson, Suo & Whitesides 2019) are introduced, utilizing the inherent physical characteristics for computational purposes. Reservoir computing represents a machine learning paradigm that seeks to replicate chaotic systems by leveraging the unique attributes of a reservoir. Initially conceptualized as a set of randomly connected nodes, the reservoir demonstrates proven nonlinearity and memory (Jaeger 2001a), essential for its computational efficacy in emulating chaotic systems such as the Lorenz system (Khovanov 2021) and the Mackey-Glass systems (Jaeger & Haas 2004). Furthermore, diverse physical systems, including a silicon arm in a water tank (Nakajima, Hauser, Li & Pfeifer 2015), a network of photonic components (Vandoorne, Mechet, Van Vaerenbergh, Fiers, Morthier, Verstraeten, Schrauwen, Dambre & Bienstman 2014), and a network of mechanical oscillators (Coulombe, York & Sylvestre 2017), have been demonstrated as effective reservoirs, showcasing a certain degree of nonlinearity and memory for computational tasks. Similarly, fluidic circuits embrace the notion that physical systems can engage in computation, emphasizing the design of soft structures within fluid delivery systems to function as logic gates, eliminating the need for traditional pumps and valves (Rothemund, Ainla, Belding, Preston, Kurihara, Suo & Whitesides 2018). For instance, a bistable soft structure activated by fluidic pressure mimics the behavior of NOT, AND, and OR digital logic gates (Preston et al. 2019). Both reservoir computing and fluidic circuits exemplify computational processes grounded in physical structures, showcasing embodied intelligence. It becomes plausible to consider a transportation system as a physical reservoir, leveraging the flow of vehicles as a computational resource.

In the rest of this paper, we will explore the embodied intelligence in transportation system in Section 2, present the studies of performing computation with physical system such as reservoir in Section 3, and discuss the concept of considering road networks and vehicles as a computation unit in Section 4.

## 2. Embodied Intelligence Components in Transportation Systems

The evolution of transportation systems has played a pivotal role amid technological advancements, significantly influencing the design and functionality of contemporary transportation systems (Picone, Busanelli, Amoretti, Zanichelli & Ferrari 2015). Anticipating future challenges, the next generation of transportation systems is envisioned to seamlessly integrate connected vehicles, connected infrastructure, and increased automation with existing technologies (Coogan, Arcak & Belta 2017).

### *2.1. Computation in Transportation Systems*

Bioinspired methods, a cornerstone in enhancing transportation system capabilities (Del Ser, Osaba, Sanchez-Medina & Fister 2019), draw inspiration from nature's intricate behavioral mechanisms and the adaptable processes of the brain (Holland 1975). Transportation systems integrate efficient, adaptive, and self-learning methods, encompassing fuzzy systems and artificial neural networks (Arbib 2003), (Engelbrecht 2007). For example, computational and distributed algorithm is a key element in efficient self-organizing strategies proposed by (Chu, Lam & Li 2020) that aims to dynamically alter road lane directions, contributing to the adaptability of autonomous vehicles. Moreover, it identifies optimal vehicle locations to cater to travel demand hotspots while supporting simultaneous vehicle-to-grid interactions demand a bio-inspired computation method such as genetic algorithm (Chu, Lam & Li 2022a).

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### *2.2. Sensing Advancements*

In the context of transportation with multiple vehicles, Crowd Sensing Intelligence (CSI) could be a useful sensing technique that introduces a paradigm where biological, digital, and robotic participants collaboratively contribute to sensing activities (Zhao, Hu, Zhu, Qiu, Chen, Jiao & Wang 2023). The envisioned progression of CSI from algorithmic to imaginative intelligence, guided by parallel intelligence (Ren, Jiang, Feng, Zhao, Liu & Yu 2022), involves digital participants operating in cyberspace, aiding in data collection and computation. Robotic participants, exemplified by intelligent vehicles, enhance sensing tasks with increased autonomy. Biological participants benefit from optimized productivity through the assistance offered by their digital and robotic counterparts (Teng, Hu, Deng, Li, Li, Ai, Yang, Li, Xuanyuan, Zhu et al. 2023), (Zhu, Wang, Zhao, Qiu, Liu, Chen & Wang 2022).

### *2.3. Design Integration*

In the realm of design, the controller proposed in (Chu, Chen, Lam & Song 2023) is designed to orchestrate the coordination of transport requests, travel schedules, and charging/discharging for electric vehicles, optimizing utility across transportation and power distribution systems. Additionally, (Zardini, Milojevic, Censi & Frazzoli 2021) presents a structured co-design approach, leveraging monotone theory, to address embodied intelligence co-design problems in autonomous vehicle hardware and software stacks. This method showcases the potential to model complex autonomous vehicles with heterogeneous components, providing a comprehensive solution. Coordination strategies (Chu & Guo 2023) also leverage resources from multiple and heterogeneous transportation system users to maximize user satisfaction and long-term system profit while ensuring privacy.

Incorporating these embodied intelligence components, transportation systems are poised to navigate the complexities of future mobility challenges with enhanced efficiency, adaptability, and safety.

## 3. Embodied Computing

Reservoir computing and fluidic computing leverage the inherent characteristics of reservoirs and fluids for computational processes. In essence, both systems involve the dynamic response of a reservoir and fluid to inputs, leading to the generation of outputs shaped by these reactions. Specifically, a reservoir computer emphasizes the nonlinear and memory attributes of the reservoir to effectively emulate dynamic systems. On the other hand, a fluidic computer places significance on memoryless properties, such as those exhibited by a Markov chain, to execute logical operations. This distinction underscores the diverse computational approaches employed in reservoir and fluidic computing, where the former capitalizes on reservoir properties for dynamic system emulation, and the latter emphasizes memoryless characteristics for logical processing.

### *3.1. Reservoir Computing*

Reservoir computing functions as an observer that extracts information from a dynamic reservoir. In this context, the reservoir's dynamism is crucial for manifesting intricate behaviors in response to varying inputs. The cornerstone of its computational prowess lies in the echo-state property, wherein the reservoir is transiently influenced by inputs, only retaining the memory of recent inputs while swiftly erasing the impact of inputs from an earlier time (Jaeger 2001b). For instance, when a tranquil reservoir receives a pulse as input, it activates, potentially oscillates briefly, and subsequently returns to a tranquil state. Notably, the reservoir retains the memory of the input during its oscillation but relinquishes that memory upon returning to a tranquil state. The echo-state property is indispensable for computational efficacy as it precludes perpetual oscillation, averting divergent output.

An additional crucial attribute of a reservoir computer is its memory, a facet partially encompassed by the previously mentioned echo-state property. However, this memory aspect specifically pertains to the retention of input information (Jaeger 2001a). A reservoir computer has to possess the capacity to remember inputs for a substantial duration (memory property) without persisting indefinitely (echo-state property). This characteristic proves instrumental in tasks requiring sequential reasoning, such as image recognition endeavors where the image is transformed into a digital sequence serving as inputs to the reservoir (Woods, Bürger & Teuscher 2015). The memory property is engendered by interconnections among nodes within the reservoir, facilitating information retention as it is passed from one node to another.

The third essential property is nonlinearity, signifying that the reservoir responds to inputs in a nonlinear fashion, showcasing diverse behaviors in response to different inputs (Maass et al. 2002). This property is instrumental in enabling the reservoir computer to replicate intricate systems, such as the Mackey-Glass chaotic system (Jaeger & Haas 2004). Leveraging this nonlinearity, the readout of the reservoir computer can adopt a straightforward linear regression approach while retaining the nonlinearity within the reservoir. This strategic approach significantly diminishes the requisite volume of data and time for training a reservoir computer, emphasizing the efficiency gained through the exploitation of nonlinear properties within the reservoir itself.

Viewing the traffic system as a dynamical system offers the potential to conceptualize it as a reservoir, contingent upon substantiating its echo-state property, memory, and nonlinearity. Nevertheless, adopting each vehicle as a node within the reservoir renders the system exceedingly intricate. Defining interactions among vehicles becomes challenging, and the complexity escalates exponentially with the increasing number of vehicles. Consequently, a methodological approach is imperative to simplify the traffic system effectively.

### *3.2. Traffic as Fluid*

Researchers in fluid mechanics have identified parallels between traffic flow and airflow, noting similarities such as the resemblance between airflow shock waves and traffic jams (Lighthill & Whitham 1955). When considering a road, it becomes evident that the influx and efflux of vehicles adhere to a scalar conservation law, thereby giving rise to a nonlinear partial differential equation (LeVeque & Leveque 1992):

$$\frac{\partial k}{\partial t} + \frac{\partial ku}{\partial x} = 0, \tag{1}$$

where $k$ is the density of vehicles, $u$ is the vehicle speed, $t$ is time, and $x$ is position. This equation bears a striking resemblance to the conservation of mass equation in airflow, implying that phenomena such as shock waves in airflow can manifest in traffic flow, commonly referred to as traffic jams (Richards 1956). By drawing parallels between traffic flow and airflow, we can streamline the model of the traffic system into mathematical equations like the one represented by Eq.1. This formulation ensures the inclusion of nonlinearity, allowing us to treat the traffic system as a reservoir for computational purposes.

### *3.3. Fluidic Computing*

Fluidic computing is centered on the construction of logic gates through fluidic circuits (Rothemund et al. 2018), providing a notable instance of leveraging fluid for computational processes, even though these circuits typically lack inherent memory. Through meticulous design of the soft fluid piping structure, a fluidic circuit can exhibit bistable behavior and effectively regulate fluidic pressure, emulating the functionality of NOT, AND, and OR gates (Preston et al. 2019). This innovative approach to piping structure design is not confined to fluidic circuits alone but can be extended to the development of a computer based on the principles of the traffic system.

In conclusion, the prospect of constructing a traffic-based computer emerges by simplifying the traffic system akin to airflow, involving the careful design of road network structures. Crucially, ensuring the incorporation of the echo-state property, memory, and nonlinearity within this simplified model is paramount to realizing a computational system inspired by traffic dynamics. This innovative approach holds promise for novel applications in computational science and underscores the adaptability of principles derived from fluid mechanics to diverse domains, including traffic-based computing.

## 4. Road Network Computing

In this section, we will first discuss the echo-state property in road networks. Subsequently, leveraging the echo-state property, we will illustrate how road networks, encompassing vehicular entities, may be construed as computation unit.

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### *4.1. Information Flow in Road Networks*

Consider a fleet of vehicles, denoted as $\mathcal{V} = \{v_1, \ldots, v_N\}$, entering a road at origin point $o$ and traversing through a complex interconnected road network, eventually exiting the network at the sole destination point $d$, where $N$ represents the total number of vehicles. Let $v_1$ be the first vehicle to pass through $o$ at time $t_o^{v_1}$, and $v_N$ be the last vehicle passing through $o$ at time $t_o^{v_N}$. Similarly, they pass through $d$ at time $t_d^{v_1}$ and $t_d^{v_N}$. The time required for vehicle $v_n$ to traverse from $o$ to $d$ is defined as $T^{v_n}od$, and the time for the fleet of vehicles to pass through $o$ and $d$ is denoted as $T_o^{v_1 v_N}$ and $T^{v_1 v_N}d$, respectively. These quantities can be computed using the following equations:

$$T_{od}^{v_n} = t_d^{v_n} - t_o^{v_n}, \tag{2}$$

$$T_o^{v_1 v_N} = t_o^{v_N} - t_o^{v_1}, \tag{3}$$

$$T_d^{v_1 v_N} = t_d^{v_N} - t_d^{v_1}. \tag{4}$$

Intuitively, for a small number of vehicles $N$, it is relatively easy to maintain a constant speed such that there is a small variance in the travel time from one vehicle to another ($Var(T_{od}^{v_n})$ is small), and the overall travel times $T^{v_1 v_N}o$ and $T^{v_1 v_N}d$ are approximately equal, where $Var(\cdot)$ denotes the variance. However, with a large number of vehicles, traffic jams may occur, resulting in inconsistent vehicle platoons and longer travel times for later vehicles. This inconsistency could manifest as $T^{v_N}od \geq T^{v_1}od$ and $T_d^{v_1 v_N} \geq T_o^{v_1 v_N}$, reflecting nonlinear properties in the traffic flow and time relationship.

Travel time can be modeled using the Bureau of Public Roads (BPR) volume-delay function (Manual 1964), given by:

$$t^{BPR}(N) = t_f \left(1 + \alpha \left(\frac{N}{C}\right)^{\beta}\right), \tag{5}$$

where $t^{BPR}(N)$ is the estimated travel time, $t_f$ is the free flow travel time, $N$ is the traffic volume, $C$ is the practical capacity, and $\alpha$ and $\beta$ are the tuning parameters. This function indicates that as traffic volume increases beyond capacity ($N > C$), travel time also increases. Other models, like Greenshield's (Greenshields, Bibbins, Channing & Miller 1935) and the Highway Capacity Manual (Manual 2000), also depict the relationships among traffic speed, flow (number of vehicles per unit time), and density (number of vehicles per unit space).

The inverse relationship between traffic speed $s$ and density $k$ is expressed as:

$$s(k) = s_f \left(1 - \frac{k}{k_j}\right). \tag{6}$$

where $s_f$ is free flow speed and $k_j$ is the jam density. On the other hand, traffic flow $\rho$ and density $k$ relationship is modeled as a concave down parabola as flow is zero at

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both zero and jam density, while reaches the maximum flow in the in between zero and jam density. Therefore, the flow-density relation is given as

$$q(k) = s_f k \left(1 - \frac{k}{k_j}\right). \tag{7}$$

Similarly, the relation between traffic speed and flow is given by:

$$q(v) = k_j s \left(1 - \frac{s}{s_f}\right), \tag{8}$$

as speed can be at zero or free-flow speed when flow is zero, reaching the maximum flow between zero and free-flow speed.

These traffic states are interrelated, and as vehicles travel from $o$ to $d$, the associated traffic information characterized by speed, flow, and density propagates. An interesting phenomenon in this propagation is the traffic wave, also known as shockwave traffic jam, stop waves, and phantom traffic jam (Sugiyama, Fukui, Kikuchi, Hasebe, Nakayama, Nishinari, Tadaki & Yukawa 2008). This occurrence involves disturbances in traffic flow propagating backward, resulting in localized slowdowns or stop-and-go traffic. Traffic waves can form without an apparent external cause, arising from the interactions between drivers and the inherent instability of traffic flow. This highlights that information transmission occurs not only through communication channels but also through the dynamic motions of vehicles.

Vehicles themselves can be considered as information carriers within a transportation system. In this context, information flow refers to the transmission of signals from input to output through the road network. The traffic flow or other measurable quantities in the road network can be analogous to voltage in an electric computer, forming the basis of digital information (0s and 1s).

### *4.2. Echo-State Property in Road Networks*

As outlined in Section 3, the echo-state property (Yildiz, Jaeger & Kiebel 2012) characterizes a reservoir's ability to preserve and reflect input signals over a specific duration, facilitating the network's capture of temporal dependencies in the data. To investigate whether a road network aligns with the characteristics of a "reservoir", we analyze the echo-state property in the context of road networks.

Consider the road network as a discrete-time echo-state network with $M^{in}$ input roads, $M$ internal roads, and $M^{out}$ output roads. Let the traffic flow $q$ at input, internal, and output in time period $t_1$ to $t_2$ be the state of the echo-state network, denoted as $x^{in}_{t_1t_2} \in \mathbb{R}^{M^{in}\times 1}$, $x_{t_1t_2} \in \mathbb{R}^{M\times 1}$, and $x^{out}_{t_1t_2} \in \mathbb{R}^{M^{out}\times 1}$, respectively. The dynamics of traffic flow in the road network can be expressed as:

$$\begin{aligned} x_{t_1+1t_2+1} &= f\left(Wx_{t_1t_2} + W^{in}x^{in}_{t_1+1t_2+1} + W^{fb}x^{out}_{t_1t_2}\right), \\ x^{out}_{t_1t_2} &= g\left(W^{out}[x_{t_1t_2}; x^{in}_{t_1t_2}]\right), \end{aligned} \tag{9}$$

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where $W^{in} \in \mathbb{R}^{M\times M^{in}}$, $W \in \mathbb{R}^{M\times M}$, $W^{fb} \in \mathbb{R}^{M\times M^{out}}$, and $W^{out} \in \mathbb{R}^{M^{out}\times(M+M^{in})}$ is the input, internal, feedback, and output weight matrices, respectively. Additionally, $f$ and $g$ denote activation functions.

Consider a simplified road network with a single road, i.e., $M^{in} = M = M^{out} = 1$, with designated input and output locations at $o$ and $d$ respectively. The output traffic flow from $t_d^{v_1}$ to $t_d^{v_N}$ equals the input traffic flow from $t_o^{v_1}$ to $t_o^{v_N}$, represented by $x^{out}_{t_d^{v_1},t_d^{v_N}} = x^{in}_{t_o^{v_1},t_o^{v_N}} = N$. We can obtain the weight matrices as:

$$W^{in} = 1, \quad W = 0, \quad W^{fb} = 0, \quad W^{out} = \begin{pmatrix} 1 & 0 \end{pmatrix}, \tag{10}$$

and $f$ and $g$ are identity functions. This configuration satisfies the echo-state property, whereby traffic flow persists in the network for a period of time from $t_o^{v_1}$ to $t_d^{v_N}$, and fades after time $t_d^{v_N}$. Therefore, a road network with specific structure exhibits the each-state property and can be conceptualized as a computational reservoir.

### *4.3. Road Network as a Computational Reservoir*

After illustrating the echo-state property in road networks, we explore their potential as computational reservoirs. A specific road network structure can be conceptualized as an echo-state network, akin to a computational "reservoir." We exemplify the computational capabilities of road networks, focusing on fundamental logic operations.

Fig. 1 demonstrates the internal structure of the echo-state network represented by the road network. By segmenting the road into blocks, we can read the traffic information of each road segment to obtain the input, internal, and output states of the road network. For example, we can consider the traffic flow per road segment as a logical one if $x_{t_1+1t_2+1}$ is larger than a threshold value $C_1$, and zero if $x_{t_1+1t_2+1}$ is smaller then $C_0$, where $C_1 \geq C_0$.

A road network shown in Fig. 2 acts as an OR logic gate, jointly receiving traffic from input roads. When either or both input roads has high traffic, the output roads will have high traffic.

Another example is the XOR and AND road networks as shown in Fig. 3. For the illustration purpose, we use the horizontal dotted line at the outputs to represent a lengthy road segment. As for the output 2 road segment, it is a detour that vehicles normally will not enter if the traffic on output 1 road is light. Vehicle prefer to enter output 2 road when there is traffic jam on output 1 road. With the above structure, it can achieve the XOR and AND logic. For XOR logic, traffic flow in either input roads will trigger the logic on output 1. However, output 1 will be jammed if both input roads have high traffic flow, resulting a high density and low traffic flow (logic zero), as discussed in the flow-density relation. For the AND logic, there is traffic on output 2 (logic one) only when both input roads have high traffic (logic one). Since some of the traffic already diverted to output 1, we assume output 2 is less susceptible to congestion than output 1.

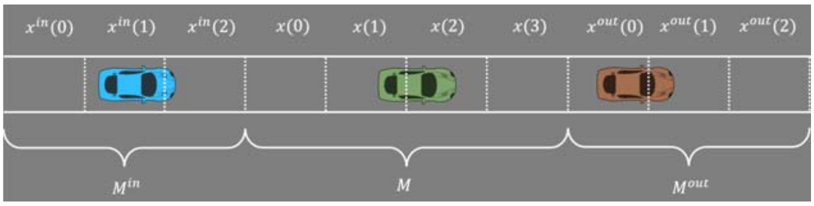


**Figure 1.** Input and read-out mechanisms of the road network computing.

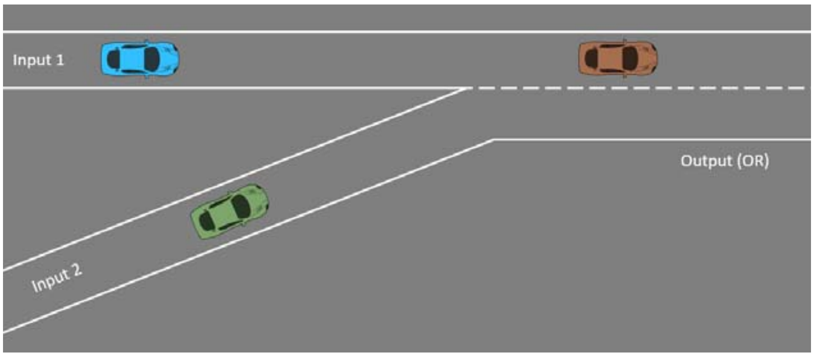


**Figure 2.** A road with two incoming road lanes exhibits OR logic.

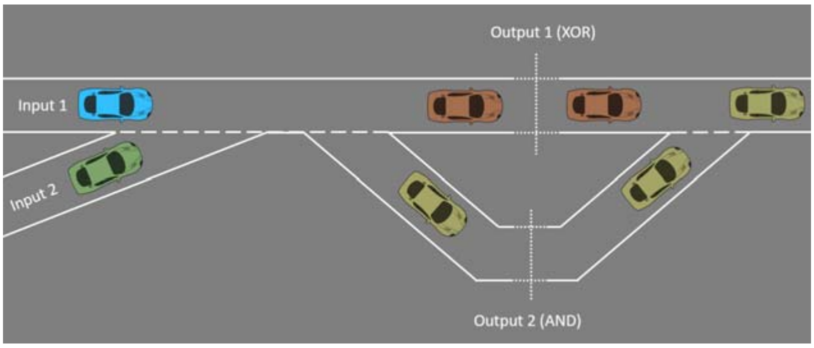


**Figure 3.** A road with two merging road lanes and a closed loop branch exhibits the XOR and AND logic.

These examples represent basic computational abilities within the network structure. Scaling up, multiple units can construct more powerful computational entities, such as a full adder using XOR and AND logic gates. In the urban city, much more complex road network are built on a city scale containing these fundamental logical components. The computational ability of such complex road network in city scale could be significant, and revolutionize the transportation systems with this new form of embodied intelligence.

## 5. Conclusion

Conceptualizing road networks and vehicles as computation units in the realm of embodied intelligence provides a novel perspective on enhancing transportation systems. This paper reviewed bio-inspired computation, reservoir computing, and fluidic computing, as fundamental theories supporting the novel perspective of road network computing. To demonstrate the effectiveness of road network computing, we analysed the echo-state property of road networks and illustrated sample road networks with OR, XOR, and AND logic capabilities.

By considering a transportation system as a computational reservoir, we can gain several significant insights and benefits. First, viewing the transportation network as a dynamic system allows for the identification of traffic flow disruptions and congestion patterns. This perspective can help pinpoint the origins of traffic jams and bottlenecks, facilitating targeted interventions to alleviate these issues. Second, treating the road network as a computational entity can optimize traffic flow by dynamically adjusting traffic signals, lane directions, and vehicle routing based on real-time data. This adaptive approach can lead to reduced travel times, lower emissions, and improved overall efficiency of the transportation system. Third, as a computational reservoir, the road network can perform real-time computations to potentially solve complex problems such as predicting traffic conditions, optimizing routing for emergency services, and managing vehicle-to-grid interactions. This capability can enhance the responsiveness and adaptability of the transportation system. This paper opens avenues for redefining transportation systems as not only physical infrastructures but also as intelligent computational entities. The consideration of road networks as computational reservoirs hints at the transformative possibilities, offering a new perspective on the future of transportation and the potential integration of embodied intelligence at a city scale.

Future research in this area holds the potential to further refine the integration of road networks and vehicles into a cohesive computational framework. Understanding how other road infrastructures and structures such as traffic lights and roundabouts play a role in road network computing could increase the possible road network computational units. The computing capability could ultimately lead to more sustainable, efficient, and functional transportation systems.

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