# From Information Networking to Intelligence Networking: Motivations, Scenarios, and Challenges

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## Abstract

By enabling information networking among people and machines, the Internet has become one of the major foundations for our socio-economic systems. After several decades of research and development of the Internet, it is relatively easy for humans/machines to obtain information. However, there are new challenges in the post-Internet era, including information overload, fake information and the design of trustworthy, cost-effective autonomous systems. In order to address these challenges, we need to think about networking in a larger timescale. Actually, in order to facilitate humans' cooperation, we have invented technologies enabling networking for matter (grid of transportation), for energy (grid of energy), and for information (the Internet). In this article, we argue that the next networking paradigm could be intelligence networking, where intelligence can be easily obtained, like matter, energy, and information. Specifically, we present the motivations, scenarios and challenges of intelligence networking. In addition, we present a novel collective reinforcement learning scheme enabled by intelligence networking. Some simulation results are presented to show the effectiveness of the proposed intelligence networking paradigm.


## Introduction

The Internet has become one of the major foundations for our socio-economic systems. By 2023, there will be 5.3 billion total Internet users (66 percent of the global population) and 29.3 billion networked devices (more than three times more networked devices on Earth than humans) [1]. By enabling information networking among people and machines, the Internet has become embedded in every aspect of our day-to-day lives, changing the way of business, education, government, healthcare, and so on [2]. After several decades of research and development of the Internet, it is relatively easy for humans/machines to obtain information.

Although the Internet has made our lives easier in some aspects, there are new challenges in the post-Internet era. For example, an excessive amount of information causes the information overload problem, which results in difficulty of decision-making and may lead to physical and psychological strain [3]. Larger and larger quantities of fake information are appearing on the Internet, which has a significant impact on business and society through influencing people's beliefs and decisions [4]. In addition, it is still difficult for us to address the existing challenges, including the development of trustworthy, cost-effective autonomous systems (e.g., autonomous vehicles), which shows the limitation of information networking.

In order to address these challenges, we need to think about networking in a larger timescale. Actually, in order to facilitate humans' cooperation in our socio-economic systems, we have invented technologies enabling networking for matter (grid of transportation), for energy (grid of energy), and for information (the Internet) [5], as shown in Fig. 1. Therefore, networking is not just for information only, as thought by most people in the networking research community. Although networking technologies for matter and energy are taken for granted by most people, they are important foundations as well. In this larger timescale, we can observe the pattern of networking paradigm evolution: a new networking paradigm is built upon the existing ones, but provides a higher level of abstraction.

On the other hand, artificial intelligence (AI) has gone through several stages in the past more than 70 years of extensive research and development, aiming to imitate the cognitive abilities of humans. Although recent public successes based on deep learning have boosted a new wave of interest in AI, it is well believed that AI remains far from human intelligence, which requires a lot less datasets and is much more flexible when adapting to new environments. According to the Big History Project [6], the unique *collective learning* capability of humans enables us to share intelligence efficiently, which explains the dominant role we play in the biosphere.

In this article, we envision that the next networking paradigm could be *intelligence networking*, which will enable intelligence to be easily obtained, like matter, energy, and information. We believe that intelligence networking can help address the challenges in our socio-economic systems and have significant impacts on our daily lives, as did the three previous networking paradigms. The contributions of this article are as follows.

We review the networking paradigm evolution and the artificial intelligence evolution, based on which we argue that networking needs intel-

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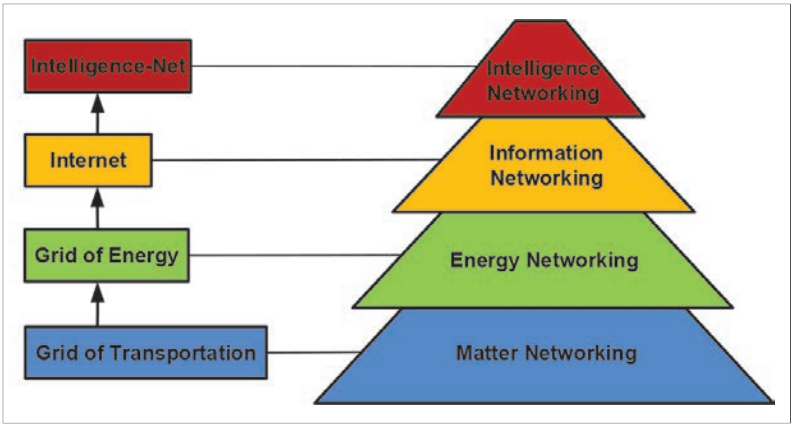


FIGURE 1. To facilitate humans' cooperation in our socio-economic systems, we have invented technologies enabling networking for matter (grid of transportation), for energy (grid of energy), and for information (the Internet). We envision that the next networking paradigm could be intelligence networking (Intelligence-Net)."

ligence, intelligence needs networking, and the next networking paradigm could be intelligence networking.

Two scenarios of intelligence networking are presented. One is a practical scenario for connected and autonomous vehicles, and another one is a theoretical scenario for collective reinforcement learning. We describe the open issues and research challenges of intelligence networking that need to be addressed in future efforts. Some simulation results are presented to show the effectiveness of the proposed intelligence networking paradigm.

The rest of the article is organized as follows. We review the networking paradigm evolution and the artificial intelligence evolution, and present the motivation of intelligence networking in the following section. Then we describe two scenarios of intelligence networking. Some open issues and research challenges are presented following that. We then discuss simulation results. Finally, we conclude the article with a discussion of future work.

## Motivations of Intelligence Networking

In this section, we present the motivations of intelligence networking, from both the perspective of networking paradigm evolution and the perspective of artificial intelligence evolution.

### Networking Paradigm Evolution

Cooperation lies at the heart of human society, from day-to-day interactions to great endeavors. Human beings are a social species that relies on cooperation to survive and thrive. It is believed that when compared to other species, humans are the only species that can cooperate flexibly in a large number [7]. In order to facilitate humans' cooperation in our socio-economic systems, we have invented technologies enabling networking for matter (grid of transportation), for energy (grid of energy), and for information (the Internet), which are briefly reviewed in this subsection. Figure 1 shows this evolution process.

**Matter Networking–Grid of Transportation:** All organisms, including humans, need matter and energy to live. In essence, the main purpose of transportation is to move matter from one location to another location, which is matter networking. There is no doubt that transportation has played a crucial role in humans' cooperation, including survival, social activity, trade, war, and so on. Before inventing any other transportation technologies, humans traveled on foot, then learned to use boats or animals for transportation to move matter. The wheel-and-axle combination was invented around 4500 BC, which is often considered to be the most important invention of all time, since it has had a fundamental impact on transportation and humans' cooperation. Many new transportation technologies were invented in the 17th and 18th centuries, such as bicycles, motor cars, trucks, trains, airplanes, and so on. In the 20th century, aircrafts, high-speed trains, and space ships are some examples of the defining transportation technologies.

**Energy Networking–Grid of Energy:** Energy is a measure of a system's ability to cause change. The First Law of Thermodynamics states that energy cannot be created or destroyed. It can, however, be transferred from one location to another location and from one form to another form. There are two broad categories of energy, kinetic energy (the energy of moving objects) and potential energy (the energy that is stored). Kinetic energy is expressed as $0.5\ m\ v^2 = 0.5\ m\ (d/t)^2$, where $m$ is the mass of an object, $v$ is speed, $d$ is distance, and $t$ is time. Therefore, kinetic energy can be thought of as how fast the matter is moved in a process.

In addition to the technologies enabling matter networking, another major innovation is the technologies enabling energy networking, which is fundamental to not only humans' survival, but also humans' thriving. With the electric energy grid, which is a network of transmission lines, substations, transformers and more, electric energy can be delivered from the power plant to our homes and businesses. Now, we can easily get energy to light up at night, power our computers, charge our phones, and cool our homes, by simply plugging into the electric energy grid.

**Information Networking–The Internet:** Following the grid of transportation and the grid of energy, the Internet has enabled humans' cooperation to a new level, and is estimated to connect 5.3 billion users and 29.3 billion devices by 2023. The primary purpose of the Internet is to move information from one location to another location. It is the global system of interconnected computer networks that uses the Internet protocol suite, TCP/IP, connecting humans and machines. The Internet has become one of the major foundations for our socio-economic systems by enabling information networking.

There is a strong connection between information and energy. The connection can be explained in Maxwell's "demon" [8], which is a thought experiment created by the physicist James Clerk Maxwell in 1867. In the thought experiment, the demon is able to convert information (i.e., the position and velocity of each particle) into energy, resulting in a decrease of the entropy of the system. This thought experiment has provoked theoretical work on the relation between thermodynamics and information theory.

Shannon's efforts to find a way to quantify information led him to the entropy formula with the same form as that in thermodynamics. Thermodynamics entropy measures the spontaneous dispersal of energy: how much energy is spread out in a process, or how widely spread out it becomes, at a specific temperature. $dS = \delta Q/T$, where $dS$ is the change of entropy, $\delta Q$ is the transferred energy, and $T$ is the temperature.

Thermodynamic entropy and Shannon entropy are conceptually equivalent: the number of arrangements that are counted by thermodynamic entropy reflects the amount of Shannon information one would need to implement any particular arrangement of matter and energy. The only salient difference between the thermodynamic entropy of physics and Shannon's entropy of information is in the units of measure: the former is expressed in units of energy divided by temperature, the latter in essentially dimensionless bits of information.

## Artificial Intelligence Evolution

Artificial intelligence (AI) is a discipline that aims to imitate the cognitive abilities of humans. Since the invention of computers, AI researchers have been developing its sciences, theories and techniques, which can let computers perform increasingly complex tasks that could previously only be delegated to humans [9]. After more than 70 years of extensive research and development, this automation remains far from human intelligence in the strict sense. AI has gone through several stages, which are described in this subsection.

**1940–1970–Birth of AI:** Technological developments during the period between 1940 and 1960 tried to bring together the functions of animals and machines. Norbert Wienner pioneered cybernetics, aiming to unify the theory of control and communication in both animals and machines. Warrent McCulloch and Walter Pitts developed the mathematical and computer model of the biological neuron in 1943. At the beginning of 1950, John Von Neumann and Alan Turing developed the architecture of our contemporary computers. In 1950, Turing speculated about the possibility of creating thinking machines, which could carry on a conversation that is indistinguishable from a conversion with a human being. The Turing Test was the first serious proposal in the philosophy of AI.

After the 1956 conference at Dartmouth College, which is considered to be the founding of the AI discipline, the period between 1956 and 1974 was the golden years for AI: computers were able to solve algebra word problems and learn to speak human languages. Researchers were optimistic that a fully intelligent machine would be built in less than 20 years. "Reasoning as search" was a popular paradigm, where searching through a maze is used to achieve some AI goal. The main difficulty of this paradigm was that for many problems, the number of possible paths was too astronomical for AI to find a solution.

The period between 1974 and 1980 was the first AI winter. AI researchers' tremendous optimism had raised expectations very high, and when the promised results failed to materialize, funding and interest for AI disappeared. In particular, the field of connectionism (or neural nets) was shut down almost completely for 10 years by Marvin Minsky's devastating criticism of perceptrons. Another approach, logic and symbolic reasoning, which is based on high-level human-readable symbolic representations (e.g., If-Then statements) of problems, was the dominant paradigm of AI research from the mid-1950s until the late 1980s.

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**1980–1990: Expert Systems:** With the advent of the first microprocessors at the end of the 1970s, AI took off again and entered the golden age of expert systems. These systems were programmed to simulate the judgment and behavior of a human or an organization that has expert knowledge in a particular field. The "inference engine" in these systems provides answers of a high level of expertise when being asked. Expert systems were widely used in industries. A famous example is IBM's Deep Blue, which took down chess champion Kasparov in 1997. The Japanese government heavily funded expert systems and other AI related endeavors in their fifth generation computer project (FGCP).

Expert systems work best with static problems but are not a natural fit for real-time dynamic issues. Development and maintenance thus became extremely problematic. An expert system can focus on a narrow definition of intelligence as abstract reasoning, very far from the capacity to model the complexity of the world. In the late 1990s, the term AI had almost become taboo and more modest variations, such as "advanced computing," were used.

**Since 2010–A New Bloom Based on Massive Data, Algorithms and Computing Power:** As a complete paradigm shift from expert systems, machine learning has become very popular since 2010. Machine learning does not need coding rules as for expert systems, but rather, letting the computer discover them on the basis of massive data. Among machine learning techniques, deep learning has become the most promising one for a number of applications, including voice and image recognition. The "deep" in deep learning refers to the depth of layers in a neural network. A neural network that consists of more than three layers, which would be inclusive of the input and the output, can be considered a deep learning algorithm. Neural networks make up the backbone of deep learning algorithms.

Significant public successes have boosted a new wave of interest in AI. In 2011, IBM's Watson won the games against two Jeopardy champions. In 2016, AlphaGO (Google's AI specialized in Go games) beat the European champion (Fan Hui) and the world champion (Lee Sedol), then herself (AlphaGo Zero). In 2020, AlphaFold solved one of biology's grand challenges, predicting how proteins curl up from a linear chain of amino acids into 3D shapes that allow them to carry out life's tasks.

Many significant research challenges remain to be addressed for the deep learning approach.

We envision that the next networking paradigm could be intelligence networking, which will enable intelligence to be easily obtained, like matter, energy, and information. Please note that intelligence is not equivalent to information. Rather, intelligence is a higher level abstraction of information.

For example, training data has significant impacts on this approach. In principle, given infinite data, deep learning systems are powerful enough to represent any finite deterministic "mapping" between any given set of inputs and a set of corresponding outputs. However, in practice, high-quality training data may not be available to the system designer due to privacy and resource constraints [10]. In addition, deep learning has the issues of integrating with prior knowledge, interpretability, and explainability.

### Motivations of Intelligence Networking

**Networking Needs Intelligence:** From the brief description of networking paradigm evolution, we can observe that each major networking paradigm enables us to move "something" from one location to another location, by which we can obtain "something" to facilitate our cooperation. Here, the "something" is matter, energy, and information in these three networking paradigms, respectively. In addition, we can observe the pattern of networking paradigm evolution: a new networking paradigm is built upon the existing ones, but provides a higher level abstraction. Energy measures how fast matter is moved, and information measures how much energy is spread.

**Intelligence Needs Networking:** Current AI algorithms involve a large volume of data, and the trustworthiness of the data is very important. AI algorithms need better sources in the exploration of data for training models to solve the problems more effectively. However, high-accurate and privacy-aware data/intelligence sharing is difficult via the current Internet of information. Therefore, most existing AI works focus on the learning of an individual agent, one that relies heavily on massive pre-defined datasets with the local environment. However, in practice, many interesting systems are either too complex to model properly with fixed, pre-defined environments, or dynamically varied [11]. Furthermore, while this approach can be validated from some studies of animal learning [12], it is far away from human learning, which requires a lot fewer datasets and is much more flexible when adapting to new environments.

What is the defining feature of human learning? According to the Big History Project [6], *collective learning* counts as a defining feature of humans. With collective learning, humans can preserve intelligence, share it with one another, and pass it on to the next generation. In other words, collective learning is the ability to share intelligence so efficiently that the ideas of individuals can be stored within the collective memory of communities and can accumulate through generations. Indeed, humans are the only species capable of sharing intelligence with such efficiency that cultural change begins to swamp genetic change [7]. Collective learning counts as a defining feature of our species, because it explains our astonishing technological precocity and the dominant role we play in the biosphere.

Therefore, we envision that the next networking paradigm could be intelligence networking, which will enable intelligence to be easily obtained, like matter, energy, and information. Please note that intelligence is not equivalent to information. Rather, intelligence is a higher level abstraction of information.

## Scenarios of Intelligence Networking

In this section, we present two scenarios of implementing intelligence networking. One is a practical scenario for connected and autonomous vehicles, and another one is a theoretical scenario for collective reinforcement learning.

### Intelligence Networking for Connected and Autonomous Vehicles

**Connected and Autonomous Vehicles:** Connected and autonomous vehicles (CAVs) use advanced technologies to connect and automate vehicles that are capable of sensing their environments and operating without human input. The accuracy and efficiency of AI technologies are crucial for the progress of CAVs. A modern CAV usually has about 60 to 100 sensors (e.g., radars, cameras, and Lidars). The number of sensors is expected to double in the near future. Although a CAV can obtain a lot of information with these sensors, it is still difficult to design a trustworthy, cost-effective CAV to make it adapt to different environments.

**Existing Approaches:** To address these issues, there are generally two existing approaches, single-vehicle intelligence and centralized learning. In the single-vehicle intelligence approach, sensor data collections, model learning and training, and decision-making occur locally in a single vehicle. The single-vehicle intelligence approach is popular among researchers for experiments and tests due to its simplicity. However, this approach has the following defects: limited on-board sensors, limited driving environments, and limited computing capability.

In the centralized learning approach, model learning and training happen in the cloud. This approach is used by several manufacturers, including Tesla. CAVs use on-board sensors to collect data and upload it to the cloud. Machine learning is performed in the cloud, and the global model is centrally and uniformly updated. During autonomous driving, a CAV makes decisions based on the real-time data from its sensors and the global model downloaded from the cloud. CAVs' over-the-air (OTA) function is used for sensor data uploads and model downloads. Although this approach is very popular among manufacturers, there are some concerns: huge data transmissions challenge the current network. A CAV can generate 40 TB of data per day. Data storage for all the CAVs is another challenge. In addition, users are also concerned about the privacy and security issues related to CAV data.

**New Approach Based on Intelligence Networking:** Based on intelligence networking, a new approach can be used for CAVs. Figure 2 shows this new framework. Compared to the traditional approaches, the main distinct feature of this new approach is that vehicles, as intelligent identities, can learn from data, preserve intelligence, and share intelligence with other vehicles. In this sce-

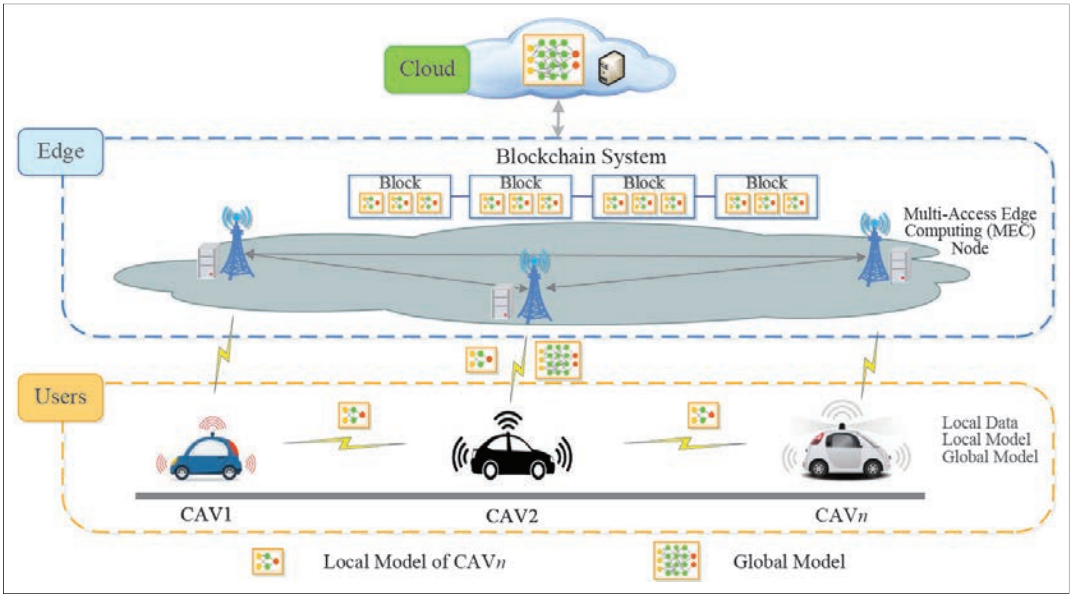


FIGURE 2. A connected and autonomous vehicles (CAVs) framework based on intelligence networking (Intelligence-Net)."

nario, intelligence refers to how to drive the vehicle in different environments. In order to achieve intelligence networking, blockchain is used in this framework.

The trustworthiness of the shared intelligence plays an important role in the Intelligence-Net. Blockchain technology can be used to address the issue of inefficient management for intelligence sharing, which is a key bottleneck of intelligence networking. Due to the trust and privacy issues, most users are concerned with sharing their data and intelligence with others. With the incentive mechanisms embedded in blockchain, distributed parties are encouraged to share intelligence. Specifically, every transaction on the blockchain is verified and stored in the distributed ledger based on the one-way cryptographic hash functions. These ever executed transactions are non-repudiable and irreversible after consensus among distributed parties. Figure 3 shows that the good features of blockchain can enable intelligence networking, including intelligence sharing, security and privacy, decentralized intelligence, collective learning, and trust issues for decision-making. Due to these good features of blockchain, it can enable provenance on intelligence networking, and significantly improve the trustworthiness of intelligence networking.

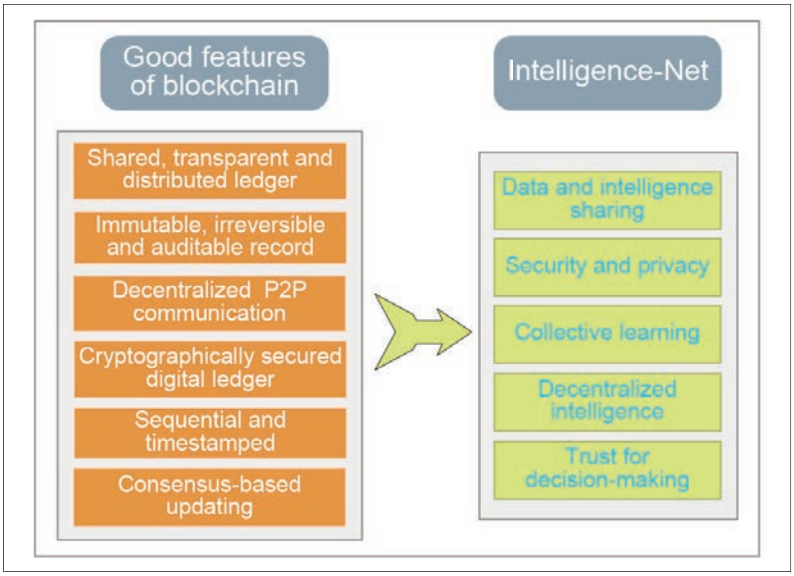


FIGURE 3. Good features of blockchain that can enable the Intelligence-Net.

## Intelligence Networking for Collective Reinforcement Learning

**Reinforcement Learning:** Machine learning can be roughly classified into three categories: supervised, unsupervised and reinforcement learning. Reinforcement learning (RL) is an important branch of machine learning, where an agent learns to take actions that would yield the most reward by interacting with the environment [12]. Deep reinforcement learning (DRL) uses deep learning and reinforcement learning principles to create efficient algorithms applied to areas like robotics, video games, networks, computer vision, education, transportation, finance and healthcare [12].

**Existing Approaches:** In traditional RL algorithms, an agent can optimize the performance measure in a previously unknown environment via its own experience. In Fig. 4, agent 1 interacts with its local environment 1 modeled by a Markov decision process (MDP). Similarly, other agents interact with their local environments. To this end, the agent needs to manage the trade-off between *exploitation*, where the agent maximizes rewards through behaviors known to be successful, and *exploration*, where the agent experiments with new behaviors unknown to be successful. The exploitation-exploration dilemma is between choosing what the agent has known and getting something close to what it expects and choosing something the agent has not known and possibly learning more [13]. In more common terms, assume that you need to choose a restaurant for dinner. If you choose your favorite restaurant, you use exploitation; if you choose a new restaurant, you use exploration.

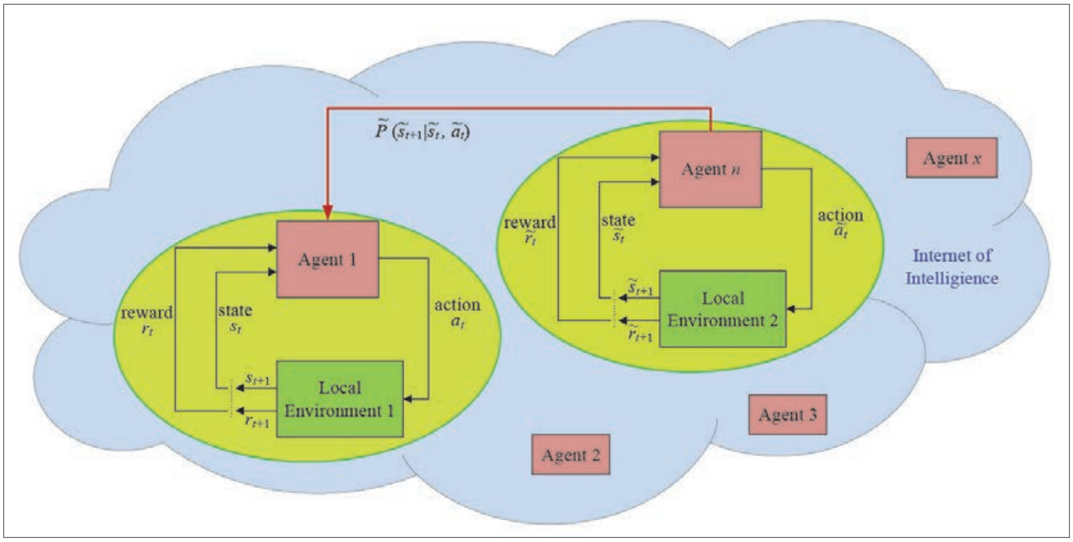


FIGURE 4. Collective reinforcement learning based on intelligence networking (Intelligence-Net).

**New Approach Based on Intelligence Networking:** Both exploration and exploitation are performed in the local environment, without help from other intelligent agents. Consequently, massive pre-defined datasets with the local environment (e.g., state, actions, rewards, and transition probability in the RL literature) are needed for training. In addition, even after extensive training with massive datasets, it is difficult for the trained agent to adapt to the new environment. In the restaurant example, if a traditional RL algorithm is used, one would need to try all the restaurants in the neighborhood to find the best restaurant.

Based on intelligence networking, we propose a novel approach of collective reinforcement learning (CRL). Unlike traditional RL, a CRL agent can not only learn from its own experience in local environments, but can also preserve the intelligence, and share it with others. In the proposed CRL, we introduce extension, which is used to enable an agent to proactively collaborate with other intelligent agents. Again, using the restaurant example, we can explain the basic idea behind this extension. Instead of trying all the restaurants in the neighborhood to find the best restaurant, one can do so by consulting with other people's experiences/opinions. Figure 4 shows the framework of this concept. Let $\alpha$ and $\beta$ be the exploration and extension trade-off coefficients, respectively. Let $L(\pi)$ be the performance measure of policy $\pi$ and $P(s_t, a_t)$ be the probability of transitioning at time $t$, given state $s_t$ and action $a_t$. The new optimization problem is as follows.

$$\max_{\pi} \underbrace{L(\pi)}_{\text{Exploitation}} + \alpha \underbrace{\mathop{\mathbb{E}}_{s_t, a_t \sim \pi} \left\{ D_{\text{KL}}(P \| P_{\theta_t})[s_t, a_t] \right\}}_{\text{Exploration}} + \beta \underbrace{\mathop{\mathbb{E}}_{s_t, a_t \sim \pi} \left\{ D_{\text{KL}}(P \| \tilde{P})[s_t, a_t] \right\}}_{\text{Extension}}, \quad (1)$$

where the exploration incentive is the average KL-divergence of $P$ from $P_{\theta_t}$, which is the model that the agent is learning. The extension incentive is the average KL-divergence of $P$ from $\tilde{P}$, which is the model from another agent.

## Open Issues and Research Challenges

While research about intelligence networking is still emerging, many open issues and research challenges need to be addressed before intelligence networking is widely deployed. In this section, we discuss some of the open issues and research challenges.

### Modeling Intelligence

In each networking paradigm, modeling the "thing" networked in the paradigm is crucial. For example, modeling information and modeling energy play a fundamental role in the Internet and grid of energy, respectively. In particular, using "entropy" to quantify information in Shannon's information theory has been crucial to the success of the Internet. Similarly, how to quantify intelligence will be crucial to the success of intelligence networking. The Turing Test was the first serious proposal to test a machine's ability to exhibit intelligent behavior equivalent to, or indistinguishable from, that of a human. However, there is no quantified measure of intelligence in the Turing Test.

From the networking paradigm evolution, we can observe that a higher level networking paradigm provides a higher level abstraction. For example, energy can be quantified as how fast matter is moved, and information can be quantified as how much energy is spread. Similarly, intelligence can be defined as a sophisticated kind of "before and after" yardstick, measuring how much information is spread out over time as a result of a learning process, or how widely spread out the information is after learning happens in comparison with its previous state. Specifically, $dL = \partial S/\partial R$, where $dL$ is the change of intelligence, $S$ is the similarity between the current order and the expected order, and $R$ is the parameter in the general sense (e.g., time, data volume, and so on). This quantified measure of intelligence can be very useful in intelligence networking, which needs more research effort.

### Architecture and Protocol Designs

In the era of information networking, the Internet has the successful "thin waist" hourglass architecture, in which the universal network layer (i.e., IP) is the center. This centered layer implements the basic functionality for global information networking. With this architecture, both lower and upper layer technologies can evolve independently. This "thin waist" hourglass architecture has successfully enabled the explosive growth of information networking. Similarly, we envision a "thin-waist" hourglass architecture for intelligence networking, which needs further research.

Intelligence discovery is another challenge. As intelligent identities are distributed across diverse geo-locations in the intelligence networking paradigm, efficient intelligence discovery mechanisms are essential to identify and locate intelligence. The publish-subscribe mechanism originated from information-centric networking (ICN) can provide benefits of intelligence discovery.

### Security and Privacy

Security and privacy are important issues in intelligence networking. Due to the security and privacy issues, users are concerned with sharing their intelligence with others. Although these issues exist in the existing networking paradigms, they are more important in intelligence networking, since an action is usually involved in intelligence. An improper action can cause more damage than improper information. In this article, we mentioned that blockchain can be used to address these issues. However, since blockchain was originally designed mainly for crypto-currencies, in order to use it for intelligence networking, a number of non-trivial issues need to be addressed in the current blockchain systems, including interoperability, scalability and other performance measures.

## Simulation Results and Discussions

In this section, the performance of the proposed intelligence networking paradigm is evaluated by computer simulations. We consider the connected and autonomous vehicles scenario, in which the intelligence is how to drive a vehicle automatically. The observable state of a vehicle includes its location, direction and speed, as well as the distances from obstacles, traffic signs/lights, and the center of the lane. In order to make the simulations more realistic, a Gaussian distribution is used to model the sensing errors. The action of a vehicle includes the angle of the steering wheel and the degrees of throttle and brake. There are multiple vehicles performing collective learning, and they can share intelligence using the vDLT blockchain platform [14].

For an individual vehicle, an actor-critic algorithm is employed to learn the decision-making solution locally. The actor is responsible for mapping states to actions using a parameterized policy network, and the critic is responsible for mapping state-action pairs to system reward with a parameterized critic network. In addition to the traditional action controlling the vehicle, an "extension" action is used by the vehicle to obtain the intelligence from other vehicles. For performance comparison, we consider an exiting scheme [15], in which deep reinforcement learning is used in the decision-making of individual vehicles, but intelligence networking is not used.

Figure 5 shows the convergence performance of different schemes. The blue curve represents the proposed scheme with intelligence networking of seven vehicles, the green curve represents the proposed scheme with intelligence networking of three vehicles, and the red curve represents the existing scheme. The shaded area represents the standard error of the mean. We can observe from Fig. 6 that the proposed scheme with intelligence networking converges much faster than the existing scheme. This is because the vehicles in our scheme can cooperate with other vehicles in collective reinforcement learning using intelligent networking. In more common terms, a vehicle in our scheme can consult other vehicles to acquire the intelligence of how to drive in a specific environment, which enables it to converge to the optimal performance faster than learning how to drive by its own trial-and-error experience. Moreover, we can also observe that consulting more vehicles can make the convergence faster in Fig. 6. Nevertheless, involving more intelligence agents in collective learning can result in more overhead of networking and computing, which will be reported in our future research due to the limitations of this article.

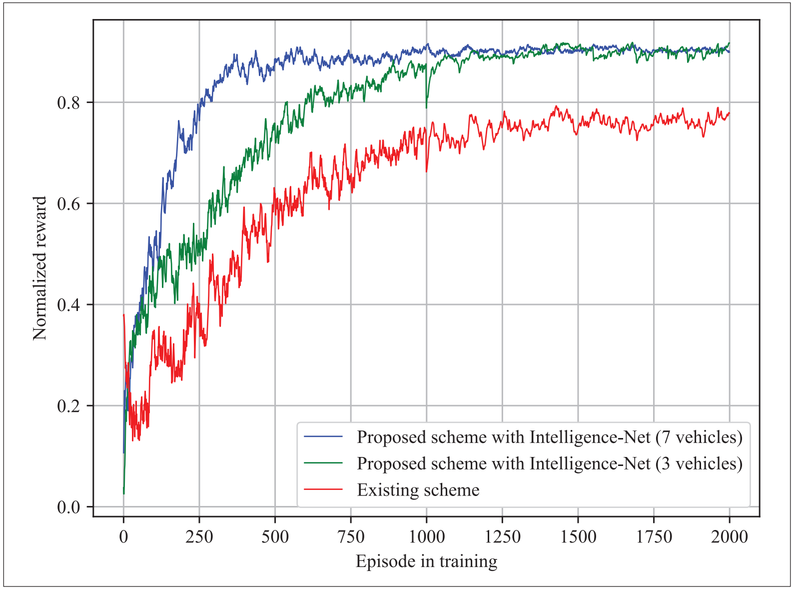


FIGURE 5. Convergence comparison of different schemes.

Figure 6 shows the success rate of vehicles in different schemes. The success of a vehicle is defined as successfully finishing the trip without any collision. We consider two weather conditions, good weather and severe weather conditions. In good weather conditions, the noise from sensors is small, whereas the noise is large in severe weather conditions. We can observe from Fig. 6 that our proposed scheme has the highest success rate in finishing the trip in both weather conditions. As shown in the figure, severe weather conditions have effects on the success rate, since higher noise from the sensors causes the vehicle to make wrong decisions. Nevertheless, the proposed scheme can still have a higher success rate when compared to the existing scheme. In addition, more vehicles in intelligence networking can improve the success rate performance, as shown in Fig. 6.

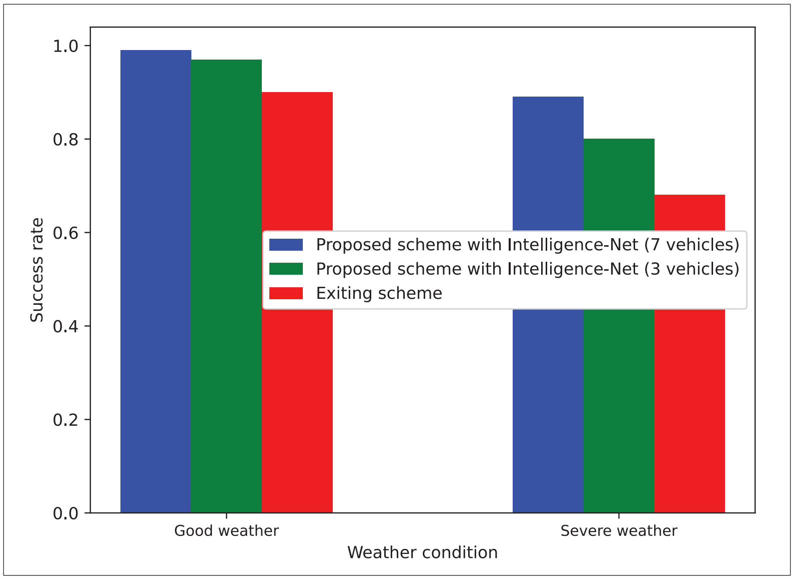


FIGURE 6. Success rate comparison of different schemes.

## Conclusion and Future Work

In this article, we reviewed the networking paradigm evolution and the artificial intelligence evolution. The networking paradigm evolution motivated us to look at humans' cooperation in a larger time scale. Three major networking technologies that facilitate humans' cooperation were discussed, including "grid of transportation," "grid of energy," and "the Internet." We observed that each of these networking paradigms enables us to move "something" to facilitate our cooperation. In addition, we observed that a new networking paradigm is built upon the existing ones, but provides a higher level of abstraction. In addition, the AI evolution motivated us to look at the networking aspects of intelligence. Based on these observations, we envisioned that the next networking paradigm could be intelligence networking (Intelligence-Net), where intelligence can be easily obtained like matter, energy, and information. Then, we presented two use case scenarios, connected and autonomous vehicles and collective reinforcement learning. Moreover, we discussed some open issues and research challenges of intelligence networking. Finally, some simulation results were presented to show the effectiveness of the proposed intelligence networking paradigm. Future work is in progress to address the open issues and research challenges of this exciting area.

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## References

[1] Cisco, "Cisco Annual Internet Report (2018–2023) White Paper," Cisco Systems White Paper, Jan. 2020.
[2] Y. Han *et al.*, "Delay-Aware Application Protocol for Internet of Things," *IEEE Network*, vol. 33, no. 1, 2019, pp. 120–27.
[3] X. S. Zhang, X. Zhang, and P. Kaparthi, "Combat Information Overload Problem in Social Networks with Intelligent Information-Sharing and Response Mechanisms," *IEEE Trans. Computational Social Systems*, vol. 7, no. 4, 2020, pp. 924–39.
[4] M. Carter, M. Tsikerdekis, and S. Zeadally, "Approaches for Fake Content Detection: Strengths and Weaknesses to Adversarial Attacks," *IEEE Internet Computing*, vol. to appear, 2021.
[5] F. R. Yu, "From the Internet of Information to the Internet of Intelligence," arXiv:1909.08068, Aug. 2019.
[6] "The Big History Project," available: https://www.bighistoryproject.com
[7] Y. N. Harari, Sapiens: A Brief History of Humankind, Harper, 2014.
[8] K. Maruyama, F. Nori, and V. Vedral, "Colloquium: The Physics of Maxwell's Demon and Information," *Rev. Mod. Phys.*, vol. 81, Jan. 2009, pp. 1–23.
[9] M. Haenlein and A. Kaplan, "A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence," *California Management Review*, vol. 61, no. 4, Aug. 2019, pp. 5–14.
[10] M. I. Jordan and T. M. Mitchell, "Machine Learning: Trends, Perspectives, and Prospects," *Science*, vol. 349, no. 6245, 2015, pp. 255–60.
[11] G. Dulac-Arnold, D. Mankowitz, and T. Hester, "Challenges of Real-World Reinforcement Learning," arXiv:1904.12901, Apr. 2019.
[12] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, Second Edition, MIT Press, 2018.
[13] Y. Wei *et al.*, "Joint Optimization of Caching, Computing, and Radio Resources for Fog-Enabled IoT Using Natural Actor–Critic Deep Reinforcement Learning," *IEEE Internet of Things J.*, vol. 6, no. 2, 2019, pp. 2061–73.
[14] F. R. Yu *et al.*, "Virtualization for Distributed Ledger Technology (vDLT)," *IEEE Access*, vol. 6, 2018, pp. 25 019–28.
[15] Y. Fu *et al.*, "A Decision-Making Strategy for Vehicle Autonomous Braking in Emergency via Deep Reinforcement Learning," *IEEE Trans. Veh. Tech.*, vol. 69, no. 6, 2020, pp. 5876–88.

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