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Research Article

Cosistency Axioms of Choice for Ismail's Entropy Formalism(IEF) Combined with Information-Theoretic(IT) Applications to advance 6G Networks

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ABSTRACT

An exposition is undertaken to analytically validate the credibility of IEF, by investigating the four axioms of consistency on IEF. More fundamentally, IE is by default the ultimate generalization to most entropy measures in the literature. The current paper also provides some applications of Information Theory to 6G Networks. Additionally, the latter review consolidates more foundational motivations and insights into further employment of information-theoretic advancements to 6G networks. Conclusions, open problems, and future directions are given.

1. INTRODUCTION

In principles, this current work supplies a complementary part of the research conducted (c.f., [1]). As the authors now feel that the task is completed and demonstrated with both analytic expressions as well as illustrative data to interpret the newly devised research results.

The non-extensive maximum entropy (NME) formalism was established in the aftermath of Rényi [2] and Tsallis [3]as a closed form expression tool for inductive reasoning mixed with "long-range" interactions-physical systems with non-extensive order. Having said that, their technique has generalized the well-known "short-range" interactions of Shannon's conventional "extensive" ME (EME) formalism [4].

Introducing Ismail's entropy, namely, $H_{(q,UG)}$ as the most generalized form ever to uniquely generalize all the available known generalized entropies in the literature, stable $M / G / 1$ queueing system probabilistic descriptors corresponding to states $\{ \boldsymbol{p_{q,UG}(n), n = 0, 1, 2}, ...\}$ based on the previous two applications in EME format to stable $M / G / 1$ queues is devised.

Normalization, $\sum_n p(n) = 1$ and Pollaczeck-Khinchin (P-K) mean queue length (MQL), $< n > = \sum_n np(n)\}$by Shore [5]. and Server utilization (SU), 1-p(0)} by [6].

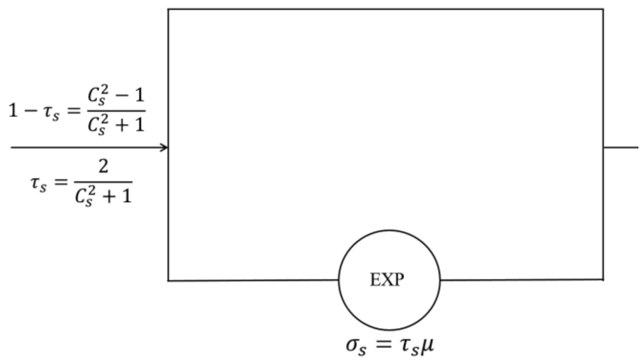

Figure 1. GE-type service time distribution with parameters $\{1/\mu, C_s^2 > 1\}$

Notably, the proposed closed form expression [6]was shown to be exact for a stable $M/G/1$ queueing system when the service (S) times followed GE distribution as described by Figure 1

$$F_s(t) = P(S \le t) = 1 - \tau_s \exp(-\mu t \, \tau_s) \quad (1)$$

$$\tau_s = \frac{2}{1 + C_s^2} \quad (2)$$

μ serves as service rate and $C_s{}^2$ serves as the service times' squared coefficient of variation (SCV). More intriguingly, the GE distribution has numerous real-life applications [3,6,7,8,9,12].

The Shannonian entropy functional $H_{1,S}(p)$ [4], is defined by:

$$H_{1,S}(p) = -c \sum_{S_n \in S} p_{1,S}(S_n) \log p_{1,S}(S_n),\ n = 0, 1, 2, \ldots \quad (3)$$

with a constant $c(c > 0)$ and $\{p_{1,S}(S_n),\ S_n \in S\}$ are the Extensive Maximum Entropy (EME) state probabilities, S_n serve as configurations or states. $H_{1,S}(p)$ is an information measure acted by $p_{1,S}(S_n)$ to a "short range" interactions-physical system [13].

If the above defined set S (c.f., equation (3)) is countably infinite or finite over the “long-range interaction”-physical system, then the proposed IE functional is defined by

$$H_{(q,UG)} = \sum_{n=0}^{\infty} \varphi((p(n)^q, a_1, a_{2,}, \ldots, a_k), k \le n \quad (4)$$

Here φ serves as any well − defined function,
$a_1, a_{2,}, \ldots, a_k$ serve as any universal paarmeters, $1 > q > 0.5$.
The EME state steady probability of a stable $M/G/1$ *queue* that maximises Shannon's entropy function [4] has been demonstrated [6].

$$H(p_{1,S}) = -\sum_{n=0}^{\infty} p_{1,S}(n) \ln(p_{1,S}) \quad (5)$$

Under the constraints:

Normalization,

$$\sum_{n=0}^{\infty} p_{1,S}(n) = 1 \quad (6)$$

1.

SU, $p_{1,S}(0) = \sum_{n=0}^{\infty} h(n) p_{1,S}(n) = 1 - \rho = \lambda/\mu \quad (7)$ *2.*

where

$$h(n) = \begin{cases} 1, & n = 0 \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

P-K MQL,

$$< n > = \sum_{n=0}^{\infty} n p_{1,S}(n) = \frac{\rho}{2}\left(1 + \frac{1+\rho C_{S,1,S}^2}{1-\rho}\right) \quad (9)$$

is given by

$$p_{1,S}(n) = \begin{cases} p_{1,S}(0), & n = 0 \\ p_{1,S}(0)\tau_s x^n & n > 0 \end{cases} \quad (10)$$

where $p_{1,S}(0) = 1 - \rho$, $\tau_s = 2/(1 + C_{S,1,S}^2)$ and $x = \frac{<n> - \rho}{<n>}$.

Theorem 1(c.f., [1]) The $H_{(q,UG)}$ NME solutions $p_{q,UG}(n)$, for the stable $M/G/1$ queue subject to (6), (7) and (9) are given by

$$p_{q,UG}(n) = \begin{cases} p_{q,UG}(0), & n = 0 \\ p_{q,UG}(0)\ \tau_s^b x^n, b = G(q, a_1, a_{2,}, \ldots, a_k), & n \ne 0 \end{cases} \quad (11)$$

Such that $p_{q,UG}(0)$ satisfies (8), namely

$$1 - p_{q,GU}(0) = \rho_{GU} \quad (12)$$

Here τ_s and x serve as Lagrangian multipliers satisfying that:

$$\tau_s = \frac{2}{1 + C_{S,1,S}^2}, \quad x = \frac{\rho}{\left(\rho + (1-\rho)\left(\frac{2}{1+C_{S,1,S}^2}\right)^b\right)}, \frac{\rho(1-x)}{(1-\rho)x} = \tau_s^b \quad (13)$$

Theorem 2(c.f., [1])

$H_{(q,UG)}$ ’s NME steady-state probability, $p_{q,UG}(n)$ is exact $f_{s,q,UG}(t)$ is determined by

$$f_{s,q,UG}(t) = (1 - \tau_{s,UG})u_0(t) + \mu \tau_{s,q,UG}^2 e^{-\mu t \tau_{s,UG}}$$

with $u_0(t)$ in the form

$$u_0(t) = \begin{cases} \infty, & t = 0 \\ 0, & \text{otherwise} \end{cases} \text{ with } \int_{-\infty}^{\infty} u_0(t) = 1 \quad (14)$$

and $\tau_{s,UG} = \tau_s^b$, $b = G(q, a_1, a_{2,}, \ldots, a_k)$, $\tau_s = \frac{2}{(1+C_{S,1,S}^2)}$.

Corollary 2.1

The CDF, $F_{s,q,UG}(t)$of the $GE_{q,UG}$ −types of service time with the pdf $f_{s,q,UG}(t)$ (c.f., (14)) is fully determined by cumulative distribution function $F_{s,q,UG}(t)$, of $S_{q,UG}(t)$and is determined by

$$F_{s,q,UG}(t) = 1 - \tau_s{}^b e^{-\mu \tau_s{}^b t}, \tau_s = 2/(1 + C_{S,1,S}^2) \quad (15)$$

Corollary 2.2 Following CDF (c.f., equation (14)), the service time’s SCV, S are given by:

$$E(s_{q,UG}) = \frac{1}{\mu} \quad (16)$$

$$E(s_{q,UG}^2) = \frac{2}{\mu^2 \tau_s{}^b} \quad (17)$$

$$C_{s,q,UG}^2 = \frac{E(s_{q,UG}^2)}{(E(S_{q,UG}))^2} - 1 = \frac{(2 - \tau_s{}^b)}{\tau_s{}^b} \quad (18)$$

where $\tau_s = 2/(1 + C_{S,1,S}^2)$.

[1] mainly contributes to:

- The Ismail's entropy (IE) measure is a generalization of all existing entropic measures in the literature.
- The provision of IE formalism of the stable $M/G/1$ queueeing system, which is the ultimate generalization to all up to date formalisms.
- Highlighting possible ME applications to energy works, which will be critical in taking energy works to the next level.

2. UNIFIED GLOBAL NME FORMALISMS VS EME CONSISTENCY AXIOMS

2.1. Uniqueness

The uniqueness axiom reads as axiom, “If the same problem is solved twice in exactly the same way, the same answer is expected in both cases i.e., the solution should be unique” [14].

Let $f_{q,UG}, h_{q,UG}$ be defined on S such that:

$$H^*_{q,a_1,a_2,\ldots,a_n,UG}(f_{q,a_1,a_{2,},\ldots,N}) = H^*_{q,a_1,a_{2,},\ldots,a_n,UG}(h_{q,a_1,a_{2,},\ldots,N}) \quad (19)$$

Hence, for $k \le n$,

$$\sum_{n=1}^{N} \varphi\left(\left(f_{q,a_1,a_{2,},\ldots,N}\right)^q, a_1, \ldots, a_k\right) = \sum_{n=1}^{N} \varphi\left(\left(h_{q,a_1,a_{2,},\ldots,N}\right)^q, a_{1,} \ldots, a_k\right) \quad (20)$$

This clearly implies

$$\varphi\left(\left(f_{q,a_1,\ldots,N}\right)^q, a_1, \ldots, a_k\right) = \varphi\left(\left(h_{q,a_1,a_{2,},\ldots,N}\right)^q, a_1, \ldots, a_k\right) \quad (21)$$

Assuming the contradictory statement, $f_{q,a_1,a_{2,},\ldots,N} \ne h_{q,a_1,a_{2,},\ldots,N}$, hence there is a constant $\gamma > 1$ satisfying:

$$f_{q,a_1,a_{2,},\ldots,N}^q = \gamma\, h_{q,a_1,a_{2,},\ldots,N}^q \quad (22)$$

Hence,

$$\sum_{n=1}^{N} \varphi\left((\gamma\,(h_{q,a_1,a_{2,},\ldots,N})^q, a_1, a_{2,}, \ldots, a_k\right) = \sum_{n=1}^{N} \varphi\left(\left((h_{q,a_1,a_{2,},\ldots,N}\right)^q, a_1, a_{2,}, \ldots, a_k\right),$$

$$k \le n \quad (23)$$

By (23) and component-wise equality, clearly it follows that

$$h_{q,a_1,a_{2,},\ldots,N}^q = \gamma\, h_{q,a_1,a_{2,},\ldots,N}^q \text{ (Contradiction)} \quad (24)$$

(24) holds if and only if $\gamma = 1$, which is a contradiction. Since φ is uniquely represented by the definition of the UG formalism. Therefore, “there cannot be two distinct probability

distributions $f_{q,a_1,a_2,\dots,N}$, $h_{q,a_1,a_2,\dots,N} \in \Omega$ with equal Ω'sNME.Thus, uniqueness holds[14].

2.2. Invariance

Invariance reads as “The same solution should be obtained if the same inference problem is solved twice in two different coordinate systems” [15]. Following analogous logic to [14], let W be transformed into a new variable V by a continuous one-to-one transformation. If the density functions of the variates are $f(w)$ and $g(v)$, then

$$g(v) = f(w)|\frac{dw}{dv}| = |\frac{dv}{dw}| \int_{-\infty}^{\infty} \varphi((f(w))^q, a_1, a_2, \dots, a_k)|\frac{dw}{dv}|^q \, dw \quad (27)$$

The entropy functional therefore changes. If however we consider a linear transformation

$$V = AW + B \quad (28)$$

We get after some manipulation,

$$H_{q,a_1,a_2,\dots,a_n,UG}(g(v)) = |A| \int_{-\infty}^{\infty} \varphi((f(w))^q, a_1, a_2, \dots, a_k) \frac{1}{|A|^q} \, dw \quad (29)$$

So, it is obvious from (28) and (29) that if the unique φ representation satisfies:

$$\varphi(\eta^q (f(w))^q, a_1, a_2, \dots, a_k) = \varphi((f(w))^q, a_1, a_2, \dots, a_k) \quad (30)$$

i.e., φ is invariant under scaling transformation it holds that in this case. For the case of multivariate distributions,

$$H_{q,a_1,a_2,\dots,a_k,UG}(g) = |A| \int_{-\infty}^{\infty} \varphi((f(x))^q, a_1, a_2, \dots, a_k) \, dx \quad (31)$$

Which show that $H_{q,a_1,a_2,\dots,a_k,UG}$ is invariant if and only if φ

is UG invariant under scale transformation.

By (26) and (27), the change is q-dependent and generally speaking, $H_{q,a_1,a_2,\dots,a_k,UG}$ is not invariant under transfo-rmation.

For the case of multivariate distributions,

$$H_{q,a_1,a_2,\dots,a_k,UG}(g) = |A| \int_{-\infty}^{\infty} \dots \dots \int_{-\infty}^{\infty} \left((\varphi(w_1, w_2, \dots, w_N))^q (|\frac{\partial(w_1, w_2, \dots, w_N)}{\partial(v_1, v_2, \dots, v_N)}|)^q \, dw_1 \, dw_2 \dots dw_N\right) \quad (32)$$

where $f(w_1, w_2, \dots, w_N)$ and $g(v_1, v_2, \dots, v_N)$ are the density functions. Hence, Invariance is defied.

2.3. System Independence

System independence reads as “It should not matter whether one accounts for independent information about independent systems separately in terms of different probabilities or together in terms of the joint probability” [15].In this context the joint probability is expressed by,

$$H_{q,a_1,a_2,\dots,a_k,N}(x_m, y_m) = \Pr(X = x_m, Y = y_m) = f_{q,a_1,a_2,\dots,a_k,N}(x_m)\, g_{q,a_1,a_2,\dots,a_k,N}(y_m) \quad (33)$$

For the joint probability $H_{q,a_1,a_2,\dots,a_k,N}(x_m, y_m)$, $H_{(q,UG)}$ of (4), reads:

$$H^*_{q,a_1,a_2,\dots,a_k,UG}(H_{q,a_1,a_2,\dots,a_k,N}) = \sum_l \sum_n \varphi(h^q_{q,a_1,a_2,\dots,a_k,N}) \quad (34)$$

Clearly, it follows from (4) that:

$$H^*_{q,a_1,a_2,\dots,a_k,N}(h_{q,N}) \neq H^*_{q,a_1,a_2,\dots,a_k,N}(f_{q,N}) + H^*_{q,a_1,a_2,\dots,a_k,N}\left(g(Y_{q,N})\right) \quad (35)$$

In information theory words, the un-equality (35) implies that "the joint EME state probability distribution of two independent non-extensive systems Q and V defies the axiom of system independence due to the presence of long-range interactions" [14].

As $q \to 1$, $\varphi(p(n)) = -p(n)ln(p(n))$,

our defined UG Entropian functional reduces to the Shannon Boltzmannian entropy and the un-equality (35) becomes equality, namely

$$H^*_1(h_{1,N}) \neq H^*_1(f_{1,N}) + H^*_1\left(g(Y_{1,N})\right) \quad (36)$$

By (36), system independence is satisfied [14], which is“an appropriate property of EME formalism, as a method of inductive inference, for the study of extensive systems with short-range interactions” [16].

2.4. Subset Independence

Subset independence reads as “It does not matter whether one treats an independent subset of system states in terms of a separate conditional density or in terms of the full system density” [15].

Consider a general non-extensive system Q that has a finite number, L ($L > 0$)of disjoint sets of discrete states $\{S^*_i, i = 1,2, \dots, L\}$, whose union is S. Let $\{x_{ij},\ i,\ j = 1,2,\dots,\ L\}$ be a conditional state in S^*_i. Let $\xi_i$be the probability that a state of the system Q is in the set $\{S^*_i, i = 1,2, \dots, L\}$ such that $\sum_i \xi_i = 1.$Moreover, let probability $f_{q,a_1,a_2,\dots,a_k,N}(x_{ij}) \in \Omega_i$, where Ω_i, isthe closed convex set of all probability distributions on S^*_i, i. e., $\{f_{q,a_1,a_2,\dots,a_k,N}(x_{ij}) = Pr\{X_i = x_{ij}\}\}$, where X_i is the state conditional random variable of the system $S^*_i, i = 1,2, \dots, L$. Moreover, let w be an aggregate state of system Q and probability $f_{q,a_1,a_2,\dots,a_k,N}(x) \in \Omega$, where Ω is the closed convex set of all probability distributions on S i.e., $f_{q,a_1,a_2,\dots,a_k,N}(x) = \Pr\{X = x\}$ where W is the random variable describing the aggregate state of the system S. Clearly, ξ_i, i = 1, 2, ...,L can be expressed by

$$\sum_{S^*_i} f_{q,a_1,a_2,\dots,a_k,N}(x_{ij}) = \xi_i \quad (37)$$

The overall non-extensive entropy function of system Q,$H^*_{q,a_1,a_2,\dots,a_k,UG}(f_q)$ is defined on the total number of states in the union S of states $\{S^*_i, i = 1,2, \dots, L\}$. Hence, it can be shown that

$$H^*_{q,a_1,a_2,\dots,a_k}(f_q) = \sum_i \sum_{S_i} \xi_i \ \varphi(f^q_{q,a_1,a_2,\dots,a_k,N}(x_{ij})) \quad (38)$$

where $f_q(x) \in \Omega$. Equ. (38) rewrites to

$$H^*_{q,a_1,a_2,\dots,a_k}(f_q) = \sum_i \xi_i (\sum_{S_i} \varphi(f^q_{q,a_1,a_2,\dots,a_k,N}(x_{ij})) \quad (39)$$

However, the conditional extensive entropy, $H^*_{q,a_1,a_2,\dots,a_k}(f_{q,i})$, defined on the set $\{S_i, i = 1,2, \dots, L\}$ is expressed by the Poisson process as,

$$H^{*}_{q,i,a_1,a_2,...,a_k}(f_q) = \sum_{S_i^*} \varphi(f^{q}_{q,i,a_1,a_2,...,a_k,N}(x_{ij}) \quad (40)$$

This implies

$$H^{*}_{q,a_1,a_2,...,a_k}(f_q) = \sum_i \xi_i (H^{*}_{q,a_1,a_2,...,a_k}(f_{q,i})) \quad (41)$$

Therefore, "maximizing the generalized aggregate entropy function, $H^{*}_{q,a_1,a_2,...,a_k}(f_q)$, subject to an aggregate set of available constraints, it is equivalent to maximizing each generalized conditional entropy function, $H^{*}_{q,a_1,a_2,...,a_k}(f_{q,i})$ individually, subject to a conditional set of available constraints. Thus, the Unified Global ME formalism satisfies the axiom of subset independence [14].

3. THE INFLUENTIAL ROLE OF INFORMATION THEORY TO ADVANCE 6G NETWORKS

The traditional strategy of avoiding or ignoring interference in wireless networks is insufficient for the ambitious ultra dense cellular networks (CNs) have high quality-of-service (QoS) requirements. However, recent breakthroughs in information theory have shifted our perception of interference from a foe to a friend. [17] has shed light on how to reap the benefits of incorporating modern interference management (IM) techniques into future CNs. To that aim, a hybrid multiple-access (HMA) scheme that decomposes the network into sub topologies of alternative IM schemes for more efficient network resource utilization was developed [17], where preliminary findings indicate that an HMA method can improve nonorthogonal multiple-access (NOMA) performance, particularly in dense user deployments.

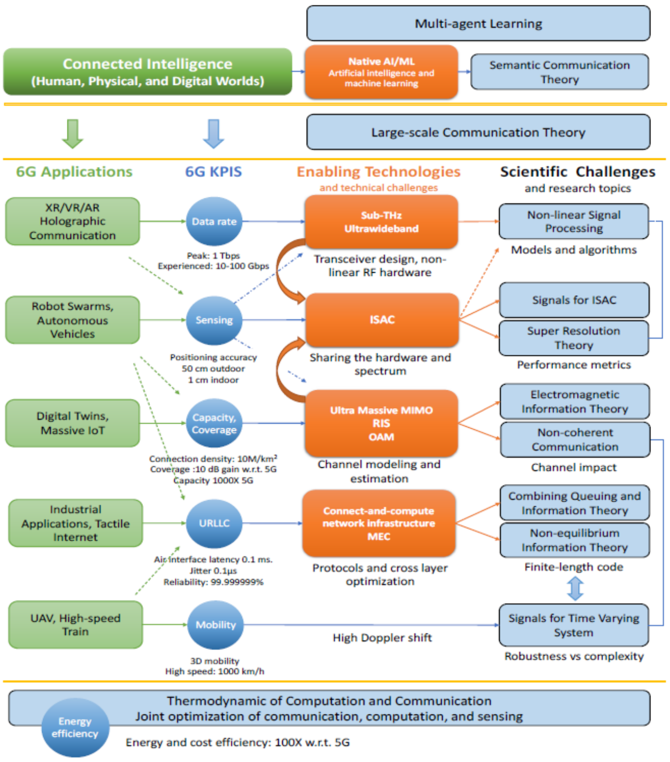

Figure 2. Collaboration amongst 6G Scientific Challenges [18].

The sixth generation [18] of wireless networks faces new challenges in meeting the requirements of emerging applications, such as high data rate, low latency, high reliability, and massive connectivity. To address these challenges, the entire communication chain needs to be optimized, including the channel and surrounding environment. Investigating large intelligent surfaces, ultra-massive multiple-input-multiple-output, and smart constructive environments, as well as considering semantic and goal-oriented communications, emergent communication, and end-to-end communication system optimization, are among the scientific challenges identified for rebuilding the theoretical foundation of communications.

Figure 2 (c.f., [18]) shows how the scientific challenges discussed in [18] are key performance indicators (KPIs)-related. The goal of 6G is to provide connectivity and computation to interconnect the digital, physical, and human worlds through a high-performance network that connects different types of sensors, actuators, and computation platforms. This concept is referred to as "connected intelligence". Thus, we can observe some triggering questions on how to steer future 6G networks.

Electromagnetic information theory (EIT) is a field that explores the interplay between information theory and electromagnetism. It focuses on developing information theory principles and antenna engineering while considering the limitations imposed by the laws of electromagnetism. This field has emerged because of the interaction between wave physics and information theory and has been studied for decades.

The development of 6G networks [18] has led to the emergence of new communication technologies such as RIS, TR, OAM, surface wave communications, and ultra-massive MIMO. However, current information-theoretic tools are insufficient to fully understand the performance limits of these technologies due to assumptions made in network design and performance analysis. EIT is expected to play a key role in characterizing the fundamental limits of these technologies and building better communication system models that are physically consistent with real propagation environments.

To meet [18] the high data rate requirements of some 6G applications, exploiting ultra-wideband at the sub-THz band is a potential technology. However, this poses technical challenges in transceiver design due to the non-linear behavior of Radio Frequency (RF) components and hardware design constraints. To address these challenges, non-linear signal processing methods are necessary, which require proper modeling of transceiver components, developing low-complexity algorithms, and evaluating information theoretical limits.

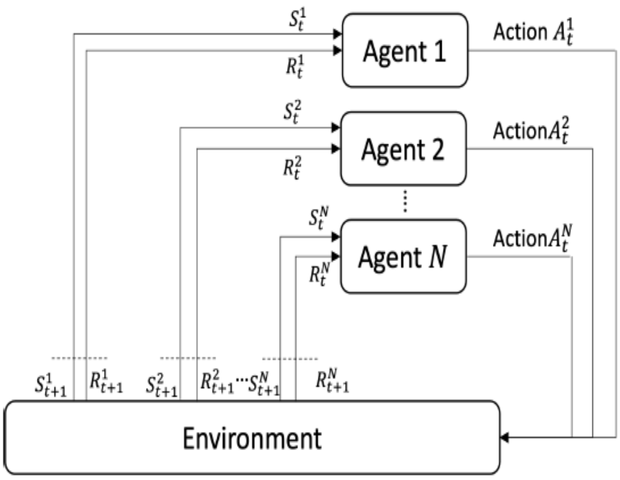

Figure 3. Multi-agent systems' architecture [21].

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The development of 6G networks [19,20] is expected to support applications that require high data rates, low latency, and high quality of service. However, the feedback theory poses a challenge to realizing the full potential of 6G due to degraded spectral efficiency and increased delay.

Multi-agent theory is a promising approach to improving network throughput and eliminating feedback overhead, but efficient mechanisms for coordinating agent formation and stability in highly dynamic networks are yet to be explored. Emergent communication in multi-agent systems can potentially reduce communication costs and processing overhead by allowing agents to learn messages instead of coding/decoding them. This is illustrated by Figure 3(c.f., [21]).

Super-resolution [22] techniques can be used in 6G networks to extract information from radio signals, such as delay, Doppler, and angles, to achieve high position precision in various applications like robotics, healthcare, and augmented reality. However, the complexity of the problem increases with the number of signal sources and non-ideal effects like hardware impairments and interference can affect the performance of conventional approaches, as illustrated by both figures 4 and 5. Therefore, further research is needed to develop new methods and investigate the theoretical limits to optimize the performance and complexity trade-off.

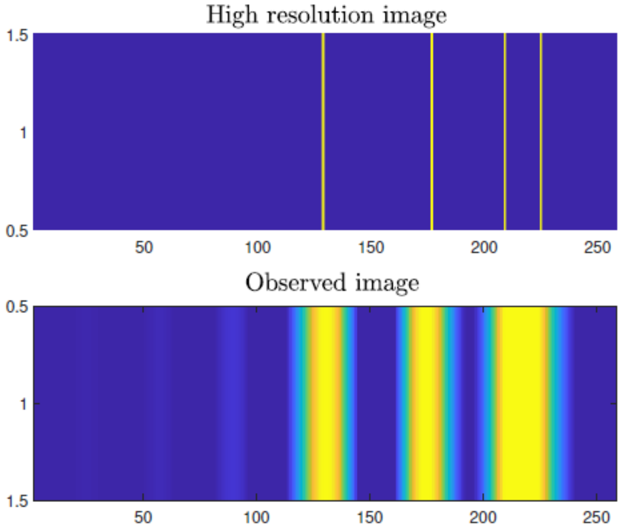

Figure 4. High-resolution picture and observed image comparison [18].

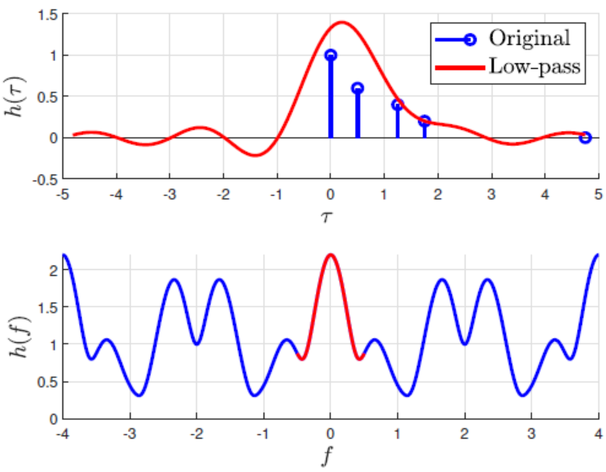

Figure 5. The observed baseband response and the multipath channel [18].

The upcoming 6G network [18] will enable new distributed applications that require extensive computation and high-speed communication with low latency. To ensure a sustainable system, new applications should consider joint optimization of communication and computation, with a focus on energy efficiency. While relying on the physical limits of communication and computation can provide insight into energy costs, practical constraints must also be considered when finding solutions to optimization problems.

6G networks [18] aim to support high mobility for various applications, which poses a challenge for estimating the communication channel due to its time-varying nature. Spreading waveforms, which distribute symbols over time and frequency, have been shown to be resilient to channel variations, but require complex iterative receivers to mitigate interference. Therefore, designing low-complexity receivers for spreading waveforms is a crucial research direction for communication signals in time-varying channels.

In [18], it is suggested that efforts should be made to integrate semantic communication in various use-cases of wireless networks, identify performance bottlenecks, and explore the potential of extending the semantic concept into communication protocol learning. Semantic communication protocols are expected to have task-specific control signaling messages, with acceptable communication, computing, energy consumption, and memory usage overhead, unlike classical medium access control (MAC) protocols.

Integrated sensing and communication [18]can be implemented using different radar architectures, such as monostatic and bistatic, but each presents its own challenges. One challenge with monostatic radar is signal leakage due to self-interference, which can be addressed by antenna separation or analog cancellation. A combination of these solutions can provide additional benefits, such as self-interference suppression by more than 70 dB, while various performance indicators can aid in designing integrated sensing and communication waveforms based on different channel models and application needs.

Large-scale communication networks [18]face challenges such as scalability, adaptivity, and automation, which can be addressed by incorporating AI. However, to better understand how AI operates and make informed decisions, it is important to develop solid mathematical foundations. Several tools, including RMT, decentralized stochastic optimization, and tensor algebra and low-rank tensor decomposition, offer potential approaches to achieve a flexible and reliable understanding of large-scale networks with AI.

The development of 6G networks [18] requires revisiting current coding schemes to ensure they can serve various use cases with different quality-of-service requirements. Joint designs for channel and source coding are being explored to replace conventional coding schemes, with the goal of achieving high data rates, shorter code lengths, and low-complexity decoding mechanisms.

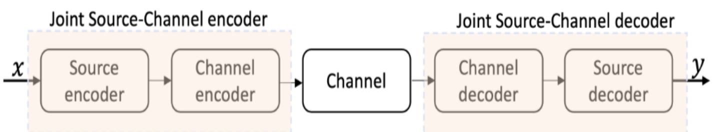

Figure 6. Source and channel coding are combined [18].

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However, this approach comes with increased overhead in terms of compression complexity, minimum coding distance optimization, and sophisticated hardware design for supporting Tbps communication, this can be illustrated by figure 6(c.f., [18]).

Queuing theory and information theory [18] are often studied independently, which can lead to suboptimal solutions in scheduling algorithm design. Queuing theory focuses on delay analysis from a queuing perspective, while information theory ignores the bursty nature of data traffic and considers delay-insensitive sources. To address this issue, a cross-layer framework that combines both queuing theory and information theory is needed to jointly adapt to source and PHY layer dynamics.

Non-coherent schemes [18], such as Grassmannian signaling and non-coherent tensor modulation, are being explored as promising approaches to modulate waveforms in wireless networks. These approaches can relieve the pressure imposed by channel state information (CSI) acquisition and show superior performance in large-scale networks. However, before their adoption in 6G networks, concerns such as constellation design and symbols mapping/demapping need to be addressed.

4. CONCLUSION

The current paper emerges a considerable number of open problems.

IE Threshold

This open problem considers the feasibility of obtaining the sophisticated thresholds for IE parameters, to decide the regions of increasability(decreasability) for IE expression as a starting step to the visualization of IE's performance.

Matching Theory

Matching theory is a mathematical approach to solving problems of matching players in two groups. Depending on the players' quota, matching problems can be classified as one-to-one, many-to-one, and many-to-many matching, and can be further categorized as matching with single- or two-sided preferences. The deferred acceptance algorithm is a powerful matching procedure in which players iteratively make proposals that are either accepted or rejected by players of other groups respecting their preferences and quota [23].

Game Theory

Game theory is a mathematical framework used to analyze interactions between rational players, and it is classified as cooperative or noncooperative based on the nature of the interactions. In the context of network topology optimization, cooperative games are more suitable, and there are two main types: coalition formation games and network formation games. Coalition formation games seek optimal coalition size and members, while network formation games consider interdependencies among partitions. Auctioning games, on the other hand, involve bidders and an auctioneer who collects bids to decide who will buy which items at what cost, and they are well-suited for PST-based relaying schemes [24].

Auctioning games

Auctioning games are a type of game theory that involves bidders and an auctioneer who collects bids to determine who will buy which items at what cost. In the context of HMA schemes, auctioning can be used for PST-based relaying schemes where users with strong channels can bid for power or spectrum from users with weak channels. Combinatorial auctions are particularly useful for modeling complex clustering scenarios where users can join multiple clusters as both spectrum sellers and power buyers [17].

Machine Learning (ML)

ML techniques can adapt to the changing wireless environment and human behavior, enabling self-organizing, self-optimizing, and self-healing HMA schemes for beyond 5G. Deep neural networks (DNNs) are a type of ML that can deal with complex and nonlinear problems, such as channel estimation, coding, modulation, and equalization. DNNs can also be used to predict traffic load, mobility patterns, and content interest, making them a powerful tool for designing and evaluating fitness functions in HMA schemes [17].

This paper contributes to validating the credibility of IEF by investigating the four consistency axioms of choice on it. Some potential information-theoretic applications on 6G network were provided, combined with posing some intriguing research questions and open problems. Future road maps of research include the explorations of finding possible solutions to these research questions and the proposed challenging open problems.

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