A Cross-Layer Green Information-Centric Networking Design Toward the Energy Internet

Quang Ngoc Nguyen, Rehmat Ullah, Byung-Seo Kim, *Senior Member, IEEE*, Rosilah Hassan, *Senior Member, IEEE*, Takuro Sato, *Life Fellow, IEEE*, and Tarik Taleb

***Abstract*—To address the energy-efficiency issue in Information-Centric Networking (ICN), this article proposes a novel Green ICN design, which adapts the power consumption of network nodes to the optimized utilization level proportionally. By learning over the consumers' interactive data traffic pattern/behavior, we introduce a new concept of cross-layer power adaption conducted through dynamically adjusting link rate corresponding to content popularity to reduce the wasteful power consumption of Content Routers (CRs). We also develop a controlling policy for each content provider to map its status to the most suitable operating mode to diminish power consumption. Moreover, we propose a smart Selective Caching Scheme (SCS) so that the caching portion in a CR's cache memory is adjusted according to content popularity and available spaces of two customized content cache spaces, namely hot and cold caching queues, for storing popular and unpopular content objects. This scheme can further decrease the power from caching since it is diminished when the traffic load is reduced via the proposed CRs' adaptive mechanism. The evaluation results with practical insights in several distinct scenarios show that the proposal can provide considerably higher energy efficiency and network performance at the same time, typically achieving at least 20% power-saving with a higher hop reduction ratio, compared to existing Internet designs with relevant state-of-the-art caching strategies.**

***Index Terms*—Information-Centric Networking (ICN), Green Networking, Future Internet, network design, Dynamic Power Scaling (DPS).**

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Quang Ngoc Nguyen is with the Department of Communications and Computer Engineering, Waseda University, Shinjuku-ku, Tokyo 169-0051, Japan and also with the Posts and Telecommunications Institute of Technology, Hanoi 100000, Vietnam (e-mail: quang.nguyen@fuji.waseda.jp).

Rehmat Ullah is with the School of Electronics, Electrical Engineering and Computer Science, Queen's University, BT9 5BN Belfast, U.K. (e-mail: rehmat_ciit@hotmail.com).

Byung-Seo Kim is with the Department of Software and Communications Engineering, Hongik University, Seoul 04066, South Korea (e-mail: jsnbs@hongik.ac.kr).

Rosilah Hassan is with Network and Communication Technology Lab, Centre for Cyber Security,Universiti Kebangsaan Malaysia, Bangi, Selangor 43600 UKM, Malaysia (e-mail: rosilah@ukm.edu.my).

Takuro Sato is with the Department of Communications and Computer Engineering, Waseda University, Shinjuku-ku, Tokyo 169-0051, Japan (e-mail: t-sato@waseda.jp).

Tarik Taleb is with the Center for Wireless Communications, University of Oulu, FI-90014 Oulu, Finland, and also with Sejong University, Seoul 143-747, South Korea (e-mail: tarik.taleb@oulu.fi).

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I. Introduction

NOWADAYS, Internet users are more interested in consuming the content rather than knowing exactly the location from where it is retrieved. Hence, communication is shifting from a host-centric to a content-centric model, where communication and network traffic volume has been grown exponentially due to huge content demands for real-time and delay-sensitive applications, e.g., multimedia streaming, and broadband services. In this context, *Information-Centric Networking* (ICN) concept has been introduced as a new promising Internet architecture to solve the existing host-centric Internet's problems of efficiency, scalability, and security [1]. ICN, with the key features of named-based content and in-network caching, has become a "hot" research theme with lots of proposals recently [2], [3].

Even though ICN matches the current huge generated content demands, its in-network caching capability [4] raises new challenges, especially *Energy Efficiency* (EE) issue, because caching itself introduces additional costs for both power consumption and caching storage. Worse still, EE is a critical concern for the real-world deployment and feasibility of future networks. Specifically, the Internet is estimated to consume about 10% of total energy in the world, and this ratio keeps increasing [5], especially today due to billions of interconnected Internet of Things (IoT) and smart devices. These key challenges and facts emphasize the need for an EE design for the near future ICN-based Internet, provided that the number of users, electricity prices, and demand for large-size content items are rapidly increasing in the Big Data era [6].

To fill the gap, in this article, we design an adaptive and concrete ICN model by jointly considering *caching strategy in ICN* and *Green Networking* to enhance the efficiency and feasibility of access networks for scalable *Future Internet* (FI). To realize a *common EE ICN-based platform* for near future implementation with practical significance, we propose a cross-layer network design approach by introducing a new concept of adaptive power consumption of network nodes through dynamically adjusting rate according to traffic load and content popularity. Typically, we use the power-aware network devices with the

Adaptive Link Rate (ALR) so that the proposed technique can adjust the operating rate of an associated link corresponding to its optimized utilization, then map the reduced resource utilization to save unnecessary operating power. Besides, the concept is enhanced by the implementation of a new smart caching scheme named *Selective Caching Scheme (SCS).* SCS works well in combination with the link adaptation mechanism for efficient real-time content delivery with high caching performance and energy savings at the same time to enable the information-centric Energy Internet.

In prior works [6]–[8], we also worked with the integration of Green Networking into ICN to efficiently reduce total network system power consumption. Particularly, the fundamental and some preliminary results have been presented in [6], [8], in which we introduced the concept of conducting power adaption in ICN nodes using ALR, then an efficient caching scheme can benefit from this methodology to further reduce power consumption via the reduced traffic. However, the evaluations were limited to a small scale, and we only considered a tree topology. The tree topology is useful for modeling and studying the performance of a network system, but it does not reflect the real network, and the model may not perform efficiently in the case of a complex network. To this end, this paper is an evolution of our prior work which fits for more complex network topologies in larger scalability (i.e., in both network of large scales and highly scalable networks) using a considerable number of network nodes for different wireless access network scenarios. The proposal also introduces the concept of optimal and adjustable local link rate of a specified *Content Node* (CN), which reflects the dynamic change of content popularity level at each node according to the real-time data analytics and user request patterns for EE optimization. In addition to that, we identify and analyze the current memory technologies for cache deployment, and the delay time for efficient dynamic control by switching/adapting CN link rate or *Content Provider* (CP) optimal operating mode with in-depth analytical energy models for a practical ICN deployment in large-scale on different topologies for FI toward smart data-driven Energy Internet.

Moreover, we propose SCS as a novel selective caching mechanism with the introduction of cold and hot caching spaces for different types of content, and the content chunks are cached progressively as the content gains a higher popularity level to improve the content diversity in ICN. Particularly, together with the ALR-based mechanism, SCS can further diminish the network power consumption for EE design via the optimized link rate of CNs gained from saved traffic load. Besides, CP takes advantage of efficient cache utilization from the proposed SCS to reduce the server operating power for overall power-saving gained from a lower server hit rate.

The contribution of this research is three-fold, as follows:

1) To enable the EE content distribution over ICN, we propose cross-layered solutions to minimize the power consumption of an ICN-based infrastructure with the necessary components, instead of considering only a few network components. In particular, by extracting knowledge from content demand, we develop an analytical model for data traffic provisioning. The proposed system assesses the popularity of particular content items and then dynamically adapts all network link rates and nodes' operating mode accordingly to save energy, while still ensuring full connections for effective content dissemination.
2) SCS employs the *hot and cold queues* with different caching policies of both partial and whole object caching according to content popularity to achieve lower latency and better user experience. Hence, SCS takes advantage of in-network caching in ICN so that the traffic reduction can be converted into energy savings via the application of the proposed ALR-based mechanism.
3) Both *analytical model and simulation results* in various practical network scenarios and topologies verify the efficiency of the cross-layer design, called *Green ICN*, where the addressed issues and the combined methods by the proposed solutions are robust, relevant, and practical from both application and research perspectives. Thus, we revisit the EE issue in ICN in an actual and feasible manner with combined techniques to enable a scalable and efficient content delivery mechanism intermsof both network caching and power-saving performance for future networks.

II. Research Background and Related Work

A. Green Networking and Dynamic Power Scaling

In Green networking, *Dynamic Power Scaling* (DPS) is a popular power management technique. It adjusts the network node operation or link rate to match the traffic load to enable power saving. One of the most notable approaches to DPS is the ALR technique [9], which is mainly applied in IP-based systems. For ALR-enabled devices, the speed of individual links can be scaled dynamically according to the traffic rate on the associated operating interface for the transmission process. Following the energy-proportional computing paradigm [10], and under the reasonable assumption that network devices consume less power when operating at a lower rate, ALR then makes power consumption more sensitive to the traffic load. Given that the network nodes rarely operate at maximum capacity, ALR can save a considerable amount of unnecessary power from the device's full-resource utilization to realize a power-awareness system with practical significance.

Low Power Idle (LPI) is another DPS strategy that allows the network devices (storage servers and nodes) to enter low-power states when transmitting less than a specified threshold number of packets. Note that LPI mode is different from sleep mode because sleep mode consumes less power but requires high power to "wake" the node up whereas LPI maintains a not-that-low level of power. For example, a simple model of a multicore server was derived with only four parameters for power consumption estimation in a large-scale infrastructure system [11]. Additionally, *Intel* demonstrated that the threshold value of power consumption in a server could be set [12]. However, server power management is a feature that is usually disabled. The reason is that this method may cause inconvenience and challenges for network administrators by making access networks more complex and difficult to manage, compared to the conventional way.

Moreover, the authors in [13] presented both power-aware routing and rate-adaptivity as an approach for reducing energy consumption using a simple power model with only two kinds of link-state (on and off). Also, Nedevschi *et al.*, [14] utilized sleeping and rate-adaptivity to save power consumption by considering the power profile of data traffic and network devices.

B. ICN in a Nutshell

The concept of ICN was firstly introduced by Jacobson *et al.* [1]. ICN offers each content a unique name, thus the transmission is based on named content, instead of content location, i.e., IP address of content providers in traditional host-centric (e.g., TCP/IP) network system. Even though ICN realizes an efficient content distribution model with naming and caching schemes, its default cache placement policy, called Leave Copy Everywhere (LCE), is highly redundant since it stores the whole content at all the nodes along the delivery path. To solve this issue, ProbCache [15] is proposed as a probabilistically decentralized caching scheme that caches content based on the distance to CP and the cache storage status of each CN along the path. WAVE [16] is another distinguished popularity-driven caching policy that populates the chunks of a content exponentially at the edge node and downstream nodes when content gets a higher number of requests. Ong *et al.* [17] proposed D-FGPC, which dynamically adjusts the content popularity threshold and keeps the most popular content in the cache space to improve the hit rate performance. Moreover, Progressive Popularity-Aware Caching Scheme (PPCS) is proposed in [18] to eliminate the cached duplicate issue of ICN by allowing no more than one replica of a specified content to be cached progressively.

Even though there are various existing ICN-based projects, our Green ICN model is mainly based on *Name Data Networking (NDN)* [19] since it is a widely used ICN platform among all ICN designs with active development and involvement in the community. There are two types of packets for data delivery in NDN: *Interest* and *Data*. A content user broadcasts Interest (content request) to other CNs, and the nearest node with the requested content (cached data) sends back the Data packet along the reversed path via respective network interfaces. The packets in NDN are forwarded according to the longest name-prefix match, and content is split into chunks for data transmission. An NDN node has three main data structures: CS (Content Store) as the node's cache storage, and FIB (Forwarding Information Base), and PIT (Pending Interest Table) for the packet forwarding.

As a clean-slate solution replacing TCP/IP is challenging to deploy in reality, we consider an overlay NDN-based network on top of TCP/IP protocols. The reason is that NDN overlay design is a well-suited extensible network framework for an incremental network infrastructure deployment in practice, e.g., our prior ICN/CDN Slice as a Service defined in [20], [21] which integrates the benefits of CDN (Content Delivery Network) and ICN (NDN design) for efficient content delivery service in practical scenarios. However, it is important to note that the proposal is not limited to NDN and can be applied to any ICN platform for future networks.

Moreover, ICN is a potential IoT enabler [22] where "things" would be resource-constrained devices, e.g., sensors and smart devices, and should be operated with diminished traffic load to match the explosive growth of the number of connected devices. Specifically, ICN realizes efficient information retrieval with content name lookup service for request handling. In ICN, the Interests toward the same content sources are aggregated at content routers for the forwarding and routing procedure to diminish network load and congestion rate. In this way, compared with IP-based Internet, ICN has better traffic management and network resource policies, which can be exploited for traffic optimization in IoT networks [23]. Provided that the 'things' are moving nodes, ICN also includes built-in consumer-mobility support to help reduce signaling overhead in access networks and cellular networks, where caching is demonstrated to facilitate the content delivery in 5G [24]. Authors in [25] realize ICN in Radio Access Network (RAN) for 5G edge computing for efficient content dissemination with low latency. Besides, different from the IP-based network, ICN provides content-based security, rather than communication channel security, that enhances content privacy via communications among the IoT networks [26].

Thus, ICN, a promising future networking architecture, can act as an ideal platform of IoT protocol at the application layer of the network design to facilitate the real-world implementation of ICN. For example, authors in [27] implement content providers as content producers' virtual sensors in the sensor cloud so that the content providers can provide the sensing services when the producers go to sleep via an information-centric prediction model of sensing data. Besides, the development of self-certifying hierarchical attribute-value names can achieve a standardized naming scheme for efficient wireless communications in IoT [28].

C. Green Networking in ICN

In recent years, plenty of interesting green networking approaches in ICN with preliminary results were conducted [29]. The authors in [30] developed a power consumption model of a multicore software NDN router and demonstrate that caching can reduce power consumption in NDN if a router's power is proportional to its traffic load. In [31], geographic forwarding is studied to leverage the name-based scheme for ICN-IoT deployment. Xu *et al.,* [32] design a green information-centric multimedia streaming (GrIMS) as a practical streaming model in vehicular ad hoc networks (VANETs) by analyzing the trade-off between EE and quality of experience.

Besides, ICN is applied in mobile ad-hoc environments for energy-efficient and reliable content delivery in a unicast manner [33]. The authors in [34] proposed an energy-efficient and QoS routing scheme with a link selection algorithm and prioritized policy in ICN. Yang *et al.* [35] present a formulation of the optimization problem of energy consumption for data caching and transportation in the ICN-based 5G system with several network topologies. Also, the study in [36] formulates an optimization problem of the ICN-based system employing base stations for different QoS requirements of IoT devices to maximize the bandwidth and sleeping probability, given the constraint of achievable data rate.

Also, there are several caching schemes aiming to specifically enhance the energy efficiency performance in ICN. In [37], the authors develop both offline and fully online approaches, called EE-OFD using global knowledge of user requests and network resources, and EE-OND allowing nodes to make local caching decisions for minimizing overall energy use. The study in [38] develops an aging popularity-based in-network caching scheme (APC) using each node's local information and shows that the energy consumption in ICN depends on the average number of response hops. Fang *et al.* formulate a non-cooperative game of energy-efficient distributed in-network caching problem and show that there exist pure strategy Nash equilibria for socially optimal configuration [39]. Choi *et al.* develop a genetic algorithm (GA) approach (termed as GA-ICN) to identify the cache locations for energy efficiency in ICN [40].

For green wireless sensor networks (WSN), the authors in [41] leverage regional caches for multi-hop cooperative caching in receiver-driven ICN. They then present a green cooperation policy with suitable cooperation decisions for each sensor based on the optimal trade-off between delay reduction and energy saving. To address the congestion control issue in ICN [42], He *et al.* improve the quality of experience (QoE) level in the content-centric IoT by considering the influence factors of both network cost and Mean Opinion Score (MOS) of users for each service [43]. The authors then present a Deep Reinforcement Learning (DRL)-based green resource allocation scheme to allocate cache capacity with a suitable transmission rate accordingly to enhance the QoE level dynamically. Also, it is shown that with a suitable replacement ratio and ratio cache for the dynamic caching scheme, the network performance in ICN can be improved [44]. In [45], a Central Control Caching (CCC) Scheme is proposed for ICN-based IoT by maintaining a table containing information of different contents on different autonomous systems (AS) for caching decision of inter-AS content exchanges. Shen *et al.* proposed an Edge Learning caching scheme for green content distribution in Information-centric IoT by using edge calculation and decision tree for intelligent delivery path selection as well as distributed coding for content transmission [46].

In our previous work, besides the concept of Green ICN for access network, we also proposed Green ICN system in a wireless environment, e.g., for efficient communications in Intelligent Transport System (ITS) by using fake interest packets and a smart scheduler [8], and the context-aware communications by classifying different content types based on priority in both wireless local area network (WLAN) and device to device (D2D) communications when WLAN is not available [6]. Additionally, we develop a game-theoretical model to study the interaction between a network equipment company and an ISP and analyze the economic incentives of key players in the context of EE in ICN [7].

As in-depth follow-up work, in this research, we take a comprehensive study of both caching scheme and EE in which energy-saving is coupled with content popularity and in-network caching in ICN to *bridge Green Networking* (particularly DPS scheme) *and ICN* for the goal of realizing a highly efficient and deployable *ICN-based Energy Internet design*.

To the best of our knowledge, this proposal is a promising work that integrates the benefit of Green networking and caching strategies into ICN with various influenced factors to eliminate possible unnecessary power consumed by unused network links and nodes substantially for the overall design goal of maximizing the ICN system power-saving toward smart Energy Internet design in various interconnected scenarios, e.g., smart green building or campus networks.

III. Proposed Cross-Layer Adaptive Green ICN Framework

A. System Model and Assumptions

The hierarchical cache system is the commonly used system model in ICN studies [47], [48]. In this work, we propose a generic multi-layer network topology, including a cluster of M servers as CPs and N distinct routers as CRs. We aim to make popular content objects/services/applications scalable. Even though the tree topology is more comfortable to manage, it simplifies the interactions between network nodes: if one intermediate node has some issue like congestion and broken links, then all of its child nodes are also affected, i.e., the network performance of tree-based topology can be affected by the network node's status.

The proposed multi-tier network has (L+1) levels where the cluster of servers (CPs) is located at the root node (level L+1). Typically, each CP stores a portion of available content items (content catalog), all CNs can cache the same number of content items, and the level of CN is set corresponding to the distance in the number of hops from the consumer (Fig. 1). The network model realizes various dynamic hierarchical network connectivity, where users seek content at the lowest levels (edge CRs), CPs store the content objects at the highest level, with several layers of CRs (intermediate nodes) in between. This interconnectivity enables practical and promising network systems when certain routes/paths can be taken offline and/or in the case of temporary down/broken links for maintenance. The hierarchical cache system also can decrease traffic consumed by the original CPs, response time, and transportation cost by serving content as close to the user as possible via an appropriate node with cached data. Moreover, this network topology is easy to be deployed, practical and convenient for the service providers and network operators since they can easily investigate and manage data traffic at different network tiers, thanks to the cache hierarchies. Hence, the interconnection is appropriate for the migration process from existing network infrastructure and can be widely applied in large-scale future network deployments.

We assume that the proposed ICN-based interconnection consists of distinguished content c, and all the content requests are independent and identically distributed (i.i.d) within the set of all available objects C (i.e., $c \in C$). The reason is that we consider content items in ICN in the same way as in web caching, in which the content distribution is usually regarded as i.i.d. [49]. Moreover, this assumption is also considered in notable studies in caching in ICN [50], [51]. Let S be the cache space of a CN.

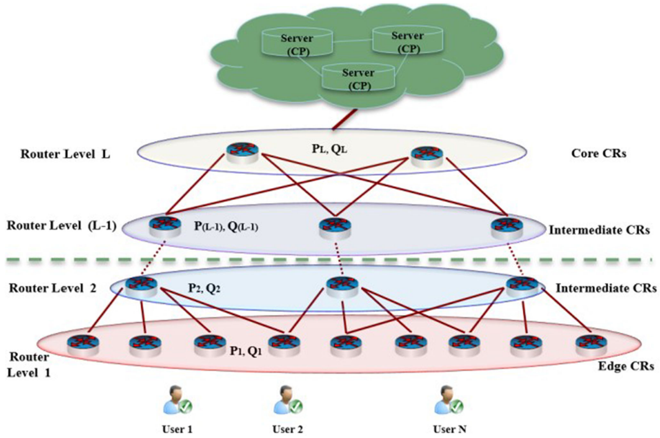


Fig. 1. The proposed interconnection of the Green ICN system.

Although we present a simplified multi-tier model, this model can beapplied to any general multi-tier/mixed topology in which a CN's level is identifiable so that the transmission route is selected as the path from the consumer's attached CR (level 1) to the core node connected to the cluster of CPs with the minimum distant in the number of hops. Various scenarios with different topologies are discussed and evaluated for multi-hop content delivery in Section VI, including generic multi-layer/hierarchical cache system, CDN tree-based model, mesh structures, and mixed networks (campus model). Table I summarizes the main notations used for the proposed Green ICN model[1].

Additionally, the intermediate nodes in the proposed hierarchical content management system design can be integrated with sensors for data generation (as content producers) to realize practical and potential IoT content access scenarios for multiple content services at different domains. Particularly, data can be produced, collected, extracted, and analyzed by sensors as 'things' for a smart data-centric IoT system with resource-constrained devices in the same way as defined in our prior study [52]. In this way, the proposal can facilitate the ubiquitous data distribution and content sharing with in-network storage and multi-path communications in ICN to realize the IoT vision in which information/content is associated with connected nodes and 'things'.

TABLE I
NOTATION USED FOR THE SYSTEM MODEL

Notations	Meaning
C	The set of all available content objects
L	Total number of network levels (tiers)
M	The number of servers (CPs)
N	The total number of CNs
N_k	The number of CN at level k of network
C_p	The set of all popular content objects
C_u	The set of all unpopular content objects
C_k	The total storage used for caching in CS of a level k-CN
p_k	The probability that one user can find a specified content c ϵ C at a level-k CN (Fig.1)
T_p	The threshold value of p_1 for all content c ϵ C to classify unpopular and popular content
p_{1t}	The minimum value of p_1 value among the most popular content classes
Q_k	The probability that a consumer has to traverse a total of k level of topology ($1 \le k \le L$) to find an interested content c (Fig. 1)
R_k	The incoming link rate to a CN at level-k
S	The cache size of each CN
S_k	The set of all distinguished content objects that users send Interest packets to a CN at level-k
R_{ICN}	The link rate capacity in the conventional ICN design
β	The ratio of CN which supports ALR function (β =1 means operating power of CN is ideally proportional to the link utilization)
$R_k^{optimal}$	The adjusted value of R_k in Green ICN model to minimize operating power of CN
L_k	Link rate ratio between Optimized R_k and R_{ICN} (Fig. 2)
L_{nk}	The local link rate ratio of a CR with index n at level k
P_O	Operating power consumed by a CR in conventional ICN
$P_{O,nk}^{optimal}$	The optimized value of operating power consumed by a CN n at level k in Green ICN model
τ	The period in which the optimized value of $Ln_k$is selected and updated
P_c	The caching ratio for storing a popular content c in the hot queue
P_f	The fixed caching ratio for partly storing a content c in the cold queue

B. *Cross-Layer Probabilistic Rate-Adaptive Mechanism for Content Routers (CRs)*

Given that all CRs of the proposed Green ICN system are equipped with the *ALR technique*, to dynamically associate the link rate with the degree of popularity of content which user asked for, we first define p_k as the probability that one consumer can find the desired content c (c ∈ C) on a CR with k-hops away from the user (a level-k CN). We assume that every CN located at the same level of the hierarchical network topology share the same value of p_k because the interests (content requests) from all users are i.i.d., i.e., the caches on the same level of the hierarchical topology tend to store the content objects with similar popularity level. Note that p_k defines the relative popularity level of a certain content, which is a cumulative value that records the total number of consumer requests to a certain level (Interest arrival rate) within a fixed period. This value can be identified from network statistical information (i.e., based on the content popularity distribution model and historical traffic patterns, provided that the request arrival rate is dynamic).

[1] For convenience, we use the terms router and node (CR and CN), CP, and server, interchangeably.

Besides, the proposed hierarchical network interconnection reflects the ICN's in-network caching feature, which spreads the popular content objects and pushes the most important ones close to the users (at the network edge). Based on this observation, we classify each content into one content popularity class based on its p_1 value. Specifically, p_1 can be considered as the *popularity indicator* of a specific content: p_1 value tends to be bigger for more popular content objects because they are likely to be located at first/initial levels. As the most popular content objects reside in lower-level nodes, they should be operated with a higher link rate so that the latency (in the number of hops) and the backbone bottleneck can be considerably diminished. Thus, we classify two kinds of content by introducing T_P as the threshold value of p_1 for a content c $\in$ C: A content c is popular if $p_1 \geq T_p$ (with the assumption that all content items share the same value of T_P). Otherwise, it is a non-popular content. We then group content objects into two sets: C_p is the set of all popular content objects, and C_u represents the set of unpopular content items (i.e., $C = C_p \cup C_u$).

Let Q_k be the probability that a content user has to "climb up" k-level (or k hops, where $k \geq 1$) of the network topology to find an interested content c $\in$ C. Then, the value of Q_k can be identified through the value of p_1, as follows:

$$\begin{cases} Q_1 \ = \ p_1 \\ \forall k \geq 2, \ Q_k \ = \ p_{k+1} \ x \ \prod_{i\,=\,1}^{k}(1 - \ p_i) \end{cases} \tag{1}$$

Next, we define dynamic CRs' operating scheme by matching the operating power of CR to its optimized utilization. For this goal, the system adjusts the corresponding link rate of CR based on the popularity of the content objects that the ICN node serves. Let R_k be incoming link rate to level-k CR (i.e., a CR which is k-hops away from the consumer) for a content c $\in$ C. Since the more popular content is expected to stay closer to the content user (i.e., at initial levels); the maximum link rate is set for the level 1 CRs (i.e., $R_1 > R_k$ with $k > 1$). In more detail, the link rate of CRs at level 1 is adapted to the lower link rate as of the conventional ICN design in case of serving unpopular content and only equals that value otherwise (i.e., the popular content is requested).

We then define S_k as the set of content comes to a level k CN. Let L_k denote the link rate ratio between R_k and R_{ICN} according to content popularity and traffic, where R_{ICN} is the link rate capacity in conventional ICN interconnections:

$$L_k = \frac{R_k}{R_{ICN}} \tag{2}$$

We can deduce that $0 < L_k \leq 1$ because the maximal value of R_k in the proposal is R_{ICN} as of the default ICN design.

For efficient dynamic rate adaptation in ICN, we then use the value of L_1 to tune the operating link rate of CNs at higher levels so that the popular content objects are pushed closer to the user(s) at the edge side via the in-network caching feature. In detail, L_1 takes the maximum value among all, and L_k (where $k > 1$) is adapted to the operating link utilization of ICN node corresponding to the L_1 value and popularity levels of all arriving content objects' Interest packets sent to it. Let C_k be the total storage used for caching at a level k-CN, the new optimized value of L_1 in the case that at least one popular content is sent to the first level CR is:

$$\begin{cases} L_1^{optimal} = \ 1, \ i.e., \ \max available \ R_1^c \ = \ R_{ICN} \\ \forall \ c \in S_1, \ S_1 \cap \ C_p \neq \ \emptyset \ \ \& \ C_1 \leq S \end{cases} \tag{3}$$

and

$$\begin{cases} L_1^{optimal} = \frac{\max \, p_1^c}{T_p} \\ \forall \ c \in S_1, \ S_1 \cap \ C_p \neq \ \emptyset \ \ \& \ C_1 \leq S \end{cases} \tag{4}$$

otherwise. This means that a content user only sends Interest packets for non-popular content objects to the CR at level 1. As distinct content objects may have different popularity levels, (4) is built to assure that the adaption mechanism offers sufficient link utilization for the Interests of the content with the highest required link rate sent to a CR.

Next, without loss of generality, the optimized link rate ratio of a level k-CR can be identified by (5) and (6) in the case of (at least one) popular content, and (all) non-popular content objects, respectively, and can be defined as follows:

$$\begin{cases} L_k^{optimal} = (1 - \beta) \ \ + \ \beta \ x \ \left(1 - min \ \sum_{i\,=\,1}^{k-1} Q_i^c\right) \\ \forall \ c \in S_k, \ S_k \cap \ C_p \neq \ \emptyset \ \ \& \ C_k \leq S \end{cases} \tag{5}$$

$$\begin{cases} L_k^{optimal} = (1 - \beta) \ \ + \ \beta \ \ x \ \frac{\max \, p_1^c}{T_P} \ x \ \left(1 - \min \sum_{i\,=\,1}^{k-1} Q_i^c\right) \\ \forall \ c \in S_k, \ S_k \cap \ C_p \neq \ \emptyset \ \ \& \ C_k \leq S \end{cases}; \tag{6}$$

where β represents the energy-efficiency indicator of equipment, which reflects the ratio of ICN CN that can support ALR function, i.e., $\beta = 1$ means the device fully supports ALR function. The constraint $C_k \leq S$ means that the total size of content chunks cached in a CR should not exceed its cache space (boundary condition). The first terms in (5) and (6) then return the ratio of CNs, which does not support the ALR function. Specifically, the expression $(1 - \sum_{i\,=\,1}^{k-1} Q_i^c)$ in (5) and (6) indicates the scale-down link rate ratio of a CN at level k with the proposed ALR function for delivering an individual content c. We then select the extreme values (max/min) from (5) and (6) because a CR needs to set its adaptive link rate to the highest value among those required by users for different content items' Interest packets. This policy ensures that the CR operates with an adequate link rate for all the content requests with different content popularity levels flowed to it. The optimized value of L_k calculation is depicted in Fig. 2.

Since content popularity would be changed when time goes by, the content popularity and L_k value should be adjusted proportionally to match the content request rate over time. We enumerate a CN at one specific level with an index number n, i.e., the n^{th} CN at that level. From L_k value, to reflect the chance that a user can find the content at a specific CR more precisely, we define the expected local link rate ratio of a specific CR n at level k, L_{nk} (where $1 \leq n \leq N_k$), as:

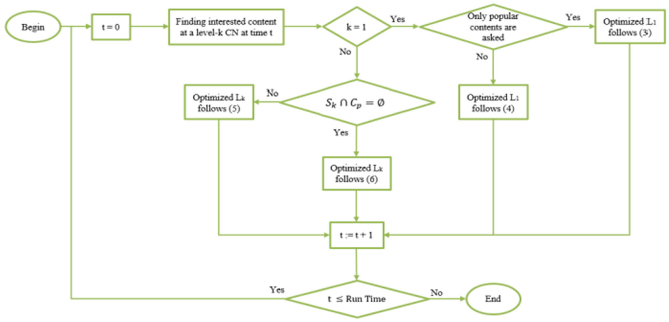


Fig. 2. Flowchart of the proposed method for identifying *Optimized* L_k value.

$$L_{nk}^{Expected} = \left[1 + \frac{(N^{actual}) - B_k}{B_k}\right] \text{ x } L_k \quad (7)$$

where N^{actual} is the actual number of content requests to CR index n at level k, and B_k is the expected number of content requests to a CR at level k:

$$B_k = \text{Total Number of Request x} \sum p_k^c \text{ }, \forall c \in S_k, \quad (8)$$

Eq. (7) returns the expected local link rate of a CR (L_{nk}) as a particular content item may have different values of local popularity at different CRs of the same level due to different local content access frequencies (i.e., different content demand locally at the CR). We denote ⌈ ⌉ as the operation for taking the ceiling value, and content c in (8) defines the set of all distinct content requests sent to the CN n (at level k). Accordingly, p_k^c only presents a prediction for the number of content requests (i.e., an estimation of the expected value) B to a specific level- k CN. To reflect the relative importance of a content at a specified CR, this expected optimized value of L_{nk} is affected by the requested rate of all content objects to the CR at level k within a period.

From this, the system adjusts/updates the optimized value of L_{nk} rapidly to track the changes over time in response to traffic demand and content type at time instance (t +1) as follows:

$$\begin{aligned} L_{nk}^{optimal} \ (t+1) = (1-x) \ . \ L_{nk}^{optimal} \ (t) \\ + \ x. \ L_{nk}^{Expected}(t+1), \end{aligned} \quad (9)$$

where x presents the update rate and $x \in [01]$. The proposed method adapts the change of locality at fixed intervals during a period of τ through the update function of local content popularity. By learning the short-term local content popularity for instantaneous link rate adaption, this function reflects the dynamic popularity and current status of a content to a specific CR based on network traffic over time. Thus, this function enables resource provisioning and management via historical access pattern/arrival rate of the requested content, rather than just defining a fixed popularity level for the content to all CNs.

Let P_O be the operating power consumed by a CR in conventional ICN design (more detail in Section V). Since we assume that the operating power of CN can be conducted as a function of the link rate, the optimized value of L_{nk} acts as a power proportional index. Thus, the optimized value of operating power consumption of a specific CN n at level k in ICN ($P_{O,nk}^{optimal}$) can be identified as:

$$P_{O,nk}^{optimal} = P_O. \ \ L_{nk}^{optimal} \quad (10)$$

where $P_{O,nk}^{optimal}$ is the power-saving ratio of the CN, i.e., the power scaling down rate of the Green ICN system compared to conventional ICN with respect to both traffic load and content popularity level (as defined from (3) to (6)).

This mechanism ensures that each CN minimizes its utilization in response to various content popularity levels together with the changes in network traffic and content demand for maximizing power savings. However, as the instantaneous ALR mechanism responds to network and data traffic rapidly, it is not easy to be adopted for real network deployment. We then name the proposed ALR defined from (9) as the *ideal Green ICN model* (instantaneous adaptation). Besides, we propose a practical network provisioning approach, called *the deployable Green ICN* model. For this model, the network devices are also provisioned with sufficient link rates for the generated traffic and different popularity levels of all content items flowing to them as of the ideal Green ICN. However, each CN re-adjusts the optimized link rate to the closest value from the multi-interoperable data rates of the actual Ethernet standard deployment, i.e., at 10/100/1000 Mb/s mode of Ethernet links. This is a feasible and practical design for real-world network deployment to save unnecessary operating power while still ensuring full connections, given that existing Ethernet links can operate at a lower data rate than their capacity in the current networking model [53].

Overall, by analyzing the correlation of various multi-tier network topologies and content popularity levels, then quickly adapting an operating link rate to its optimized value, the proposed ALR-based technique can diminish power consumed by CRs considerably via the reduced traffic load, thanks to ICN's in-network caching feature. Also, this ALR-based mechanism is a potential contribution to the emerging field of Energy Internet since the energy flow of the electrical power network should match the user Interest arrival patterns and power demands (shared among nodes) which change dynamically based on the local user requirements to enable an efficient and uninterrupted energy supply.

IV. The Green ICN Model With Enhanced Green Network Design for Energy Internet

Besides ALR for power saving from network provisioning as defined in the previous section, we consider the LPI-based mechanism and propose a new caching scheme, namely SCS, for overall system design toward data-driven Energy Internet.

A. Selective Caching Scheme (SCS)

Having the optimized model, called Green ICN, by mapping the utilization of network nodes to their power consumption, we then aim to further reduce the power consumed by each CN by minimizing the network traffic load and network usage. As

CNs are equipped with the ALR technique to save power, we propose SCS as a popularity-based caching scheme at chunk-level, which enhances the cache efficiency and optimizes the content placement for the goal of minimizing traffic load and network resource usage. Particularly, we optimize the utilization of cache storage of CS by dividing it into two parts: the *hot cache space* and the *cold cache space* according to the content arrival. For efficient cache resource allocation, the cache storage in SCS adjusts the caching ratio (i.e., number of chunks per each object for content caching) dynamically according to the variation of content objects stored in CS of each CN to maximizes the number of Interests can be served locally, rather than always caching the whole objects as of existing studies on ICN caching. Given that a chunk is the caching unit of one content for data delivery, to allocate content caches at the two proposed queues of CS, the content items are cached either partially or entirely on the cache as follows:

- The *hot cache space* (privileged queue) stores the popular content objects (i.e., content with $p_1 \geq T_p$), but only the most popular content objects are cached as a whole in a CR. The remaining popular content objects are then partially cached at chunk-level in CS of a CR corresponding to its popularity level rather than entirely cached as the following formula:

$$P_c = \frac{p_1}{p_{1t}} \tag{11}$$

where P_c is the portion of caching for non-top popular content and p_{1t} denotes the threshold value of p_1 for the most popular content objects. Thus, hot space caches all the data of the most popular content objects (with $p_1 > p_{1t}$) and a major ratio of other popular content items.

- Different from the hot space, the *cold cache space* (unprivileged queue) is mainly reserved for storing non-popular content objects. For this, a CN cold space only caches the beginning part of non-popular data, which is identified as the foremost chunks corresponding to a fixed small ratio of the content size (P_f). The reason is that most videos/multimedia files have a higher access chance for the foremost chunks, i.e., forepart chunks of a content have a higher popularity level than other chunks within a file [54].
- Once the content access frequency of cached content in *the cold queue* exceeds a certain threshold within a given time interval, it evolves to be a popular content and is moved to *the hot queue*. In this way, SCS lets the system learn the content popularity over time and reflects the dynamic content traffic so that only the most popular and recent content items are cached to serve the potential future content requests.

Particularly, for a content in SCS, the caching ratio range is then from 0 to 1 in which a value of 1 indicates that all the chunks of content are cached for the most popular content objects (Fig. 3). This strategy matches the consumer demands of content items in the future, which are large-size content (high definition/resolution) as the multimedia content objects, e.g., streaming content and VoD (Video on Demand), will take the significant ratio of Internet traffic.

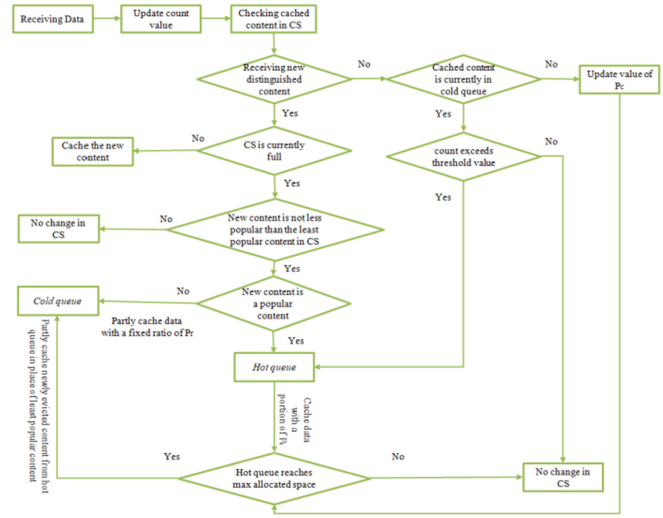


Fig. 3. SCS operating mechanism.

For the cache eviction policy, if a new distinct content (i.e., not-yet-cached content) is received and CS has spare cache storage, the CN will cache the new content (until CS is full). When CS is full, the least popular content with the lowest value of p_1 in the cache of a CN will only be replaced by the new content in case the new content has higher popularity (i.e., higher p_1 value). Otherwise, the new content item will be discarded. If some content objects in CS have the same popular level (p_1 value), then the system performs the LRU (Least Recently Used) replacement policy. We use LRU, which is the default and widely-used replacement policy in ICN due to its good performance despite the simple implementation. This replacement policy then filters the inactive content items and avoids the replacement of popular content objects by unpopular items.

The interesting point is that SCS has a dynamic cache partitioning policy, and the size of each queue is not pre-set. Instead, the cache space is dynamically allocated based on the type of content so that the *hot space size* is within its *maximum allocated capacity*. Additionally, when the hot queue reaches this allocated space, the newly evicted content from the hot queue will not be evicted immediately: Its beginning part will be moved to cold queue with a fixed small caching ratio of P_f (same as that of unpopular content) when space is needed instead (Fig. 3). The cold cache space then acts as a secondary cache in CS in which only the least popular content will be discarded (when the cache is full) to improve the cache diversity and ensure the availability of content with high demand recently.

Overall, as the two customized cache spaces in CS employ two different caching policies, SCS prioritizes the cache storage allocation across content popularity classes as an effective selective and incremental caching mechanism. Particularly, by jointly analyzing user behaviors via content access patterns and content popularity over time, SCS makes the full use of limited cache storage of CR (CS) to make the edge network realize the popular content objects whereas less popular content

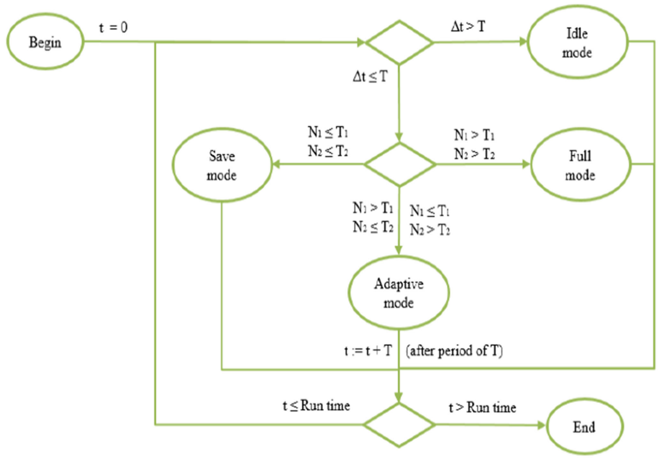


Fig. 4. The controlling rules for selecting the optimal operating mode of an individual server.

chunks are stored on CRs close to CP/original producer at higher levels in the hierarchical cache system. From the reduced number of Interest packets transmitted to CPs and higher levels, the ALR-based technique (defined in Section III-B) adjusts the link rate dynamically to match reduced traffic load and the popularity of requested content as well for maximizing power savings from CNs. The detailed mechanism of SCS is depicted in Fig. 3 in which count denotes the current number of requests from users sent to a specified CR for a particular content.

B. Controlling Policy for Decision Making of CP's Optimized Operating Modes

In this section, we apply the idea of the Mealy machine to model a server as a finite-state machine and identify its optimal working mode within a specific period of T to save considerable power consumption from the cluster of servers, given that each produces much more power compared to a router [7].

For this goal, the system uses traffic provisioning to put the CP into its optimal mode, which is an LPI state to achieve considerable power savings. Particularly, we design four distinguished practical operating modes for a CP: SM (Save Mode), F (Full Mode), I (Idle), or A (Adaptive mode). Supposed that the proposed ICN system uses servers whose upper bound value of power consumption can be set [12], only the server in F mode works with 100% power capacity to enable power savings. Besides, while the threshold power of I mode and SM mode can be predefined, that of A mode is calculated dynamically based on the traffic load to a server.

We then schedule a CP with its optimal operating mode for a period T to enable power savings from the server. Let Δt be the arrival-time difference between two consecutive requested packets sent to a server. The dynamic optimal controlling scheme then first checks whether to activate the I mode for the server by comparing the values of T and Δt (Fig. 4).

The traffic load is identified by *two input variables*: the number of content requests (Interests) and the number of distinct consumers sent requests to a specific server s_i during a period T. Fig. 4 depicts the scheduling algorithm for the optimal operating mode of a particular CP of the server cluster in which T_1, N_{1i}, *and* T_2, N_{2i} are the threshold values and the number of Interest packets and that of distinguished consumers sent requests to the server s_i for a period T, respectively. For the sake of Denial of Service (DoS) prevention, we adapt T_2 value with respect to that of T_1: A consumer should only send up to a specific number of Interests to a server s_i over a period T to enhance the cache robustness and prevent cache pollution attack by the injection of a huge number of repeated Interests for unpopular content objects.

Let P_A be the upper bound of the power consumption for A mode of a certain server s_i, then its value can be dynamically computed as:

$$P_A = P_F \text{ x}\left[1 - \left(w.\ \frac{T_1 - N_{1i}}{T_1} + (1-w).\ \frac{T_2 - N_{2i}}{T_2}\right)\right] \quad (12)$$

where w is the weighting values of the first input variable (number of Interests). P_F is the power consumed in F mode. In (12), if $T_1 < N_{1i}$ then let $(T_1 - N_{1i}) = 0$ whereas if $T_2 < N_{2i}$ then let $(T_2 - N_{2i}) = 0$.

The objective of this scheduling algorithm is to identify the optimal operating mode of a CP over a period, then minimize the overall power consumed by the cluster of servers. Better still, as stated, since SCS helps to diminish the chance that a CP needs to work in F mode, together, the dynamic control rules for optimal operating mode of CP act as an efficient way to save the power consumption of a server gained from its lower operating time.

C. Memory Technologies for Proposed Green ICN Infrastructure Deployment

In this section, we investigate the current memory and hardware technologies for the possible caching deployment of the proposed Green ICN model.

From the study of current memory technologies on energy consumption in [55], we select Dynamic Random Access Memory (DRAM) for the CR's deployment since DRAM offers higher power consumption saving, bigger memory size, and much lower cost compared to other existing advanced RAM technology. Also, we use Solid State Drives (SSD) for each CP's storage as currently, SSD is a high-speed technology for a device with high storage capacity at a reasonable cost.

Let n_c, cs, and P_{ca} be the number of content objects cached in a specific CR, the size of a content, and the power efficiency (in W/MB) for caching content in the CR buffer, respectively. Then, the caching energy of a specific CR for a period t ($E_c^{optimal}$) is:

$$E_c^{optimal} = n_c \text{ x} cs \text{ x} P_{ca} \text{ x} t. \quad (13)$$

Similarly, the storage energy of a specific CP for a period t ($E_s^{optimal}$) is:

$$E_s^{optimal} = C\text{x } cs\text{x}P_s\text{x}t, \quad (14)$$

where C is all the number of content objects stored at a CP, and P_s is the power efficiency for data storage of the CP.

V. Energy Models for Energy-Efficiency Analysis

To evaluate the EE performance of different network system approaches, we assume that a network system includes two major network components: N CRs and M servers/CPs (cluster of servers). From these network elements, we develop the energy models of our Green ICN model and existing network system designs. This section presents our in-depth energy models with further comprehensive analysis from the prior research models [7][56] for the energy models of conventional/non-green ICN and regular IP designs. Note that for both conventional ICN and IP systems, all network elements work with their maximum capacity as no greening mechanism is applied. In contrast, the EE objective function of the Green ICN design can be achieved by adapting all links and network nodes to their optimized values, as stated in the previous sections.

A. Energy Consumption of an IP-Based Network System

The energy consumption of an IP-based network system E_{IP} can be calculated as:

$$\begin{aligned} E_{IP} &= N \text{ x } E_{R-IP} + M \text{ x } E_S \\ &= N \text{ x } T_w \text{ x } (P_{E-IP} + P_{O-IP}) \\ &\quad + M \text{ x } T_w \text{ x } (P_{S1} + P_{S2} + P_{S3}), \end{aligned} \tag{15}$$

where $E_{R\text{-}IP}$ and E_S are the energy consumed by an IP router and by a server; and $P_{\text{E-IP}}$ and $P_{\text{O-IP}}$ are the embodied power and working power of an IP router. P_{S1}, P_{S2}, and P_{S3} are the embodied power, power for server storage, and operating power of a server, respectively. T_w is the operating time of the whole network system.

B. Energy Consumption of a Conventional ICN System

The energy consumption of a conventional ICN network approach E_{ICN} is identified as:

$$\begin{aligned} E_{ICN} &= N \text{ x } E_{R-ICN} + M \text{ x } E_S \\ &= N \text{ x } T_w \text{ x } (P_{E-ICN} \\ &\quad + P_{C-ICN} + P_{O-ICN}) + M \text{ x } E_S, \end{aligned} \tag{16}$$

where $P_{E\text{-}ICN}$, $P_{O\text{-}ICN}$, and $P_{C\text{-}ICN}$ are the embodied power, working power, and power to cache memory of a CR, respectively. Regarding power consumption evaluation, both the ICN system and the current IP-based system share the same power consumption for servers, whereas an ICN router incurs slightly higher power compared to a normal IP router due to extra energy needed for the caching capability.

C. Energy Consumption of the Proposed Green ICN System

The proposed Green ICN energy consumption $E_{GreenICN}$ is a combination of two optimized values defined in previous sections:

$$E_{GreenICN} = \sum_{k=1}^{N} E^{optimal}_{R-ICN,\, r_k} + \sum_{i=1}^{M} E^{optimal}_{S-ICN,\, s_i} \tag{17}$$

where the optimized energy consumption of all CRs is:

$$\begin{aligned} \sum_{k=1}^{N} E^{optimal}_{R-ICN,\, r_k} &= N \text{ x } T_w \text{ x } (P_{E-ICN} + P_{C-ICN}) \\ &\quad + \sum_{k=1}^{N} P^{optimal}_{O-ICN,\, r_k} \text{ x } T_{Or_k}, \\ &\quad + \sum_{k=2}^{N} P^{optimal}_{O-ICN,\, r_{k-1}} \text{ x } t_{d1} \end{aligned} \tag{18}$$

and the optimized value of the cluster of CPs:

$$\begin{aligned} \sum_{i=1}^{M} E^{optimal}_{S-ICN,\, s_i} &= M \text{ x } T_w \text{ x } (P_{S1} + P_{S2}) \\ &\quad + \sum_{i=1}^{M} P^{optimal}_{S3,\, s_i} \text{ x } (T_{O_{s_i}} + x_{s_i} \text{ x } t_{d2}) \end{aligned} \tag{19}$$

where T_{Or_k} is the operating time of router r_k with proposed ALR design, and $T_{O_{s_i}}$ is the operating time of a certain server s_i in the server cluster with optimal power mode (Section IV.B). x_{s_i} is a binary variable, which indicates whether the upcoming optimal operating mode of a server is different from its current operating mode. Specifically, a value of one means the next optimal operating mode is different from the current one. Also, to show the trade-off of delay with and without the adaptive mechanism, t_{d1} and t_{d2} denote delay time between consecutive CR link rate adaptations and CP optimized operating mode' switches, respectively.

VI. Performance Evaluation

A. Environmental Setup

In this section, we validate the benefits of the proposed Green ICN framework for future access networks by conducting intensive simulation using ndnSIM [57], which is a well-known ICN simulator based on the ns-3 platform. Also, ndnSIM is a widely used network simulator tool in the NDN research community. We simulate with 1000 concurrent content users (consumers), and the content users are connected to a CR at level-1 to realize a realistic/practical network scenario. User requests for a content object follow the Poisson process with the rate of five Interest packets per second. The cluster of CP includes two servers, and each serves half of the entire available content (content catalog). We model the content popularity distribution using a Zipf distribution [58] as it is the most popular and efficient model for content distribution. We simulate with the Zipf's skewness factor value alpha of 0.8 ($\alpha = 0.8$) since it is a common value used in literature where actual traces are observed from CDNs and Internet Service Providers (ISPs) [59], [60]. The key parameters used for simulation in ndnSIM are shown in Table II.

TABLE II
THE KEY PARAMETERS FOR SYSTEM'S EVALUATIONS

Parameter	Value
Number of content items	160,000
Number of servers (M)	2
Number of CNs (N) and the number of tiers (L)	Varies correspo ding to net ork topology
Server storage capacity	80 TB
Content size (cs)	100 0 MB
Chunk payload size	1 KB
Interest arrival rate	5 Interests each user/s
Number of concurrent content users	1,000
Link capacity (bandwidth)	100 Mbps for links between users and edge CRs, and 1 Gb/s otherwise
T_p, p_{1t}	p_1 value of top 20% and 10% most popular content, respectively
Power consumptions of I and SM mode	25% and 45% server power capacity
Content popularity distribution model	Zipf-like distribution [31] with $\alpha = 0.8$
Number of content popularity classes	1,000 (100 content items each class)
Maximum allocated space for the hot queue	70% CS size
P_f	20% of data from the foremost chunk
β value	1
T_1	20% link capacity
t_{d1}, t_{d2}	1 ms
τ, T	3s, 5s
w1, w2, x	0.5, 0.5, 0.5

We evaluate different networks, including conventional *ICN (default NDN approach)*, *proposed Green ICN*, and *IP-based design*, using a complete six-level tree model with a degree of three (ternary tree). We do not compare our EE performance with other state-of-the-art "greening" studies in ICN as the benchmark since they do not operate in a similar way to save energy consumption (i.e., do not work with ALR in a hierarchical network topology). To evaluate the EE performance of the proposal for a potential ICN infrastructure deployment for FI, we simulate with *both ideal and deployable GreenICN* approaches as defined in Section III in which (9) is used for Ideal Green ICN cases. Cache policy is SCS for the Green ICN system, whereas the LCE with LRU scheme is used for other network systems.

Besides the tree topology, to make our analysis on power saving and efficiency of the proposal as realistic as possible for potential adoption in complex network structures to solve future network needs, we also apply the idea of the proposed Green ICN model into three different network topologies with multiple network links, as follows:

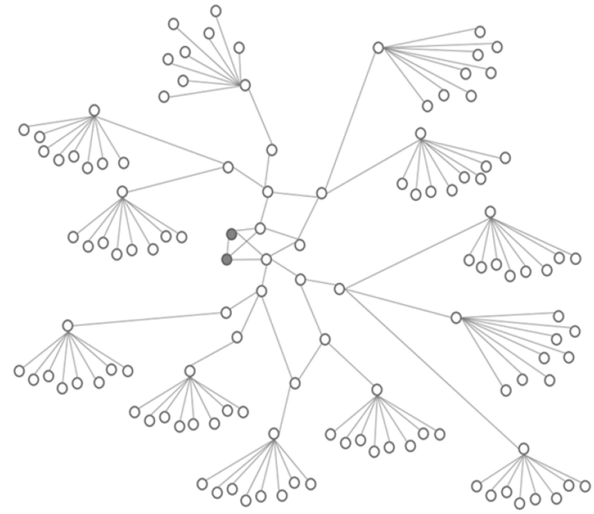


Fig. 5. Campus network structure.

- *Partial Mesh*: Some nodes can interact with other same-level or one-level-up nodes rather than just their dedicated (single) parent or child nodes. For the sake of simplification, we extend this topology from the general six-level tree topology so that 40% CRs at each level have more than four links connected to other nodes.
- *Campus Network*: An instance of a hybrid network that includes core network and access networks in a form of tree topology for multiple buildings. Typically, the campus has a diameter of 6 hops with 12 levels-2 CRs, and each CR level-2 is connected to 8 level-1 CR, supposed that a subnetwork is designed for a building with 8 floors. The two darken nodes represent content producers, which connect to 2 level-5 CRs in the center (Fig. 5). We compare the EE performance of this campus network to a 5-level ternary tree connected with a cluster of two CPs to form a 6-level network with the same number of CRs as of the campus network.
- *Tree-Based CDN Network Infrastructure*: An extension of the default six-level ternary tree topology by replacing some ICN nodes at different levels of network topology with CDN cache servers (10 TB storage for each). A CDN (cache) server is considered as a sub-CPs (distributed data center), and lower levels have more CDN caches due to the higher number of CRs to distribute CDN services to numerous content users in a flexible and scalable way.

As discussed in Section III-A, for the feasible real-world implementation, we select the generic multi-tier topology, in which the level of the network nodes can be identified using the concept of the shortest path in terms of the number of hops from end-users to the node with the matching content with the assumption that the edge nodes are at level 1. Also, this kind of ICN implementation approach which scales down in the edge nodes can be found in recent notable studies regarding ICN edge deployment [61], [62].

TABLE III
THE NETWORK ELEMENTS AND POWER CONSUMPTIONS

Network Element	**Power consumption (W)**
$P_{R1\text{-}IP}$, $P_{R2\text{-}IP}$	13, 116
$P_{R1\text{-}ICN}$128, 192, 256, 512, 768, 1024, 1280, 1536 GB	14, 14.5, 15, 17, 18.5, 20, 22, 24
$P_{R2\text{-}ICN}$128, 192, 256, 512, 768, 1024, 1280, 1536 GB	118, 119, 120, 121, 122, 123, 125, 127
$P_{R3\text{-}ICN}$ N	0.053
P_{ca},P_s	0.023, 0.00001 (W/MB)
P_{S1}, P_{S2}, P_{S3} (for each 10 TB)	68, 20, 731

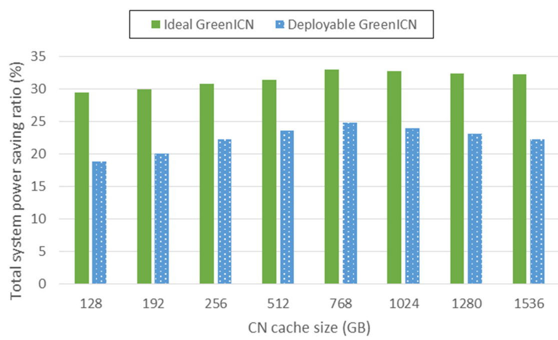


Fig. 6. Total power-saving ratio vs. various CN cache sizes.

B. Results and Discussion

The primary goal of this research is to minimize the network system power consumption, so we take average power as the primary network metric for the evaluation. It can be identified as the quotient of the total system energy (defined by energy models from Section V) and the network operating time (simulation time). The power consumption values of the key network elements are presented in Table III, referred to [55], [56]. Also, to assess the impact of the proposed Green ICN model, we include server hit rate and hop count reduction ratio in our evaluations since they are critical measures to assess an ICN caching scheme for content delivery as follows:

1) Impact of CN Cache Size on Total System Power-Saving Ratio: We investigate the proposal's EE performance over conventional ICN (NDN) with various CR cache sizes ranging from 128 to 1536 GB. As illustrated in Fig. 6, when the CN cache size is not less than 192 GB, the Green ICN system can save at least 20% total power consumption compared to conventional ICN (more than 30% for the Ideal model). Moreover, we achieve the highest power saving ratio at the CR cache size of 768 GB. As this result suggests the optimal CR cache size selection for sustainable ICN infrastructure deployment in the same network scenario, hereafter, we evaluate ICN systems using *768 GB cache size CRs* to maximize the in-network caching merit from the cache resource deployment.

2) Impact of Average CN Power-Saving Ratio at Different Network Tiers: We observe that by varying the CN link rate for the EE goal, the proposed Green ICN model realizes a monotonically increasing function, which enables more power savings at higher network tiers (Fig. 7). This similar tendency can be realized for both Ideal Green ICN and deployable model in which the link rate for transmission is only selected from the available rates, and the power saving performance gap between two models is narrowed down at higher tiers, i.e., we can save substantial power at high levels' CNs. The reason is that thanks to SCS, more content objects (especially the popular ones) can be served by the edge side directly. This leads to less resource utilization at the higher tier nodes which is, in turn, converted to a higher value of the energy-saving with the application of the proposed adaptive mechanism as described in Sections III and IV. Hence, when the network grows larger, the benefits of the proposed rate-adaptation mechanism and caching scheme in ICN become clearer.

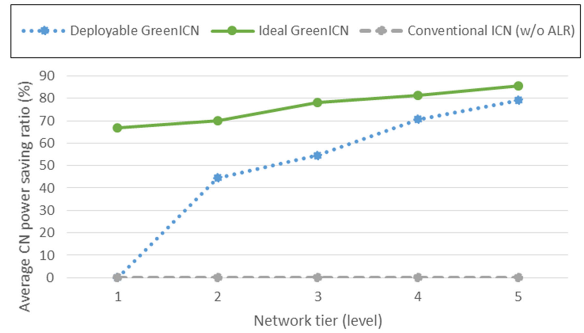
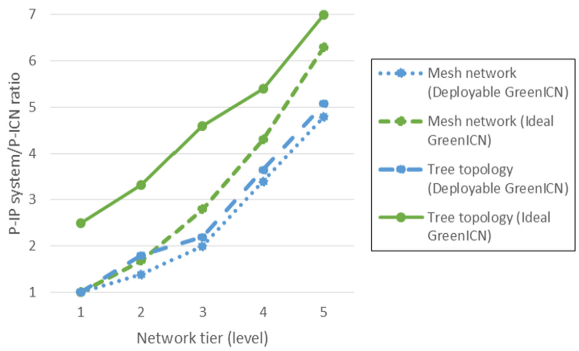
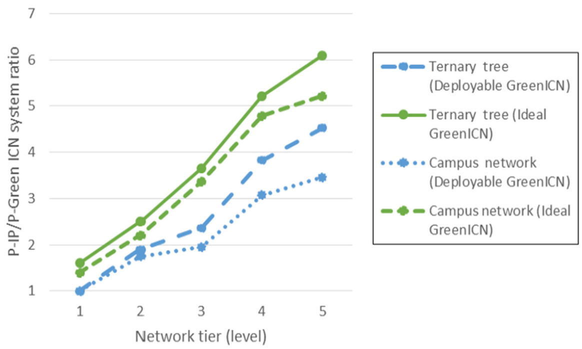


Fig. 7. Average CN power-saving ratio of ICN systems at different network tiers.

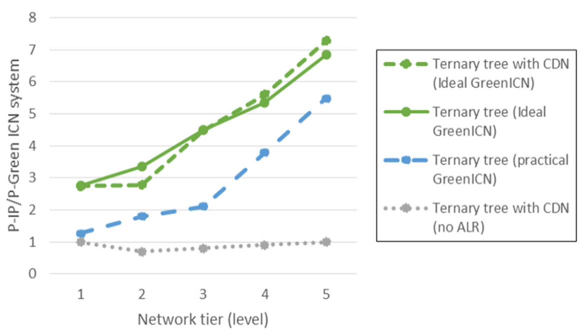
3) Impact of the Power-Saving Ratio of CNs (at Different Network Levels) Under Various Network Topologies: Fig. 8 shows that the proposal performs at its best in the case of tree topology due to the simple structure and the limited number of connections. For CDN tree-based topology, it performs worse than IP in terms of power savings if we do not apply ALR because CRs incur higher operating and manufacturing power compared to IP routers. In contrast, as expected, CDN caches produce lower power at the higher level of tree topology in case ALR is used since CDN servers can decrease traffic load considerably by employing a relatively large storage capacity in the large-scale network. In addition, although the hybrid (campus network) and mesh structure gain lower power saving compared to respective tree network configurations with the same number of CNs and tiers due to excessive connection/links and computation burden, both the ideal and deployable Green ICN models still perform much better than conventional ICN. Besides, in a much more distributed environment like that of CDN in which the edge sides may include multiple CDN sub-servers with much bigger cache storage compared to a conventional network node so that the popular content objects can be pushed close to the end-user side, the proposed Green ICN system can efficiently save energy and user response time (latency) at the same time. Hence, the proposal is suitable for dynamic services with QoS like VoD, content-based services in real life. We also observe a similar trend of more power saving at higher-level CNs in all evaluated scenarios. These results then show the great scalability for possible ICN deployment in complex networks.



(a)



(b)



(c)

Fig. 8. Power saving ratio over IP of CNs at various tiers with different Green ICN systems and network topologies. (a) Partial mesh network vs. respective tree topology. (b) Campus network vs. respective tree topology. (c) Tree-based CDN and respective tree topology.

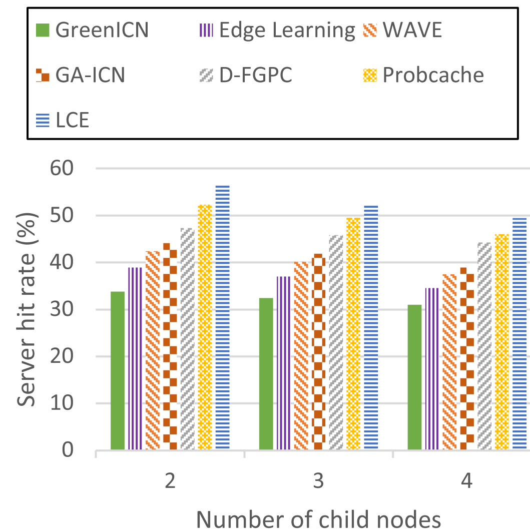


Fig. 9. Server hit rate.

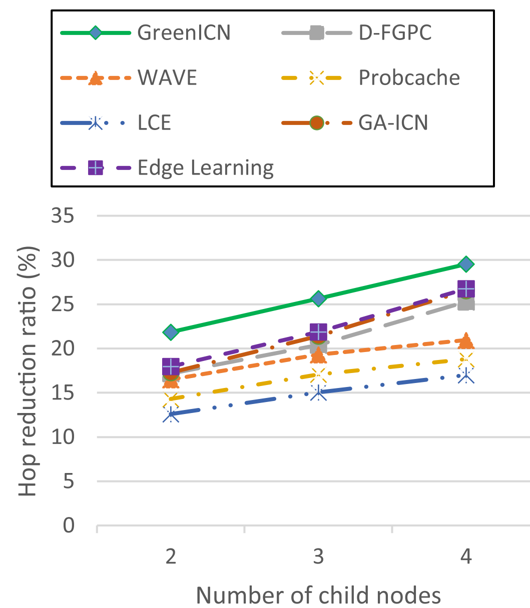


Fig. 10. Hop reduction ratio. Performance evaluation of ICN systems adopting different caching schemes vs. the number of child nodes.

4) Impact of the Server Hit Rate With and Hop Count Reduction Ratio Different Caching Schemes and the Number of Child Nodes: To evaluate the efficiency of the proposed caching scheme (SCS), we compare SCS with other relevant five widely used caching schemes in ICN: Edge Learning, WAVE, GA-ICN, D-FGPC, ProbCache, and LCE, discussed in Section II.A. Fig. 9 shows that for all caching schemes, a larger value of child nodes corresponds to a lower hit rate. This is because when the network scale enlarges, popular content objects can be cached more efficiently at initial levels, then decreases network load and average/expected number of hops that content users can find the interested content. Specifically, LCE has the highest server hit rate as it does not consider content popularity and always caches the whole content data along the path. In contrast, by improving CS's content diversity to make as many content requests that can be served locally from CNs' cache storage as possible, SCS achieves the best performance and highest scalability among all other caching approaches, including both full-object and chunk-based partial caching (like WAVE).

A similar tendency can be realized regarding distance in the number of hops, except in the case of WAVE, which does not perform well in saving the number of hops, compared to other relevant caching schemes (Fig. 10). This tendency occurs because opposite from SCS, WAVE caches the beginning part of the content at the core routers in a downstream manner along the delivery path. In general, thanks to the application of edge-based calculation, decision tree as well as distributed coding method, the performance of Edge learning-ICN is closest to that of the proposed Green ICN system. While Edge-learning ICN with edge computing reaches the second-highest performance in terms of server hit rate, its hop reduction ratio performance is similar to that of GA-ICN. Particularly, after formulating total energy consumption in ICN as a programming problem, GA-ICN uses a genetic algorithm (GA) to find energy-efficient cache locations, which is demonstrated to enable high energy savings for very popular content and small-sized catalog [40]. Also, GA-ICN is the closest caching approach to our proposal among all the benchmarks for enhancing EE performance in ICN since both schemes use reported energy efficiency of computational hardware and network equipment for the goal of greening the ICN system via a realization of a practical in-network caching deployment. The evaluation results in Fig. 9 and Fig. 10 suggest that the Green ICN model employing SCS can provide a small stretch path to download the desired content, where stretch can be defined as the distance in the number of hops traveled by a user request to retrieve content from an appropriate source (i.e., the nodes with cached data). Specifically, the closer the cached content to the user(s) (i.e., lower stretch), the less energy will be consumed in the network. As a result, an efficient caching scheme can further diminish the power consumption from the user to the cached data.

Better still, using the proposed ALR mechanism, we can sharply diminish the operating power of network devices and CPs by serving content items closer to users at the edge side via the in-network caching mechanism of ICN. Although this way also increases caching power, Green ICN design can save overall network power consumption because the network system power is dominated by network nodes' operating power [36].

Overall, by further exploring the correlation between caching schemes and power consumption for efficient network resource utilization corresponding to content popularity levels and network traffic, we demonstrate that having data closer to the consumers does not only reduce network traffic through CR's depth in the network but also has the potential to reduce considerably energy consumption where certain CRs can then be taken offline. In other words, the performance gain of GreenICN system is not solely due to the design of ALR, but it is the result of the combined techniques of the ALR-based method (Section III), and the optimal operating mode selection for the CP/server together with the proposed caching scheme, namely SCS (Section IV). In particular, while SCS helps reduce the traffic load by putting a higher priority on the more popular content, ALR and the optimal server operating selection algorithm further convert this traffic reduction into the power saving for enabling an overall power-aware network system for the future green networks. The proposal is then significant for the goal of Energy Internet design toward sustainable green future network deployment.

VII. Conclusion and Future Work

In this article, we have developed a novel scalable *Green ICN* model with a focus on *EE design for FI*. The proposed system can save a significant amount of unnecessary power under different network topologies with suitable memory technology and power-awareness network devices by efficiently tuning the CP optimal operating mode and switching network node links smartly, instead of consuming fixed power even in the ideal periods as of traditional suboptimal network system. To realize a smart distribution network system with self-optimized and data-driven management policies, we also propose a novel probabilistic popularity-based caching scheme (SCS) to improve the content diversity and cache utilization of CS. SCS minimizes the height of user requests needed to travel before it encounters a CR that is currently caching the data. Typically, the higher number of content requests that can be successfully served locally from ICN caches via a cache hit, the higher the power saving that the Green ICN system can achieve, thanks to the significant reductions in server hit rate and traffic load in ICN. In addition, the proposed Green ICN model can operate with different caching schemes to further reduce the overall power consumption through diminished network traffic efficiently.

By achieving at least 20% power-saving compared to the existing distribution network designs, the research suggests that the proposed Green ICN framework can be deployed for complex and practical access network designs, such as core network with mesh structure while edge network with tree-topology, to gain substantial power saving and high performance at the same time with a simple and deployable infrastructure implementation.

The proposal also acts as a potential contribution to both distributed data processing and power provisioning, measurement, analytics, and control in real-time for the smart interconnected Energy Internet system with real-world network services and applications, e.g., smart homes, transportation systems, smart buildings, and campuses toward IoT-based and connected cities with data-oriented services at different places. Typically, by realizing the concept of learning from consumers' interactive generated data traffic and pattern for predictive data analytics, our proposed Green ICN system with network resource provisioning for flexible and adaptive services acts as a promising network infrastructure solution in which all nodes are connected, and data can be exchanged efficiently in the network, given that content and electric demands are characterized by large geographical spread and complex topology. In this way, the research can realize an automated, adaptive, and self-configurable management framework toward Energy Internet with hierarchical control via the decision criteria over the intermediate nodes of the multi-hop distribution (power) networks.

For future potential research directions, given that ubiquitous Internet access is needed for numerous services and transactions [63], to facilitate the IoT launching procedure leveraging the key features of ICN, we intend to add an optional computing layer at IoT sensor connecting to CNs for the realization of green IoT data-centric enhanced services as we did in [52]. We also plan to further investigate and verify whether the higher number of levels can be more power-efficient in larger-scale networks. Besides, we identify that the deep reinforcement learning (DRL)-based method would be a feasible and appropriate benchmark for future work to further validate the efficiency of the proposal. Also, for field experiment evaluations, we intend to implement and evaluate the proposed Green ICN model in a real campus network topology.

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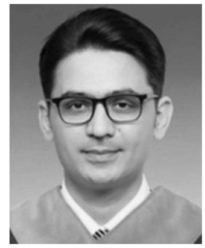
Quang Ngoc Nguyen received the B.Eng. degree in information technology (Honor Computer Science Program conducted in English) from the Posts and Telecommunications Institute of Technology (PTIT), Hanoi, Vietnam, in 2012, and the M.Sc. and Ph.D. degrees from Waseda University, Tokyo, Japan, in 2015 and 2019, respectively. He became one of the youngest Faculty Members of the Posts and Telecommunications Institute of Technology. He is currently an Assistant Professor with the Faculty of Science and Engineering, Waseda University, where he has been a Research Associate since 2018. He has hosted and participated in many research projects, including the collaborative EU-Japan research projects funded by the European Commission's Horizon 2020 Programme, such as the Green ICN and 5G! Pagoda projects, and the Ministry of Internal Affairs and Communication (MIC) of Japan. His research has also been funded by the Ministry of Economy, Trade and Industry (METI) of Japan, Waseda University, and Fujitsu Ltd. and Fujitsu Lab. He was the sole Awardee of Asia Special Scholarship for Fall 2013 admission to the Graduate School of Global Information and Telecommunication Studies (GITS), Waseda University. He was also the recipient of young author recognition awarded by the International Telecommunication Union for young first-author of highly potential research under 30 years old, and actively contributed to many ITU-T standardization activities related to Information-Centric Networking (ICN) and Future Internet architecture. He is the Guest Editor and Keynote Speaker at the 2nd International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM 2020), Shanghai, China, and IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA 2021), June 2021, Dalian, China. He was the sole and lead Editor of a book entitled *Congestion Control: Design, Applications and Protocols*, Nova Science Publishers, March 2021. He is the Topic Editor of *Electronics*, Switzerland and the Series Editor of Atlantis Highlights in Engineering, and *Advances in Engineering Research* (WoS). He is currently the Senior Advisor to the Strategic Council for Science and Technology with PTIT.

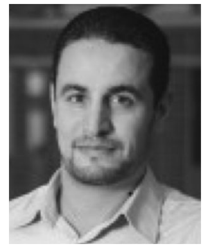


Rehmat Ullah received the B.S. and M.S. degrees in computer science from COMSATS University, Islamabad, Pakistan, in 2013 and 2016, respectively, and the Ph.D. degree in electronics and computer engineering from Hongik University, Seoul, South Korea, in February 2020. He is currently a Postdoctoral Research Fellow with the recently established Edge Computing Hub, Queen's University Belfast, Belfast, U.K., in collaboration with the industry, Rakuten Mobile, Japan. Prior to joining Queen's University Belfast, he was an Assistant Professor with the Department of Computer Engineering, Gachon University, Seongnam, South Korea. He is a Member of the Technical Program Committees of several flagship conferences such as ACM IMC, ACM MobiHoc, IEEE VTC, and IEEE ICC. He is an Invited Reviewer of numerous high-impact journals, such as IEEE, ELSEVIER, ACM, and WILEY. His work has appeared in more than 40 research papers in peer reviewed conferences and top journals such as the IEEE INTERNET OF THINGS JOURNAL, *IEEE Wireless Communications Magazine*, *Journal of Network and Computer Applications*, and *Future Generation Computer Systems*. His research interests include network and distributed systems particularly the development of architectures, algorithms, and protocols for emerging paradigms, such as edge computing, Internet of Things, information centric networking, and 5G evolution and beyond with a recent focus on federated learning for edge computing systems. This includes the design, measurement studies, prototyping, testbed development, and performance evaluations.

Byung-Seo Kim (Senior Member, IEEE) received the B.S. degree in electrical engineering from In-Ha University, In-Chon, South Korea, in 1998, and the M.S. and Ph.D. degrees in electrical and computer engineering from the University of Florida, Gainesville, FL, USA, in 2001 and 2004, respectively. His Ph.D. study was supervised by Dr. Yuguang Fang. Between 1997 and 1999, he was with Advanced Technology Research and Development (ATR&D), Motorola Korea Ltd., PaJu, South Korea, as a Computer Integrated Manufacturing (CIM) Engineer. From January 2005 to August 2007, he was with Networks and Enterprises, Motorola Inc., Schaumburg, IL, USA, as a Senior Software Engineer. His research with Motorola Inc. focuses on designing the protocol and network architecture of wireless broadband mission-critical communications. From 2012 to 2014, he was the Chairman of the Department of Software and Communications Engineering, Hongik University, Seoul, South Korea, where he is currently a Professor. His works appear in around 220 publications and 22 patents. His research interests include the design and development of efficient wireless, wired networks including link-adaptable, cross-layer-based protocols, multiprotocol structures, wireless CCNs/NDNs, mobile edge computing, physical layer design for broadband PLC, and resource allocation algorithms for wireless networks. He was the General Chair of 3rd IWWCN 2017, and the TPC Member for the IEEE VTC 2014-Spring and the EAI FUTURE2016, and ICGHIC 2016∼2019 conferences. He was the Guest Editor of special issues of the *International Journal of Distributed Sensor Networks* (SAGE), IEEE ACCESS, and *Journal of the Institute of Electrics and Information Engineers*. He was also a Member of the Sejong-city Construction Review Committee and Ansan-city Design Advisory Board. He is an Associative Editor for IEEE ACCESS.

Rosilah Hassan (Senior Member, IEEE) received the B.Sc. degree in electronic engineering from Hanyang University, Seoul, South Korea, the M.E.E. degree in computer and communication from the Universiti Kebangsaan Malaysia (UKM), Bangi, Malaysia, in 1999, and the Ph.D. degree in mobile communication from the University of Strathclyde, Glasgow, U.K., in May 2008. She is currently an Associate Professor with the Faculty of Information Science and Technology, UKM. Before joining UKM in 1997, she was an Engineer with Samsung Electronic Malaysia, Seremban, Malaysia. Besides being a Senior Lecturer, she got experience in management posts for the university as the Deputy Director of Academic Entrepreneurship for more than seven years. She is also the Head of the Network Communication Technology (NCT) lab in her Faculty. Her research interests include mobile communications, networking, IoT, and Big Data. She has had experience as an External Examiner for the Ph.D. and master's for both national and international levels. She is also an Active Member of the IEEE, WIE, Malaysia Society for Engineering (MySET), Malaysian Board of Technologists (MBoT), and IET.

Takuro Sato (Life Fellow, IEEE) received the B.E. and Ph.D. degrees in electronics engineering from Niigata University, Niigata, Japan, in 1973 and 1993, respectively. In 1973, he joined the Research and Development Laboratories, OKI Electric Industry Co., Ltd., Tokyo, Japan, where he was a Senior Research Manager and Research Director with Communication Systems Laboratory. In 1995, he joined the Niigata Institute of Technology as a Professor. He contributed to the standardization process in IEEE 802.11a. He established the Venture Company Key Stream to provide LSI integrated circuits to 802.11 wireless LAN systems. In 2004, he joined GITS, Waseda University, Tokyo, as a Professor and is currently the Dean. He has developed a wideband CDMA system for personal communication systems and joined the PCS standardization committee in the USA and Japan. His contributions are mainly in high-speed cellular modem standardization for ITU, 2.4GHz PCS for ITA, and WLAN technology (IEEE 802.11). He has authored 11 books and more than 200 papers. His current research interests include next wireless communications, information-centric network (ICN) technology, mobile edge computing technologies based on ICN to apply for 5G mobile communication networks, ICT in smart grid, and their global standardizations. He is a Life Fellow of IEICE.



Tarik Taleb received the B.E. degree (Hons.) in information engineering and the M.Sc. and Ph.D.degrees in information sciences from Tohoku University, Sendai, Japan, in 2001, 2003, and 2005, respectively. He is currently a Professor with the School of Electrical Engineering, Aalto University, Espoo, Finland. His research interests include architectural enhancements to mobile core networks, network softwarization and slicing, mobile cloud networking, network function virtualization, software-defined networking, mobile multimedia streaming, inter-vehicular communications, and social media networking. He is a Member of the IEEE Communications Society Standardization Program Development Board. He is the General Chair of the 2019 edition of the IEEE Wireless Communications and Networking Conference to be held in Marrakech, Morocco. He is/was on the Editorial Board of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, *IEEE Wireless Communications Magazine*, IEEE INTERNET OF THINGS JOURNAL, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE COMMUNICATIONS SURVEYS AND TUTORIALS, and a number of Wiley journals. From 2006 to 2010, he was also the Vice-Chair of the Satellite and Space Communications Technical Committee of IEEE ComSoc. Until 2016, he was the Chair of the Wireless Communications Technical Committee, largest in IEEE ComSoC. He is the Guest Editor-in-Chief of the IEEE JSAC Series on Network Softwarization and Enablers. He is also with Sejong University, Seoul, South Korea and University of Oulu, Oulu, Finland.