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Latency-Optimal Network Intelligence Utilization in SDN/NFV-enabled Energy Internet Communication Network

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ABSTRACT

Energy internet (EI) is a very complex system with various applications that have specific and strict requirements of reliability, flexibility, latency, and security. To fulfill all requirements, communication with network intelligence utilization, in which deep examining information-flows in real-time is inevitable. In the future internet architecture, a set of network intelligence services can be applied virtually in a consolidated middlebox. The network function virtualization (NFV) has a role in providing those services, and the software-defined networking (SDN) has a position to glue them, and they become SDN/NFV-enabled network. However, how to place and manage network intelligence middleboxes is a complex and time-consuming decision problem. Hence, this paper proposes a placement and resource allocation strategy for the latency-optimal network-intelligence utilization in SDN/NFV-enabled EI communication network. The investigation of several existing approaches helps to reformulate the objective function with three main constraints, i.e., the middlebox processing power capacity, the forwarding node resource, and the communication link configuration. The heuristic solution expects the use of an integrated graph clustering analysis and dynamic resource allocation scheme minimizing both packet-delivery time and processing latency. The evaluation shows that the approach improves latency minimization significantly with the average information-flows latency reaching 24.43% and 11.34% lower than the baseline approaches on two network topologies, i.e., Abilene and FatTree, respectively. The results of these works may provide the best option to the communication service providers (CSP) in providing a flexible, reliable, and real-time capable communication network for EI ecosystem.

INDEX TERMS Energy internet, latency, network intelligence, NFV, SDN

I. INTRODUCTION

RECENTLY, the penetration of renewable energy generation, such as building integrated photovoltaics (BIPV) has been increased in many countries [1]–[3]. With renewable energy generation, customers can be transformed into prosumers, a new type of energy users with the capability to produce electricity and sell their excessive energy to the market. To accommodate the high penetration of prosumer with locally operating distributed renewable energy resources (DRERs) and distributed energy storages (DESs), various new smart grid technologies and applications have been proposed [4]. These smart grid technological advancements bring opportunities to transform the current power system to energy internet (EI). Using the so-called energy router, EI improves energy utilization containing all novel phases of energy generation, transmission, storage, and distribution.

In the EI ecosystem, electricity system transforms to be more decentralized. Prosumers can be joined flexibly and seamlessly to the closest local area energy network (E-LAN). As depicted in Figure 1, the EI ecosystem consists of all energy actors which are distributed and connected each other over the networks. With bidirectionally electricity direction, the energy can be exchanged and transferred between one node to another node. The energy sharing economy can be realized [5], in which enable energy customers to obtain the supplies directly from the nearest producers. Moreover, the cascading failure or blackout could also be resisted by an extensive interconnection of energy delivery and management system, which improves the stability of whole power systems.

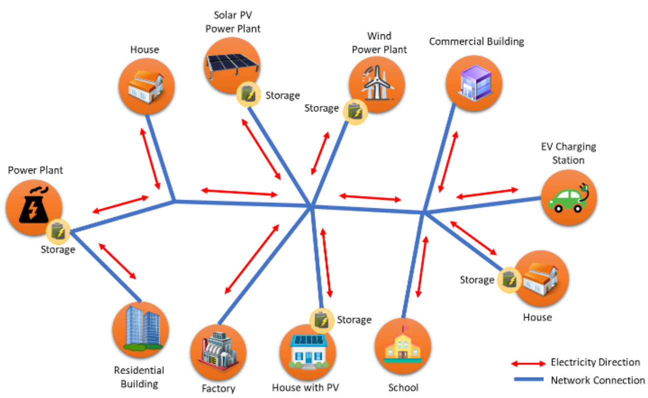

FIGURE 1. Energy internet ecosystem.

It should be noted that the EI has attracted increasing attention of government and institution in many countries. As a response to the Fukushima nuclear crisis, a large group of Japanese firms is starting to explore internet business model of electricity grid [6]. Besides, the Chinese government and the state grid corporation of China (SGCC) launches the global energy internet action plan throughout a whole nation [7]. They believe, the EI can be an ultimate solution to reorganize the country's power system, which shifts from centralized to decentralized control with various energy resources. Furthermore, EI is the most promising solution to enable the internet of microgrids for rural electrification in Indonesia, a country with more than 17,000 islands [8]. However, being in its infancy stage, EI business values and social benefits are becoming increasingly apparent with the advances in smart grid technologies. Many works need to be performed in the smart grid development to support the diverse and rigorous requirements of reliability, flexibility, latency, and security in EI ecosystem. Thus, the emerging technical initiative (ETI) on smart grid communications (SGC) has issued a positioning paper in 2018, which include EI as one of the eight structure research agenda [9].

The core task of EI construction is the building of open platforms for implementing end-to-end interactions across the entire value chain. However, EI is a very complex system with various applications that have specific and strict functional requirements to deliver both information and energy-flows [10], [11]. Many applications, including distribution automation, load control signaling, and outage alarming, are described to require a real-time capable communication network. Although some other applications, e.g., smart-meter data collection, are more latency tolerant, however, they need to have a high level confidentially, availability, and integrity. Thus, deep learning aided prediction for improving cybersecurity in energy internet has been proposed in [12]. Hence, to fulfill all requirements, network intelligence utilization, in which deep examining information-flows in real-time using network security applications, traffic analysis elements, and so forth is inevitable.

In recent years, the ETI for network intelligence have works together to utilize software-defined networking (SDN) technology, network function virtualization (NFV) technology, and artificial intelligence techniques in future internet architecture. Most recently, SDN/NFV-enabled network, in which NFV as a role in providing network service functions, and SDN has a position as a glue between those services, allows us to provide network intelligence middleware in a consolidated middlebox [13]. By taking service policies as the inputs, a set of functions in consolidated middlebox fulfilling all requirements requested by applications in term of minimum bandwidth, reliability, maximum latency, service level agreement, security and so forth. However, how to place and manage network intelligence middleboxes in the SDN/NFV-enabled communication network is a big challenge. Some previous research works proved that this problem is a non-deterministic polynomial-time (NP)-hard, which is complex and time-consuming decision problem [14]–[16].

Some middleboxes placement approaches with different objectives have been proposed. J. Liu *et al.* [14] formulate two objective functions, i.e., delay and bandwidth consumption minimization, with considering three constraints. The first constraint is middlebox resources capacity, having the capability to make sure that each middlebox has enough processing power to perform network intelligence functions. The second and last constraints are employed to make sure that each middlebox should be successfully deployed at a desired location in the network. On the other hand, Y. Chen *et al.* [15] handle the middlebox placement as a contrasts problem with the previous works. Their objective is to balance hardware set-up cost and bandwidth consumption having effects on the network intelligence performance and processing latency. Hence, we could not find the optimal solution for all purposes. However, a relaxation optimization method would be useful to achieve a suboptimal solution.

In this paper, we propose a placement and resource allocation strategy as a relaxation optimization method to achieve latency-optimal network-intelligence utilization in SDN/NFV-enabled EI communication network. The main contribution of this paper is as follows:

1) We investigate several existing network intelligence utilization approaches, which helps to reformulate our objective function and considered constraints.
2) We formulate an objective function for latency minimization, which is essential for the most applications in EI ecosystem.
3) We consider three main constraints, i.e., the middlebox processing power capacity, the forwarding nodes resource, and the communication links configuration.
4) We propose our heuristic solution which consists of two steps, those are, i) a graph clustering analysis, and ii) a dynamic CPU allocation mechanism.

5) We evaluate our approach along with the baseline methods on two communication network technologies, i.e., FatTree and Abilene. We expect that these represent two possible network topologies for EI communications.

We believe that this work may provide the best option to the communication service providers (CSP) in providing latency-optimal network, meanwhile fulfilling all functional requirements using network intelligence in EI ecosystem.

The rest of this paper is organized as follows. In the next section, we provide our investigation of existing approaches to enable network intelligence services. Section III describes our system model and problem formulation. Section IV explains the proposed solution, section V presents our evaluation, and finally, section VI concludes this paper.

II. BACKGROUND AND RELATED WORKS

A. SERVICE ABSTRACTION MODEL

In recent years, the national institute of standards and technology (NIST) and the open smart grid (OpenSG) network task force have comprehensively analyzed all possible functional requirements of various applications for future EI ecosystem. Currently, not less than 1400 application data flows have been specified in details, including their payload size, payload types, security, latency, reliability, data transmission frequency, and so forth [17]. There are also several groups that work together to specify the quality of services (QoS) requirements for the specific application. For example, the North American synchrophasor initiative network (NASPInet), a working group with the mission to improve power system reliability and visibility through wide area measurement and control. They have contextualized synchrophasor application data quality and determine five types of data services with specific traffic attributes as depicted in Table 1. Class A is to support the needs of high-performance feedback control applications. Thus, the communication network for this class is critically essential, which should have a fast data rate and very low latency, as well as provides a high level of data availability. Classes B and C are to provide applications with less strict latency requirement such as feed-forward estimator enhancement and view only applications, respectively. Class D is to support the need for post-mortem event analysis, and class E is intended for testing, research, and development. To understand all requirements above and provide network intelligence services correctly, a service abstraction model is indispensable.

To the best of our knowledge, SDN/NFV-enabled network does not have a formalized model for describing the dynamic aspect of service function requirements yet. One existing service abstraction model has been proposed by Gde *et al.* in [19]. In their model, the service function requirements are represented by three sets of parameters, i.e., content, context, and resources. To be detailed, the content provides the service related parameters such as payload type, payload size, maximum delay, minimum bandwidth, and so forth. Furthermore, the context serves the users/applications related

TABLE 1. NASPInet traffic attributes [18].

Traffic Attribute	*A*	*B*	*C*	*D*	*E*
Low Latency	4	3	2	1	1
Availability	4	2	1	3	1
Accuracy	4	2	1	4	1
Time Alignment	4	4	2	1	1
High Message Rate	4	2	2	4	1
Path Redundancy	4	4	2	1	1

Key: 4-Critically Important, 3-Important
2-Somewhat Important, 1-Not very Important

parameters concerning interest, such as data transmission frequency, schedule, and location. Last, the resources supply the requirements of network service resources such as networking medium, computing power, memory space, etc. Figure 2 depicts the service abstraction model template for any types of application data services.

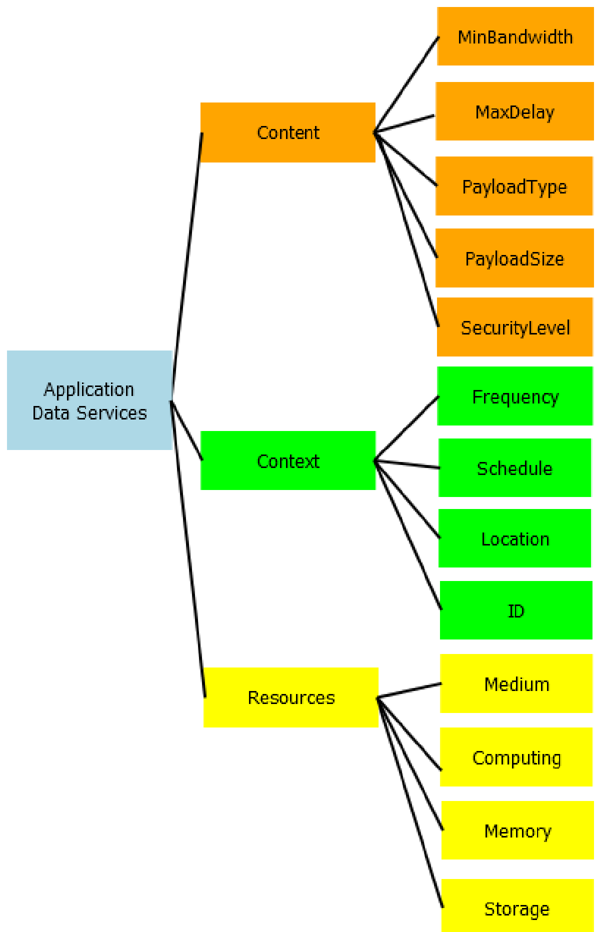

FIGURE 2. Service abstraction model template for application data services.

B. NETWORK INTELLIGENCE APPLICATIONS

The evolution and growth of internet technologies offer possibilities for CSP to provide new types of network products and services. To create and deliver differentiating services, a network intelligence function captures the detailed information and provides the analysis of user demand, as well as manages the usage once deployed. Some essential applications of network intelligence are listed in Table 2.

TABLE 2. Network intelligence applications.

Purpose	Example Applications
Understand Customer Demand	• User behavior analysis • Customer segmentation • Personalized services
Manage Services	• Resources optimization • Quality of experience analysis • Regulatory compliance • Denial of services detection

Recently, many research have been conducted to utilize machine learning (ML) algorithm for improving network intelligence functionality, in term of traffic classification [20], traffic prediction [21], accelerates service provisioning [22], intrusion detection [23], and so forth. Moreover, some experiential networked intelligence (ENI) have been started recently to utilize ML, SDN, and NFV combined together in providing an intent-driven and autonomous driving network. For example, the securing against intruders and other threats through an NFV-enabled environment (SHIELD) project in [24], demonstrates a framework to detect network attacks in SDN/NFV-enabled network using a policy-driven control loop intelligently. Adopting this framework to EI communications, we can utilize ML-based attack detection and mitigation recipes through an intent-based security policy to fulfill the main cybersecurity requirements in EI ecosystem as follows [25]

1) **Attack detection and resilience operations**. The need to monitor network traffic in real-time, detect abnormal incidents due to various attacks, and the self-healing ability to continue operations in the presence of attacks.
2) **Identification, authentication, and access control**. To verify the identity of a device/user before granting access to resources, especially for accessing users information and consumption data. It is essential to ensure that resources are accessed only by the appropriate entities that are correctly identified.

Hence, secure and efficient communication network are both required for reliable information-flow delivery in EI. However, these objectives usually contradict each other. Some network intelligence services, e.g., firewall, deep packet inspection (DPI), distributed denial-of-service (DDoS) prevention, and so forth, may produce processing delay time that affects to total latency over than requirement threshold. Thus, optimal tradeoffs are required to balance information security and communication efficiency when designing a communication network for EI ecosystem.

As depicted in (1), the latency minimization is an important factor for the reliability of EI ecosystem, expressed as

$$P_s \int_0^L f_{D|s}(t)dt \geq R, \tag{1}$$

where P_s is the probability that the payload reaches the destination node, L is the application latency requirement, R is the reliability requirement, and $f_{D|s}(t)$ is the delay density of a payload, conditioned on successful delivery. Hence, because the reliability requirement is defined, the successful delivery of the application data flow with a delay greater than the threshold is still considered as a failure [26].

C. EXISTING PLACEMENT APPROACHES

Some existing works have proposed flow routing schemes to manage data flows in the SDN/NFV-enabled network infrastructure. A constrained shorted path has been formulated as

$$r^* = \arg\min_r \{f_C(r) | r \in R_{st}, f_D(r) \leq D_{\max}\}, \tag{2}$$

that is, finding a forwarding route r from a set of all routes R_{st} that minimizes the objective function $f_C(r)$ such that the delay variation $f_D(r)$ to be less than or equal to the threshold value D_{max} [27]. Furthermore, the constraints could be varied, ranging from traffic-chaining ratio, bandwidth consumption, deployment cost, energy consumption, and so on [28]. However, no matter what flow routing scheme is used, the network intelligence placement strategy provides the most significant effect on network latency. To handle this, some approaches have been proposed. [14] formulates the latency minimization function as

$$\min \quad D^{tot}, \tag{3}$$

$$s.t. \sum_{\forall s_l \in \mathcal{S}} x_{i,l} = 1, \forall q_i \in \mathcal{Q}, \tag{4}$$

$$\sum_{\forall q_i \in \mathcal{Q}} R(q_i) x_{i,l} \leq C(s_l), \forall s_l \in \mathcal{S}, \tag{5}$$

$$x_{i,l} = 0, \forall q_i \in \mathcal{Q}, \forall s_l \in \mathcal{S}, \tag{6}$$

where D^{tot} is the total end-to-end delay of all service policies, $x_{i,l}$ is the binary variables to represent placement scheme in a switch s_l, $l = \{1, 2, ..., N_s\}$, in the set of switch $\mathcal{S}$, and N_s is the total number of switch. Furthermore, $R(q_i)$ is the required resource to deploy network intelligence middlebox q_i inside the set of $\mathcal{Q}$, $i = \{1, 2, ..., N_q\}$,N_q is the total number of middlebox, and $C(s_l)$ is resource capacity of each switch inside $\mathcal{S}$.

To provide latency minimization, they consider three constraints, i.e., constraints (4), (5), and (6). The constraint in (4) is to guarantee that each middlebox should be successfully deployed at one location, where $x_{i,l}$ = 1 denotes that middlebox q_i is connected to switch s_l, otherwise $x_{i,l}$ = 0. Furthermore, the constraint in (5) is to guarantee that the total resource demand for network intelligence deployment at one location should not exceed the switch resource capacity. Next, the constraint in (6) is to accommodate for middleboxes that can only be placed in certain places. It is considering that a middlebox may require a power supply and acceleration by some dedicated platforms, which are available only at some locations.

On the other hand, with omitting the subscript i from the equations for simplicity explain the type m middlebox, [29] formulates the objective function for latency minimization as

$$\min\ d_f,\ \forall f \in F_m, \tag{7}$$
$$s.t.\quad r(s_l) \leq R(s_l),\ \forall s_l \in \mathcal{S}, \tag{8}$$
$$\sum_{f\in F_m} o_f \leq \sum_{j=1}^{q_m} O_{m_j}. \tag{9}$$

$f \in F_m$ is a flow from a set of data-flows which require network intelligence services type m, d_f is the total latency of each data-flow from source ingress-switch to destination egress-switch via corresponding network intelligence middleboxes. Furthermore, q_m is the number of middleboxes type m in the network, o is the requested processing power, and O is the maximum processing power capacity. In this context, we have two constraints, i.e., constraints (8) and (9). Constraint (8) is the switch resource constraint, which is utilized to confirm that a switch has available memory for storing new route table entries. Constraint (9) is the middlebox capacity constraint, to ensure that a corresponding middlebox has enough processing power capacity to process the network intelligence services requested by data-flows.

[29] solves latency minimization problem with two intuitive properties. The first property is derived from [14], that it is better to place network intelligence middlebox as close as possible to the most-common switches. Next, the second property is their own intuitive belief, that it may better to divide network such that the data-flows with a set of ingress-switches that are close to each other to share the same middlebox in a cluster. Taking advantage of the basic idea of [14], [29], we reformulate the network intelligence placement and resource allocation problem for latency minimization in the context of EI communications. The following section describes our system model and problem formulation in details.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

Let the EI communications using SDN/NFV-enabled network infrastructure is represented as a simple directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{v_1, v_2, v_3, ..., v_i\}$ is the set of nodes and $\mathcal{E} = \{v_i, v_j\}$ is the set of links, where we apply again the subscript i and j as the subscript of the node couple in general. Let denotes the maximum number of policies can be stored in a switch $\mathcal{S} = \{s_1, s_2, s_3, ..., s_i\} \in \mathcal{V}$ is P_s, thus the number of policies that are currently stored in a switch flow tables is denoted as $p_s \in P_s$. If the set of all network intelligence services is denoted as $\mathcal{C} = \{c_1, c_2, c_3, ..., c_k\}$, then a middlebox which supplies those services is $\mathcal{B}_c \in \mathcal{V}$. There may be $n = \{1, 2, 3, ..., \mathcal{N}\}$ number of middlebox available in the network, thus let us denoted $\mathcal{N}_{\mathcal{B}c}$ as the number of network intelligence middleboxes. Each middlebox has a maximum processing power capacity $\mathcal{O}_b$ to perform a set of network intelligence services. This processing power capacity depends on the available CPU in each middlebox, which is represented in Mbps unit. Table 3 depicts example of network intelligence services and their resource requirements.

TABLE 3. Example of network intelligence services and their resource requirements [16].

Services	*CPU Required*	*Processing Capacity*
Firewall	4	900 Mbps
Proxy	4	900 Mbps
IDS	4	600 Mbps

Following service abstraction model as described in the previous section, an information-flow f can be described as $f_k = \{source_k, dest_k, c_k, o_k\}$, where $source_k$, and $dest_k$ are the source and the destination node, c_k is the must be visited network intelligence services of an information-flow's network traffic from source to destination, and o_k is the amount of middlebox processing power capacity occupies by a flow. With the knowledge of all information in advance, we can generate $F_{\mathcal{B}c}$, a set of information-flows which require network intelligence services from a network intelligence middlebox.

B. PROBLEM FORMULATION

Let us define total latency, as

$$D_f^{tot} = \sum_{\forall o_k} \sum_{\forall v_{ij}\in\mathcal{V}} d_{if,bf} + \sum_{\forall o_k} \sum_{\forall v_{ij}\in\mathcal{V}} d_{bf,ef}, \tag{10}$$

where, $d_{if,bf}$ is the aggregate latency from the source ingress-switch to the corresponding network intelligence middlebox and $d_{bf,ef}$ is the aggregate latency from the corresponding middlebox to the destination egress-switch. The aggregate latency depends on the packet delivery time $\alpha = d_{v_i,v_j}$ in each link between two nodes and the services processing delay in each middlebox. The packet delivery time and the services processing delay estimation are depicted in (11) and (12), as

$$d_{v_i,v_j} = \frac{Z_{max}}{B_r} + \frac{Xv_i, v_j}{L_s}, \tag{11}$$

$$d_{c_k,o_k} = \frac{M_{c_k} * o_k}{\beta\, O_b}, \tag{12}$$

where, M is the number of information-flow traffics which request network intelligence services k and β is the percentage of processing power resource allocation for each service. The satisfaction of services processing delay follows the logarithmic utility function as depicted in Figure 3. As the percentage of resource allocation increases, satisfaction rate will also increases, which means delay decreases. Furthermore, Z_{max} is the maximum packet size in bit, B_r is the transmission bit rate in bit/s, Xv_i, v_j is the distance or the length of transmission medium in meter, and L_s is the ratio of actual propagation speed to the speed of light of the medium in m/s. To the best of our knowledge, the propagation speed depends on the physical medium of the link, e.g., 2 x 10^8 m/s for copper wires and 3 x 10^8 for wireless communication.

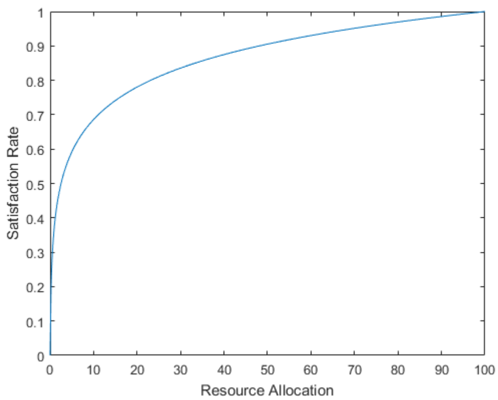

FIGURE 3. Services processing satisfaction rate.

We need to find all network intelligence placement and resource allocation scheme that minimizes the total latency of each flow $f \in \mathcal{F}_{\mathcal{B}_c}$ as follows, as

$$\min\ D_f^{tot}\ \forall f \in \mathcal{F}_{\mathcal{B}_c}\ \text{ according to (10)}, \tag{13}$$
$$s.t. \quad \alpha > 0, \tag{14}$$
$$0 \leq \beta \leq 1, \tag{15}$$
$$\sum_{\forall s_i \in \mathcal{S}} x_{N,i} = 1, \forall B_c \in \mathcal{V}, \tag{16}$$
$$\sum_{f_i \in F_{\mathcal{B}c}} o_k f_i \leq \sum_{j=1}^{N_{B_c}} O_{b_j},\ \forall \mathcal{B}_c \in \mathcal{V}, \tag{17}$$
$$p_s \leq P_s,\ \forall \mathcal{S} \in \mathcal{V}. \tag{18}$$

In this problem, we have several constraints, those are, the constraint (14), (15), (16), (17), and (18). Constraint (14) and (15) as explained above, constraint (16), $x_{N,i} = 1, \text{otherwise} = 0$, is to guarantee that each network intelligence middlebox should be successfully connected to any SDN switch in the network. Furthermore, constraint (17) is the network intelligence processing power, to ensure that a corresponding middlebox having capacity to process the network intelligence services requested by information-flows. Next, the constraint (18) is the switch resource constraint, which used to confirm that a switch has available memory for storing new policy entries.

IV. HEURISTIC SOLUTION

We develop a placement and resource allocation strategy as the relaxation optimization approach for latency minimization. Firstly, adoption the basic idea of [14], [29], we construct a graph clustering analysis method which considering several additional conditions as follows

1) SDN-enabled EI communication infrastructure is a hierarchical network architecture to connect all groups of micro-grid cluster and the global power grid as depicted in Figure 4.
2) Since the objective of the clustering is to minimize the latency. The cluster center initialization method plays a significant role. Randomly choosing initial center will not guarantee that the packet delivery time between the cluster center and other nodes in the sub-network to be shortened.
3) The recalculated cluster center should be selected from switch that guarantee there is a physical connection between the cluster center and other nodes.
4) Otherwise, the distance calculation method need to accommodate indirect connection between nodes which may not physically be connected.

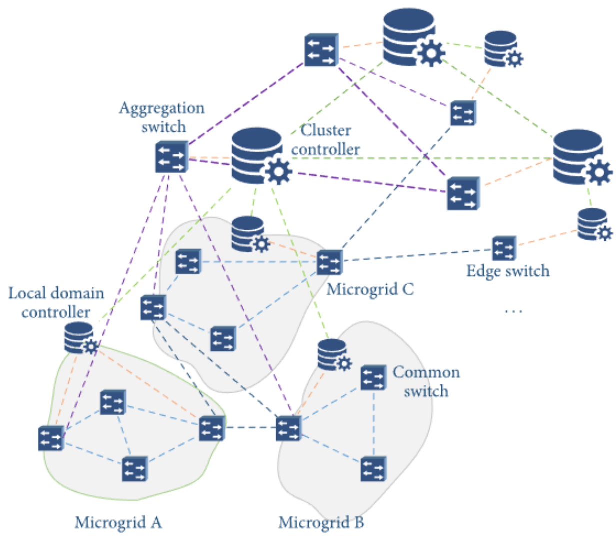

FIGURE 4. SDN-based energy internet communication network [30].

In this context, we employ a popular clustering techniques, K-means clustering algorithm [31] with some modification as depicted in Algorithm 1. Denote $C = \{c_1, c_2, ..., c_k\}$ as the set of clusters and let $M = \{\mu_1, \mu_2, ..., \mu_i\}$ is the nearest mean of each cluster, K-means usually uses to partition n observations into $k(\leq n)$ clusters in which each observations belong to the cluster C_i with the nearest mean μ_i as expressed as

$$J(C, M) = \arg\min_{C} \sum_{i=1}^{k} \sum_{n \in C_i} ||n - \mu_i||^2, \tag{19}$$

since the results of partitioning in K-means clustering is following the Voronoi cells, the Euclidean or Manhattan distance employs to measure silhouette value for validating similarity and dissimilarity of each point to its own cluster and other clusters, as

$$sv(n) = \frac{b(n) - a(n)}{max(a(n), b(n))}, \tag{20}$$

where, $a(n)$ is the average distance from n-th point to other points within the same cluster, $b(n)$ is the minimum of all

Algorithm 1 Graph Clustering Analysis using Modified K-means Algorithm.

Input: $G = (S, E)$, F_{B_c}, $S_{B_c} \in S$
Output: Set of switches in K clusters

1: **Step 1**: Compute the shortest path $d_{SP(s_i,s_j)}$
2: **Step 2**: Initialize cluster $K_0 = s_0$ and select one node from $S_{B_c} \in S$ as the first initial center ($K_c(0)$) of G
3: **Step 3**: Calculate packet delivery time from s_f to existing cluster center as $d_{s_f,K_c(i)}$.
   If $d_{s_f,K_c(i)} \geq \Theta_b$ **then**
   create a new cluster to contain s_f,
   else $K_c = K_c \cup s_f$
4: **Step 4**: Update cluster centre $K_c^{'}$ to find the closest switch to each obtained cluster, where the sum of shortest path delay time to reach all ingress-switches in a cluster is minimized.
5: **Step 5**: Calculate p_s for each switch $s_i \in K$
   If $\exists s_f \in K$ *such that* $p_s \geq P_s$ **then**
   s_f unqualified, continue to s_{f+1},
6: **Step 6**: Repeat steps 3, 4, 5 until the flow-network is partitioned into optimal or defined K sub-networks.

average distance from the n-th point to the points in each k-th cluster. Let the $sv(n)$ range is from -1 to 1, for $sv(n)$ that is close to 1 indicates that the i-th point lies well with the cluster it belongs.

Let a cluster K is composed of the ingress-switches of corresponding flows, that is $K = (s_1, s_2, ..., s_f)$, where s_f is the ingress-switch of a flow f. If $\mathcal{S}_{B_c} \in S$ is the set of ingress-switches of corresponding flows in F_{B_c}, then to determine the packet delivery time between each pair of switches, we calculate the shortest path (SP) delay time between them, as

$$d_{s_i,s_j} = d_{SP(s_i,s_j)}, \text{for } \forall\ s_i, s_j \in \mathcal{S}_{B_c}, \tag{21}$$

Using (21), we determine the packet delivery time thresholds Θ_b for each cluster as follows

$$\Theta_b = min\ d_{s_i,s_j} + \frac{max\ d_{s_i,s_j} - min\ d_{s_i,s_j}}{N_{B_c}}\ \forall\ s_i, s_j \in \mathcal{S}_{B_c}. \tag{22}$$

After collecting the SP computation, we initialize the first cluster K_0 and select one node from the set of ingress switch as the first initial cluster $K_c(0)$. Thus, indifferent with the basic K-means, the network partition uses the selected cluster center position as the cluster centroid instead of using the nearest mean, as expressed as

$$J(K, Me) = \arg\min_K \sum_{i=0}^{k} \sum_{s_f \in K_i} ||s_f - K_c(i)||^2\ , \tag{23}$$

where $Me = \{K_c(0), K_c(1), ..., K_c(i)\}$.

The cluster center of each cluster is then updated to minimize the sum of shortest path delay time to reach all ingress-switches. However, to satisfy the SDN switch resource constraint as in (18), we check and calculate the number of policy in each switch. Finally, repeat the steps until the flow-network is partitioned into optimal or defined K sub-networks.

Secondly, we design a dynamic CPU resource allocation scheme in each network intelligence middlebox. Taking the information-flows historical data as inputs, the CPU allocation for each service at a particular time depends on the ratio of those services repeatedly requested by applications/users in a corresponding cluster. Network intelligence services which have usage-ratio higher than a particular threshold θ_j is subject to be considered as one of important service, as

$$UR_{ij} = \frac{n \mid \sum_{t=1}^{T} P_{ijn}(t) \geq \theta_j}{N}, \tag{24}$$

where, i and j are indices of targeted cluster and network intelligence services respectively, n is the number of time-windows that services have been operated, $Pijn$ is the amount processing power of target services occupied by the information-flows in previous time windows n, N is the total number of observed time-windows. The usage ratio is in the range of UR_{ij} [-1:1].

Using the usage-ratio information, we define the resource allocation capacity for each service is as

$$RA_{ij} = Resv_{ij} + (Resv_{ij} * UR_{ij}), \tag{25}$$

where, $Resv_{ij}$ is the guarantee CPU allocation percentage for a service at the previous time-window. Figure 5 shows an example of the differentiate CPU allocation for a set of services at a particular time. The network intelligence services with a higher potential score will get higher resource allocation in the next period and vice versa. Furthermore, to protect network intelligence services from failures due to excess and un-predicted requests in a particular time-window, we employ NFV-Throttle [32]. When the volume of the request exceeds the resource allocation capacity, we evaluate the fraction of the request to drop as

$$\text{drop\_rate} = 100 \cdot \left(1 - \frac{RA_{ij}}{\text{incoming\_request}}\right), \tag{26}$$

if incoming_request $\geq$ max_capacity ; otherwise, drop_rate = 0.

V. EVALUATION

A. PLACEMENT WITH CLUSTERING

We implement a testbed based on NFV infrastructure emulation platform (NIEP) [33] in two separate machines, and each machine has 3.40 GHz eight-core CPUs and 8192 MB RAM. In more detail, NIEP utilizes the Mininet [34] and the Click-on-OSv [35] to deploy a complete emulated SDN/NFV-enabled network infrastructure. We decide to use two network topologies, i.e., Abilene and FatTree, which we expect

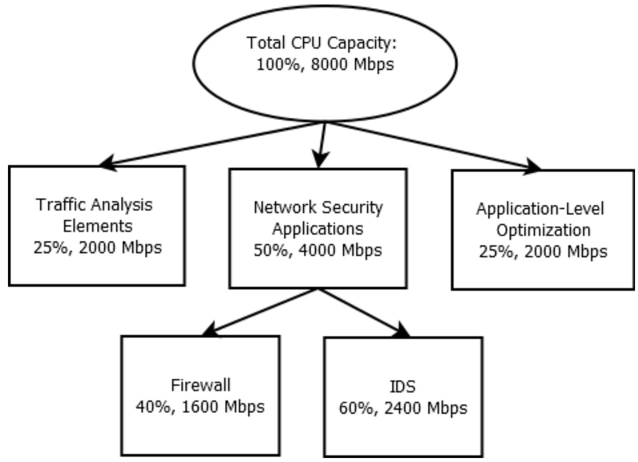

FIGURE 5. Differentiate CPU allocation.

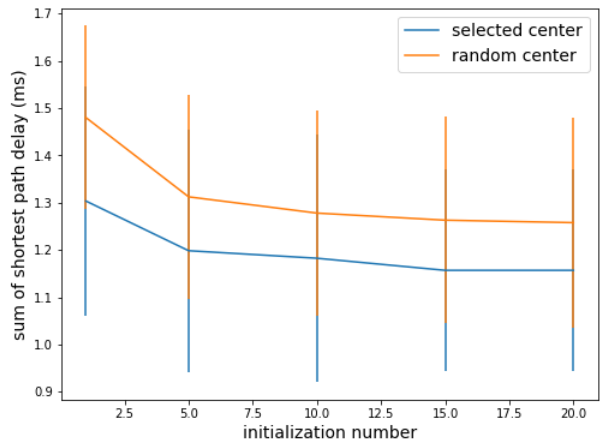

FIGURE 6. Average sum of shortest path delay for various initialization.

to represent two possible communication network topologies for EI. The characteristics of these network topologies are summarized in Table 4.

TABLE 4. The characteristic of network topologies.

Topology	*FatTree*	*Abilene*
S	20	11
E	32	14

We set our testbed with several assumptions as follow. First, the communication medium between two nodes is a copper-wires with randomly assigned losses following the normal distribution. Second, the transmission bit rate in each switch-port is 100 Mbps, but the distances between the two switches are randomly different. Third, there are five NFV-based middleboxes in each simulation, and those middleboxes could provide five kinds of network intelligence services. Next, there are a different number of the information-flows set that randomly request specific services. Last, the maximum number of clusters follows the total number of middleboxes. The summary of the parameters setting is described in Table 5.

TABLE 5. Parameter setting for the performance evaluation.

Parameter	*Value/Range*
B_c	5
C	5
F_{Bc}	30, 40, 50
o_k (Mbps)	From 0.1 to 1
$P(s)$	25
Z_{max} (bytes)	1500
B_r (Mbps)	100
L_s ratio (m/s)	from 0.6 to 0.9 * 2 x 10^8
Xs_i, s_j (m)	from 0.4 to 0.8

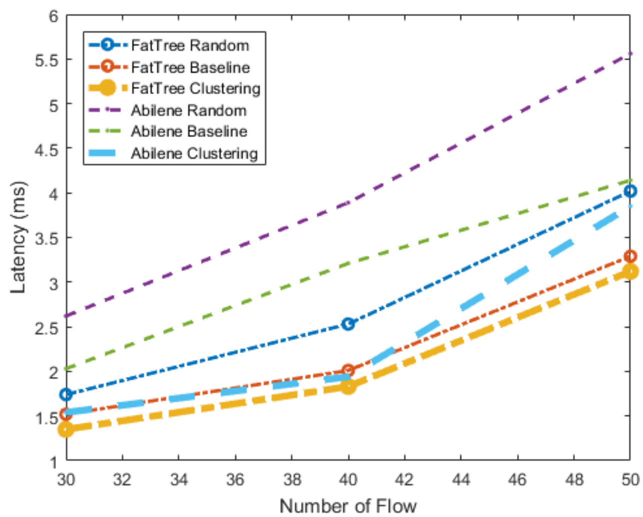

FIGURE 7. Average of network latency.

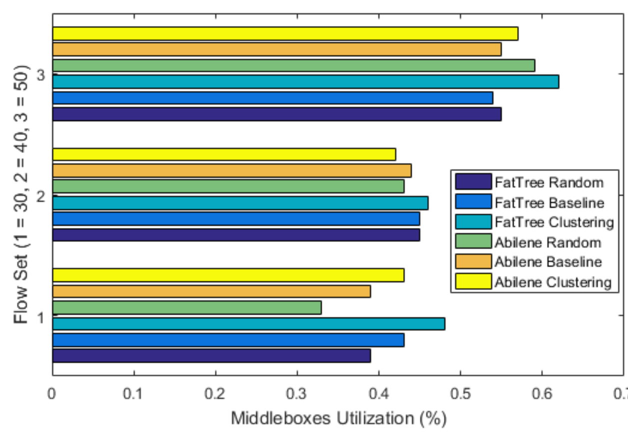

FIGURE 8. Average of middleboxes utilization.

For the first evaluation, we compare our selected cluster center initialization approach with the random method in the K-means clustering algorithm. Figure 6 depicts the results

TABLE 6. Recent works on SDN-enabled energy internet communications.

Relevant works	Achievements	Limitations
Z. Lu *et al.* [30]	General SDN-enabled communication network framework for information-flow control in energy internet.	Security issues for both information-flow and controller are not considered yet.
G. Zhang *et al.* [36]	Specific SDN communication network architecture for intelligent energy management (IEM) application.	High-latency in control networks, many works need to perform to handle all communication requirements.
W. Zhong *et al.* [37]	SDN energy internet architecture for both information-flow and energy-flow control, application with electric vehicle case study.	Initial works, thus the latency, security, and scalability requirements are left for future.
This paper	SDN communication network architecture with latency-optimal NFV-based network intelligence utilization for flexible, reliable, and real-time capable energy internet communications.	Energy saving scenario for network intelligence operation is left for future work.

of the average sum of shortest path delay time for various initialization in both random method and our proposed solution. The results show that our approach could guarantee that the packet delivery time between the cluster center and other nodes in the sub-network to be shortened.

We then evaluate the network latency for each generated flows set in the network. Figure 7 depicts the average of each flow network latency in both simulated network topologies. The results show that the graph clustering analysis implementation provides an enormous impact on reducing network latency compared to the random and baseline placement approaches. The average latency minimization improves around 20.19% and 7.10% in the Abilene and FatTree topologies, respectively. Hence, these results prove the intuitive properties and our considerations, as mentioned in the previous subsection. Furthermore, with the knowledge of information-flow in advance, it is better to put the middleboxes as near as possible to the set data flow ingress-switches and group them into one cluster.

Next, Figure 8 shows the average of middleboxes resource utilization. Based on these results, we could not find a direct relationship between middleboxes placement strategy to resource utilization. However, we conclude that the utilization increases along to the increasing number of flows. If the requested network intelligence services from all information-flows reach the middlebox processing capacity, it affects the service processing delay. It should be noted that the middlebox processing power capacity depends on the available CPU in each middlebox. Thus, to minimize the service processing delay and to avoid functionality failures, we need to apply the CPU bandwidth resource allocation mechanism.

B. EFFECTS OF RESOURCE ALLOCATION

We evaluate the effects of resource allocation by the following scenario. We generate a set of data-flows starting from 30 flows and increase one by one until 70 flows. We record the types and amount of requested network intelligence services from each generated set at a particular time. Using the recorded information, our proposed method reallocates the CPU resource for each service dynamically.

Figure 9 depicts the effects of CPU resource allocation to latency minimization. The average latency minimization improves around 4.24% compared to just merely clustering analysis approach. Hence, in total, the implementation of our network intelligence placement and resource allocation strategy provides average latency around 24.43% and 11.34% lower than the baseline approach, in the Abilene and FatTree topologies, respectively.

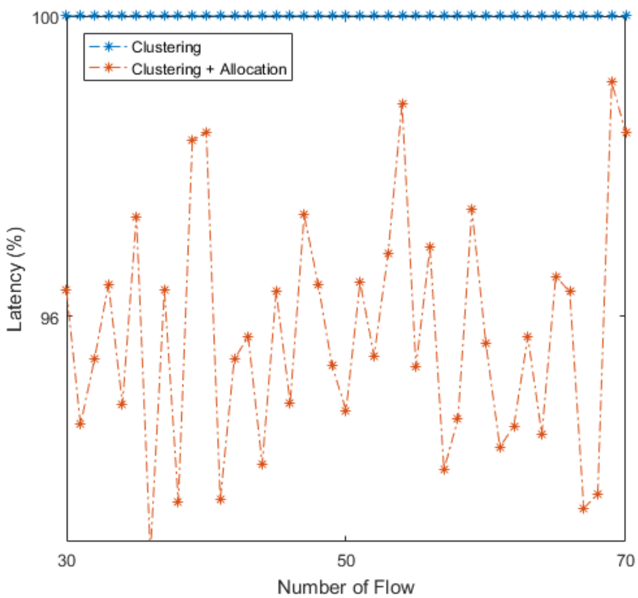

FIGURE 9. Effect of CPU resource allocation to latency minimization.

C. MANUSCRIPT POSITIONING

SDN technology is expected to be utilized to link energy stakeholders in a way that encourages active participation in building the EI ecosystem. The initial adoption of SDN in EI ecosystem has been presented in [30], [36], [37]. All were implementing SDN-based communication network hierarchically from microgrid cluster zone level to the global grid network. By applying this hierarchical architecture, we can manage applications data-flow from a higher abstraction level view. However, the existing works only focus on the underlying network implementation by merely comparing the traditional internet protocol (IP) network with the SDN-based EI communication network. This paper fills the gap on supporting various functional requirements needed by applications in EI ecosystem. Meanwhile fulfilling the requirements using network intelligence services, we develop a placement and resource strategy for latency-optimal implementation. Table 6 depicts the detailed comparison of our contribution to the related works in realizing the full functionality of EI using SDN-enabled communications.

VI. CONCLUSION

This paper is the first research works that introduce the utilization of NFV-based network intelligence for fulfilling functional requirements in the energy internet ecosystem. However, how to place and manage network intelligence middleboxes in the SDN/NFV-enabled energy internet communication network is a big challenge. By implementing our heuristic solution, we can fulfill the requirements with the latency-optimal network. Our results have verified that the graph clustering analysis and the CPU resource allocation scheme could reduce the total latency significantly. The graph clustering analysis supplies the latency minimization around 20.19% and 7.10% higher than the baseline approach in two network topologies, Abilene and Fat-Tree, respectively, while for both topologies the dynamic CPU resource allocation optimizes further the reduction around 4.24%. Even though the main objective of this paper is minimizing network latency, more targets such as energy saving can be implemented, meanwhile fulfilling all requirements in the future.

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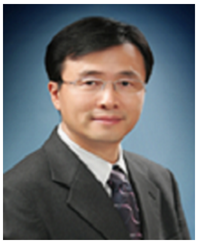

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