General Multi-constrained QoS Routing Using Nonlinear Function and Weighted Metrics

Maneenate Puongmanee and Teerapat Sanguankotchakorn
Information and Communication Technology Field of Study
School of Engineering and Technology
Asian Institute of Technology, Thailand
Email: st110595@ait.asia; teerapat@ait.ac.th

***Abstract*—**Quality of Service (QoS) is an essential mechanism to provide and manage restricted resources for various services and demands. Additionally, it is a crucial factor to guarantee application's requirements in computer communication and network. Generally, each application needs more than one QoS metric with different significance levels. Thus, the path satisfying all QoS metrics simultaneously with the same significance level is somewhat not realistic and too complicated. This research proposes the algorithm to optimally assign the appropriate weight to each QoS metric by using requirements and slackness to search for the best path satisfying multi-constrained QoS metrics. The proposed algorithm is called General Multi-constrained QoS routing using Weighted Metrics (G_MQW), which adopts the nonlinear cost function and relaxed Dijkstra's algorithm. The general mathematical closed-form is derived and the Look-ahead Dijkstra's algorithm is relaxed to accommodate the weighted QoS metrics. Additionally, we propose two control variables of the weight and verify their effects in finding the shortest path satisfying multi-constrained QoS. We evaluate the algorithm by simulation using Matlab on Waxman network topology. The performance evaluation metrics used here are Success Ratio (SR) and Computational Complexity. The results are compared with MPLMR, TAMCRA, H_MCOP, MPMP and BMCOP. It is shown that our proposed G_MQW provides the highest Success Ratio under the same environments as the other ones, while the computational complexity is comparable.

***Index Terms*—**Control variables, look-ahead, nonlinear, multi-constrained

I. Introduction

In the era of Internet, computer network, mobile devices, services and applications have become the fifth elements for well-being of human's life. They have been rapidly growing in use and likely to be essential elements of human community such as mobile clinic, emergency rescue, remote education and weather forecast. However, the fundamental structure of Internet and computer communication, Internet Protocol (IP), has basic fashion to provide the best effort services which is non-reliable.

In fact, the existing services and applications are required to provide different user demands, different fashion of services and resources. Quality of Service (QoS) embracing some significant attributes such as reliability and predictability, are considered as a long-term solution to support various services and applications. Due to different QoS demands of each application, more than one constraint of links along a path from a source to a destination are needed to be satisfied simultaneously. In traditional path selection, the routing protocol including network information such as link state, resource allocation and availability are deployed to find a feasible path according to the application requirements. Consequently, it is likely to have several paths satisfying different single constrained QoS metric while there may have no path satisfying multi-constrained QoS metrics. To find the path satisfying multi-constrained QoS simultaneously is NP-complete problem [1] in which several algorithms for paths selection have been proposed [2]-[4]. It cannot be exactly solved in polynomial time and has high computational complexity [5].

Three types of QoS routing algorithms have been defined roughly, they are 1) Restricted Shortest Path (RSP), which searches for the feasible path satisfying one QoS constraint 2) Multi-Constrained Path (MCP), which searches for the feasible paths satisfying multiple constrained QoS and 3) Multi-Constrained Optimal Path (MCOP), which selects the path having minimum cost parameter from the overall feasible paths satisfying multiple constrained QoS [4]. Additionally, QoS metrics are usually categorized into two classes; additive and non-additive (concave) metrics. For additive QoS metrics (e.g., jitter, delay, hop count, etc.), the cost of the whole path from a source to a destination can be calculated by the accumulation of each QoS metric along the path. Some multiplicative metrics namely reliability, probability of successful transmission, etc., can be calculated as additive metrics by taking logarithm, therefore, they are categorized as the additive metrics. In case of the non-additive (concave) metric (e.g., bandwidth), it is defined as all links which satisfy QoS constraints according to the minimum or maximum value along the path. In general, the concave metrics can be easily measured by discovering the minimum or maximum value while additive metrics must be calculated along the whole path. In this work, the additive metrics are mainly considered.

The additive QoS metrics can be characterized based on their link correlations; positive, negative and no-correlation. In case of positive link correlation, the value

Manuscript received November 12, 2019; revised May 11, 2020.
doi:10.12720/jcm.15.6.480-495

of one QoS metric has the same trend as another one. For example, the larger number of hops can produce longer delay and jitter. In case of negative link correlation, the value of a QoS metric has the opposite trend as another one. For instance, the path with high reliability has mostly low delay or low jitter. However, in case of no-correlation, there is no relationship among all QoS metrics. Several existing QoS routing algorithms [3]-[4], [6]-[8] consider multiple QoS metrics having the same significance level. In fact, the QoS metrics for each application in a real network have different levels of significance. For instance, the real time application usually requires the extremely low delay while the loss level is tolerable [9]. On the other hands, file transferring is loss-sensitive application, where the loss parameter is a major factor affecting this service rather than the other parameters [10]. QoS metrics on existing resources are dynamically changed which lead to the link correlation change between two QoS metrics. Several algorithms propose solutions to classify QoS as different priorities for different types of link correlations according to the demand of services. In general, the weight is deployed as a key to allocate the existing network resources appropriately for services and applications. It is almost generated from state and network information in routing protocols.

For additive metric in multi-constrained QoS routing, the feasible path satisfying the ith QoS metric is computed based on the accumulation of link cost with respect to the ith QoS metric between a source and a destination. Suppose L_i and C_i represent accumulated link cost and link constraint with respect to the ith QoS metric, respectively. The accumulated link cost, L_i, can be represented as the required resource with respect to the ith QoS metric along the path. In order to meet a feasible path, the required resource with respect to the ith QoS metric normally must not violate link constraint ($L_i \leq C_i$). However, in several requests, L_i is too small and lower than C_i. This means the resource with respect to the ith QoS metric is available to the other requests. In this research, the remaining resources which are available for the others is called *slackness*. Suppose, NL_i denotes normalized link cost and satisfies the link constraint ($NL_i \leq C_i$) with respect to the ith QoS metric, then *slackness* is represented as $1 - NL_i$.

In this research, we propose a heuristic method based on concept of slackness to generate and assign the appropriate weight for each QoS metric with optimized shortest path under multiple constraints. A suitable path according to the ith QoS metric, relies on either any path that satisfies the required metric or the slackness. Each weight metric can be generated by using the required resources and slackness with various values of control variables (Cv) under different types of link correlations. Our proposed algorithm is called General Multi-constrained QoS routing using Weighted Metrics (G_MQW). The proposed G_MQW relies on the nonlinear cost function and Dijkstra's algorithm to search for k suitable paths satisfying multiple QoS constraints. The Dijkstra's algorithm is relaxed to accommodate the weighted QoS metrics, while the weight consists of control variables depending on normalized cost and normalized slackness. They are allocated to QoS metrics based on the application requirements where the QoS metrics may have different correlations. The solution is provided in general mathematical closed form.

The proposed algorithm is adopted to enhance the probability of finding the feasible paths under various types of link correlations by applying weight on each metric. Additionally, it is extended to provides multi-constrained optimal path selection with minimum cost.

The performance of our proposed algorithm is evaluated by simulation using Matlab. The effect of each control variables in finding the path satisfying multi-constrained QoS using weight metrics is verified under three types of QoS metrics' correlation; no-correlation, positive and negative. This work is limited on path selection under additive QoS metric for unicast communication in network layer. The success ratio and computational complexity are adopted as performance evaluation metrics. The simulation results of our proposed G_MQW are compared with the existing algorithms: TAMCRA [3], Multi-constrained Optimal Path Selection [4], MPMP [11], MPLMR [12] and BMCOP [13]. According to the simulation results, it is obvious that our proposed G_MQW provides the highest success ratio among all existing algorithms. Additionally, the complexity of our proposed algorithm is lower, if not the lowest, compared to the existing ones.

The rest of this paper is organized as follows: The definition of MCOP problem and nonlinear function including the basic concept of G_MQW are briefly described in Subsection A, while the relevant works are revised in Subsection B of Section II. The algorithm for appropriate weights allocation to each QoS metrics are proposed and explained in Section III. The topologies as well as parameters used in our simulation are defined in Section IV while Section V discusses the results. The work is concluded in Section VI.

II. Preliminaries and Related Works

A. Preliminary

Definition 1 Multi-Constrained Optimum Path (MCOP) problem:

Consider a network that is represented by a directed graph $G(V, E)$ where V is the set of nodes and E is the set of links. Each link between arbitrary node u and $v, ((u, v) \in E)$ is associated with a primary cost parameters $h(u, v)$ and the q additive cost $c_i(u, v)$ where $i = 1,2, \dots, q$. Given q QoS constraints C_i, $(i = 1,2, \dots, q)$, the MCOP problem is to find a path p from source s to destination t such that:

(a) $L_i(p) \equiv \sum_{(u,v)\in p} c_i(u, v) \leq C_i$ for $i = 1,2, \dots, q$ and

(b) $h_p \equiv \sum_{(u,v)\in p} h(u,v)$ is minimized overall feasible paths satisfying (a).

where $L_i(p)$ is the accumulated link cost of path p with respect to the ith QoS metric.

A path satisfying (a) is called *a feasible path* or *feasible solution*, and a path satisfying both (a) and (b) is called *an optimal solution*. If the second condition is not satisfied, then the problem is MCP.

Definition 2 Let $X_i(p)$ and $S_i(p)$ represent the normalized cost and normalized slackness with respect to the ith QoS metric of path p, respectively. Both can be defined as follows:

$$X_i(p) = \frac{L_i(p)}{C_i} \tag{1}$$

$$S_i(p) = 1 - X_i(p) \tag{2}$$

For any path p from a source s to a destination t, the nonlinear cost function can be illustrated as follows:

$$g_\lambda(p) = \sum_{i=1}^{q} \left[\frac{c_i(p)}{C_i}\right]^\lambda \tag{3}$$

When $\lambda = 1$, (3) becomes linear cost function [14]. In general, the link cost of path p has to satisfy $c_i(p) \le C_i$ to provide QoS guarantee. When $\lambda \to \infty$, the nonlinear cost function defines the maximum normalized cost of path p as follows:

$$\widetilde{\Phi}(p) = g_\infty(p) = max\left[\frac{c_1(p)}{C_1}, \frac{c_2(p)}{C_2}, \dots, \frac{c_q(p)}{C_q}\right] \tag{4}$$

B. Related Works

The research on multi-constrained QoS routing has been carried out extensively. Several well-known algorithms are, for example, Tunable Accuracy Multiple Constraints Routing Algorithm (TAMCRA) [3] and Heuristic Multi-Constrained Optimal Path (H_MCOP) [4], [15]-[16]. TAMCRA considers and stores only non-dominated sub-paths with predefined and fixed number of k shortest path, while H_MCOP employs the backward and look-ahead methods to find a single post-path for updating the set of shortest k pre-paths. The linear cost function is used to combine all costs to compute the feasible shortest path in backward direction while nonlinear cost function is used to estimate the feasible paths in forward direction. Then, the optimization is performed to select the shortest path minimizing combined cost function. However, TAMCRA and H_MCOP find k feasible pre-paths with only single post-path.

In [16], the effect of a specific correlation structure between the link costs on QoS routing is studied. There are four factors mainly affecting the shortest path selection with multiple constraints: the underlying topology, link costs, negative correlation of the link costs and the values of the constraints. They found that the larger value of the constraints is, the higher the possibility of easily finding a feasible path becomes, and vice versa [6], [14], [17].

In [17], Optimized Multi Constrained Routing (OMCR) uses ON and OFF states to update network state information for finding the feasible paths [18]. After that, it performs optimal function to transform multi-constrained parameters into a single one. Distributed Heuristic Multi-Constrained Optimal Path (DHMCOP) [19] is an approach to find the feasible paths with minimum cost and guarantee QoS demands while minimizing time computation and protocol overhead. In [20], the shortest path for different types of services using fitness function is found and optimized in Particle Swarm Optimization (PSO). The path with the smallest value is the best path. For routing devices, energy-performance is an important element to select a suitable path in the Internet. [21] proposes the solution to minimize power consumption of network links. A feasible path is a network link with minimal energy consumption and satisfy QoS constraints in term of delay by applying non-linear programming formulation.

There are some works proposed for mobile ad hoc networks as well. For instance, the multi-constrained QoS routing algorithm, Generalized Multi-Constrained Path (G_MCP) [22] proposes to use the special parameter called weighted Connectivity Index (CI) to find the feasible paths and compare the result with H_MCOP. The improvement of packet delivery ratio is achieved. In wireless network, [23] proposes the Dynamic Path Switching (DPS), which is the solution to prevent path breakage instead of trying to maintain them. QoS-based with multi-constrained is applied in routing protocol for VANETs [24] to support intelligent transport system and infotainment application among vehicles while travelling. Additionally, the concept of repair-based for multi-constrained routing [25] is used for congestion control in wireless mesh networks. In wireless network for smart distribution grid, [26] presents a delay-constrained cost optimization model to satisfy cost and QoS requirements by queuing and delay-constrained for dynamically allocate heterogeneous data to different output networks. In wireless networks, several nodes are not always attached to each other. [27] presents Selfish Secondary Users algorithm with dynamic rate allocation multipath routing to discover path stability under an available channel and prioritized for different session.

Some works namely Nonlinear Lagrange Relaxation Multipath Constrained Problem (NLR_MCP) [28], Tabu Search Multi-Constrained Optimum Path (TS_MCOP) [29] and Path-Constrained Path-Optimization (PCPO) [30] are developed by extending H_MCOP with nonlinear Lagrange relaxation under constraint factors selection. In NLR_MCP, the technique to select the appropriate constraint factors on network links is proposed to provide higher success probability and optimality. In TS_MCOP, the function called Branch_and_Bound is presented for achieving the higher probability of the optimal path finding while PCPO presents the mathematical models to solve the modern routing problems with multiple criteria. Additionally, several solutions [31]-[35] apply the

concept of ant colony (the smart agent to search and keep history and information of network traffic) for optimal path selection in wireline and wireless sensor networks.

Regarding the centralized data architecture, Server-Centric Multi-Constrained Routing Algorithm (SCRAT) [36] is proposed to select a feasible path in server-centric data centers for DCell [37] and BCube [38] to reduce the complexity of path selection and give optimal and feasible paths. Additionally, in [39], it offers topological-related routing algorithm which relies on neighbor node and path-length metrics to reduce the time complexity and increase the number of optimal paths under additive and non-additive metrics.

Several works handle the problem of overhead packets for QoS negotiation in network (e.g., stateless QoS routing and MPLS). For example, the Bidirectional Multi-constrained routing algorithm (BMCOP) [40], presents a k shortest paths algorithm using bidirectional path search to alleviate the forwarding state scalability and select the convergence of existing QoS routing algorithms.

Time complexity is also a major challenge in finding a feasible path for network with multi-constrained QoS. In [41], it assesses and analyses the performance of QoS network using discretizing QoS network while an Enhanced version of Fully Polynomial Time Approximation Scheme (EFPTAS) [42] evaluates the guaranteed paths with low time complexity using auxiliary graph. In [43], the algorithm to improve time complexity for finding feasible path by using a customized lightweight evolutionary strategy [44] is presented.

Some works adopts the Genetic algorithm solution with crossover of feasible sub-path as well. For instance, in [45], it proposes cross-over refine operation which can increase the possibility as well as reduce the number of iterations of finding the feasible path. Meanwhile, [46] presents genetic algorithm with repairer to select crossover path. Then, it makes mutation path which can reduce number of times to explore more feasible paths.

In [12], the algorithm called Multi-postpath-based lookahead multi-constraint QoS routing (MPLMR) is proposed to find a shortest path from a source to a destination using several sub-paths consisting of multi-pre-path and multi-post-path via intermediate nodes. Similar to [3],[15] MPLMR uses improved look-ahead method but applies the suitable weighting on each QoS metric. Additionally, in order to increase the number of feasible paths, relaxed nonlinear cost function is deployed for post-path selection based on QoS metric for different types of application as presented in [40].

Although [12], [15] and [28] propose appropriate weights with respect to each constraint, most of them are defined to have the same priority while applications require different types of QoS metrics. Therefore, the approach to consider multiple QoS metrics with different weight is needed. The basic concept of the proposed research was published before by the authors in [47], but this paper investigates further in the great details and provides many results that has never published before.

III. Proposed Algorithm

In this section, the concept and components of our proposed G_MQW is described in detail. The general idea of our proposed G_MQW is presented in Fig. 1.

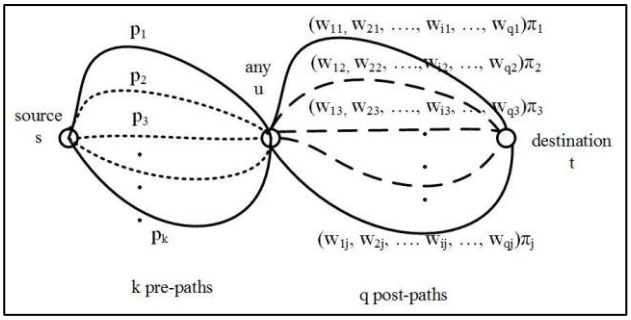

Fig. 1. The general idea of our proposed algorithm.

A *pre-path* is a subpath from source node s to an intermediate node u while a *post-path* is a subpath from an intermediate node u to destination node t. A full path is the combination of pre-path and post-path. In this work, the pre-path is calculated based on the nonlinear link cost ($\lambda > 1$ in Eq. (4)), however the post-path is calculated based on the linear link cost ($\lambda = 1$ in Eq. (3)). The proposed algorithm has been developed based on MPLMR. This approach proposes the algorithm to find k pre-paths using nonlinear link cost and q post-paths using linear link cost with weight allocation. The main difference between our proposed G_MQW and MPLMR is the method to calculate the post-paths. That is, MPLMR finds the post-paths based on $\sum_{j=1}^{q} X_i\,(p + \pi_j(u))$, while our proposed G_MQW finds the post-paths based on $\sum_{i=1}^{q} X_i\,(p + \pi_j(u))$, where $X_i\left(p + \pi_j(u)\right)$ is the normalized cost with respect to the ith QoS metric of shortest full path found by the combination of pre-path p and shortest post-path calculated with respect the jth QoS metric. In addition, the weight w_{ij} adopted in our proposed G_MQW is governed by two control variables (Cv), m and n, which can be adjusted according to the change of normalized cost and normalized slackness. An intermediate node u stores the combination of these sub-paths with weight on each QoS metric. The basic concept, pseudo code and algorithm of the G_MQW are described in the following Subsections.

A. Basic Concept and Components of Proposed Algorithm

The proposed algorithm consists of four elements, namely eligible pre-path, multiple post-paths with weight, path combinations and control variables (Cv) for weights of QoS metrics.

1) Eligible Pre-paths

The algorithm for the pre-path selection is similar to previous approaches such as MPLMR, TAMCRA and H_MCOP. That is, each node keeps at most k pre-paths and updates these paths during the procedure of link state routing protocol.

Let p be a pre-path from a source node s to an intermediate node u. Let $\pi_i(u)$ and $\pi_j(u)$ denote the shortest post-paths from an intermediate node u to destination node t with respect to any i^{th} and j^{th} QoS metrics, respectively, where $i, j = 1,2, \dots, q$. If the pre-path p is feasible and not dominated by the other pre-path p', p will be declared as an eligible pre-path. Then, either post-path $\pi_i(u)$ or $\pi_j(u)$ are extended to an intermediate node u. Therefore, the full path is $p + \pi_i(u)$ or $p + \pi_j(u)$. If $X_i(p + \pi_i(u))$ and $X_i\left(p + \pi_j(u)\right) > 1$ (in Definition 2) and p is not dominated by p', then, neither the full path $p + \pi_i(u)$ nor $p + \pi_j(u)$ is feasible path.

2) Multiple post-paths

Firstly, we find a set of feasible post-paths which have minimum accumulated link cost and does not violate constraint C_i for $i = 1,2, \dots, q$. For each post-path, we propose to use the relaxed Dijkstra's algorithm to find the shortest path based on each QoS metrics with weights and control variables in reversed direction from destination t to intermediate node u. The accumulated link cost with respect to each QoS metric is computed for any intermediate node u to a destination node t. Next, we deploy a look-ahead algorithm to approximate the nonlinear link cost of the shortest pre-path p then the shortest pre-path is combined with the set of feasible post-paths. The concept of the proposed algorithm is shown in Fig. 1.

3) Path combinations

After the pre-path is combined with the set of post-paths, the feasible shortest full path is selected from the smallest value of maximum normalized QoS metric.

Let $p_s(p)$ be the shortest full path, when a feasible pre-path p is extended by post-path $\pi(*)$, where $\pi(*)$ is the corresponding post-path of any node u (i.e., $p_s(p) = p + \pi(*)$).

Let $\tilde{X}_j(p_s(p))$ represents the normalized QoS metrics of the shortest full path $p_s(p)$ (extended by the post-path $\pi_j(u)$ at node u) with respect to the j^{th}QoS metric. From Definition 1. and 2., the shortest path is shown as follows:

$$\tilde{X}_j\left(p_s(p)\right) = \sum_{i=1}^{q} w_{ij}\, X_i\left(p + \pi_j(u)\right) \tag{5}$$

where $X_i(p)$ denotes the normalized cost of path p with respect to the ith QoS metric (in Definition 2.). The weight w_{ij} in Eq. (5) must satisfy Eq. (6) and can be illustrated as follows:

$$\sum_{i=1}^{q} w_{ij} = 1\,; for\ i, j = 1,2, \dots q \tag{6}$$

The selected path estimated by nonlinear cost function of $(p_s(p))$ from Eq. (5) is denoted as follows:

$$\tilde{\Phi}_i\left(p_s(p)\right) = \max_{j=1,2,\dots,q} \tilde{X}_j(p_s(p)) \tag{7}$$

For eligible k pre-paths combining with q post-paths, the smallest normalized cost of $\tilde{\Phi}_i\left(p_s(p)\right)$ is selected as the feasible full path on an intermediate node u. It can be presented as follows:

$$\tilde{\Lambda}\left(p_s(p_s)\right) = \min_{j=1,2,\dots,q} \tilde{\Phi}_i(p_s(p)) \tag{8}$$

4) Control Variables (Cv), m and n

Let m and n be non-negative real constants $(m, n \geq 0)$. The weight w_{ij} in Eq. (5) and Eq. (6) can be denoted as follows:

$$w_{ij} = \frac{\alpha_j}{[X_i(p+\pi_j(u))]^m\, [1-X_i(p+\pi_i(u))]^n} \tag{9}$$

where, α_j is the value satisfying Eq. (10) as follows:

$$\alpha_j = \left(\sum_{i=1}^{q} \frac{1}{[X_i(p+\pi_j(u))]^m\, [1-X_i(p+\pi_i(u))]^n}\right)^{-1} \tag{10}$$

According to the ith QoS metric, m is adopted to control $[X_i(p + \pi_j(u))]$ (normalized cost defined in Definition 2), while n is adopted to control $\left[1 - X_i\left(p + \pi_i(u)\right)\right]$ (normalized slackness of $X_i(p + \pi_i(u))$ defined in Definition 2). Thus, m and n have impact on the relative contribution to w_{ij}. If $X_i\left(p + \pi_j(u)\right) = 0$ or $X_i\left(p + \pi_i(u)\right) = 1$, we cannot compute Eq. (9), therefore, we set $\tilde{X}_j(p_{s(p)}) = 0$ if $X_i\left(p + \pi_j(u)\right) = 0$, and simply get rid of p from the consideration if $X_i\left(p + \pi_i(u)\right) = 1$ and $u \neq t$ (recall that if $X_i\left(p + \pi_j(u)\right) = 0$ and $u = t$, then the routing procedure terminates as $p + \pi_j$ is a feasible path).

The property of m and n in Eq. (9) and Eq. (10) can be classified into the following cases:

- Case I $(m > n)$:

The variable m is adopted to control $[X_i\left(p + \pi_j(u)\right)]$, while n is adopted to control $[1 - X_i\left(p + \pi_i(u)\right)]$. If a pre-path p is eligible, π_i and π_j are the shortest path from an intermediate node u to a destination node t with respect to the ith and the jth QoS metric, respectively, then $X_i(p) \leq 1$, $X_i(p + \pi_i(u))$ and $X_i\left(p + \pi_j(u)\right) \leq 1$. If $m > n$ and both m and n are increased, this makes $\left[X_i(p + \pi_j(u))\right]^m < [1 - X_i(p + \pi_i(u)\,]^n$. Thus, the weight, w_{ij}, becomes the highest value when $i = j$, e.g., w_{11}, w_{22}, w_{33} for$i, j = 1,2, \dots, q$. The largest weight is given by $[X_i\left(p + \pi_j(u)\right)]$ and $[1 - X_i\left(p + \pi_i(u)\right)]$, where $\pi_i(u) = \pi_j(u)$. This property makes $\tilde{X}_j(p_s(p))$ closed to $X_i\left(p + \pi_i(u)\right)$ with respect to the ith QoS metric where $i = 1,2, \dots, q$

- Case II $(m < n)$:

Due to $\pi_i(u)$ and $\pi_j(u)$ are the shortest path from an intermediate node u to a destination node t with respect to the ith and the jth QoS metric, respectively, $p +$

$\pi_i(u)$and $p+\pi_j(u)$ are the pre-path p extended by the post-path $\pi_i(u)$ and $\pi_j(u)$ at node u, respectively. $X_i(p+\pi_i(u))$ and $X_i\left(p+\pi_j(u)\right)$ are normalized QoS metrics of the full path $p+\pi_i(u)$ and $p+\pi_j(u)$ with respect to the ith QoS metric. They can be represented as the probability of a feasible full path with respect to the ith QoS metric. Thus $[1-X_i(p+\pi_i(u))]$ can be represented as normalized slackness with respect to the ith QoS metric of $X_i(p+\pi_i(u))$.

Since $[1-X_i(p+\pi_i(u))]$ is always less than 1, then $[1-X_i(p+\pi_i(u))]^n < [X_i(p+\pi_j(u))]^m$ for the increasing values of m and n, where $X_i\left(p+\pi_j(u)\right) \neq 0$ and $X_i(p+\pi_i(u)) \neq 1$ with eligible pre-path p. If w_{ij} is not closed to 0 ($w_{ij} \nrightarrow 0$), then $m<n$ makes the weight w_{ij} closed to the ith QoS metric of different post-path $\pi_j(u)$ such as w_{11}, w_{12}, w_{13} where $j=1,2,\dots,q$. Thus, this property makes $\widetilde{X_j}(p_s(p))$ closed to $X_i\left(p+\pi_j(u)\right)$ for $i=1,2,\dots,q$, e.g., w_{11}, w_{12}, w_{13} for $i,j=1,2,\dots,q$.

- Case III ($m=n$):

If $m=n$, the tendency of w_{ij} is similar to case II. That is, $\widetilde{X_j}(p_s(p))$is closed to $X_i\left(p+\pi_j(u)\right)$for $j=1,2,\dots,q$. Additionally, the following characteristics of weight w_{ij} can be summarized as follows: if $X_i\left(p+\pi_j(u)\right) \leq 1$, $X_i\left(p+\pi_j(u)\right) \neq 0$ and $[1-X_i(p+\pi_i(u))]^n < 1$ then $[1-X_i(p+\pi_i(u))]^n \leq [X_i(p+\pi_j(u))]^m$

B. Pseudo Code of the Proposed Algorithm

In this section, the pseudo code of the proposed G_MQW is presented in Algorithm 1 (Fig. 2). Firstly, the notations of our proposed algorithm are defined as follows:

- $R_i[v]$, $i=1,2,\dots,q$ denotes the accumulated i^{th} QoS metric in the post-path from an intermediate node v, while an intermediate node u is stored in $Pre_r(u)$, where u is a predecessor of v.
- $G_i(u)$ and $D_i(u,v)$, $i=1,2,\dots,q$ denote the accumulated i^{th} QoS metric in the pre-path up to u, where u is stored in $Pre_g(u)$, and accumulated i^{th} QoS metric between u and v, respectively.
- $r[u]$ and $g[u]$ denote the cost of post-path from u to t and the cost of pre-path from s to u, respectively.
- C_i denotes the path constraints.
- w_{ij} and $\rho[u]$ represent the weight for each QoS metric and the cost of complete path via node u, respectively.

In our proposed G_MQW, we employ two algorithms to find a feasible path: Reverse_Dijkstra and Look_Ahead_Dijkstra, as shown in Algorithm 2 (Fig. 3) and Algorithm 3 (Fig. 3), respectively. If the summation of QoS metric from s to t via u is less than or equal to its constraint value, a feasible path is returned.

Algorithm 2 tries to search for the best post-path with respect to the ith QoS metric. Once, it is found, then it is stored at node u until q post-paths are found. After that, in Algorithm 3 (Fig. 4), an eligible pre-path is found by Look_Ahead_Dijkstra and is extended by the best q post-path with respect to the ith QoS metric. In Algorithm 4 (Fig. 5), the shortest full path is the combination of the pre-path and post-path that have the smallest cost value and do not violate each QoS constraint. Algorithm 5 (Fig. 6) shows the way to update the k feasible paths if there is a new complete path with minimum cost value.

Algorithm 1: Pseudo code of G_MQW

Data: G_MQW $(G(V,E), s, t, u, v, c_i, D_i, C_i, w_{ij}, i,j=1,2,\dots,q)$
Reverse_Dijkstra_Relax $(G(V,E), u, t)$
1: **if** $(r[u]>1)$ **then**
2: **return NULL** */* no feasible path */*
3: **else**
4: **Look_Ahead_Dijkstra_Relax** $(G(V,E), s, u)$
5: **if** $(G_i[t] \leq C_i, \forall_i, i=1,2,\dots,q$ **then**
6: **return** a feasible path
7: **return NULL**

Fig. 2. Algorithm 1: Pseudo code of G_MQW

Algorithm 2: The relaxation procedure of subroutine Reverse_Dijkstra

1:**Reverse_Dijkstra_Relax** $(G(V,E), u, v)$
2:**if** $r[u] > \sum_{i=1}^{q}\left(\frac{R_i[v]+D_i(u,v)}{C_i}\right)^{\lambda}; \lambda=1$ **then**
3: $r[u] = \sum_{i=1}^{q}\left(\frac{R_i[v]+D_i(u,v)}{C_i}\right)^{\lambda}$
4: $R_i[u] = R_i[v] + D_i(u,v)$
5: $Pre_r[u] = v$
6:**return** $\boldsymbol{r[u]}$ */*a reverse feasible path through node u*/*

Fig. 3. Algorithm 2: The relaxation procedure of subroutine Reverse_Dijkstra

Algorithm 3: The relaxation procedure of subroutine Look_Ahead_Dijkstra

1:**Look_Ahead_Dijkstra_Relax** $(G(V,E), u, v)$
2: $tmp = temporary\ node$
3: $g[tmp] = \frac{G_i[u]+D_i(u,v)}{C_i}$
4: $\rho[tmp] = \sum_{i=1}^{q}\left(w_{ij} * \frac{G_i[u]+D_i(u,v)+R_i[v]}{C_i}\right)^{\lambda}; \lambda \to \infty$
5: **if Prefer_the_best** $(tmp, v) = tmp)$ **then**
6: $g[v] = g[tmp]$ **then**
7: $G_i[v] = G_i[tmp], for\ i,j=1,2,\dots,q$
8: $\rho[v] = \rho[tmp]$
9: $Pre_g[u] = v$
10: **return** $\mathbf{g[u]}$ */*look_ahead path through node u*/*

Fig. 4. Algorithm 3: The relaxation procedure of subroutine Look_Ahead_Dijkstra

Algorithm 4: The preference rule for Look_Ahead_Dijkstra in G_MQW

1: **Prefer_the_best** $a, b)$
2: **if** $g[a] < g[b]$ and $G_i[a] + R_i[a] \leq C_i$
3: **then return (a)**
4: **if** $g[b] < g[a]$ and $G_i[b] + R_i[b] \leq C_i$
5: **then return (b)**
6: **if** $\rho[a] < \rho[b]$ **then return (a)**
7: **return (b)**

Fig. 5. Algorithm 4: The preference rule for Look_Ahead_Dijkstra

Algorithm 5: The modified H_MCOP for G_MQW

1: **Modified H_MCOP** $(G(V,E), s, t, c_i, D_i, C_i, \widetilde{\Phi}_i(j), \widetilde{\Lambda}(j), i,j = 1,2,\dots,q)$
2: $P_j \leftarrow MCP\_Heuristic(G(V,E), s, t, C_i, L_i, i, j = 1,2,\dots,q)$
3: **if** $(P_j \neq NULL)$ and $(k < j)$ /*k; *feasible paths**/ **then**
4: $\widetilde{\Phi}_i(j) = \max_{i=1,2,\dots,q}[P_i(j)]$
5: $\widetilde{\Lambda}(P_i(j)) = \min_{i=1,2,\dots,q}[\widetilde{\Phi}_i(j)]$
6: **if** $(P_j^{new} \leftarrow MCP_{Heuristic})$ and $(P_j^{new} \leftarrow P_j)$
where $(k = j)$; /* *k; feasible path**/
7: **then**
8: $\widetilde{\Phi}_i(j) = \max_{i=1,2,\dots,q}[P_i^{new}(j)]$
9: $\widetilde{\Lambda}(P_i(j)) = \min_{i=1,2,\dots,q}[\widetilde{\Phi}_i(j)]$
10: **return** $\widetilde{\Lambda}(P_i(j))$

Fig. 6. Algorithm 5: The modified H_MCOP for G_MQW

C. Comparison Schemes by an Example

For the sake of understanding, we explain and compare path selection schemes between MPLMR and our proposed G_MQW by an example displayed in Fig. 7, where the same scenario as shown in MPLMR [12] is adopted here.

Assume each link has two QoS metrics with constraint value $C_1 = C_2 = 10$, a source node is s and a destination node is t. There are three pre-paths p_1, p_2 and p_3 extended by two post-paths p_4 and p_5. An intermediate node u is in the middle among all paths. It is considered as a passage node to keep feasible pre-paths and post-paths.

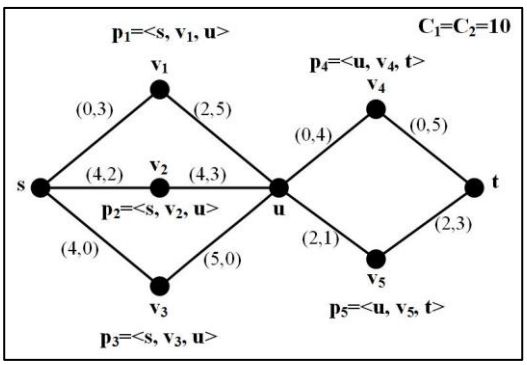

Fig. 7. Example of our proposed algorithm using network topology and parameters of [12].

TABLE I: NORMALIZED COST OF ALL PATHS IN FIG.7

$X_1(p_1 + \pi_1(u)) = 0.2$	$X_2(p_1 + \pi_1(u)) = 1.7$
$X_1(p_1 + \pi_2(u)) = 0.6$	$X_2(p_1 + \pi_2(u)) = 1.2$
$X_1(p_2 + \pi_1(u)) = 0.8$	$X_2(p_2 + \pi_1(u)) = 1.4$
$X_1(p_2 + \pi_2(u)) = 1.2$	$X_2(p_2 + \pi_2(u)) = 0.9$
$X_1(p_3 + \pi_1(u)) = 0.9$	$X_2(p_3 + \pi_1(u)) = 0.9$
$X_1(p_3 + \pi_2(u)) = 1.3$	$X_2(p_3 + \pi_2(u)) = 0.4$

TABLE II: WEIGHT OF EACH QOS METRIC WHERE $m = 5, n = 1$ IN G_MQW

p_2		p_3	
$a_1 = 0.0584$	$a_2 = 0.0527$	$a_1 = 0.0506$	$a_2 = 0.0060$
$w_{11} = 0.8910$	$w_{12} = 0.1090$	$w_{11} = 0.857$	$w_{21} = 0.1430$
$w_{12} = 0.1060$	$w_{22} = 0.8940$	$w_{12} = 0.016$	$w_{22} = 0.9840$

In [12], MPLMR applies the nonlinear path length to select pre-path. An example is shown in Table I, where Cv adopted here is $m = 5, n = 1$, the number of pre-paths $k = 1$. The path p_1 is represented as $< s, v_1, u >$ and path cost of $\widetilde{\Phi}(p_1)$ is max[(0+2)/10,(3+5)/10] = 0.8, while $\widetilde{\Phi}(p_2)$ and $\widetilde{\Phi}(p_3)$ are 0.8 and 0.9, respectively. From (3), our proposed G_MQW relies on nonlinear cost function to select the pre-paths. Thus, the pre-path cost of $\widetilde{X}(p_1)$, $\widetilde{X}(p_2)$ and $\widetilde{X}(p_3)$ are similar to MPLMR. Each pre-path is appended by linear cost function of post-path $p_4 =< u, v_4, t >$ or π_1 and $p_5 =< u, v_5, t >$ or π_2.

From Table I, MPLMR produces the normalized cost of full path $X_2(p_1 + \pi_2(u)) = 1.2 > 1$. The path p_1 is not eligible, then MPLMR discards and does not consider path p_1. The normalized cost of full path for p_2 and p_3 are $\tilde{X}_1(p_2) = w_{11}X_1(p_2 + \pi_1(u)) + w_{12}X_1(p_2 + \pi_2(u)) = 0.884$, $\tilde{X}_2(p_2) = 0.926$, $\tilde{X}_1(p_3) = 0.910$ and $\tilde{X}_2(p_3) = 0.447$, respectively. Thus, MPLMR selects p_3 first for $k = 1$.

In G_MQW, a feasible full path is the combining path of pre-path and post-path with weight as illustrated in Eq. (5) and Eq. (6), respectively. The values of weights are shown in Table II. Similar to MPLMR, the pre-path p_1 is not eligible for the combining path in G_MQW. Thus, there are four feasible full paths for consideration, such as $\tilde{X}_1(p_2) = w_{11}X_1(p_2 + \pi_1(u)) + w_{21}X_2(p_2 + \pi_1(u)) = 0.8651$, $\tilde{X}_2(p_2) = 0.9318$, $\tilde{X}_1(p_3) = 0.9054$ and $\tilde{X}_2(p_3) = 0.4147$.Then, our proposed G_MQW chooses p_3 and stores in node u.

IV. SIMULATIONS

In this section, the network environment, simulation parameters, scenarios and setting including performance measurement for G_MQW are described. These simulations, implemented by using Matlab, consists of two comparisons under different network scenarios: comparison of G_MQW with MPLMR and comparison of G_MQW with BMCOP. The main objective of these simulations is to find appropriate values of control variables $Cv\,(m,n)$ that provide the highest Success Ratio (SR).

A. Simulation Parameters and Scenarios for Comparison of G_MQW with MPLMR

In this subsection, G_MQW is compared with MPLMR and the other algorithms described in [12]. This scenario is simulated under a specific value of link correlation coefficient. The network topology, simulation parameters and performance measurement adopted here are similar to all setting in MPLMR. The Waxman model [48] is used to generate a topology because it closely represents a real network environment. Additionally, various link correlation coefficients of each QoS metric are considered. All simulation parameters are presented in Table III.

- *Simulation Scenarios*

There are three main parts of simulations. Firstly, we investigate the values of Cv that provide the highest SR

in case of two and three QoS metrics. Then, we compare the SR of our proposed algorithm using the appropriate values of Cv with MPLMR, where MPLMR adopts the specific values of $Cv, m = 5$ and $n = 1$ (results shown in Subsection A of Section V). Next, we adopt link cost correlation coefficient as an essential element between two QoS metrics on every link, since the weight generation depends on normalized cost and normalized slackness. The SR versus various constraint values are evaluated and compared under uniform and normal distributions of link costs (results shown in Subsection B-1 of Section V). The simulations are performed using three types of link cost correlations; negative (-0.8, -0.4), no-correlation (0) and positive (0.4 and 0.8). Finally, the values m and n to provide the highest SR are investigated (results shown in Subsection B-2 of Section V).

B. *Simulation Parameters and Scenarios for Comparison of G_MQW with BMCOP*

In this subsection, G_MQW is compared with Bidirectional Multi-Constrained Routing Algorithms (BMCOP) and the relevant works defined in [13]. In this scenario, correlation between QoS metrics on each link is simulated under static and random correlation coefficient in a specific range. The simulation parameters are displayed in Table III, where the Waxman topology and setup are similar to values defined in [13].

- *Simulation Scenarios*

This subsection consists of two main scenarios. Firstly, we investigate the appropriate values of $Cv\ (m, n)$ to give the highest SR under set of static constraint values for 100 nodes in Table IV (results shown in subsection B-3 of Section V). Secondly, the suitable values of $Cv\ (m, n)$ are explored under random constraint values illustrated for 50, 100 and 200 nodes in Table III. The Constraint values are $C_i \sim [1.5c_i(p_i), 2.0c_i(p_i)]$ for $i = 1, 2$ .The correlation between QoS metric on each link relies on three types of correlation coefficients with uniform distribution as shown in Table V (results shown in subsection B-4 of Section V).

TABLE III: SIMULATION PARAMETERS FOR COMPARING G_MQW WITH MPLMR AND BMCOP

Parameters	**Setup values for comparing with**	
	MPLMR	**BMCOP**
Network topology	Waxman, $\alpha = 0.8, \beta = 0.06$	
Number of nodes	200 nodes with approximately 567 links per network topology	100 nodes of constant constraint values, 50,100 and 200 for random constraint values
Number of connection requests	10,000	
Link cost correlation type (values)	Negative (-0.8 and -0.4) No-correlation (0) Positive (0.4 and 0.8)	Negative No-correlation Positive
Link constraint value	18	$C_i \sim [1.5c_i(p_i), 2c_i(p_i)]$ $i = 1,2$
Link cost distributions	Uniform and Normal	Uniform
Range and Mean of link cost distribution	[1,3], 2	N/A
Standard Deviation of link cost distribution	0.577	N/A
Number of pre-paths	1 and 2	N/A
Number of simulations per data point	20	

TABLE IV: SET OF SPECIFICATION CONSTRAINT VALUES

Set	**Constraint Values**
1	100/100
2	125/150
3	150/200
4	175/200
5	250/300
6	300/350
7	350/400
8	275/450
9	300/500

TABLE V: CORRELATION OF LINK COST

Negative	No-correlation	Positive
$c_1 \sim [1-50]$ $c_2 \sim [100-200]$ OR $c_1 \sim [50-100]$ $c_2 \sim [1-100]$	$c_1 \sim [1-100]$ $c_2 \sim [1-200]$	$c_1 \sim [1-50]$ $c_2 \sim [1-100]$ OR $c_1 \sim [1-100]$ $c_2 \sim [100-200]$

C. *Performance Measurement*

The performance of our proposed algorithm is evaluated using two metrics as follows:

- ***Success Ratio:*** *can be defined as follows:*

$$SR = \frac{Number\ of\ successful\ connections}{Totalnumber\ of\ connection\ requests}$$

- **Computational Complexity:** the indirect measurement of the complexity of the proposed algorithm. We measure the time to complete the computational process based on the same platform and environment.

V. RESULTS AND DISCUSSION

In this section, the simulation results of our proposed algorithm, G_MQW, comparing with MPLMR and BMCOP under several scenarios are shown. All graphs are plotted with 95% confidence interval.

A. *Values of Control Variables (Cv)*

In this part, the appropriate values of Cv, m and n that provide the highest Success ratio (SR) in case of two and three QoS metrics ($q = 2, q = 3$) are explored and shown in Table VI and Table VII, respectively. Then, the comparison results of SR between our proposed G_MQW using the appropriate values of Cv achieved here and the other algorithms, namely MPLMR, TAMCRA, H_MCOP and MPMP for ($q = 2, q = 3$) are presented in Table VIII and Table IX, respectively. The simulations are carried out under two link cost distributions; uniform and normal distributions, with different link cost correlation coefficients.

TABLE VI: APPROPRIVATE VALUE OF Cv, m AND n FOR TWO QOS METRICS ($q = 2$) IN WAXMAN WITH 200 NODES TO ACHIEVE THE HIGHEST SR

Correlation Coefficient	-0.8			-0.4			0			0.4 and 0.8		
a) Uniform distribution												
$q = 2, k = 1$	m	n	remark	m	n	remark	m	n	remark	m	n	remark
	0-0.5	0-1	$m \le n$	0-0.25	0-0.5	$m \le n$	0-5	0-5	any value	0-5	0-5	any value
	0.75-5	0-5		0-5	0-5							
$q = 2, k = 2$	m	n	remark	m	n	remark	m	n	remark	m	n	remark
	0-2	0-5	$m \le n$	0-1	0-5	$m \le n$	0-5	0-5	any value	0-5	0-5	any value
b) Normal distribution												
$q = 2, k = 1$	m	n	remark	m	n	remark	m	n	remark	m	n	remark
	0.75-5	0-5	$m > n$	0-5	0-0.75	$m > n$	0-5	0-5	any value	0-5	0-5	$m > n$
$q = 2, k = 2$	m	n	remark	m	n	remark	m	n	remark	m	n	remark
	0.75-2	0-1	$m > n$	0.5-5	0-5	$m > n$	0-5	0-5	any value	0-2	0-5	$m \le n$

TABLE VII: APPROPRIATE VALUES OF Cv, m AND n FOR THREE QOS METRICS ($q = 3$) IN WAXMAN WITH 200 NODES TO ACHIEVE THE HIGHEST SR

Correlation Coefficient	-0.8			-0.4			0			0.4 and 0.8		
a) Uniform distribution												
$q = 3, k = 1$	m	n	remark	m	n	remark	m	n	remark	m	n	remark
	0-0.5	0	$m > n$	0.25-5	0-5	$m > n$	0-5	0-5	any value	0-5	0-5	any value
	0.25-5	0.5-5										
$q = 3, k = 2$	m	n	remark	m	n	remark	m	n	remark	m	n	remark
	0.75-5	0-5	$m > n$	0-1	0-5	$m \le n$	0-2	0-5	$m \le n$	0-0.5	0-5	$m \le n$
										2	0-2	

For uniform distribution of link cost with $q = 2$, and the number of pre-path $k = 1$ and $k = 2$ as illustrated in Table VI, the appropriate values of (m, n) to achieve the highest succes ratio are $m \le n$ for negative link correlation while values of m can be any number in the same range as n for no-correlation and positive link. We found that the path selection relies on $X_i\left(p + \pi_j(u)\right)$, that is, the ith QoS metric of post-path $\pi_j(u)$, for $j = 1, 2, \dots, q$. In scenario of $m \le n$ under a specific range, when the weight for the ith QoS metric of each post-path $\pi_j(u)$ is increased, $\tilde{X}_j(p_s(p))$ is close to $X_i(p + \pi_j(u))$ for negative correlation. In case of positive and no-correlation, any values of (m, n) which are in the range of ([0-5], [0-5]) provide the identical opportunity to select $X_i(p + \pi_i(u))$ and $X_i\left(p + \pi_j(u)\right)$ as feasible path.

However, for normal distribution of link cost with two QoS metrics ($q = 2$), and the number of pre-path $k = 1\ and\ 2$, as shown in Table VI, the appropriate values of control variables (m, n) can be any arbitrary numbers within the range ([0-5], [0-5]) for no-correlation of link cost. However, for the other link correlations, value of m must be greater than n ($m > n$) in order to achieve the highest SR. In case of $q = 2$ and $k = 2$, the appropriate values of (m, n) are $m > n$ and $m \le n$ for negative and positive correlation, respectively. That means, $\tilde{X}_j(p_s(p))$ is nearby $X_i(p + \pi_i(u))$ for $k = 1$ while $\tilde{X}_j(p_s(p))$ is nearby $X_i\left(p + \pi_j(u)\right)$ for $k = 2$.

Regarding uniform distribution of link cost with three QoS metrics ($q = 3$), the link correlations of the first two QoS metrics are implemented as negative and positive while the last one has no-correlation with each other. The appropriate values of (m, n) for this case are shown in Table VII. It is obvious that in case of $q = 3$ and the number of pre-paths $k = 1$, the appropriate values of (m, n) are ([0.25-5], [0-5]) and $m > n$ has to be satisfied for negative correlation. But they can be any number in the specific range ([0-5], [0-5]) for positive and no-correlation. This means that a feasible path relies on $X_i(p + \pi_i(u))$ for negative and nearly becomes $X_i\left(p + \pi_j(u)\right)$ for positive and no-correlation of link cost.

For $q = 3$ with number of pre-path $k = 2$, the feasible path with negative link correlation of 0.8 relies on $X_i(p + \pi_i(u))$ where $m > n$ and (m, n) = ([0.75-5], [0-5]), while it is likely close to $X_i(p + \pi_j)$ where $m \le n$ and (m, n) = ([0-1], [0-5]), ([0-2], [0-5]) and ([0-0.5], [0-5]), for negative link correlation of 0.4, no-correlation, and positive correlation of 0.4 (and 0.8 as well), respectively.

Table VIII presents SR of our proposed G_MQW comparing to the other algorithms for two QoS metrics under uniform and normal distributions with various values and types of link correlation coefficients (negative, none and positive). While Table IX describes the similar comparison of SR but for three QoS metrics and under only uniform distribution. In this case, the link correlations of the first two QoS metrics are similar to Table VIII while the third QoS metric is uncorrelated with each of the first two.

According to the results shown in Table VIII and Table IX, it is obvious that our proposed algorithm provides the highest SR among all schemes for all types of correlations and distributions of link cost. SR = 1 means that the proposed algorithm can successfully find at least one feasible full path satisfying multiple QoS constraints. This is because G_MQW contains additional control variable, n to increase probability for slacking path while

MPLMR has only one control variable m to increase probability for satisfying path.

TABLE VIII: SUCCESS RATIO (SR) IN WAXMAN WITH 200 NODES FOR TWO QOS METRICS ($q = 2$) UNDER UNIFORM AND NORMAL DISTRIBUTIONS

Correlation Coefficient	-0.8	-0.4	0	0.4	0.8
a) Uniform					
G_MQW ($k = 1$)	1	1	1	1	1
MPLMR ($k = 1, m = 5$)	0.9993	0.9999	1	1	1
TAMCRA ($k = 1$)	0.9779	0.9847	0.9899	0.9954	0.9983
H_MCOP ($k = 1$)	0.9873	0.9260	0.9957	0.9981	0.9999
MPMP ($k = 1$)	0.9969	0.9988	0.9995	0.9997	1
G_MQW ($k = 2$)	1	1	1	1	1
MPLMR ($k = 2, m = 5$)	1	1	1	1	1
TAMCRA ($k = 2$)	0.9916	0.9954	0.9967	0.9992	0.9997
H_MCOP ($k = 2$)	0.9912	0.9952	0.9975	0.9987	0.9999
MPMP ($k = 2$)	0.9995	0.9999	0.9999	1	1
b) Normal					
G_MQW ($k = 1$)	1	1	1	1	1
MPLMR ($k = 1, m = 5$)	0.9995	0.9998	1	0.9998	1
TAMCRA ($k = 1$)	0.9754	0.9860	0.9972	0.9958	0.9993
H_MCOP ($k = 1$)	0.9872	0.9931	0.9960	0.9978	0.9992
MPMP ($k = 1$)	0.9966	0.9981	0.9992	0.9999	1
G_MQW ($k = 2$)	1	1	1	1	1
MPLMR ($k = 2, m = 5$)	1	1	1	1	1
TAMCRA ($k = 2$)	0.9754	0.9860	0.9927	0.9958	0.9993
H_MCOP ($k = 2$)	0.9872	0.9931	0.9960	0.9978	0.9992
MPMP ($k = 2$)	0.9966	0.9981	0.9992	0.9999	1

TABLE IX: SUCCESS RATIO (SR) IN WAXMAN WITH 200 NODES FOR THREE QOS METRICS ($q = 3$) UNDER UNIFORM DISTRIBUTION

Correlation Coefficient	-0.8	-0.4	0	0.4	0.8
G_MQW ($k = 1$)	1	1	1	1	1
MPLMR ($k = 1, m = 5$)	0.9999	0.9999	0.9998	0.9999	1
TAMCRA ($k = 1$)	0.9759	0.9817	0.9849	0.9858	0.9896
H_MCOP ($k = 1$)	0.9860	0.9901	0.9922	0.9946	0.9941
MPMP ($k = 1$)	0.9974	0.9992	0.9985	0.9990	0.9996
G_MQW ($k = 2$)	1	1	1	1	1
MPLMR ($k = 2, m = 5$)	1	1	1	1	1
TAMCRA ($k = 2$)	0.9915	0.9947	0.9961	0.9961	0.9969
H_MCOP ($k = 2$)	0.9895	0.9934	0.9958	0.9972	0.9960
MPMP ($k = 2$)	0.9993	0.9998	1	1	1

B. Success Ratio

In this section, we compare the Success Ratio of our proposed G_MQW with the other algorithms under various link correlations and link constraints.

1) Success ratio under link correlations

We compare our proposed G_MQW with MPLMR [12] under the environment defined in MPLMR. Firstly, we investigate the appropriate values of Cv (m, n) to achieve the highest SR under two QoS metrics with no-correlation and negative correlation coefficients for the number of pre-path $k = 1$. The values of link constraint C_1 and C_2 are set to 18 which is the challenge value to produce the lowest SR defined in MPLMR [12].

According to the simulation results shown in Fig. 8, we found that the suitable value of (m, n) in case of G_MQW with uniform distribution is ([0.75-5], 0.5) for no-correlation and ([0.75-5], [1-5]) for negative correlation, respectively. While in normal distribution, the appropriate values of (m, n) are the same as uniform distribution for no-correlation, but they are equal to ([0.75-5], [0-1]) for negative correlation, as shown in Fig. 9. In MPLMR [12], the control variables Cv are defined to be $(m, 1)$, where the value of $m = 5$ is selected from the range [3-10] for uniform and normal distribution in all scenarios.

In our proposed G_MQW, the normalized $X_i(p)$ of the ith QoS metric, m is adopted to control $[X_i\left(p + \pi_j(u)\right)]$ while n is adopted to control invert path as $\left[1 - X_i\left(p + \pi_i(u)\right)\right]$. From the results, the value of m is almost unchanged while the value of n has to be changed according to the type of link correlations. That means the variable n affects the path discovery that satisfies link constraint of the ith QoS metric for no-correlation and negative correlation coefficients. We found that n is likely to have more influence than m to produce the best SR.

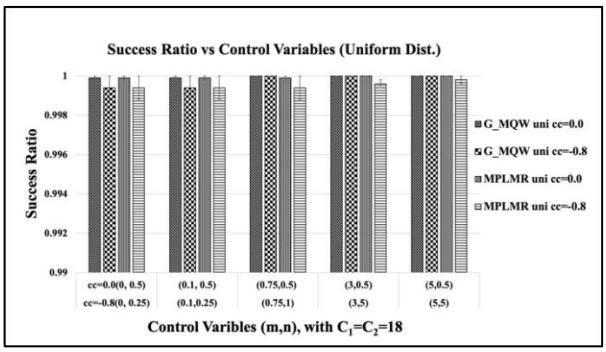

Fig. 8. Comparison of Success Ratio vs Control Variables between G_MQW and MPLMR under Uniform Distribution of Link Cost and Fixed QoS Constraint

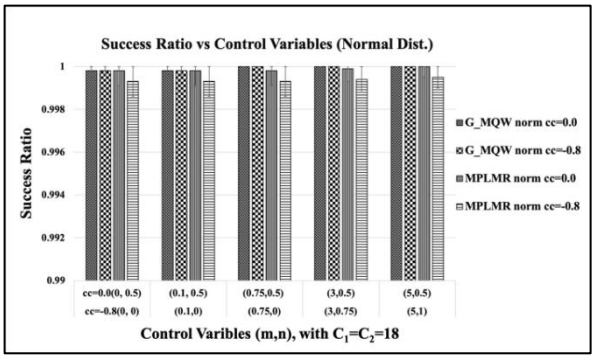

Fig. 9. Comparison of Success Ratio vs Control Variables between G_MQW and MPLMR under Normal Distribution of Link Cost and Fixed QoS Constraint

2) Success ratio under link constraints

In this section, we explore SR under various values of link constraints for two and three QoS metrics ($q = 2, q = 3$) with pre-path $k = 1$. Each set of link constraint for all QoS metrics are in the same value (defined in MPLMR [12] under uniform and normal distributions. We apply value $m = 5$ (defined in MPLMR [12] and $n = 0.5$ (achieved in Subsection A Values of Control Variable of G_MQW of Section V.).

For $q = 2$, the correlation coefficient between the first and the second constraint is -0.8. For $q = 3$, the correlation coefficient of first two constraints is -0.8 and the last one has no-correlation. The maximum SR of the proposed algorithm for uniform distribution of link cost are higher than MPLMR under constraint values of 18, 18.5 and 19, as shown in Fig. 10. Additionally, the proposed algorithm gives higher SR than MPLMR under constraint values of 18.5 for normal distribution as shown in Fig. 11 We found that G_MQW can increase SR when constraint values are increased. This is because the increment of constraint values loose link constraints and increase SR.

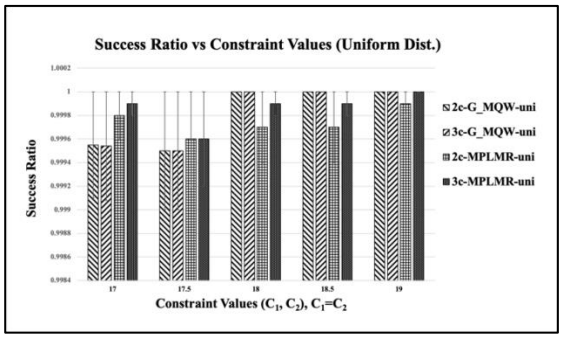

Fig. 10. Comparison of success ratio vs constraint values between G_MQW and MPLMR under uniform distribution of link cost

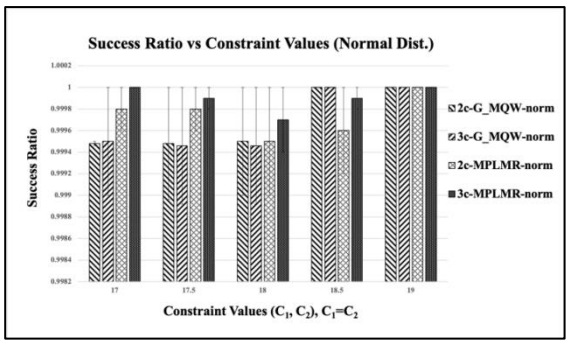

Fig. 11. Comparison of success ratio vs constraint values between G_MQW and MPLMR under normal distribution of link cost

3) Success ratio under static constraints

This subsection displays results of comparison between SR and set of static constraint values in various levels with respect to different types of correlation coefficients for 100 nodes. It is obvious from Fig. 12, Fig. 13 and Fig. 14 that G_MQW can produce higher SR than other algorithms under all sets of predefined constraints. The appropriate values of control variables (m, n) to give the best SR are displayed in Table X. We found that values of m are less than or equal to n $(m \leq n)$ for all sets. From the properties of m and n, $m \leq n$ makes $\tilde{X}_j(p_s(p))$ close to $X_i\left(p + \pi_j(u)\right)$. This mean that a feasible path relies on the ith QoS of each post-path $\pi_j(u)$ for $j = 1, 2, \ldots, q$. It is apparent that when constraint values are increased, SR values have tendency to become large.

For tiny constraint values (set1 to set3), other algorithms provide lower SR than G_MQW for all types of correlations. For medium constraint values (set4 to set6), SR of other algorithms are sharply increased while SR of G_MQW are slightly increased. This is because G_MQW explores the best post-path $\pi_j(u)$ according to the jth QoS metric. G_MQW applies w_{ij} on the post-path relying on normalized cost and normalized slackness (remaining or invert resources) according to the ith QoS metric. The weight can increase probability to discover a feasible path when a pre-path, p, is combined with the post-path as $\tilde{X}_j(p_s(p))$ for $\pi_j(u)$, $j = 1, 2, \ldots, q$. For multiple pre-path k and multiple post-path q, the smallest of maximum cost of path combination with respect to the normalized i^{th} QoS metric $\tilde{\Phi}_i(p_s(p))$ are selected as feasible full path.

For larger constraint values (set7 to set9), tendency of SR belonging to other algorithms are significantly increased while slightly changed by G_MQW. These results can be explained that G_MQW provides higher SR when constraint values are lager. The appropriate values of (m, n) are any value in specific range ([0-5], [0-5]) that make loosely weight values, w_{ij}, to enhance normalized cost and slackness and close to the highest SR.

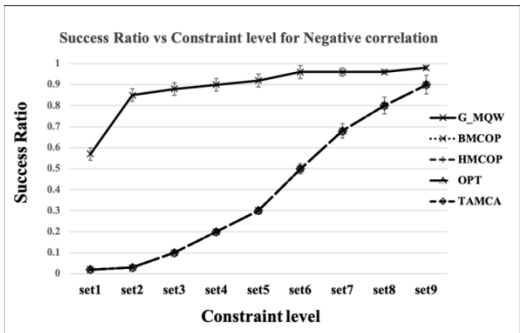

Fig. 12. Comparison of success ratio vs set of constraint levels in static values under negative correlation of G_MQW, BMCOP, HMCOP, OPT and TAMCRA

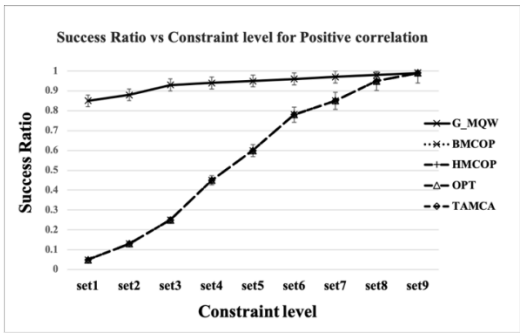

Fig. 13. Comparison of success ratio vs set of constraint levels in static values under positive correlation of G_MQW, BMCOP, HMCOP, OPT and TAMCRA

TABLE X: APPROPRIATE VALUES OF Cv, m AND n FOR STATIC CONSTRAINT

Values of *Cv*	Negative correlation			No-correlation			Positive correlation		
	m	n	remark	m	n	remark	m	n	remark
Set1	0-5	0-5	$m \leq n$	0-5	0-5	$m \leq n$	0-5	0-5	$m \leq n$
			SR = 0.57			SR = 0.75			SR = 0.85
Set2	0-5	0-5	$m \leq n$	0-5	0-5	$m \leq n$	0-5	0-5	$m \leq n$
			SR = 0.85			SR = 0.84			SR = 0.88
Set3	0-5	0-5	$m \leq n$ n	0-5	0-5	$m \leq n$	0-5	0-5	$m \leq n$
			SR = 0.88			SR = 0.91			SR = 0.93
Set4	0-5	0-5	$m \leq n$	0-5	0-5	$m \leq n$	0-5	0-5	$m \leq n$
			SR = 0.9			SR = 0.95			SR = 0.94
Set5	0-5	0-5	*any value*	0-5	0-5	*any value*	0-5	0-5	*any value*
			SR = 0.92			SR = 0.95			SR = 0.95
Set6	0-5	0-5	*any value*	0-5	0-5	*any value*	0-5	0-5	*any value*
			SR = 0.96			SR = 0.96			SR = 0.96
Set7	0-5	0-5	*any value*	0-5	0-5	*any value*	0-5	0-5	*any value*
			SR = 0.96			SR = 0.97			SR = 0.97
Set8	0-5	0-5	*any value*	0-5	0-5	*any value*	0-5	0-5	*any value*
			SR = 0.96			SR = 0.97			SR = 0.98
Set9	0-5	0-5	*any value*	0-5	0-5	*any value*	0-5	0-5	*any value*
			SR = 0.98			SR = 0.98			SR = 0.99

4) Success ratio under random constraints

For random constraint, values of SR are investigated and compared under network consisting of 50, 100 and 200 nodes. The comparison results of negative, positive and no-correlation coefficients are illustrated in Fig. 15, Fig. 16 and Fig. 17, respectively. We found that G_MQW can explore feasible path and produce the highest SR for 50, 100 and 200 nodes.

TABLE XI: APPROPRIATE VALUES OF Cv, m AND n FOR RANDOM CONSTRAINT

Values of *Cv* for set of constraint	Negative correlation			No-correlation			Positive correlation		
	m	n	remark	m	n	remark	m	n	remark
50-node	0.75-5	0-1	$m > n$	0.25-5	0-5	$m > n$	0.5-5	0-5	$m \geq n$
			SR =1			SR = 1			SR = 1
100-node	0.75-5	0-1	$m > n$	0-5	0-5	$m > n$	0.25-5	0-5	$m \geq n$
			SR = 1			SR = 1			SR = 1
200-node	0.5-5	0-2	$m > n$	0-5	0-5	$m > n$	0.25-5	0-5	$m \geq n$
			SR = 1			SR = 1			SR = 1

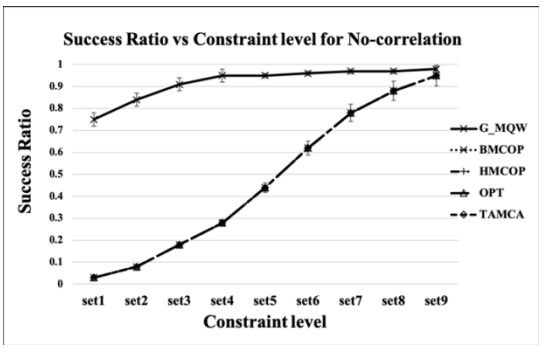

Fig. 14. Comparison of success ratio vs set of constraint levels in static values under no-correlation of G_MQW, BMCOP, HMCOP, OPT and TAMCRA

The appropriate values of (m, n) applied in this scenario are shown in Table XI. For all types of correlations, we found that the appropriate values of (m, n) are in a particular value and specific range. For instance, values of m are equal to or more than n $(m \geq n)$ for positive while values of m are larger than n $(m > n)$ for negative and no-correlation. The value $(m > n)$ makes $\tilde{X}_j(p_s(p))$ close to $X_i(p + \pi_i(u))$ while $(m \geq n)$ makes a feasible path slightly close to $X_i\left(p + \pi_j(u)\right)$ also. When the number of nodes is increased, the values of control variables in each range are also expanded. According to all of results, it is clear that the control variables $(m,\ n)$ in G_MQW can increase probability of finding the feasible path.

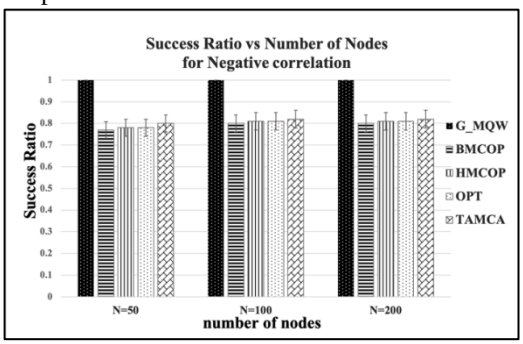

Fig. 15. Comparison of Success Ratio vs Random Constraint Values under Negative correlation of G_MQW, BMCOP, HMCOP, OPT and TAMCRA

C. Computational Complexity Discussion and Results

In this section, the computational complexity of our proposed G_MQW is discussed. Let a and b be the number of nodes and the number of links on each node, respectively. Let q be the number of QoS metrics and k be the maximum number of pre-paths to be stored at each node.

In our proposed algorithm G_MQW, we adopt the same procedures of searching the pre-path for each node as MPLMR, therefore, the computational complexity of this procedure of our proposed algorithm is identical to MPLMR [12]. Regarding the procedure to find the shortest post-path of our proposed algorithm, even though it is modified from MPLMR, but the traditional Dijkstra's algorithm is adopted. Therefore, the computational complexity of post-path calculation is $O(bq + aqlog(a))$ [49], which is the computational complexity of Dijkstra's algorithm. In conclusion, the total computational complexity of our proposed algorithm is $O(aqlog(a) + aklog(ak) + k^2bq + kba + ka^2q^2)$, which is identical to MPLMR. It is said in [11] that, if the maximum number of pre-paths per node (i.e., k) is fixed, the computational complexity is polynomial. Therefore, the computational complexity of our algorithm is polynomial as well. For the sake of comparison, H_MCOP has the computational complexity as$O(a\,log(a) + kb\,log(ka) + b(k^2 + 1))$ [15], while the computational complexity of TAMCRA and BMCOP are $O(ka\log(ka) + k^3bq$ [3] and $O(|a|\log(|a|) + |b|)$ [13] respectively.

Here, the computational complexity is illustrated indirectly by measuring the average execution time of the algorithm using the same parameters on the same platform and environment and then, compared with MPLMR, MPMP, TAMCRA and H_MCOP. This experiment adopts 200 nodes. The link cost is distributed uniformly with two uncorrelated QoS metrics for $k = 2$. The detail of platform for this simulation is shown in Table XII.

TABLE XII: DETAIL OF SIMULATION PLATFORM

Platform	Values
CPU	Intel Core i5 processor 2.1 GHz
Memory/Hard Disk	32 GB/ 100 GB
Operating System	Linux Ubuntu

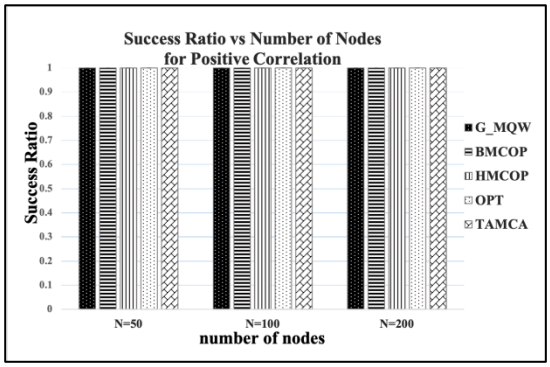

Fig. 16. Comparison of Success Ratio vs Random Constraint Values under Positive correlation of G_MQW, BMCOP, HMCOP, OPT and TAMCRA

The computational complexity in terms of average execution time is presented in Fig. 18. It is obvious that the average execution time of our proposed G_MQW $(time = 0.28945\ s)$, $(m, n) = (5, 0.5)$ is relatively close to MPLMR $(time = 0.28952\ s)$, $(m, n) = (5, 1)$. Both algorithms provide the lowest average execution time while TAMCRA $(time = 1.4\ s)$ provides the highest time. H_MCOP $(time = 0.7\ s)$ provides the second longer time after TAMCRA while MPMP $(time = 0.31\ s)$ is the next one. It can be concluded that our proposed G_MQW has the same level of computational complexity as MPLMR and MPMP.

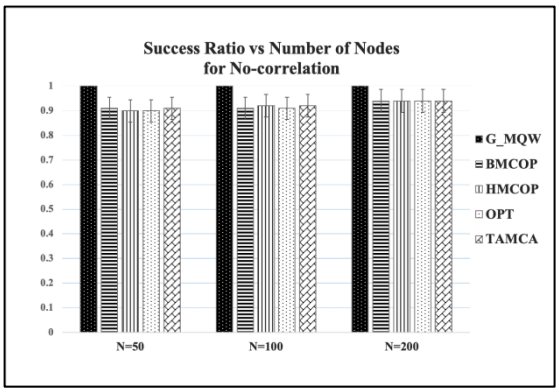

Fig. 17. Comparison of Success Ratio vs Random Constraint Values under No-correlation of G_MQW, BMCOP, HMCOP, OPT and TAMCRA

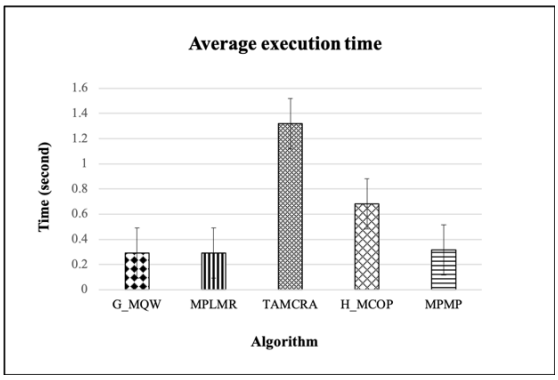

Fig. 18. Average execution time of our proposed algorithm G_MQW comparing with various algorithms

VI. CONCLUSIONS

In this work, we propose the algorithm called G_MQW, which is a general form of the algorithm for path selection under multi-constrained QoS metrics using different weight allocation. In addition, the control variables to generate the appropriate weight according to the application requirements as well as the slackness of resources are introduced. The solution is provided in the mathematical closed form. We simulate and measure the performance of our proposed G_MQW in terms of Success Ratio and Computational Complexity and then compare the results with the other algorithms, namely, MPLMR, TAMCRA, H_MCOP, MPMP, BMCOP and OPT. The simulations are carried out to find the appropriate values of control variables to provide the highest Success Ratio under different values (high or low) and types of link cost correlations (negative, positive and no-correlation). The link costs are allocated based on two distributions; uniform and normal distributions.

According to the simulation results, it is obvious that our proposed G_MQW algorithm can provide the highest

success ratio among all algorithms under consideration by applying control variables which are adjustable depending on link cost correlations. The appropriate values of control variables to provide the highest success ratio are given in a specific range.

Regarding the computational complexity, G_MQW provides the same level as MPLMR and lower than TAMCRA, H_MCOP and MPMP. This is because G_MQW is developed based on modification of MPLMR, the computational complexity for path selection is quite similar. Additionally, when constraint value is decreased, our proposed algorithm can increase number of feasible paths found (in terms of success ratio) comparing with MPLMR and BMCOP.

For future work, the dynamically allocation of values of control variables under different link correlation coefficients should be investigated further.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Maneenate Puongmanee conducted the research including mathematics analysis simulations and wrote the paper. Teerapat Sanguankotchakorn helped in formulating the problem and provided advice regularly. All authors had approved the full version.

REFERENCES

[1] M. R. Garey and D. S. Johnson, *A Guide to the Theory of NP-Completeness*, Computers and Intractability, 1990.

[2] S. Chen and K. Nahrstedt, "On finding multi-constrained paths," in *Proc. IEEE International Conference on Communications Conference Record Affiliated with SUPERCOMM'98*, Atlanta, GA, 1998, pp. 874-879.

[3] H. D. Neve and P. V. Mieghem, "Tamcra: A tunable accuracy multiple constraints routing algorithm," *Computer Communications*, vol. 23, pp. 667-679, 2000.

[4] T. Korkmaz and M. Krunz, "Multi-Constrained optimal path selection," in *Proc. IEEE INFOCOM 2001 Conference on Computer Communications Twentieth Annual Joint Conference of the IEEE Computer and Communications Society*, Anchorage, AK, USA, 2001, pp. 834-843.

[5] P. V. Mieghem and F. A. Kuipers, "Concepts of exact QoS routing algorithms," *IEEE/ACM Transactions on Networking*, vol. 12, pp. 851-864, October 2004.

[6] J. M. Jaffe, "Algorithm for Finding Paths with Multiple Constraints," *Networks*, pp. 95-116, 1984.

[7] X. Xiao and L. M. Ni, "Internet QoS: A big picture," *IEEE Network*, pp. 8-18, March 1999.

[8] T. Korkmaz and M. Krunz, "A randomized algorithm for finding a path subject to multiple QoS constraints," in *Proc. Seamless Interconnection for Universal Services. Global Telecommunications Conference*, Rio de Janeireo, Brazil, 1999, pp. 1694-1698.

[9] T. Henderson and B. Bhatt, "Networked games: A QoS-Sensitive application for qos-insensitive Users?" in *Proc. ACM SIGCOMM Workshop on Revisiting IP QoS: What Have We Learned, Why do We Care*, NY, USA, 2001, pp. 141-147.

[10] D. C. W. Pao and S. P. Lam, "Cell scheduling for ATM switch with delay-sensitive and loss-sensitive traffic," *Computer Communications*, pp. 1153-1164, September 1998.

[11] D. E. K. P. C. Shin and H. J. Siegel, "A multi-constraint QoS Routing scheme using a modified Dijkstra's algorithm," in *Proc. Joint International Conference on Wireless LANs and Home Networks (ICWLHN 2002) and Networking (ICN 2002)*, Atlanta, USA, 2002, pp.65-76.

[12] D. Shin D, E. K. P. Chong, and H. J. Siegel, "Multi-postpath-based Lookahead Multiconstraint QoS Routing," *Journal of the Franklin Institute*, pp. 1106-1124, April 2012.

[13] B. Zhang, J. Hao and H. T. Mouftah, "Bidirectional Multi-Constrained Routing Algorithms," *IEEE Transactions on Computers*, vol. 63, pp. 2174-2186, September 2014.

[14] R. P. Feynman and F. L. J. Vernon, "The theory of a general quantum system interacting with a linear dissipative system," *Annals of Physics*, 1963. pp. 118-173.

[15] G. Feng, "On the performance of heuristic H_MCOP for multi-constrained optimal-path," in *Proc. 18th International Conference on Advanced Information Networking and Applications*, vol. 2, 2004, pp. 50-53.

[16] F. A. Kuipers, P. V. Mieghem, T. Korkmaz, and M. Krunz, "An overview of constraint-based path selection algorithms for QoS routing," *IEEE Communications Magazine*, vol. 40, no. 12, pp. 50-55, 2002.

[17] P. S. Prakash and S. Selvan, "Optimized multi constrained path quality of service routing protocol," *World Scientific and Engineering Academy and Society (WSEAS)*, pp. 80-95, February 2011.

[18] G. Feng, "The impact of correlated link weights on QoS," *IEEE INFOCOM*, 2003.

[19] T. Sanguankotchakorn and N. Perera, "Hybrid multi-constrained optimal path QoS routing with inaccurate link state," in *Proc. Ninth International Conference on Networks*, 2010, pp. 321-326.

[20] H. Cui, J. Li, X. Liu, and Y. Cai, "Particle swarm optimization for multi-constrained routing in telecommunication networks," *International Journal of Computer Network and Communication Security*, pp. 10-17, June 2011.

[21] S. Zhu, Y. Zeng, and H. Zhang, "An integer non-linear programming model of power consumption of the internet under QoS constraints," *Journal of Communications*, pp. 66-72, January 2013.

[22] K. Kunavut and T. Sanguankotchakorn, "Generalized multi-constrained path (G_MCP) QoS routing algorithm for mobile ad hoc networks," *Journal of Communications*, pp. 246-257, March 2012.

[23] A. W. Awajan, O. S. Al-Dabbas, F. A. Albalas, and R. S. Abujassar, "Dynamic path-switching: A multiple

constrained QoS routing algorithm for MANETS," *World Applied Sciences Journal*, pp. 1-8, January 2013.

[24] M. Oche, A. B. Tambawal, C. Chemebe, R. M. Nor, and S. Distefano, "VANETs QoS-based routing protocols based on multi-constrained ability to support ITS infotainment services," *Springer*, October 2018.

[25] B. Shin and D. Lee, "An efficient local repair-based multi-constrained routing for congestion control in wireless mesh networks," *Wireless Communications and Mobile Computing*, November 2018.

[26] S. Xu, N. Xing, S. Guo and L. Meng, "Delay-Constrained optimal traffic allocation in heterogeneous wireless networks for smart grid," *Journal of Communications*, October 2015.

[27] L. Zhang, C. Bai, F. Zhuo, H. Xu, and W. Huang, "Dynamic rate allocation for multipath routing under path stability and prioritized traffic session constraints for cognitive radio ad hoc networks with selfish secondary users," *Journal of Communications*, pp. 462-470, May 2016.

[28] G. Feng, "The Revisit of QoS Routing based on Nonlinear Lagrang," *International Journal of Communication Systems*, pp. 9-22, 2007.

[29] Q. Fang, J. Han, L. Mao, and Z. Li, "Exact and heuristic algorithm for multi-constrained optimal path problem," in *Proc. IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing*, Sydney, NSW, 2011, pp. 45-51.

[30] K. Stachowiak and P. Zwierzykowski, "Lagrangian relaxation and linear intersection based QoS routing algorithm," *International Journal of Electronics and Telecommunications*. pp. 307-314, December 2012.

[31] S. Chen and K. Nahrstedt, "Overview of quality of service routing for next-generation high-speed networks: Problems and solution," *IEEE Network*, pp. 65-79, November 1998.

[32] S. Dewen, T. Meixia, F. Hao, F. Xujian, and X. Haitao, "Multiple constrained dynamic path optimization based on improved ant colony algorithm," *International Journal of u- and e- Service, Science and Technology*, pp. 117-130, December 2014.

[33] B. Liang and J. Yu, "One multi-constraint QoS routing algorithm CGEA based on ant colony system," in *Proc. 2nd International Conference on Information Science and Control Engineering (ICISCE)*, Shanghai, 2015, pp. 848-851.

[34] C. Liu, L. An, and X. Zhang, "Optimization research of multi constraint routing algorithm based on fast search tree," *Boletin Tecnico/Technical Bulletin*, vol. 55, no. 10, pp. 51-57, October 2017.

[35] D. Kumar and T. Kaur, "AntMQoS: An ant-based multi-constrained QoS routing protocol for wireless sensor networks," in *Proc. World Congress on Engineering and* Computer *Science 2017, (WCECS 2017)*, San Francisco, USA, vol. 1, 2017, pp. 106-111.

[36] K. Qiang, H. Wang, C. Hu, C. Zhang, and Y. Zhao, "Multi-constrained multi-path routing for server-centric data center networks," in *Proc. Internet Conference of China; Frontier in Internet Technologies (ICoC 2014)*, 2014, pp. 1-15.

[37] C. Guo, K. Wu, K. Tan, L. Shi, Y. Zhang, and S. Lu, "DCell: A scalable and fault-tolerant network structure for data centers," in *Proc. ACM SIGCOMM 2008 Conference on Data Communication*, Seattle, WA, 2008, pp. 75-86.

[38] C. Guo, G. Lu, D. Li, H. Wu, X. Zhang, Y. Shi, C. Tian, Y. Zhang, and S. Lu, "BCube: A high performance, server-centric network architecture for modular data centers," in *Proc. ACM SIGCOMM 2009 Conference on Data Communication*, Barcelona, Spain, 2009, pp. 63-74.

[39] F. Shang and X. Chen, "Multi-constrained routing optimization for data center network," in *Proc. Asia-Pacific Engineering and Technology Conference (APETC 2017)*, Kuala Lumpur, 2017, pp. 1348-1353.

[40] R. Hou, R. Lui, *et al.*, "Performance analysis of quantization-based approximation algorithms for precomputing the supported QoS," *Journal of Network and Computer Applications*, April 2014, pp. 244-254.

[41] J. Huang, X. Huang, and Y. Ma, "Routing with multiple quality-of-services constraints: An approximation perspective," *Journal of Network and Computer Applications*, vol. 35, no. 1, pp. 469-479, January 2012.

[42] S. Torkzadeh, H. Soltanizadeh, and A. A. Orouji, "Multi-constraint QoS routing using a customized lightweight evolutionary strategy," *Soft Computing*, pp. 693-706 January 2019.

[43] T. M. Anh and N. C. Trinh, "A new localized multi-constraint QoS routing algorithm," *Journal of Information and Communications*, pp. 34-44, July 2017.

[44] N. Abdullah, O. A. Al-wesabi, M. Baklizi, and M. M. Kadhum, "Intelligent routing algorithm using genetic algorithm," in *Proc. 2nd International Conference of Reliable Information and Communication Technology (IRICT 2017)*, 2017, pp. 255-263.

[45] P. T. A. Quang, J. M. Scanner, C. Morin, and Y. Hadjadj-Aoul, "Multi-Objective multi-constrained QoS routing in large-scale networks: A genetic algorithm approach," in *Proc. SaCoNet 2018-7th IEEE International Conference on Smart Communications in Network Technology*, El Oued, Algeria, 2018, pp. 1-6.

[46] T. Sanguankotchakorn, S. Maneepong, and N. Sugino, "A relaxing multi-constraint routing algorithm by considering QoS metrics priority for wired network," in *Proc. Fifth International Conference on Ubiquitous and Future Networks (ICUFN)*, Da Nang, 2013, pp. 738-743.

[47] M. Puongmanee and T. Sanguankotchakorn, "Multiple constraints QoS routing priority metrics with control variables," in *Proc. 19th IEEE International Conference on Networks*, Singapore, 2013, pp. 1-6.

[48] B. M. Waxman, "Routing of multipoint connections" *IEEE Journal on Selected Areas in Communications*, pp. 1617-1622, September 2006.

[49] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms Third Edition*, The MIT Press, New York, 2009.

Maneenate Puongmanee was born in 1975. She received the B.S. in Computer Science and M.S. in Computer Engineering from Prince of Songkla University, Thailand, in 1999 and 2006, respectively. She is currently pursuing the doctoral degree in Information and Communication Technology at School of Engineering and Technology, Asian Institute of Technology. Her current research interests include communication and networking, wireless, mobile, ad hoc network and delay tolerant network (DTN).

Teerapat Sanguankotchakorn was born in Bangkok, Thailand on December 8, 1965. He received the B.Eng in Electrical Engineering from Chulalongkorn University, Thailand in 1987, M.Eng and D.Eng in Information Processing from Tokyo Institute of Technology, Japan in 1990 and 1993, respectively. In 1993, he joined Telecommunication and Information Systems Research Laboratory at Sony Corporation, Japan where he holds two patents on Signal Compression. Since October 1998, he has been with Asian Institute of Technology where he is currently an Associate Professor at Telecommunications Field of Study, School of Engineering and Technology. Dr. Sanguankotchakorn is a Senior member of IEEE and member of IEICE, Japan. He also holds various positions in the industries, namely Board of Governors of Thai Public Broadcasting Service (ThaiPBS) and Board of Directors of Banpu Public Company Limited.