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Multi-Objective Optimization for Location Prediction of Mobile Devices in Sensor-Based Applications

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ABSTRACT A mobile ad hoc network (MANET) can be constructed when a group of mobile users need to communicate temporarily in an ad hoc manner. It allows mobile services to be shared through device-to-device links and composed by combining a set of services together to create a complex, value-added, and cross-organizational business application. Nevertheless, various challenges, especially the reliability and quality-of-service of such a MANET-based mobile service composition, are yet to be properly tackled. Most studies and related composition strategies assume that mobile users are fully stable and constantly available. However, this is not realistic in most real-world scenarios where mobile users are mobile. The mobility of mobile users impact the reliability of corresponding mobile services and consequently impact the success rate of mobile service compositions. In this paper, we propose a reliability-aware mobile service composition approach based on prediction of mobile users' positions. We model the composition problem as a multi-objective optimization problem and develop an evolutionary multi-objective optimization-based algorithm to solve it. Extensive case studies are performed based on a real-world mobile users' trajectory data set and show that our proposed approach significantly outperforms traditional ones in terms of composition success rate.

INDEX TERMS Mobile service, service composition, quality-of-service, reliability.

LIST OF ABBREVIATIONS

D2D	Device-to-Device communications
EMO	Evolutionary Multi-objective Optimization
HV	Hyper-Volume
MANET	Mobile Ad Hoc Network
MDEMS	Multi-objective Differential Evolution for Mobile Service composition
MOO	Multi-Objective Optimization
MODE	Multi Objective Differential Evolution
MSSC	Mobile Service Sharing Community
QoS	Quality-of-Service
SLA	Service-Level-Agreement

LIST OF SYMBOLS

$\xi(x)$	Estimated reliability of service composition x
ρ	Operational probability of edge in a MANET
$\tau(x)$	Estimated response time of service composition x
$\phi(p, r)$	Function for identifying if there are available paths between node p and r in a MANET
ω	Number of max iteration generations of an MDEMS algorithm
Θ	Decision space in a composition problem
y	Population size of MDEMS

n	Task count in a composition plan
p	A mobile service composition plan
C_i	Dynamic crossover rate of MDEMS in the i-th iteration
D	User-recommended constraint of the response time of a service composition
E	Set of edges for every communication path
F	Scale factor of MDEMS
G	Mobile users' history trajectories
M	Number of all trajectory patterns in GMM
N	Set of mobile users and sink nodes in MSSC
P	Resource pool of available mobile services
R	Set of precedence relations among tasks in a mobile service composition plan
$S(t)$	State of MSSC at time t
T	Task set of a mobile service composition plan

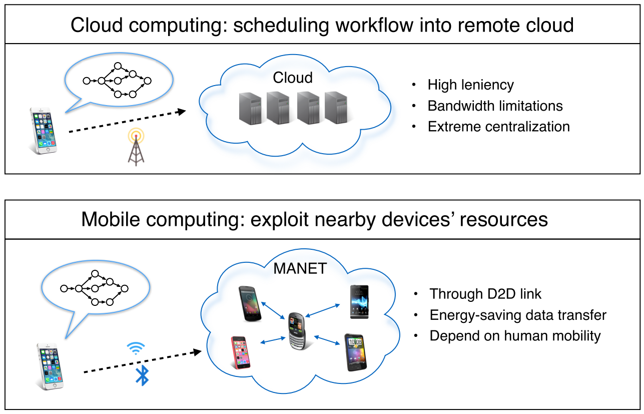

FIGURE 1. **Mobile computing.**

I. INTRODUCTION

In recent years, the world has witnessed the rapid growth and advances of mobile devices, e.g., smart phones, tablet computers, and wearable devices, as well as mobile services. Mobile devices are changing the way people access information in their daily lives. In the mobile service computing environment, mobile users can exploit nearby resources [1], e.g., computing nodes and network connectivity, through utilizing mobile services shared in a mobile ad hoc network (MANET). MANET is a self-organized local mobile network created by nodes within each other's communication fields.

As illustrated in Fig. 1, the core idea of mobile service computing in MANET is sharing. In this paradigm, mobile users are allowed to utilize resources and services shared by other users nearby, and thus the provisioning capability of involved services is expanded through exploiting direct physical contacts among users. These available resources and services can be shared directly among users in an elastic and on-demand way without time-consuming and energy-requiring communications with pre-existing infrastructure, for example, cellular networks and traditional centralized cloud datacenters. Note that, mobile tasks over MANET (e.g., TensorFlow Lite, Photo editing on mobile, and Online video sharing) usually require huge computational resources or data transfer. Nearby mobile service providers are thus more adept, in terms of timeliness and energy-efficiency, at executing these tasks than the remote services with the help of device-to-device (D2D) communications such as Bluetooth, Wi-Fi and NFC. D2D communications are featured by extensively-reduced inter-device delays and energy consumption than traditional cellular networks [2]. It is widely believed to have potential to improve Quality-of-Service (QoS) of mobile services over MANET by providing increased user throughput, reduced cellular traffic, and extended network coverage [3].

However, users in a MANET often have high mobility, thus resulting in topological changes in the MANET over time. Under such circumstances, it has become a great challenge how to compose and schedule reliable mobile services over a versatile MANET and fulfill users' QoS requirements in the meantime.

To address the aforementioned challenges and concerns, in this study, we propose a predictive reliability-aware mobile service composition approach over MANET. We first present the concept of mobile service sharing communities (MSSC) and a probability-based method to evaluate mobile service reliability. Then a Gaussian mixture model (GMM) for user position prediction is used to capture the dynamic trend of service reliability during service provisioning. Finally, we develop an improved multi-objective differential evolution algorithm for mobile service composition. Predicted service reliability values are fed into this algorithm to yield composition schedules. The results of experiments conducted on a real-world user movement dataset show that our approach is capable of dynamically capturing the mobility of mobile users and achieving higher success rates of mobile service compositions than traditional ones.

II. RELATED WORK

Mobile service composition allows users to compose mobile services over MANETs to fulfill their various needs. Recent technological advances made in the hardware and software of mobile devices, especially wireless networking, facilitate a mobile environment where the mobile devices all around a user, either carried by nearby users, or embedded as part of a smart space, can provision mobile services to be shared over MANETs. Users sometimes demand new services that cannot be found on any devices. With mobile service composition techniques, they can build new services by dynamically composing existing services over a MANET. Extensive studies have been carried out in this direction. For example, Deng *et al.* [1] classify mobile service composition methods into three categories: Cloud to Mobile (C2M), Mobile to Mobile (M2M) and Hybrid. They also discuss related challenges, e.g., performance guarantee, energy efficiency, and security. Later, they propose an MSSC model and extend the random way point model to describe users' mobility. They employ a meta-heuristic algorithm to decide the near-optimal service composition [4]. Sadiq *et al.* [5] use a Levy walk model and Self-similar Least-Action-Walk model to generate user traces, where each node is equally likely to meet any other one and the connectivity among devices is implemented by using multi-hop paths. Groba and Clarke [6] present a protocol for mobile service composition, which allocates service providers opportunistically to serve consumers with the aim to minimize the impact of changes on topology. Yang *et al.* [7] propose a QoS model for mobile service selection. They consider not only the characteristics of mobile wireless networks but also user-perceived factors. Wang [8] employ a probability-free model and a probabilistic model to characterize uncertainty during mobile service invoking. They assume that mobile services can tolerate the mobility of service providers to a certain level.

However, it can be observed that the above studies fail to exploit users' historical trajectory information for their potential use in service composition. Although some of them consider Brownian motion or probabilistic motion models, the knowledge behind mobile users' historical trajectory information is underexploited, which can be applied to avoid the invocations of unavailable services. This limitation potentially leads to low success rates and high Service-Level-Agreement (SLA) violation rates of mobile service compositions. Fortunately, the recent progress in human mobility prediction models enlightens mobile service composition techniques. It is shown in later sections that, with the help of user mobility prediction models, our mobile service composition algorithm clearly outperforms traditional ones in terms of their success rates.

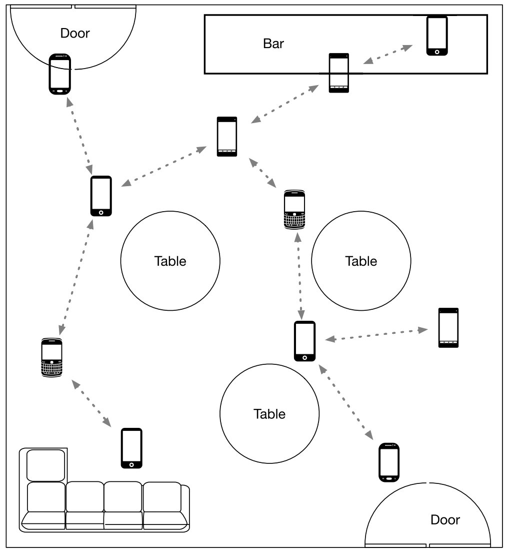

FIGURE 2. An MSSC example in a cafe.

III. PRELIMINARIES

A. MOBILE SERVICE SHARING COMMUNITIES

An MSSC is a mobile ad hoc network for mobile service sharing [4]. It is usually constructed by nearby mobile users and sink nodes. It can be formally described as a 2-tuple $MSSC = (N, E)$, where N is the set of mobile users and sink nodes in an MSSC, E the set of edges for every communication path. Fig. 2 shows an example MSSC established in a coffee shop, where mobile users are within each other's D2D transmission ranges.

An MSSC has three characteristics: (1) locality: A mobile user can perceive and invoke mobile services exposed by other users in the same MSSC, and locality of services can thus be exploited and utilized; (2) mobility: In an MSSC, it is not uncommon that service requesters and providers are constantly moving during service provisioning time; (3) dynamicity: Mobile users may join or leave an MSSC automatically when they enter or leave a participating user's transmission range.

B. MOBILE SERVICE RELIABILITY

It can be seen that services composed and executed over a MANET is unreliable due to the high mobility of service requesters and providers. In this paper, the reliability of D2D links between two nodes in MANET is considered when evaluating the reliability of mobile services provisioned over these links. Suppose that there are $|N|$ nodes and $|E|$ edges in an MSSC at time t, the reliability of a mobile service provided by provider p for requester r can be calculated as the reliability between nodes p and r. In an MSSC, each edge has its operational probability ρ, which is calculated based on a received signal strength indicator (RSSI) value [9]. The state of MSSC at time t can thus be represented as $S(t) = [S_1(t), S_2(t), \ldots, S_{|E|}(t)]$, where the i-th element $S_i(t)$ is assigned to 1 if the i-th edge is working at time t, otherwise 0. Thus, the probability of an MSSC being in a given state can be calculated as follows:

$$P(S(t)) = \prod_{i=1}^{|E|} \rho_i^{S_i(t)}(1-\rho_i)^{1-S_i(t)} \tag{1}$$

Then the reliability of a D2D link between p and r can be expressed as:

$$RL_{(p,r)}[G(t)] = \sum_{all\ S(t)} \phi(S(t), p, r)P(S(t)) \tag{2}$$

where $\phi(S(t), p, r)$ is the function for identifying whether there are available paths between node p and r. If in state $S(t)$, there is at least one path between p and r, then $\phi(S(t), p, r) = 1$, otherwise 0.

It can be seen that the reliability of a mobile service in a MANET varies over time and is closely related to the communication distance between a service requester and provider. A service currently observed to be available may become unavailable in the near future due to this distance's change.

C. GMM FOR USER POSITION PREDICTION

A recent study [10] reports that there is a potential 93% average predictability in user mobility. For example, Fig. 3 shows pedestrians' trajectories on a campus. We can see that most trajectories share similarity and regularity patterns. Such similarity, periodicity, and regularity can be formally and properly described with novel methods [11]–[13].

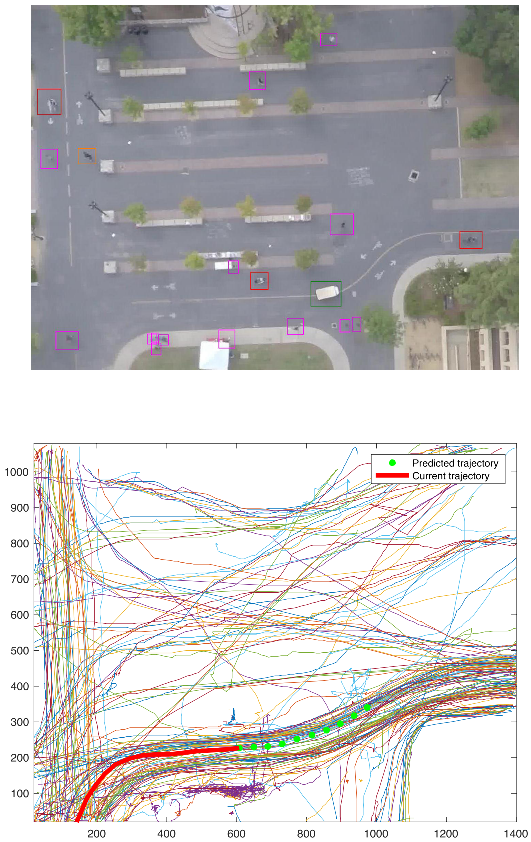

FIGURE 3. Trajectories of pedestrians in a campus.

Human trajectories usually follow multiple mobility patterns, depending on the subjective destination, the limit of objective environment, other people's movement and so on. Each pattern within a trajectory can be effectively described by a Gaussian process and the entire trajectories can thus abstracted into a Gaussian Mixture model (GMM).

In GMM, users' history trajectory data can be described as follows:

$$\begin{aligned} G &= \{\Gamma_1, \Gamma_2, \ldots, \Gamma_n\} \\ &= \{(\overrightarrow{x_1}, \overrightarrow{y_1}), (\overrightarrow{x_2}, \overrightarrow{y_2}), \ldots, (\overrightarrow{x_n}, \overrightarrow{y_n})\} \\ &= \{\overrightarrow{X}, \overrightarrow{Y}\} \end{aligned} \tag{3}$$

where Γ_i denotes the i-th user's trajectories, $\overrightarrow{X}$ and $\overrightarrow{Y}$ the mapping vector of these trajectories in X and Y directions, respectively. A trajectory $\Gamma_i = (\overrightarrow{x_i}, \overrightarrow{y_i})$ can be expressed as a multiple different Gaussian processes as follows:

$$\begin{aligned} p(\overrightarrow{x_n}|\lambda) &= \sum_{i=1}^{M} \omega_i GP(\overrightarrow{x_n}|\mu_{(x,i)}, \sigma_{(x,i)}) \\ p(\overrightarrow{y_n}|\lambda) &= \sum_{i=1}^{M} \omega_i GP(\overrightarrow{y_n}|\mu_{(y,i)}, \sigma_{(y,i)}) \end{aligned} \tag{4}$$

where $GP(\overrightarrow{x_n}|\mu_{(x,i)}, \sigma_{(x,i)})$ denotes the probability function of trajectory Γ_n's X direction in the i-th trajectory pattern, M the number of all trajectory patterns, ω_i the weight of the i-th trajectory pattern with $\sum_{i=1}^{M} \omega_i = 1$, $\mu_{(x,i)}$ and $\mu_{(y,i)}$ the means of the i-th trajectory pattern in directions X and Y, $\sigma_{(x,i)}$ and $\sigma_{(y,i)}$ the covariance of the i-th trajectory pattern in directions X and Y, respectively. We use λ to denote the set of $\{\omega_i, \mu_i, \sigma_i\}, i \in \{1, 2, \ldots, M\}$. The likelihood function of GMM for a training set $G = \{\overrightarrow{X}, \overrightarrow{Y}\}$ is:

$$\begin{aligned} P(\overrightarrow{X}|\lambda) &= \prod_{n=1}^{M} p(\overrightarrow{x_n}|\lambda) \\ P(\overrightarrow{Y}|\lambda) &= \prod_{n=1}^{M} p(\overrightarrow{y_n}|\lambda) \end{aligned} \tag{5}$$

The forecasting process consists of three steps: (1) applying a Gaussian Mixture clustering method [14] to trajectory dataset G to obtain M clusters, which correspond to M different trajectory patterns; (2) an expectation-maximization algorithm is applied to estimate parameter λ; (3) forecast a mobile user's future position based on his/her recent trajectory. The prediction process is employed in Section IV to obtain the prediction results of service providers' position. Then the service reliability evaluated based on its predicted position is further fed into the optimization formulation to facilitate mobile service composition schedules.

IV. PROBLEM FORMULATION AND SOLUTIONS

A. PREDICTIVE MOBILE SERVICE COMPOSITION

As shown in Fig. 4, the process for predictive mobile service composition consists of three typical steps: (1) a service composition plan is constructed when a service requester wants to create a composite service. A service composition plan usually has multiple tasks that are arranged via some control statements, e.g., parallel, choice or loop. Each task in a service composition plan represents a function point and it can be implemented by one of the candidate services that have similar functions and interfaces; (2) then, it begins to discover potential service providers and their exposed services in the same MSSC. At the same time, the reliability of services is evaluated according to the predicted user positions. A resource pool containing available candidate services able to complete all needed tasks is built in this step; (3) it decides which services to select for each task to realize the mobile service composition with satisfactory response time and reliability. Decision making is transformed into a multi-objective optimization (MOO) problem. Then an evolutionary-based algorithm named MDEMS is employed to yield a set of

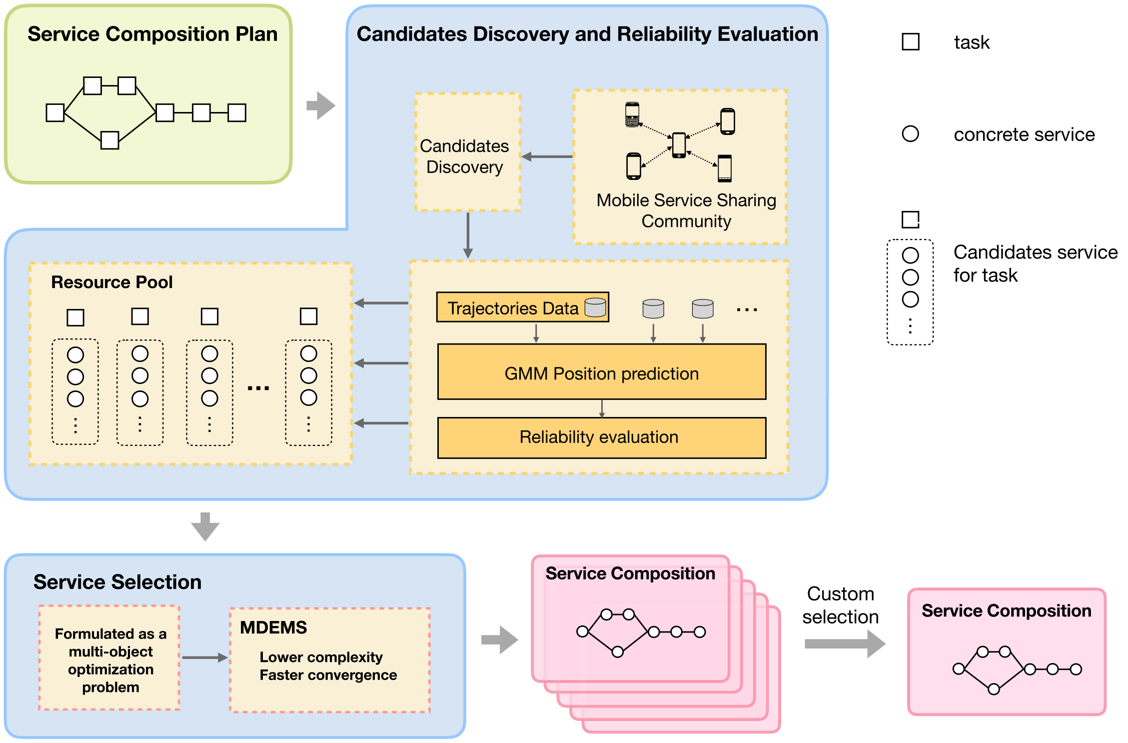

FIGURE 4. **The process of mobile service composition.**

solutions, which are equally optimal from the view of Pareto fronts [15] and can be selected based on user preferences.

B. PROBLEM FORMULATION

A mobile service composition plan can be described as $p = \{T, R\}$ where $T = \{t_1, t_2, \ldots, t_n\}$ is the task set and $R = \{r(t_i, t_j)|t_i \in T, t_j \in T\}$ the precedence set between tasks. $r(t_i, t_j) = 1$ indicates that t_j can only start after t_i is finished due to the dependency constraint. A mobile user can perceive services exposed by other mobile users in the same MSSC. These available services constitute a service pool $P = \{s_1^i, s_2^j, \ldots, s_n^k\}$, where s_n^k indicates that there are k mobile services available for task t_n in MSSC. Then, the problem of service composition in MSSC over MANET can be formulated as follows:

$$\begin{aligned} Min:\ & y = f(x) = (1 - \xi(x), \tau(x))^T \\ s.t:\ & \tau(x) \leq D \\ & x = [x_1, x_2, \ldots, x_n]^T \in \Theta \\ & x_i^{min} \leq x_i \leq x_i^{max} \quad (i = 1, 2, \ldots, n) \end{aligned} \tag{6}$$

where $\xi(x)$ and $\tau(x)$ are the estimated reliability and response time of service composition x, respectively. They can be calculated by a reduction method, as presented in [16] and [17]. The details of such method are omitted here. D is a user-defined deadline and Θ stands for a decision space (i.e., resource pool). Since reliability and response time tend to conflict each other, we consider Pareto domination as the measure of the optimality of candidate solutions. Consequently, for solution $u, v \in \Theta$, u dominates v when:

$$\begin{aligned} \forall\, i \in [1, n]\ &:\ f_i(u) \leq f_i(v) \\ \exists\, j \in [1, n]\ &:\ f_j(u) < f_j(v) \end{aligned} \tag{7}$$

A solution x^* is Pareto-optimal if it is not dominated by any other solution. The set of all Pareto-optimal solutions in the objective space is called a Pareto front. For the mobile service composition problem, solution u dominates solution v if $\xi(u) \leq \xi(v) \wedge \tau(u) < \tau(v)$ or $\xi(u) < \xi(v) \wedge \tau(u) \leq \tau(v)$.

C. MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION FOR MOBILE SERVICE COMPOSITION

For the problem formulated in the previous subsection, methods such as multiple-objective-integer-linear-programming and multi-objective-branch-and-bound can be used for solutions. However, such methods are usually considered to be with high time-complexity and thus could be impractical due to the fact that the problem space could be very large (the number of candidate service providers for one task can be 100+ for some typical cases, e.g., shopping mall and subway station. The number of tasks could be 50+ for some typical complex business processes, e.g., airline-ticket-booking and new-customer-registration). In contrast, Multi-objective differential evolution (MODE) has been shown to be a simple yet efficient evolutionary algorithm for MOO problems in diverse domains. It is featured by its strong parallelizability of genetic operators and good convergence properties than other traditional evolutionary MOO algorithms. For the above problem formulated, we propose an improved MODE algorithm, named MDEMS, short for Multi-objective Differential Evolution for Mobile Services to find solutions.

MDEMS developed in this work is a kind of meta-heuristic procedure similar to the process of natural selection. It is used to yield high-quality solutions for optimization and searching problems by employing bio-inspired operations, e.g., mutation and crossover. A population of its candidate solutions to an optimization problem keeps evolving toward better solutions. The initial population with n individuals consists of three parts: (1) one individual i_1 with the highest $\xi(i_1)$ regardless of its response time; (2) one individual i_2 with the shortest $\tau(i_2)$ regardless of its reliability; and (3) $n-2$ individuals are randomly generated according to the current resource pool.

The mutation operator simulates an evolutionary activity that an individual directionally learns from other individuals. To speed up convergence and optimize exploration ability, we consider an improved mutation strategy as follows:

$$V_i = X_i + F(X^* - X_i) + F(X^\# - X_i) + F_i(X_r^1 - X_r^2) \tag{8}$$

where F is a scale factor, V_i an offspring individual, X_i mutation target, X_r^1 and X_r^2 two random individuals chosen from the current population, X^* and $X^\#$ the individuals randomly chosen from top k best individuals in the population ordered by their estimated reliability and response time, respectively, k is set to 15% in this paper. This top-k strategy can accelerate the convergence speed and in the meantime avoid trapping into local optima. The pseudo code of the proposed mutation operator is shown in Algorithm 1.

The crossover operator simulates a genetic activity that an individual obtains characteristics from other individuals controlled by a crossover rate. We employ dynamic changing crossover rates in order to avoid useless crossover operations. The crossover rate in the i-th generation, C_i, is randomly generated from a Gaussian distribution as:

$$C_i = G(C_m, 0.1) \tag{9}$$

where C_m is calculated from the historical value of C_i, C_m in its first generation is 0.6. We use $\mathbb{C}$ to indicate the set of crossover rates used in previous generations. C_m can be calculated as follows:

$$C_m = w_C \times C_m + (1 - w_C) \times mean_{Pow}(\mathbb{C}) \tag{10}$$

where

$$mean_{Pow}(\mathbb{C}) = \sum_{i=1}^{|\mathbb{C}|} [\frac{(C_i)^n}{|\mathbb{C}|}]^{\frac{1}{n}} \tag{11}$$

where w_C is a real value randomly generated from [0.9, 1] and $n = 1.5$. The pseudo code of the proposed crossover operator is shown in Algorithm 2.

Suppose that there are k available mobile users in MSSC, the time complexity of forecasting users' future position is $O(k^2)$. The time complexity of initializing an individual is $O(n)$, and thus population initialization requires $O(ny)$, where y is the size of initial population. The reliability and response time evaluation for each individual has the

Algorithm 1 Mutation Operator

Input: Population X; Task count n; Scale factor F; Resource pool P
Output: Mutated population V;

estimate reliability and response time of each individuals in population X
Top_{Rel} $\leftarrow$ get top 15% best individuals according to estimated reliability
Top_{Ms} $\leftarrow$ get top 15% best individuals according to estimated response time
for each individual X_i **in** population X **do**
  X_r^1 $\leftarrow$ choose one individual from X randomly
  X_r^2 $\leftarrow$ choose one individual from X randomly
  X^* $\leftarrow$ choose one individual from Top_{Rel} randomly
  $X^\#$ $\leftarrow$ choose one individual from Top_{Ms} randomly
  $V_i \leftarrow X_i + F_i(X^* - X_i) + F(X^\# - X_i) + F_i(X_r^1 - X_r^2)$
  for $j = 1$ **to** n **do**
    if $V_i[j] < P.LowBounds[j]$ **or** $V_i[j] > P.UpperBounds[j]$ **then**
      $V_i[j]$ $\leftarrow$ choose one executor between low bounds and upper bounds of executors randomly
    end if
  end for
  add V_i into mutated population V
end for
return V

Algorithm 2 Crossover Operator

Input: Population X; Mutated population V; History crossover rate $\mathbb{C}$; Task count n;
Output: Population after crossover operation X';

calculate $mean_{Pow}$ according to history crossover rate $\mathbb{C}$ by (11)
calculate C_m by (10)
calculate crossover rate C_i by (9)
for each individual X_i in population X **do**
  for $j = 1$ **to** n **do**
    if $rand() < C$ **then**
      $Cv[j] \leftarrow 1$
    else
      $Cv[j] \leftarrow 0$
    end if
  end for
  for $j = 1$ **to** n **do**
    $X_i'[j] \leftarrow X_i \wedge (1 - Cv[j]) + V_i \wedge Cv[i]$
  end for
  add X_i' into X'
end for
return X'

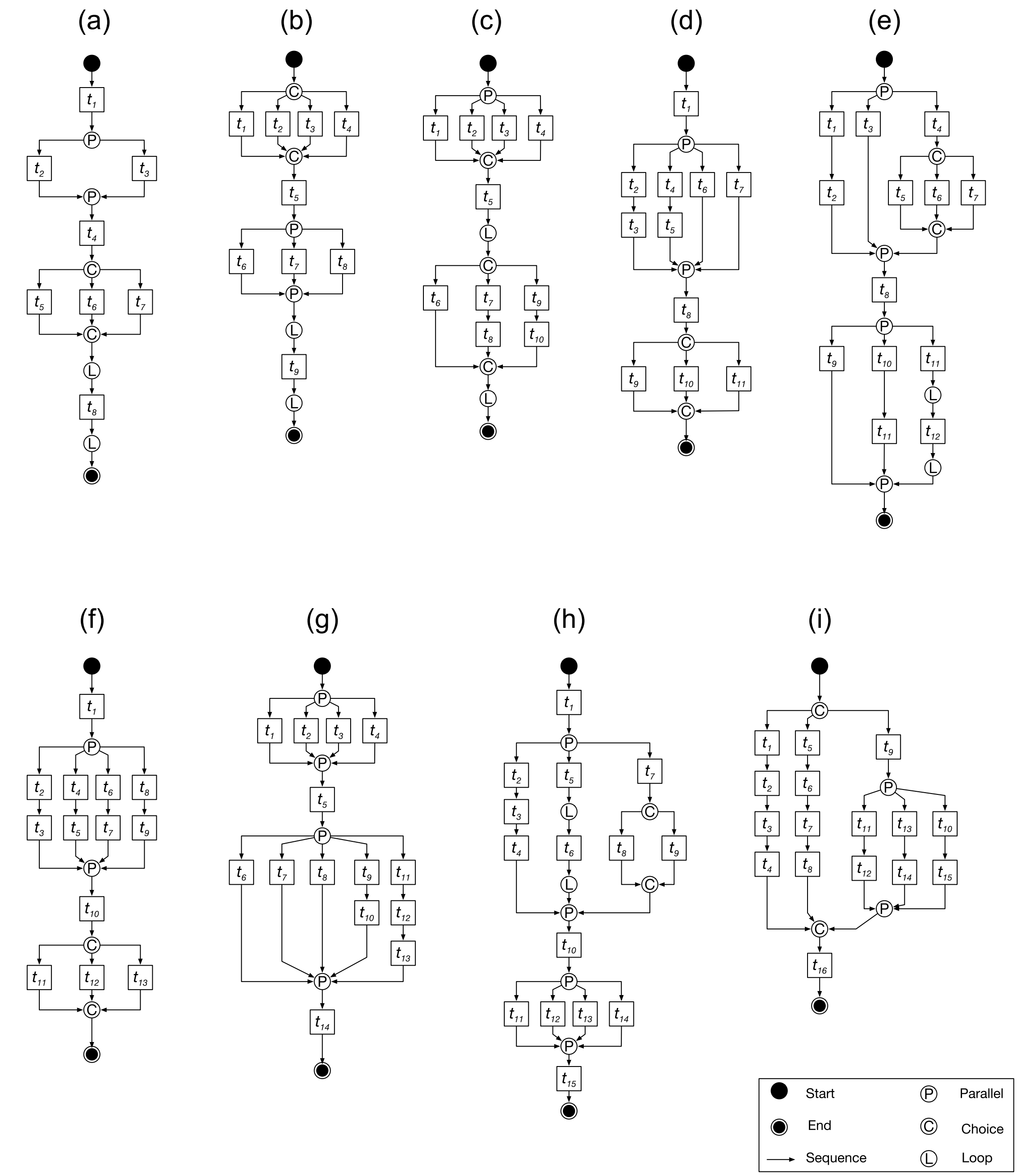

FIGURE 5. Service composition plans for experiment.

time complexity of $O(nlog|R|)$ and thus reliability and response time evaluation for initial population of size y with ω generations has the time complexity of $O(y\omega nlog|R|)$. The time complexity for mutation, crossover, and dominance selection operations are $O(ny)$, $O(ny)$, and $O(y^2)$, respectively. Consequently, the total time complexity of mutation, crossover and dominance selection with ω generations is $O(\omega ny) + O(\omega ny) + O(\omega y^2)$. Finally, the total time complexity of the proposed approach is thus $O(k^2) + O(y\omega nlog|R|) + O(\omega ny) + O(\omega ny) + O(\omega y^2)$. Generally, $nlog|R|$ is large than y, and thus the total time complexity of our approach is $O(k^2 + y\omega nlog|R|)$, thereby suggesting high scalability.

V. EXPERIMENTS AND ANALYSIS

To evaluate the effectiveness of our approach, we conduct experiments on a real-world user trajectory dataset, a service QoS dataset, and multiple composition plans in a wide range of application scenes.

TABLE 1. HV and runtime comparison between MDEMS and traditional MOO algorithms.

Scene	Task count	NSGA-II		MOPSO		MOEA\D		SPEA2	
		HV	runtime	HV	runtime	HV	runtime	HV	runtime
bookstore	8	23.85%	1.20	51.37%	1.60	64.03%	2.51	28.37%	3.00
	10	7.29%	1.25	131.22%	1.63	215.56%	2.73	48.22%	3.12
	12	144.71%	1.30	15.38%	1.67	45.42%	2.97	23.57%	3.21
	14	2.00%	1.32	81.13%	1.76	31.51%	3.40	23.52%	3.75
	16	22.00%	1.72	11.85%	2.11	29.32%	3.59	5.12%	4.15
gates	8	40.05%	1.12	75.25%	1.50	135.08%	2.01	41.57%	2.90
	10	16.98%	1.14	3.35%	1.57	-1.78%	2.43	3.30%	2.99
	12	4.91%	1.24	2.40%	1.60	20.11%	2.83	0.48%	3.39
	14	12.30%	1.22	7.24%	1.62	11.17%	2.92	-3.85%	3.56
	16	-0.93%	1.55	12.34%	1.90	22.43%	3.30	7.00%	3.72
deathcicle	8	2.40%	1.14	2.67%	1.54	7.02%	2.17	38.57%	2.93
	10	55.40%	1.14	-0.31%	1.56	57.55%	2.60	0.30%	3.16
	12	-6.46%	1.15	12.81%	1.59	12.52%	2.91	3.60%	3.41
	14	0.66%	1.20	2.34%	1.60	124.27%	3.28	-2.02%	3.84
	16	94.40%	1.26	7.85%	1.75	67.37%	3.32	0.56%	3.97
hyang	8	173.24%	1.05	19.72%	1.52	40.68%	2.15	33.49%	2.77
	10	229.82%	1.12	77.03%	1.53	466.24%	2.26	-1.66%	2.90
	12	115.98%	1.15	1.63%	1.55	61.50%	2.40	38.74%	3.15
	14	2.16%	1.31	49.81%	1.59	42.26%	2.43	28.62%	3.66
	16	68.72%	1.85	17.24%	2.96	90.27%	3.55	32.44%	3.81

TABLE 2. Success rate comparison between MDEMS and non-prediction-based approaches.

Scene	Task count	MDEMS	EMOABC[20]	ADE-NSGA-II[21]	MOPSO[22]
bookstore	8	87.16%	80.59%	79.12%	77.77%
	10	85.21%	79.07%	80.64%	76.32%
	12	85.63%	79.91%	78.47%	79.13%
	14	81.02%	80.68%	76.21%	77.86%
	16	85.31%	82.55%	81.05%	79.66%
gates	8	66.72%	66.02%	64.85%	63.50%
	10	83.02%	75.29%	73.93%	74.40%
	12	65.44%	77.73%	76.32%	74.75%
	14	74.03%	55.32%	61.36%	56.23%
	16	82.12%	73.28%	68.96%	69.48%
deathcicle	8	83.70%	63.77%	64.54%	61.09%
	10	74.78%	66.86%	65.57%	64.06%
	12	75.30%	62.44%	63.24%	59.81%
	14	78.69%	64.36%	63.12%	61.66%
	16	74.86%	60.57%	62.40%	58.01%
hyang	8	98.55%	70.37%	69.21%	67.51%
	10	96.42%	84.44%	82.99%	83.02%
	12	98.84%	72.30%	71.09%	69.36%
	14	96.17%	69.49%	68.34%	66.67%
	16	92.94%	76.11%	74.83%	73.03%

The Stanford Drone dataset [18] is a user trajectory dataset collected from Stanford campus. In this dataset, all pedestrians' movement trajectories in a certain scene are recorded for consecutive periods. We choose bookstore, gates, deathcicle, and hyang these four scenes with varying crowd density in the experiments. There are four scenes, with 189, 85, 56 and 31 pedestrians, respectively. Pedestrians within the same scene establish an MSSC. The quality of candidate services are randomly selected from the widely used QWS dataset [19]. As shown in Fig. 5, the service composition plans used to evaluate our proposed method are randomly generated with the number of tasks ranging from 8 to 16.

Table 1 shows the differences between MDEMS and it peers, i.e, NSGA-II, MOPSO, MOEA\D and SPEA2, in terms of HV value (a comprehensive evaluation index used to judge a multi-objective optimization method, the higher the better) and runtime with varying task counts. The ratios are used to offer a clearer comparison, for example, the HV improvement ratios can be calculated as follow:

$$\frac{HV(MDEMS)}{HV(Peer)} - 1 \tag{12}$$

Similarly, the runtime comparison ratios between our method and peers can be calculated as follows:

$$\frac{RunTime(Peer)}{RunTime(MDEMS)} \tag{13}$$

where

$$Peer \in \{NSGA\text{-}II, MOPSO, MOEA\backslash D, SPEA2\}$$

It can be seen that, MDEMS achieves a higher HV value in most cases. This advantage is achieved in a way that the individuals, with the help of MDEMS, are more likely to learn from a group of other individuals with high reliability and low response time estimates, rather than learning from a single individual with seemingly highest optimality achieved by traditional algorithms. It also shows that MDEMS achieves higher time-efficiency in all cases (twice faster than MOPSO on average, and 3 times faster than MODE and SPEA2 on average).

We also compare MDEMS with traditional non-prediction-based service composition algorithms [20]–[22], which assume stable service reliability. As shown in Table 2, our proposed approach clearly outperforms non-prediction-based approaches in most cases. To be specific, the success rate achieved by our method is 5.35%, 6.81%, 21.8% and 29.57% higher than EMOABC on average in four scenes, respectively; 7.3%, 8.76%, 24.19% and 31.77% higher than ADE-NSGA-II; and 9.16%, 11.06%, 27.15% and 35.05% higher than MOPSO.

VI. CONCLUSION AND FURTHER WORK

This paper targets at an unreliable mobile service composition problem in a dynamic mobile service computing environment. We propose a position-prediction-based mobile service composition approach in the context of MANET. We evaluate the reliability of mobile services dynamically based on forecasted uses' positions through a Gaussian mixture prediction model. Mobile services are selected and composed by an evolutionary multi-objective optimization algorithm. The knowledge and patterns behind users' mobility are thus excavated to compose and schedule reliable mobile services over a versatile MANET. Experimental results show that our proposed algorithm outperforms a number of traditional approaches in term of composition success rate.

As future work, we plan to consider soft deadline constraints (where response time is allowed to exceed a threshold value with a bounded given rate) and introduce corresponding algorithms to generate run-time mobile compositions. Besides, more metrics, including service scalability and service reputation, should be modeled and investigated and recent intelligent optimization methods [23], [24] should be explored.

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