Modeling and Fitness Landscape Analysis for Flexible MBMS Radio Resource Allocation

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***Abstract*—The Multimedia Broadcast Multicast Service (MBMS) system supports efficient diffusion of multicast multimedia services in cellular networks. We develop a flexible model to perform dynamic radio resource allocation for MBMS service by using metaheuristic approach. We conduct fitness landscape analysis to study the characteristics of the proposed problem, which helps us to select appropriate search strategies. Simulation results show that the proposed algorithm provides better performance than existing algorithms.**

***Index Terms*—modeling; fitness landscape analysis; multimedia multicast service; radio resource management**

I. Introduction

The MBMS system [6] specified by the 3GPP is considered as a substantial and efficient platform for multicast service over cellular networks. The MBMS service over UMTS Terrestrial Radio Access Network (UTRAN) interfaces could be carried by PTM (point-to-multipoint) and PTP (point-to-point) mode. In PTM mode, service is carried by a Forward Access Channel (FACH) covering the whole cell. Each FACH needs one channel code serving large amount of users, but may waste power when users are very close to the base station [7]. The PTP mode uses Dedicated Transport Channel (DCH) or High-Speed Downlink Shared Channel (HS-DSCH). Each DCH needs one channel code serving one dedicated user and the shared channel occupies up to 15 channel codes for users. PTP mode provides better link quality than PTM mode but the served user number is limited due to power and channel code restrictions [5]. In UTRAN where the radio resources (power and channelization codes) are limited, the selection of transmission mode is crucial for the allocation efficiency. The related work on this topic are:

MBMS Power Counting (MPC) proposed to establish PTP connections for one MBMS service when the estimated power consumption is under an operator-defined threshold [5]. The switch from PTP to PTM occurs when power exceeds the threshold, and vice versa. MPC is easy to implement but it has limited flexibility because it only considers the delivery of service for all users with the same service quality.

Dual transmission mode (DTM) allows the co-existing usage of PTP and PTM mode for one MBMS service [8]. FACH coverage is adapted for the users who are close to the base station, meanwhile the DCH connections are released or established for the users near the cell edge. However, simulation concludes that DTM is only beneficial for up to 5 users [2]. Hence it is rather limited by only applying FACH and DCH for co-existing of transmission modes.

Scalable FACH Transmission (S-FACH) saves transmission power for MBMS service by integrating scalable video coding technology [9]. The scalable encoded service can be divided into single layer (SL) and multiple layer (ML) transmission schemes. ML service can be splitted into several flows with lower bit rate hence with lower QoS requirement compared with a non-scalable stream. (e.g. 256 kbps service is splitted into two 128 kbps flows). S-FACH transmits flows through common channels with predefined coverage [9]. The basic flow is sent to all subscribers to guarantee service reception, the advanced flow is sent within 50% coverage to enhances service quality on top of basic layer. The trade-off can be made between QoS and the transmission power consumption. However, S-FACH is still based on the fixed coverage so that the resource allocation can not be optimal.

One key feature of radio resource allocation problem in the mobile environment is that the user scenario can be quite dynamic and flexible: the user number, user distributions and service requests can be quite different from time to time. The above existing approaches, however, has the limited flexibility such that the solution space can not be deeply explored. To address this problem, we propose a Flexible Radio Resource Management Model (F2R2M) and we aim to explore the solution space by using metaheuristic approach over the proposed model. In the proposed model, two neighborhood operators and a lexicographic-order criterion are proposed to evaluate the solution quality. Moreover, to understand the structure of solution space and the neighborhood space, we conduct the fitness landscape analysis of two neighborhood functions for different scenarios. The operation selection is further discussed and verified by simulations.

This paper is structured as follows. The proposed model is formulated in section II. Fitness landscape analysis of the model are discussed in section III. The simulation result is showed in section IV and section V is the conclusion and perspective.

II. Model Description

This section describes the proposed model, which allows flexible resource allocation for scalable encoded multimedia multicast service.

A. A Three–Phase Model

As shown in Figure 1, F2R2M is implemented in each radio network controller (RNC), performing radio resource allocation for simultaneous multicast service in the same cell through three phases. A cell is the coverage of one base station.

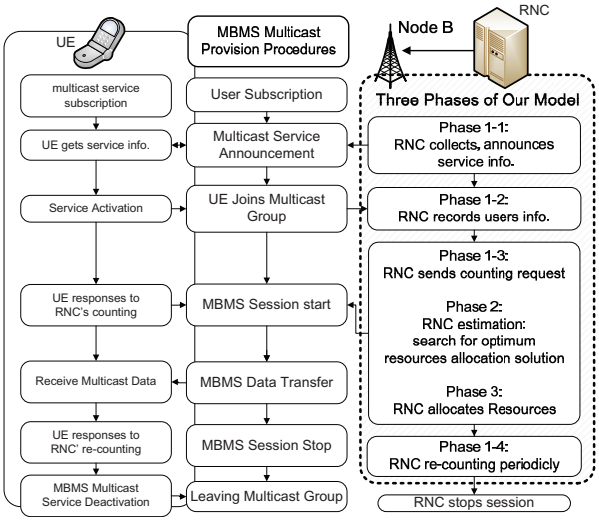


Fig. 1. Three phases of F2R2M

In the first phase (the collect phase), RNC periodically collects service and user information. Any change of MBMS session state (e.g. user mobility, new MBMS session) will trigger the second phase (the estimation phase) to search for proper allocation scheme. After that, according to the solution obtained in the previous phase, the third phase (the allocation phase) establishes the transmission power and channel codes allocation for selected users.

In the collect phase, RNC receives following variables as the input of model:

- $T(c) = \{t_1, ...t_{Nt}\}$, a set of users located in cell c.
- $C(c) = \{(x_1, y_1), ..., (x_{Nt}, y_{Nt})\}$, the instantaneous geometry coordinates of $T(c)$.
- $S(c) = \{s_1, ..., s_{Ns}\}$, A set of services is going to be transmitted to multicast groups within c.
- $F(s_i) = \{f_{s_i,1}, f_{s_i,2}[f_{s_i,3}]\}$ or $\{f_{s_i,0}\}$, the flows (and their bandwidth) of service s_i. $f_{s_i,0}$ indicates s_i is SL transmission, and $f_{s_i,j}$, $(j > 0)$ is the sublayer of ML scheme service.
- $Dist(s_i) = \{t_n, t_m, ...\}$, $s_i \in S(c)$, the multicast group of s_i is constructed by users in $T(c)$.

F2R2M allows the flexible allocation of PTM and PTP modes for each flow, hence the possible assignment of transport channel include:

- pure PTM mode: only FACH,
- pure PTP mode: DCH or HS-DSCH,
- mix of PTP mode: DCH and HS-DSCH transfer the same flow content to different users,
- mix of PTP and PTM mode: co-existing of FACH, DCH or/and HS-DSCH.

Therefore, for each flow $f_{s,j}$ of service s, we partition the multicast group $Dist(s)$ into four disjointed sets: $\mathrm{UE_{fach}(f_{s,j})}$: users served through a FACH; $\mathrm{UE_{dch}(f_{s,j})}$: users transfered through DCHs; $\mathrm{UE_{hs}(f_{s,j})}$: users sharing HS-DSCH and $\mathrm{UE_{noch}(f_{s,j})}$ includes non-served users.

The user partition are firstly determined in solution initialization, and to be modified in each iteration of optimization procedure. We define $Rt(f_{s,j})$ to represent the users who are receiving $f_{s,j}$: $Rt(f_{s,j}) = \mathrm{UE_{fach}(f_{s,j})} \cup \mathrm{UE_{dch}(f_{s,j})} \cup \mathrm{UE_{hs}(f_{s,j})}$. The decision of user sets follow two principles:

1) $Rt(f_{s,j}) = Dist(s)$,$j = 0, 1$,
2) $Rt(f_{s,j}) \subseteq Rt(f_{s,j-1})$, $j \geq 2$.

The principle 1 is to guarantee the service coverage, which means all users in multicast group should be selected to receive $f_{s,0}$ or $f_{s,1}$. The principle 2 restricts that the advanced flow is only sent to users who also receive lower flow, that is to avoid the redundant content transfer to the same user.

The user partition for $f_{s,j}$ should be in accord with channel characteristics:

1) $d_{t_i} \leq d_{thr}, \forall t_i \in \mathrm{UE_{fach}}$,
2) $d_{t_j} > d_{thr}$, $\forall t_j \in \mathrm{UE_{dch}} \cup \mathrm{UE_{hs}} \cup \mathrm{UE_{noch}}$,
3) $\mathrm{UE_{ch_m}} \cap \mathrm{UE_{ch_n}} = \phi$, $ch_m, ch_n \in \{\mathrm{fach, dch, hs, noch}\}$.

In these constraints, d_{t_i} is the distance of user t_i from the base station. d_{thr} is the distance threshold determined during optimization procedure. FACH is a common channel and can be listened by all users within its coverage, the constraint 1 is to guarantee that $\mathrm{UE_{fach}(f_{s,j})}$ includes the nearest users in multicast group. is determined during optimization procedure. In the constraint 2, the users in multicast group, farther than the FACH coverage, are assigned to HS-DSCH or DCH. When there is no available channel code for a given users, this user is switched to $\mathrm{UE_{noch}(f_{s,j})}$. Constraint 3 guarantees that user sets for each flow does not overlap. Since sending the same flow to user through more than one channel will waste resource.

Consequently, according to $\mathrm{UE}_{type}(f_{s,j})$ and requested flows bandwidth, available channel codes(s) is associated with a nonempty user set. This allocation procedure corresponding to the orthogonal principle of OVSF (Orthogonal variable spreading factor) codes [1], if one code on the OVSF tree is used, all codes underneath it are no longer usable.

When user and channel code allocation are determined, the power consumption of transport channels is implicitly determined. As shown in Figure 2, the downlink transmission power of FACH depends on its cell coverage [3], i.e.the user distribution in $\mathrm{UE_{fach}(f_{s,j})}$.

The total transmission power of DCH for n users in a cell [13] is calculated by Equation 1:

$$P_{\mathrm{DCHs}} = \frac{P_p + \sum_{i=1}^{n} L_{p,i} \cdot \frac{P_n + x_i}{\frac{W}{(E_b/N_o)R_{b,i}} + p}}{1 - \sum_{i=1}^{n} \frac{p}{(E_b/N_o)R_{b,i}} + p} \qquad (1)$$

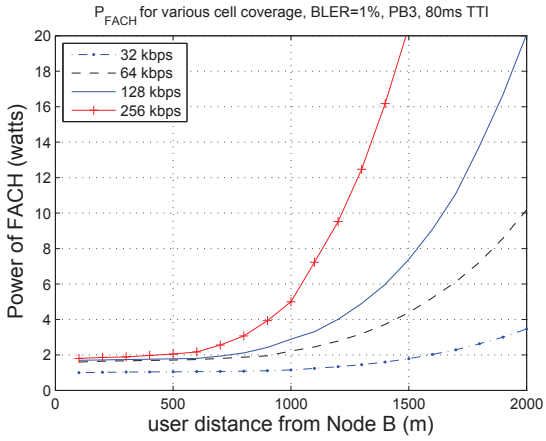


Fig. 2. Power of FACH [3]

where P_p is common channel power, P_n is the background noise, $L_{p,i}$ is path loss of ith user, W is the bandwidth in UMTS, $R_{b,i}$ is user transmit rate, E_b/N_o is the target experienced signal quality of user, p the orthogonality factor ($p = 0$ represents perfect orthogonality). x_i is the intercell interference observed by ith user, expressed by $x_i = \sum_{j=1}^{M} \frac{P_{Tj}}{L_{ij}}$, P_{Tj} is the transmission power in neighbor cell c_j ($j = 1...M$), L_{ij} is the path loss from ith user to jth cell.

The transmit power to guarantee a required HS-DSCH throughput [12] is expressed as:

$$P_{\mathrm{HS-DSCH}} \geq SINR \times [p - G^{-1}] \frac{P_{\mathrm{own}}}{SF_{16}} \qquad (2)$$

in which P_{own} is the own cell interference experienced by user, G is the geometry factor defined by $G = \frac{P_{\mathrm{own}}}{P_{\mathrm{other}}+P_{\mathrm{noise}}}$, related with the user position. For a user at the cell edge, The interference from the neighboring cells for is higher than the interference at its own cell, thus G is expressed by a lower value. In the macrocell (hexagonal layout with 1000 m base station spacing), users within 80% coverage experience a geometry factor of -2.5dB or better, within 95% a geometry factor at least -5.2dB [10]. With the target BLER and the channel quality information (CQI) from users, we obtain the Signal to Interference Noise Ratio (SINR) by applying the CQI and target BLER (i.e. 1%) from the analytic formulation driven by link-level simulation results in [11]. The CQI is obtained through the target bandwidth and mapping table of MAC-hs Bit Rates versus CQI [4]. Then P_{hs} is calculated by applying SINR and G into equation $P_{\mathrm{HS-DSCH}}$.

B. Fitness Values and Evaluation Criteria

The optimization target of F2R2M is first to guarantee the QoS requirement, then to minimize the transmission power while avoiding power saturation. The solution fitness is defined to reflect these aspects. The first objective is to minimize the loss of throughput in one cell:

$$Th(x) = \sum_{s_i \in S(c)} \sum_{f_j \in F(s_i)} \sum_{t_u \in Dist(s_i)} \max\left[-\Delta_{j,u}, 0\right] \qquad (3)$$

subject to: $SF_m(f_{s_i,j}) \perp SF_n(f_{s_i,j}), f_{s_i,j} \in F(s_i)$

The constraint guarantees the OVSF code orthogonality: channel codes are chosen to be orthogonal to each other in the same cell. $\Delta_{j,u}$ in Equation 3 is the difference between allocated channel bit rate (determined by its OVSF code(s) [1]) and the flow bandwidth. For example, user t_u receives $f_{s,j}$ (64 kbps) through DCH channel with bandwidth 32 kbps (SF = 64), then $-\Delta_{j,u}$ is: $-(32 - 64) = 32$ kbps.

The second optimization objective is to minimize the power consumption of cell:

$$Po(x) = \sum_{s_i \in S(c)} \sum_{f_j \in F(s_i)} \sum_{ch_l} P(f_{s_i,j}, ch_l), ch_l \in \{\mathrm{fach}, \mathrm{dch}, \mathrm{hs}\}$$

meanwhile, $Po(x) \leq P_{\mathrm{MBMS\_budget}}(c)$, which enforces the total power consumption of one cell to simultaneous MBMS services does not beyond the maximum power budget.

With the two-dimensional fitness value, the comparison of a new solution x' and current solution x is conducted in lexicographic order: x' is evaluated as better solution when $Th(x') = Th(x)$ and $Po(x') \leq Po(x)$, or $Th(x') < Th(x)$.

C. Solution Representations and Distance Measurement

To analyze the relationship between solutions and landscape, the distance between two feasible solutions need to be developed. We propose two solution representations and corresponding distance measurement.

1) Representation A: In the first representation, the solution of one cell is represented as a matrix of Nt rows and Nf columns:

$$x = \begin{array}{c} \begin{array}{cccc} f(s_1,1) & f(s_1,2) & \ldots & f(s_{Ns},0) \end{array} \\ \begin{pmatrix} ch_{1,1} & ch_{1,2} & \ldots & ch_{1,Nf} \\ \ldots & \ldots & \ldots & \ldots \\ ch_{i,1} & ch_{i,2} & \ldots & ch_{i,Nf} \\ ch_{j,1} & ch_{j,2} & \ldots & ch_{j,Nf} \\ \ldots & \ldots & \ldots & \ldots \\ ch_{Nt,1} & ch_{Nt,2} & \ldots & ch_{Nt,Nf} \end{pmatrix} \end{array},$$

$$d(t_i) \leq d(t_j), i < j; ch_{i,j} \in \{-1, 0, 1, 2, 3\}$$

Nf is the number of flows of all services in cell. Nt is the number of all users in cell. $x(i,j)$ indicates the channel allocation of user t_i for flow f_j. Values 0, 1, 2, 3 represent user is allocated to UE(noch,fach,dch,hs), -1 means the user does not belong to the multicast group.

Hamming distance is a well-known distance in combinational optimization, it corresponds to the number of different elements between two solutions. For solution representation A, we use hamming distance d_{Ham} to measure the distance between two feasible solutions represented by method A.

2) Representation B: In the second mathematical representation, the solution of flow $f_{s,j}$ is a vector of users:

$$x(f_{s,j}) = (\underbrace{0, 1, 2, \ldots,}_{\mathrm{UE(fach)}} \underbrace{0, i, \ldots,}_{\mathrm{UE(dch)}} \underbrace{0, j, \ldots,}_{\mathrm{UE(hs)}} \underbrace{0, k, \ldots, t_{Nt}}_{\mathrm{UE(noch)}})$$

The four user sets are separated by 0 and listed in fixed order. In each set itself, users are ordered with increased distance from the base station. Then the solution representation B of cell c is a vector consisting solutions of transmitted flows:

$$x(c) = \{x(s_1), \ldots, x(s_{Ns})\}$$
$$= \{\ldots, x(f_{s_i,0}), [x(f_{s_i,1}), x(f_{s_i,2}), \ldots], \ldots, \}, \forall s_i \in S(c)$$

3) Comparative Distance: For solution representation B, we design the distance with structural comparisons, named comparative distance d_{com}. Assume we have two solutions based on representation B: x_B and x'_B. For the solution of same flow in x_B and x'_B, we count the number of users that are allocated to different channels, then the number of counted users is then marked as d_{Com}.

The comparative algorithm measures the exact minimum number of applications based on insert operator. It could also be utilized to measure the approximate distance of solutions generated by hybrid-moves operator. d_{Com} is essential the same value as d_{Ham}, the latter compares the different allocated values for all users in cell. Solution representation B as well as the comparative distance only include the users within multicast group for each flow, hence requiring less memory cost, we use the solution representation B and the comparative distance for following analysis.

D. Neighborhood Operators

At each iteration, a move is made to transform each solution into a neighbor solution. Based on the channel characteristic and solution representation, we define two neighborhood operators.

1) Hybrid-moves operator: The "Hybrid-moves" operator δ_H is implemented in three steps: 1) choose one channel ch_o, with non-empty user allocation, UE_{ch_o} is a "output" set; 2) select another user set UE_{ch_i} as an "input" set $(ch_i \neq ch_o)$; 3) randomly select user t_k from UE_{ch_o}, δ_H moves this single t_k or a block of users including t_k from UE_{ch_o} to UE_{ch_i}. In the third step, the moved users depends on the chosen ch_i and ch_o. For example, once we decide to move t_k from UE_{hs} to UE_{fach}, we will enlarge the FACH coverage to t_k, in that case, all the users that nearer than t_k can now hear from FACH, thus, no matter what user sets they are currently allocated at, they need to stay or be inserted in FACH user set. Therefore, once we choose a user t_k to be moved to FACH set, we need to first check the user distributions served by the other channels, and pick out the users within the enlarged FACH coverage to UE_{fach}. By contraries, once we decide to move users out of UE_{fach}, i.e. reduce the FACH coverage, in that case, all users farther than t_k within UE_{fach} should be picked out and moved to the chosen ch_i.

In the following example, two steps of hybrid-moves operator are conducted, moving x_{h1} to x_{h2} then to x_{h3}:

$$x_{h1} : (0\ 1\ \underline{2\ 12}\ 0\ 4\ 5\ 7\ 8\ 0\ 6\ 9\ 0\ 10\ 11)$$
$$x_{h2} : (0\ 1\ 0\ \underline{2\ 12}\ 4\ 5\ 7\ 8\ 0\ \underline{6}\ 9\ 0\ 10\ 11)$$
$$x_{h3} : (0\ 1\ 0\ 2\ 12\ 4\ 5\ \underline{6}\ 7\ 8\ 0\ 9\ 0\ 10\ 11)$$

- $x_{h1} \rightarrow x_{h2}$: ch_o = FACH, ch_i = DCH, $t_k = t_2$. FACH coverage is reduced. Both t_2 and t_{12} are moved to DCH user set, because t_{12} is farther than t_2.
- $x_{h2} \rightarrow x_{h3}$: ch_o = HS-DSCH, ch_i = DCH, $t_k = t_6$.

2) Insert Operator: The insert operator δ_I moves only one user for each operator application. When FACH is chosen as ch_i or ch_o, t_k is determinately selected: the nearest user within $\mathrm{UE_{hs}} \cup \mathrm{UE_{dch}} \cup \mathrm{UE_{noch}}$, or the farthest user within $\mathrm{UE_{fach}}$.

Consider x_{h1} and x_{h3} in previous example, three steps of insert operator are needed:

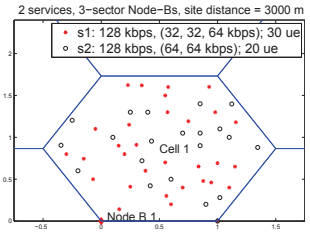
$$x_{i1}(x_{h1}) : (0\ 1\ 2\ \underline{12}\ 0\ 4\ 5\ 7\ 8\ 0\ 6\ 9\ 0\ 10\ 11)$$
$$x_{i2} : (0\ 1\ \underline{2}\ 0\ \underline{12}\ 4\ 5\ 7\ 8\ 0\ 6\ 9\ 0\ 10\ 11)$$
$$x_{i3}(x_{h2}) : (0\ 1\ 0\ \underline{2}\ 12\ 4\ 5\ 7\ 8\ 0\ \underline{6}\ 9\ 0\ 10\ 11)$$
$$x_{i4}(x_{h3}) : (0\ 1\ 0\ 2\ 12\ 4\ 5\ \underline{6}\ 7\ 8\ 0\ 9\ 0\ 10\ 11)$$

- $x_{i1} \rightarrow x_{i2}$: ch_o = FACH, ch_i = DCH, the farthest user t_{12} in $\mathrm{UE_{fach}}$ is moved to $\mathrm{UE_{dch}}$.
- $x_{i2} \rightarrow x_{i3}$: ch_o = FACH, ch_i = DCH, t_2 is determined.
- $x_{i3} \rightarrow x_{i4}$: ch_o = HS-DSCH, ch_i = DCH, t_6 is selected.

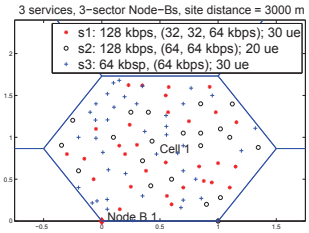
III. Fitness Landscape Analysis

Fitness landscape was originally proposed in a study of evolutionary theory [15]. This notion was then applied to characterize a combinatorial optimization problem [14]. In order to get insight into the given problem, we conduct fitness landscape analysis on the proposed model.

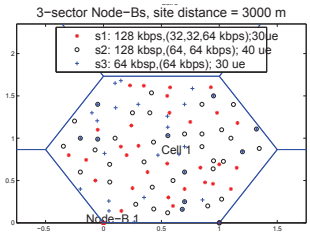
We designed six scenarios with different service parameter settings and user distributions as in Figure 3. Each subfigure presents two scenarios with the same multicast groups and traffic load, but service s_2 is transmitted as one 128 kbps flow in one of the two scenarios, while in another scenario it is transmitted as two flows at 64 kbps.



(a) scenario 1,2: 2s-50u-sn/ss



(b) scenario 3,4: 3s-80u-snn/ssn



(c) scenario 5,6: 3s-100u-snn/ssn

Fig. 3. User Distribution of Simulation Scenarios

The simulation parameters are listed in Table I. Consider one cell in a hexagonal structure of 19 cells, only multicast

services are transmitted in this cell. The maximum power for MBMS in one cell is 19 w (total transmission power minus the power for common channel).

TABLE I
PARAMETER SETTING

Parameters	Value	Parameters	Value
Base station transmit power	43 dBm	Background noise	-100 dBm
Power of neighbor cell	37 dBm	Propagation models	Cost 231
Common channel power	30 dBm	COI's	CQI 1-6

In F2R2M, two fitness landscapes L_{hy} and L_{in} are defined by neighborhood functions δ_H and δ_I. In this paper, we focus on the following properties of a fitness landscape: 1) the distribution of feasible solutions within the search space; 2) the distribution of fitness space; and 3) the links between the distance and the solution fitnesses. To perform these analysis, two populations of solutions S_{ini} and S_{lo} are required. S_{ini} is composed of 600 initial solutions randomly chosen from solution space. S_{lo} is the population of local optima solutions found by applying hill climbing (HC) to S_{ini}. From solution x, HC evaluates all the feasible neighbors of x and replaces x by the neighbor which has the best fitness. HC stops when all neighbors are worse than x.

A. Analysis of Search Space

To study the distribution of feasible solutions in each space, we define two kinds of distance: d_{ini} and d_{lo} are the distances among any two solutions in S_{ini} and S_{lo}, respectively. Tables II(b) and II(a) present the minimum, the maximum and the median values (first and third quartile are also given) of these distances.

TABLE II
ANALYSIS OF SEARCH SPACE: SOLUTION DISTANCE

(a) Distance between solutions of L_{in}

Scen.	d_{ini} in $S_{ini,in}$			d_{lo} in $S_{lo,in}$		
	Min	$\text{Med}_{\text{Q1,Q3}}$	Max	Min	$\text{Med}_{\text{Q1,Q3}}$	Max
scen.1	15	$62_{54,72}$	109	17	$62_{54,71}$	108
scen.2	20	$64_{55,74}$	114	20	$65_{55,75}$	117
scen.3	20	$64_{55,73}$	116	20	$64_{55,74}$	116
scen.4	26	$66_{56,76}$	148	20	$66_{56,76}$	148
scen.5	10	$53_{44,63}$	92	12	$54_{45,63}$	99
scen.6	21	$64_{55,73}$	130	19	$65_{55,76}$	180

(b) Distance between solutions of L_{hy}

Scen.	d_{ini} in $S_{lo,hy}$			d_{lo} in $S_{lo,hy}$		
	Min	$\text{Med}_{\text{Q1,Q3}}$	Max	Min	$\text{Med}_{\text{Q1,Q3}}$	Max
scen.1	19	$62_{53,71}$	108	0	$34_{23,45}$	109
scen.2	23	$64_{54,73}$	121	0	$33_{22,46}$	127
scen.3	21	$65_{54,73}$	115	0	$43_{30,57}$	138
scen.4	20	$64_{55,73}$	116	0	$35_{24,49}$	156
scen.5	24	$55_{64,73}$	114	0	$63_{39,86}$	157
scen.6	21	$64_{55,73}$	129	0	$38_{23,56}$	194

The statistics of d_{ini} shows that the random initial solutions for both search spaces are homogeneous. But the space of local optima are different for two landscapes. In $S_{lo,hy}$, the minimum value of 0 indicates that there are same local optima found from different initial solutions. While in $S_{lo,in}$, no local optima solution have the same value. The quartiles (median, Q1 and Q3) show the space of $S_{lo,hy}$ is more concentrated than $S_{lo,in}$. Therefore, for the population of local optima, L_{hy} appears closer than L_{in}.

B. Analysis of Fitness Space

The fitness value represents the quality of a solution. Figure 4 shows the distribution of fitness values of S_{ini} and S_{lo} for *3s-100u-snn*.

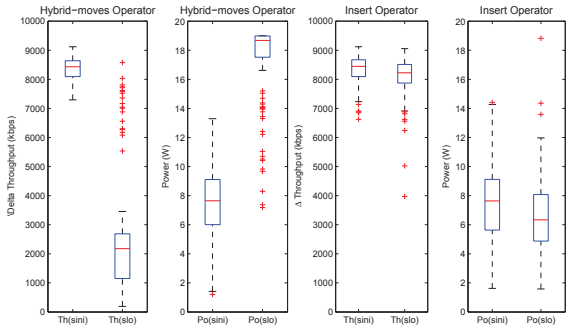


Fig. 4. Two fitness spaces of scenario 5 (3s-100u-snn)

We can observe that the fitness values of S_{ini} is well diversified, according to the similarity of the statistics in S_{ini} for all scenarios (Table II), we verify that the random initial populations are uniformly distributed. Then, all the fitness of local optima for both operators are better than the associated random initial solutions.

Moreover, in the first and third subfigures of Figure 4, the fitness of local optima for two operators are not flat, actually the quality of $S_{lo,hy}$ is better than that of $S_{lo,in}$ ($Th_{hy} < Th_{in}$), the same situation for the other scenarios are shown in Table III, which shows the statistics of solution fitness of local optima in two landscapes, hence gives global information about the quality of S_{lo} determined by neighborhood operators. In Table III we can see δ_H finds solutions with smaller $Th(c)$, hence better solutions than δ_I. This can be explained by the fact that, unlike δ_I, δ_H moves a block of elements which explores larger search space, so that it can easily escape from the local optimal.

C. Analysis of Links between Distance and Fitness

The step length is the number of moves from an initial solution to its associated local optima. In F2R2M, the step length is defined as the number of implemented operator applications by using hill climbing method.

Table IV presents the statistics of the step lengths to find local optima through δ_H and δ_I. Generally, δ_I moves shorter distance than δ_H, which may makes δ_I walks nearby the initial solution without exploring to much better solution. Therefore,

TABLE III
ANALYSIS OF FITNESS SPACE

(a) Fitness values of $S_{lo,in}$

Scenarios		Min	$\text{Med}_{Q1,Q3}$	Max	Mean
scen.1	Th(c) %	4.5	$57.5_{52.25,62}$	69	56.21
	Po(c) w	1.5	$6.53_{5.03,8.33}$	18.54	6.44
scen.2	Th(c) %	0	$58.75_{54,62}$	69.5	10.74
	Po(c) w	1.69	$6.24_{4.69,7.93}$	16.3	6.44
scen.3	Th(c) %	37	$87.5_{82,92}$	99	86.61
	Po(c) w	2.10	$6.56_{4.96,8.21}$	18.96	6.74
scen.4	Th(c) %	20.5	$88_{83.5,91.5}$	99	86.34
	Po(c) w	2.1	$6.56_{4.96,8.21}$	18.96	6.75
scen.5	Th(c) %	20.5	$88_{83.5,91.5}$	99	86.34
	Po(c) w	2.1	$6.56_{4.96,8.21}$	18.96	6.75
scen.6	Th(c) %	15.88	$75.88_{72.64,77.94}$	82.35	74.4
	Po(c) w	1.37	$65.36_{4.82,8.24}$	18.95	6.65

(b) Fitness values of $S_{lo,hy}$

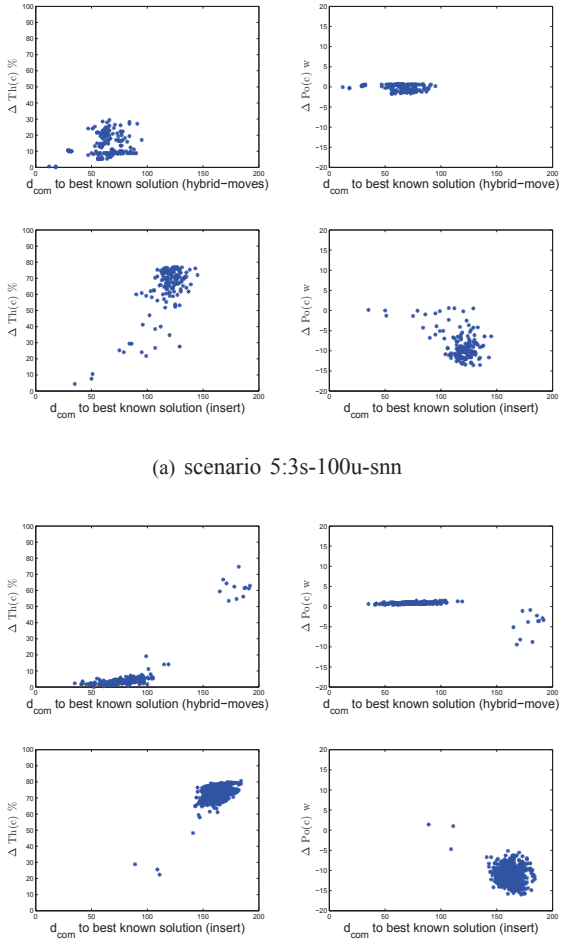
Scenarios		Min	$\text{Med}_{Q1,Q3}$	Max	Mean
scen.1	Th(c) %	0	$0_{0,0}$	58	1.7
	Po(c) w	7.08	$14.89_{12.95,18.18}$	19.0	15.28
scen.2	Th(c) %	0	$0_{0,0}$	62.5	0.94
	Po(c) w	5.81	$14.63_{14.36,15.02}$	16.58	14.57
scen.3	Th(c) %	0	$4_{0,15}$	91.5	9.43
	Po(c) w	5.543	$17.29_{15.92,18.79}$	18.99	17.2
scen.4	Th(c) %	0	$1_{0,2}$	93.5	3.8
	Po(c) w	6.38	$17.57_{17.22,17.63}$	19.0	17.2
scen.5	Th(c) %	0	$1_{0,2}$	93.5	3.8
	Po(c) w	6.38	$17.57_{17.22,17.63}$	19.0	17.2
scen.6	Th(c) %	1.76	$4.12_{4.12,5.88}$	78.24	7.29
	Po(c) w	5.67	$18.38_{18.25,18.41}$	18.99	18.11

TABLE IV
STEP LENGTHS OF TWO LANDSCAPES

Scen.	step length in L_{in}				step length in L_{hy}			
	Min	Med	Max	Mean	Min	Med	Max	Mean
scen.1	1	7	80	9.70	1	18	57	25.97
scen.2	1	7.5	126	10.74	1	21	62	26.93
scen.3	1	6	85	8.78	2	43	100	42.69
scen.4	1	7	127	11.1	1	61	114	67.61
scen.5	1	7	126	8.94	1	19.5	93	99.88
scen.6	1	11	181	12.62	5	105	166	99.88

L_{in} seems "shallower" than L_{hy}, which explains that in Table II(a) the search space of $S_{lo,in}$ does not concentrate the $S_{ini,in}$. Besides, local search with δ_I may be faster, that is because the descent is deeper on landscape L_{hy}.

To investigate how the population of local optima is distributed in the search space relative to the optimum solution, we present fitness distance scatter plots of all scenarios (Figure 5 and Figure 6). These plots provide the fitness between local optima and the best found solution against their distances. The plots determine how closely the fitness and the distance related to the nearest optimum in the search space. When the distance to the best found solution becomes smaller, if fitness difference is decreased, then search procedure is expected to be easy to explored.



(a) scenario 5:3s-100u-snn

(b) scenario 6:3s-100u-ssn

Fig. 5. Fitness-distance plots with local optima

Figure 5 reveals that all local optima are converged on a small region of the search space. The local optima found by δ_H are more closer to the found best solution than the local optima found by δ_I. When points locate in the different distance from the best found solution, their fitness difference are varied, that means both search space are rugged. But in the search space of δ_I, the fitness and the distance to the best found solution is less correlated than in the search space of δ_H. The same situation appears for the other instances (Figure 6), hence the problem difficulty with L_{in} is harder than L_{hy}. Meanwhile, scenarios 1, 2 (Figure 6(a) and Figure 6(b)) have higher correlation than in scenarios 5 and 6, that indicates the difficulty of search space is increased with the increasing scenario complexity.

The study of fitness landscape reveals that local optima in L_{hy} are closer to each other than in L_{in}, and that δ_H can explore larger neighborhood space to achieve better solution than δ_I. Therefor L_{hy} outperforms L_{in}.

IV. Comparison Results

To prove the influence of landscape on optimization performance, 500 trails of greedy local search is implemented for two neighborhood operators on F2R2M.

TABLE V
COMPARISON RESULTS WITH CONVENTIONAL APPROACHES

	MPC	DTM	S-FACH	S-MPC	F2R2M-in	F2R2M-hy
scen.1	0% 27.19	0% 30.45	**65% 10.23**	28% 21.51	**4.5% 18.5**	**0% 10.19**
scen.2			**47% 15.4**	**16% 18.4**	**0% 15.58**	**0% 13.06**
scen.3	0% 32.47	0% 37.68	25.4% 26.95	44.6% 21.51	**25.4% 16.9**	**0% 15.0**
scen.4			36.2% 22.63	**47.4% 18.37**	**15.4% 16.5**	**0% 14.4**
scen.5	0% 37.73	0% 37.69	**59.41% 5.95**	0% 31.1	**36.47% 18.82**	**1.76% 18.39**
scen.6			**51.18% 15.9**	0% 31.79	**15.9% 18.12**	**1.76% 17.5**

two-dimensional cost: lost throughput in percentage, power consumption in watts

The found best solutions of our model are shown in Table V. Competing allocation approaches are implemented on the same platform. To prove the advantage of layer based channel allocation, we applied MPC for each flow (S-MPC). We can observe that when services are transmitted in non-scalable mode, neither MPC nor DTM can obtain feasible solutions. S-FACH solves the power saturation problem of MPC and DTM for three scenarios. It reduces the coverage for the advanced flows hence consuming less power and provides service coverage (all service can be transmitted). However, in S-FACH, the trade-off between service quality and power is not efficient with fixed coverages. When most users are far from the base station (e.g. *3s-80u*), S-FACH achieves power saturation.

The result of S-MPC shows that scalable transmission costs less power than non-scalable scheme thus has higher possibility to obtain feasible solution. From the results of S-MPC for *2s-50u-sn/ss* or *3s-80u-snn/ssn*, with the same user distribution and total traffic load, the scalable transmission of $s2$ consumes less power. However, for scenarios having more users (*3s-100u*), S-MPC increases the possibility of power saturation because it allocates only pure transmission mode per flow.

The F2R2M with local search outperforms the other algorithms. For the scenario that could obtain proper solutions with the conventional algorithms, F2R2M avoids unneeded QoS decrease. F2R2M-in with greedy local search can find feasible solutions, hence balance the consumption between power and channel codes. However, for scenario with increased complexity, its solution quality is reduced since $Th(x)$ is higher. While F2R2M-hy found the best solution among all approaches, it always obtain feasible solution with much less $Po(x)$ and almost achieve 100% bandwidth requirement.

The statistics of fitness values of found solutions are computed in Table VI, which proves the feasibility of all solutions obtained with F2R2M. δ_H can always offer good enough solutions: higher QoS with less power consumption than the competing approaches. Besides, the performance of δ_H is better than δ_I, which proves the discussion in section III that δ_H has capacity of "jump" from local optima, while δ_I can only stay in basins. In Table VII, the average consuming time of search procedure for two operators are both acceptable, δ_H costs almost double time than δ_I, that is because δ_H can move further than δ_I.

TABLE VI
PERFORMANCE OF LOCAL SEARCH WITH δ_I AND δ_H

Scen.	F2R2M-in			F2R2M-hy		
	best	mean	std.	best	mena	std.
scen.1	4.5% 18.5	56.2% 6.4	8.12 8.12	0% 10.19	1.7% 15.28	8.18 2.56
scen.2	0% 15.58	57.29% 6.44	7.82 2.27	0% 13.06	0.94% 14.57	6.46 0.9
scen.3	25.4% 16.9	66.62% 6.73	5.53 2.29	0% 15	7.25% 17.12	11.77 2.0
scen.4	15.4% 16.5	66.42% 6.75	6.73 2.45	0% 14.4	2.9% 17.2	11.26 1.23
scen.5	36.47% 18.82	74.98% 6.58	4.5337 2.3244	1.76% 18.39	19.57% 18.03	12.61 1.5856
scen.6	15.9% 18.12	74.4% 6.65	7.13 2.55	1.76% 17.5	7.29% 18.12	11.93 1.4

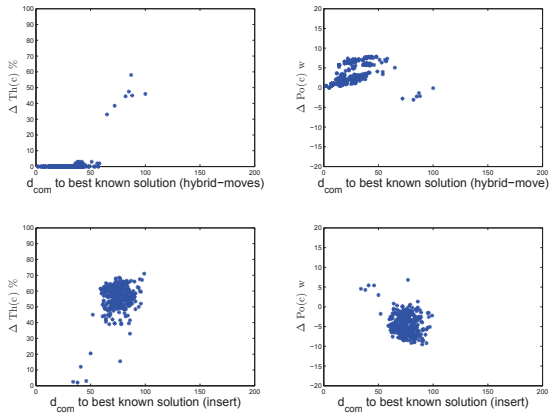
TABLE VII
AVERAGE TIME COST (S) OF F2R2M

Scen.	F2R2M-in	F2R2M-hy	Scen.	F2R2M-in	F2R2M-hy
scen.1	0.062	0.160	scen.2	0.122	0.259
scen.3	0.18	0.322	scen.4	0.117	0.279
scen.5	0.196	0.368	scen.6	0.313	0.773

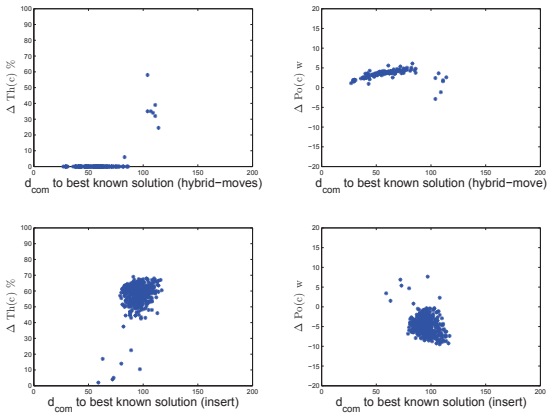
V. Conclusion and Perspective

In this paper, we present a mathematical model which enables flexible radio resource allocation for simultaneous MBMS services. This model integrates scalable transmissions and dynamic power setting along with transmit mode selection. The proposed evaluation criterion guides the search to satisfy two objects in a lexicographic order: first to achieve the QoS requirement of multicast service and then to minimize the power consumption.

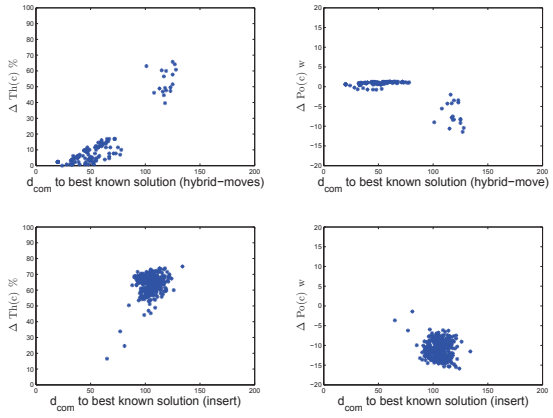
In order to understand the problem behavior differentiated by the proposed two neighborhood functions, we developed the mathematic solution representation and the distance measurement between two feasible solutions, based on which, the fitness landscapes analysis is conducted. The fitness distance plot shows both search space are rugged, and the δ_H is more powerful than δ_I in terms of escaping from the local optima. Following by that, simulations are carried out in a variety of scenarios. Both operators in our model are capable of producing high quality solutions with a preferable balance



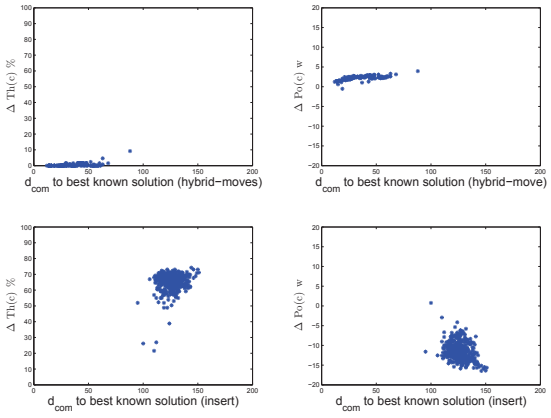
(a) scenario 1:2s-50u-sn



(b) scenario 2:2s-50u-ss



(c) scenario 3:3s-80u-snn



(d) scenario 4:3s-80u-ssn

Fig. 6. Fitness-distance plots with local optima

between radio resource consumption, service coverage and service quality. In particular, the hybrid-moves operator is able to find near-optimum solutions in all scenarios.

However, robustness against local optima still has to be improved in our search algorithms. In other words, the greedy local search method does not always reach the theoretical best found solution in every trial. That is because that the algorithm terminates when it reaches a state where no further improvement can be found. In the future work, we are interested in applying the effective metaheuristics capable of escaping from local optima (e.g. simulated annealing and Tabu search) to our model to obtain solutions with higher stability.

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