Modeling and Fitness Landscape Analysis for Flexible MBMS Radio Resource Allocation

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***Abstract*—Multimedia traffic is constantly increasing and will soon dominate traffic flows in radio networks. The Multimedia Broadcast Multicast Service (MBMS) system provides efficient mechanisms for multimedia multicast services in mobile networks. We develop a flexible model to perform dynamic radio resource allocation for MBMS service by using metaheuristics approach. We conduct fitness landscape analysis to study the characteristics of the proposed problem, which helps us to select appropriate search strategy. Simulation results show that the proposed algorithm provides better performance than existing algorithms.**

***Index Terms*—modeling; fitness landscape; multimedia multicast; 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 network. The MBMS service over UMTS Terrestrial Radio Access Network (UTRAN) interfaces could be carried by PTM and PTP 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 there is small number of users or users are very close to Node B [7]. The PTP mode uses the dedicated channel (DCH) or 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 controls link quality better than PTM but the served user number is limited due to power and channel code restriction [5]. In UTRAN where the radio resources (power and channelization codes) are limited, the selection of transmission mode is crucial to the allocation efficiency. The related work on this topic are:

- **MBMS Power Counting** (MPC) that defined by 3GPP [5] is to minimize power requirement. Before data transfer, when the estimated power consumption of MBMS service in a cell is under an operator-defined threshold, network will establish PTP connections. The switch from PTP to PTM occurs when power exceeds the threshold, and vice versa. MPC has limited flexibility because it only considers delivering service for all users with full service quality.
- **Dual transmission mode** (DTM) allows the co-existing usage of PTP and PTM mode for one MBMS service [8]. For users with better link quality, FACH coverage is adapted by changing transmission power, meanwhile the DCH connections are released or established for the users near the cell edge. DTM enriches the candidate transmission modes for MBMS, however, simulation concluded 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) is a potential power saving technology for multicast [9]. With scalable video coding, service can be divided into single layer (SL) and multiple layer (ML) transmission schemes. ML service can split into several streams with lower bit rate hence with lower QoS requirement compared with a non-scalable stream. (e.g. 256 kbps service has two 128 kbps flows). S-FACH transmits flows through common channels with predefined coverage [9]. the basic flow to all subscribers (95% geographical coverage) to guarantee service reception, the advanced flow is sent to users within 50% coverage. The reception of advanced layers enhances service quality on top of basic layer. Basic flow's transmission power is reduced with lower bit rate, and so do the advanced flows with smaller coverages.

Although MBMS RRM in 3G network has been extensively studied, several aspects are still not well balanced with existing approaches. especially when transmission power or channel codes are saturated. For example, should we transmit service through basic quality with full coverage or through advanced quality with smaller coverage? Should we select transmission mode based on less power consumption or less occupation of channel codes? To address these demands, we propose a Flexible Radio Resource Management Model (F2R2M) combining transmission mode selection and multimedia scalability. This model could answer these questions mentioned above by using metaheuristics approach. Two neighborhood operators and lexicographic-order criteria are proposed to evaluate the quality of resources allocation in terms of service satisfaction and resource consumption. Moreover, to understand the structure of solution space and the neighborhood space to characterize the given problem, we conducted the fitness landscape analysis of two neighborhood functions for different scenarios. Then the operator selection are discussed and proved with local search.

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 gives the description of the proposed model, which allows combinational allocation of transport channel for scalable encoded multimedia multicast service.

A. Phases of Model

As shown in Figure 1, F2R2M is implemented in each RNC, performing radio resource allocation for simultaneous multicast service through three phases.

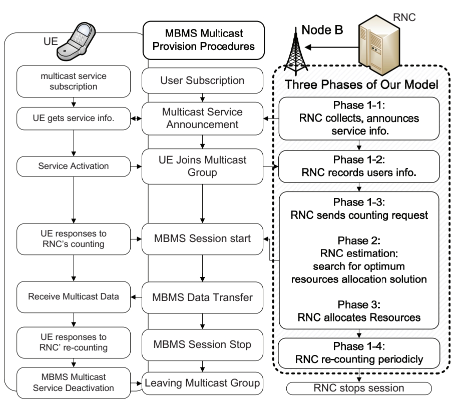


Fig. 1. Three phases of F2R2M

In the first phase (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 (estimation phase) to search for proper allocation scheme. In the begin of MBMS data transfer, the third phase establishes the planned transport channel for selected users according to the solution obtained in the previous phase.

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 $T(c)$. With $C(c)$, the distance of user t_i from Node B (d_{t_i}) is obtained.
- $S(c) = \{s_1, ..., s_{Ns}\}$, 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.
- $Dest(s_i) = \{t_n, t_m, ...\}$, $s_i \in S(c)$, the multicast group of s_i is constructed by users in $T(c)$.

F2R2M allows the combination 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 $Dest(s)$ 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,
- $\mathrm{UE_{noch}(f_{s,j})}$: users not served.

$Rt(f_{s,j})$ is defined to represent the users receiving $f_{s,j}$: $Rt(f_{s,j}) = \mathrm{UE_{fach}(f_{s,j})} \cup \mathrm{UE_{dch}(f_{s,j})} \cup \mathrm{UE_{hs}(f_{s,j})}$. Then the decision of user sets follow two principles:

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

Principle 1 is to guarantee service coverage, which means all users in multicast group should be selected to receive f_0 or f_1, unless all channel codes are fully occupied. Principle 2 restricts the advanced flow is only sent to users which also receive lower flow, that is to avoid the redundant content transfer to the same user.

Then the partition of users 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) $\mathrm{UE_{ch_m}} \cap \mathrm{UE_{ch_n}} = \phi$, $ch_m, ch_n \in \{\mathrm{fach, dch, hs, noch}\}$.

FACH is a common channel and can be listened by all users within its coverage, constraint 1 is to guarantee that $\mathrm{UE_{fach}(f_{s,j})}$ includes the nearest users in multicast group, with distance from Node B under a threshold, d_{thr} is determined during optimization procedure. In 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 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:

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

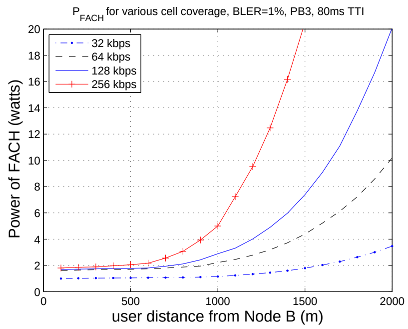


Fig. 2. Power of FACH [3]

where P_p is the power for common control channel, 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 neighboring 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:

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

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

F2R2M aims at finding solution to guarantee the QoS requirement in terms of the bandwidth of allocated channels, and minimize the transmission power while avoiding power saturation. Fitness value of solution is defined to reflect these aspects. The first objective is to minimize the loss of throughput in one cell:

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

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

Constraint guarantees the OVSF code orthogonality: channels' 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 bandwidth of requested service(s). 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:

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

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

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 conduct the analysis of relationship between solutions and landscape, The distance metrics for solutions need to be developed. We propose two mathematic representations for solution and corresponding measurement method to represent the distance between two feasible solutions.

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

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

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

Nf is the number of flows of all services in cell. Nt is the number of all users in cell. Element in the i^{th} row j^{th} column 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 bits 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 terminals within $Dist(s)$:

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

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

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

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

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

- $x_{h1} \to x_{h2}$: 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.
- $x_{h2} \to x_{h3}$: ch_o = HS-DSCH, ch_i = DCH, $t_k = t_6$.

2) Insert Operator: The insert operator δ_I is a typical case of δ_H, it 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:

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

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

III. Fitness Landscape Analysis based on Model

Fitness landscape was originally proposed in a study of evolutionary theory [15]. This notion was then applied to characterize a combinatorial optimization problem [14]. To study the behavior of the flexible MBMS RRM problem, we implemented fitness landscape analysis based on the proposed model.

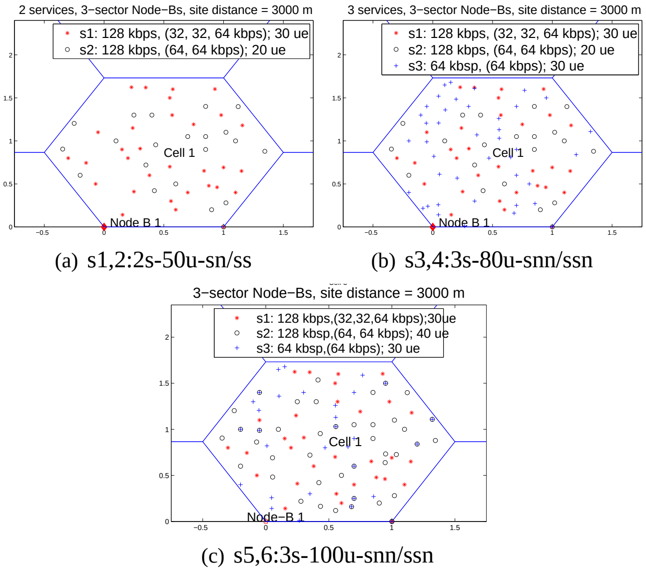
In order to get insight in the given problem, we designed six problem instances with different service parameter setting and user distribution as in Figure 3. The simulation parameters are listed in Table I. Consider one cell in a hexagonal structure of 19 cells, only multicast services are transmitted in this cell, then the maximum power for MBMS in one cell is 19 w (total transmission power minus the power for common channel).

TABLE I
System Simulation Parameters

Parameters	Value	Parameters	Value
Node B 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

Three couples of instances (e.g. *3s-80u-snn* and *3s-80u-ssn*) have the same multicast groups and traffic load, but service s_2 is transmitted as one 128 kbps flow and two 64 kbps flows respectively.

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 search space; 2) the distribution of fitness space; and 3) the links between distance and fitnesses of solutions. To perform these analysis, two populations of solutions S_{ini} and S_{lo} are required. S_{ini}



(a) s1,2:2s-50u-sn/ss (b) s3,4:3s-80u-snn/ssn

(c) s5,6:3s-100u-snn/ssn

Fig. 3. User Distribution of Problem Instances

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 calculated 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	Med$_{Q1,Q3}$	Max	Min	Med$_{Q1,Q3}$	Max
s1	15	$62_{54,72}$	109	17	$62_{54,71}$	108
s2	20	$64_{55,74}$	114	20	$65_{55,75}$	117
s3	20	$64_{55,73}$	116	20	$64_{55,74}$	116
s4	26	$66_{56,76}$	148	20	$66_{56,76}$	148
s5	10	$53_{44,63}$	92	12	$54_{45,63}$	99
s6	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	Med$_{Q1,Q3}$	Max	Min	Med$_{Q1,Q3}$	Max
s1	19	$62_{53,71}$	108	0	$34_{23,45}$	109
s2	23	$64_{54,73}$	121	0	$33_{22,46}$	127
s3	21	$65_{54,73}$	115	0	$43_{30,57}$	138
s4	20	$64_{55,73}$	116	0	$35_{24,49}$	156
s5	24	$55_{64,73}$	114	0	$63_{39,86}$	157
s6	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 is the same. The quartiles (median, Q1 and Q3) show the space of $S_{lo,hy}$ is more concentrated than $S_{lo,in}$. Therefore, from 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*.

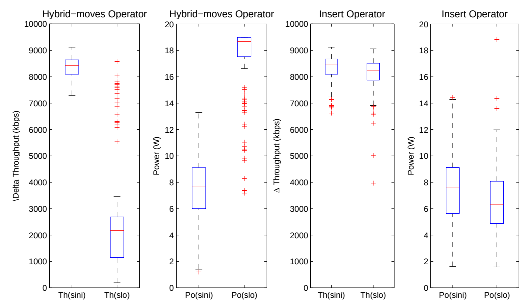


Fig. 4. Comparison of two fitness spaces for 3s-100u-snn

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 normally 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. δ_I gets many local optima with bad qualities that may easily block the search. Therefore, the probability to obtain the best solution by using δ_H is greater.

C. Analysis of Links between Distance and Fitness

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, L_{in} seems "shallower" than L_{hy}, which explains that in Table

TABLE III
ANALYSIS OF FITNESS SPACE

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

Scenarios		Min	$\mathrm{Med}_{Q1,Q3}$	Max	Mean
s1	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
s2	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
s3	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
s4	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
s5	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
s6	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	$\mathrm{Med}_{Q1,Q3}$	Max	Mean
s1	Th(c) %	0	$0_{0,0}$	58	1.7
	Po(c) w	7.08	$14.89_{12.95,18.18}$	19.0	15.28
s2	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
s3	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
s4	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
s5	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
s6	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

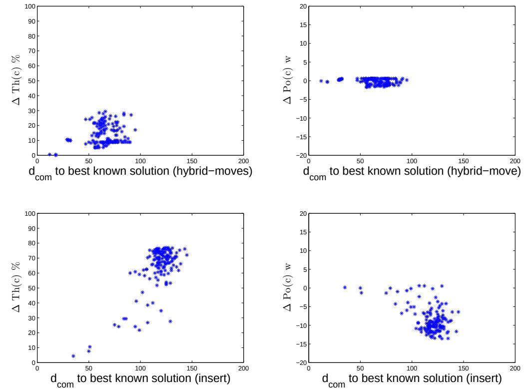
TABLE IV
STEP LENGTHS OF TWO LANDSCAPES

Scen.	step length in L_{in}				step length in L_{hy}			
	Min	Med	Max	Mean	Min	Med	Max	Mean
s1	1	7	80	9.70	1	18	57	25.97
s2	1	7.5	126	10.74	1	21	62	26.93
s3	1	6	85	8.78	2	43	100	42.69
s4	1	7	127	11.1	1	61	114	67.61
s5	1	7	126	8.94	1	19.5	93	99.88
s6	1	11	181	12.62	5	105	166	99.88

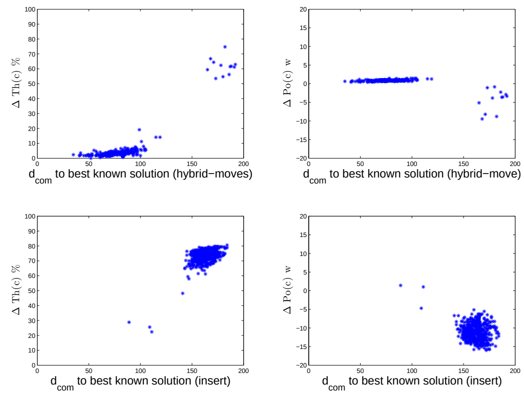
II(a) the search space of $S_{lo,in}$ does not concentrate the $S_{ini,in}$. Besides, local search with δ_I may be faster, since the descent is deeper on landscape L_{hy}.

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 to of all scenarios in Figure 5 and Figure 6.

These plots provide the fitness between local optima and the best found solution against their distances. The plots determines how closely fitness and distance to the nearest optimum in search space are related. 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) s5:3s-100u-snn



(b) s5:3s-100u-ssn

Fig. 5. Fitness-distance plots with local optima

As the plots in Figure 5 reveal, all local optima are concentrated 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 located 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 of the local optima 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 (6(a) and 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 revealed that local optima in L_{hy} are closer to each other than in L_{in}, 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
s1	0% 27.19	0% 30.45	**65%** **10.23**	28% 21.51	**4.5%** **18.5**	**0%** **10.19**
s2			**47%** **15.4**	**16%** **18.4**	**0%** **15.58**	**0%** **13.06**
s3	0% 32.47	0% 37.68	25.4% 26.95	44.6% 21.51	**25.4%** **16.9**	**0%** **15.0**
s4			36.2% 22.63	**47.4%** **18.37**	**15.4%** **16.5**	**0%** **14.4**
s5	0% 37.73	0% 37.69	**59.41%** **5.95**	0% 31.1	**36.47%** **18.82**	**1.76%** **18.39**
s6			**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 F2R2M with greedy local search 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 coverage for 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 Node B, (e.g. *3s-80u*) S-FACH achieves power saturation.

The results of S-MPC reveal 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 for each flow.

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

TABLE VI
Performance of local search with δ_I and δ_H

Scen.	F2R2M-in			F2R2M-hy		
	best	mean	std.	best	mena	std.
s1	4.5% 18.5	56.2% 6.4	8.12 8.12	0% 10.19	1.7% 15.28	8.18 2.56
s2	0% 15.58	57.29% 6.44	7.82 2.27	0% 13.06	0.94% 14.57	6.46 0.9
s3	25.4% 16.9	66.62% 6.73	5.53 2.29	0% 15	7.25% 17.12	11.77 2.0
s4	15.4% 16.5	66.42% 6.75	6.73 2.45	0% 14.4	2.9% 17.2	11.26 1.23
s5	36.47% 18.82	74.98% 6.58	4.5337 2.3244	1.76% 18.39	19.57% 18.03	12.61 1.5856
s6	15.9% 18.12	74.4% 6.65	7.13 2.55	1.76% 17.5	7.29% 18.12	11.93 1.4

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 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 bad solutions, 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.

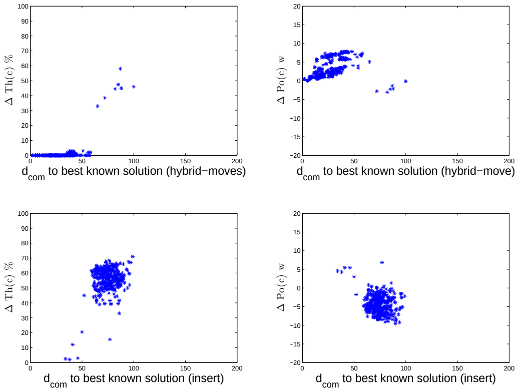
TABLE VII
Time cost (s) of F2R2M with Greedy local search

	F2R2M-in	F2R2M-hy		F2R2M-in	F2R2M-hy
s1	0.062	0.160	s2	0.122	0.259
s3	0.18	0.322	s4	0.117	0.279
s5	0.196	0.368	s6	0.313	0.773

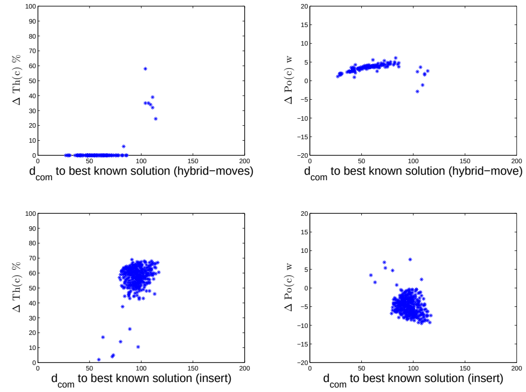
V. Conclusion and Perspective

In this paper, we present a mathematical model describing the allocation of radio resource for simultaneous MBMS services. This model integrates scalable transmissions and dynamic power setting along with transmit mode selection. We propose lexicographic order evaluation criteria to guide solution satisfying two objectives: to achieve the QoS requirement of multicast service and to minimize the power consumption.

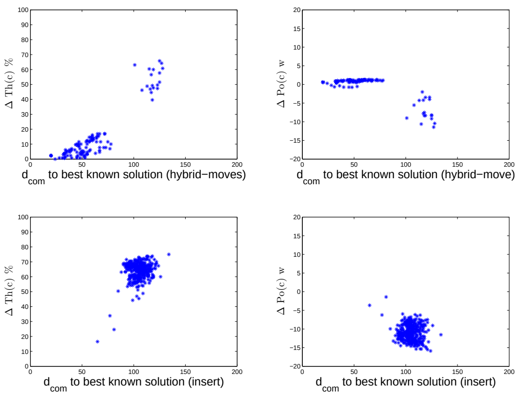
In order to understand the problem behavior differentiated by the proposed two neighborhood functions, we developed the mathematic solution representation and the distance measurement between two feasible solutions, based on which, the fitness landscapes analysis is conducted. The fitness distance plot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



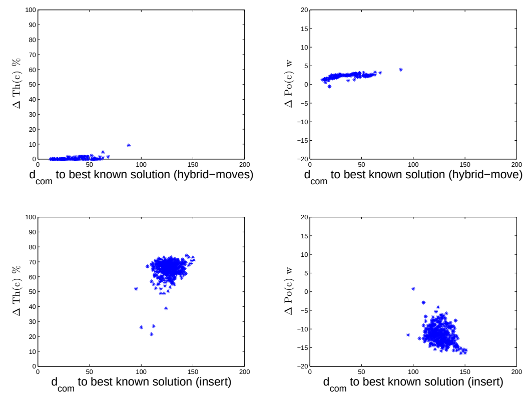
(a) s1:2s-50u-sn



(b) s2:2s-50u-ss



(c) s3:3s-80u-snn



(d) s4:3s-80u-ssn

Fig. 6. Fitness-distance plots with local optima

of producing high quality solutions with a preferable balance between radio resource consumption, service coverage and service quality. In particular, the hybrid-moves operator is able to find near optimum solutions a few percent below the best-found solutions, and the search procedure is sufficient to find the sub-optimal solutions of all problem instances.

However, the quality of solutions with F2R2M based on greedy local search highly depend on the initial solution, in other word, the greedy local search method does not reach the best found solution in each trial because the algorithm terminates when it reaches a state where no further improvement can be found. In the future work, we are interested in applying effective metaheuristics to our model (e.g. Tabu search) to obtain solutions with higher stability.

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