Photon Netw Commun (2010) 19:103–109
DOI 10.1007/s11107-009-0215-9

# A Lagrangean relaxation based near-optimal algorithm for advance lightpath reservation in WDM networks

**Steven S. W. Lee · Alice Chen · Maria C. Yuang**

Received: 23 October 2008 / Accepted: 31 August 2009 / Published online: 17 September 2009


**Abstract** Advance lightpath reservation is a new research topic for connecting high-speed computer servers in lambda grid applications and for dynamic lightpath provisioning in the future optical internet. In such networks, users make call requests in advance to reserve network resources for communications. The challenge of the problem comes from how to jointly determine call admission control, lightpath routing, and wavelength assignment. In this paper, we propose an efficient Lagrangean relaxation (LGR) approach to resolve advance lightpath reservation for multi-wavelength optical networks. The task is first formulated as a combinatorial optimization problem in which the revenue from accepting call requests is to be maximized. The LGR approach performs constraint relaxation and derives an upper-bound solution index according to a set of Lagrangean multipliers generated through subgradient-based iterations. In parallel, using the generated Lagrangean multipliers, the LGR approach employs a new heuristic algorithm to arrive at a near-optimal solution. By upper bounds, we assess the performance of LGR with respect to solution accuracy. We further draw comparisons between LGR and three heuristic algorithms—Greedy, First Come First Serve, and Deadline First, via experiments over the widely-used NSFNET network. Numerical results demonstrate that LGR outperforms the other three heuristic approaches in gaining more revenue by receiving more call requests.

**Keywords** Advance lightpath reservation · Call admission control · Routing and wavelength assignment · Lagrangean relaxation

S. S. W. Lee (✉)
Department of Communications Engineering, National Chung Cheng University, Taiwan, ROC
e-mail: ieeswl@ccu.edu.tw

A. Chen · M. C. Yuang
Department of Computer Science, National Chiao Tung University, Taiwan, ROC
e-mail: alice_chen@itri.org.tw

M. C. Yuang
e-mail: mcyuang@csie.nctu.edu.tw

A. Chen
Information and Communications Research Laboratories, Industrial Technology Research Institute, Taiwan, ROC

## 1 Introduction

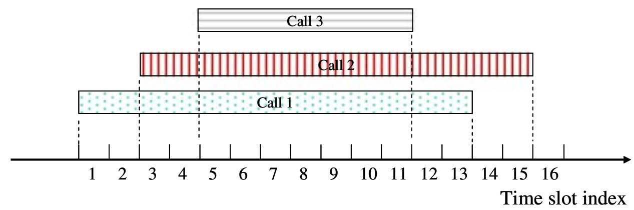
With advances in optical Wavelength Division Multiplexing (WDM) technologies and its potential of providing virtually unlimited bandwidth, optical WDM networks have been widely recognized as the dominant transport infrastructure for future Internet backbone networks. Applications like lambda grid and virtual private optical networks usually need many high-speed lightpaths for connecting computer servers in diverse enterprise campuses. A major feature of such applications is that traffic demands are requested to the network in advance before the connections are set up [1–4].

The advance lightpath reservation problem is in short referred to as ALR in this paper. One major challenge arising in ALR has been to jointly determine call admission control, scheduling, and routing and wavelength assignment (RWA) [5]. Particularly, for optical network without wavelength conversion capability, the problem deals with RWA between source and destination nodes subject to the wavelength-continuity constraint [6]. It has been shown that RWA is an NP-complete problem [6]. Therefore, the ALR problem is also NP-complete since an RWA problem is a special case of the ALR problem.

Several algorithms for resolving the ALR problem have been proposed in the literature. In [1], the authors present a basic framework for automated provisioning of advance reservation service based on GMPLS protocol suites. In [7], the ALR problem is classified into several types depending on the flexibility of call arrival time and call duration. Heuristic to RWA algorithms are also demonstrated for the problems. In [2], a simulated annealing based algorithm is proposed to find a solution on predetermined $k$-shortest paths. For lambda grid networks, Miyagi et al. [3] consider how to reserve a wavelength for deadline-aware application. Performance for blocking probability is evaluated under Greedy based and Deadline First based heuristic algorithms.

Lagrangean relaxation (LGR) based method has been shown to be an effective method in solving WDM network problems, for instance in [8]. In this paper, we propose a new LGR algorithm, which is used for the first time to our best knowledge to precisely and efficiently solve the advance lightpath reservation problem. In this paper, ALR is first formulated as a combinatorial optimization problem in which the revenue from admitting call requests is maximized. The LGR approach performs constraint relaxation and derives an upper-bound solution according to a set of Lagrangean multipliers generated through subgradient-based iterations. In parallel, using the generated Lagrangean multipliers, the LGR approach employs a new primal heuristic algorithm to arrive at a near-optimal solution. By upper bounds, we delineate the performance of LGR with respect to accuracy and convergence speed under different parameter settings and termination criteria. We further draw comparisons between LGR and a set of heuristic approaches via experiments over the widely-used NSFNET network. Numerical results demonstrate that LGR outperforms the other heuristic approaches in both accuracy and call blocking probability.

The remainder of this paper is organized as follows. In Sect. 2, we first give the ALR problem formulation. In Sect. 3, we present the LGR approach and its primal heuristic algorithm. In Sect. 4, we demonstrate numerical results of the performance study and comparisons under benchmark of the NSFNET network. Finally, concluding remarks are made in Sect. 5.




Call 1: start time =1, end time =13
Call 2: start time =3, end time =15
Call 3: start time =5, end time =11
Time event set T={1,3,5,11,13,15}
$\sigma_{1*}$={1,1,1,1,1,0}
$\sigma_{2*}$={0,1,1,1,1,1}
$\sigma_{3*}$={0,0,1,1,0,0}

**Fig. 1** Example of ALR problem

## 2 Problem formulation

We consider a WDM network where each WDM link consists of a pair of unidirectional fiber links with a number of wavelengths on each fiber. The network is under centralized control. There is a central controller responsible for call admission control, RWA so as to establish lightpaths for all connection requests on behalf of all network nodes.

The ALR problem is formulated as an integer linear programming problem stated as follows. Given a physical topology and each call information (start time, end time, revenue), determine the scheduling of routes and wavelengths of lightpaths, such that the total revenue from admitting calls is maximized under the wavelength continuity constraint. The bandwidth demand is one wavelength in the context of this paper. Throughout the paper, we use connection and call interchangeably. For ease of illustration, we assume in the sequel that the number of available wavelengths on each link is the same.

Before describing the model, we first give an example for the ALR problem. In Fig. 1, there are three calls requests. Call 1 goes from time slot 1 to time slot 13. Call 2 and call 3 start from time slots 3 and 5, and end at time slots 15 and 11, respectively. Hence we have six time events (1, 3, 5, 11, 13, and 15) that need to be taken care of. Those six event points form the six members of the set $T$. Let us denote $\sigma_{kt}$ as a binary index to represent if call $k$ includes event time $t$. Since, in this example, call 1 goes over event index 1, 2, 3, 4, and 5, we could derive that $\sigma_{11} = 1, \sigma_{12} = 1, \sigma_{13} = 1, \sigma_{14} = 1, \sigma_{15} = 1$, and $\sigma_{16} = 0$.

We summarize the notation used in the formulation as follows:

**Input values:**

$L$: set of optical links;
$N$: set of optical cross-connects;
$W$: set of wavelengths on each link (same for all links);
$|W|$: number of wavelengths available on each fiber link;
$K$: set of connection requests;
$|K|$: number of call requests;
$r_k$: revenue for accepting call request $k$;
$P_k$: candidate path set for call $k$;
$\delta_{pl}$: = 1, if path $p$ includes link $l$; = 0, otherwise;
$T$: set of time events;
$\sigma_{kt}$: = 1, if call $k$ goes through event time $t$; = 0, otherwise;

**Decision variables:**

$x_{pw}$:= 1, if lightpath $p$ uses wavelength $w$; = 0, otherwise;
$y_k$: = 1, if call $k$ is accepted by the network; = 0, otherwise;

**Problem (P):**

$$\max \quad \sum_{k\in K} r_k y_k$$

subject to:

$$y_k = \sum_{p\in P_k}\sum_{w\in W} x_{pw} \qquad \forall k \in K \tag{1}$$

$$\sum_{p\in P_k}\sum_{w\in W} x_{pw} \le 1 \qquad \forall k \in K \tag{2}$$

$$\sum_{k\in K}\sum_{p\in P_k} x_{pw}\delta_{pl}\sigma_{kt} \le 1 \qquad \forall w \in W, l \in L, t \in T \tag{3}$$

$$x_{pw} = 0 \text{ or } 1 \qquad \forall p \in P_k, k \in K, w \in W \tag{4}$$

$$y_k = 0 \text{ or } 1 \qquad \forall k \in K \tag{5}$$

The objective function is to maximize the total revenue. Usually the revenue is proportional to the call duration. If we set $r_k$ to be one for all requests $k$, the problem becomes to maximize the number of accepted calls. In that case, the problem is also equivalent to minimize call blocking. Constraints (1) and (2) require that at most one lightpath to be selected for each request. If the connection of call $k$ is rejected, in which case the corresponding variable $x_{pw}$ is 0, a zero revenue contributes to the objective function. Constraint (3) guarantees no over-booking on any wavelength channel at any time slot. It requires that for any wavelength on a link, there is at most one lightpath using it. Constraint (4) states the 0/1 binary constraint on routing variable $x_{pw}$. Please note that, we use time event $T$ in our model, instead of directly using time slot index. The reason to use set $T$ is to reduce the problem size. There are at most $2|K|$ members in $T$. That is usually far smaller than the total number of time slots. For example, in Fig. 1, the total number of time slots is 16 while the total number of events is six. By using this technique, we can reduce the total number of constraints significantly. Finally, whether a call request is accepted or not is determined by constraint (5).

If we set all call requests with the same duration, the above ALR problem is reduced to a general RWA problem which has been proved to be NP-complete. Therefore, it is unlikely to obtain an exact solution for realistic networks in real-time. The problem is approximated using the LGR approach presented in the next section.

## 3 Lagrangean relaxation based heuristic algorithm

LGR [8,9] has been successfully employed to solve complex mathematical problems by means of constraint relaxation and problem decomposition. Particularly for solving a linear integer problem, unlike the traditional linear programming approach that relaxes integer into non-integer constraints, the Lagrangean-based method generally leaves the integer constraints in the constraint sets while relaxing complex constraints such that the relaxed problem can be decomposed into independent manageable subproblems. Through such a relaxation and decomposition, the LGR method is shown to provide tighter bounds and shorter computation time on the optimal values of objective functions than those provided by the linear programming relaxation approach in many instances [9].

Essentially, the original primal problem is first simplified and transformed into a dual problem after some constraints are relaxed. If the objective of the primal problem is a maximization or minimization function, the solution to the dual problem is a respective upper or lower bound to the original problem. Such Lagrangean bound is a useful by-product in resolving the LGR problem. Next, due to constraint relaxation, the upper bound solutions generated during the computation might be infeasible for the original primal problem. However, these solutions and the generated Lagrangean multipliers can serve as a base to develop efficient primal heuristic algorithms for achieving a near-optimal solution to the original problem.

### 3.1 Dual problem and upper bound

In the relaxation process, constraint (3) is first relaxed from the constraint set. The expression corresponding to the constraints, is multiplied by Lagrangean multipliers $u_{wlt}$, and then summed with the original objective function. Problem (P) is thus transformed into a dual problem, called Dual_P, given as follows:

**Problem (Dual_P):**

$$\begin{aligned} Z_{\text{dual}}(\boldsymbol{u}) &= \max\left\{\sum_{k\in K} r_k y_k - \sum_{w\in W}\sum_{l\in L}\sum_{t\in T} u_{wlt} \times \left(\sum_{k\in K}\sum_{p\in P_k} x_{pw}\delta_{pl}\sigma_{kt} - 1\right)\right\} \\ &= \max\left\{\sum_{k\in K}\left(r_k y_k - \sum_{p\in P_k}\sum_{w\in W}\sum_{l\in L}\sum_{t\in T} u_{wlt}x_{pw}\delta_{pl}\sigma_{kt}\right) + \sum_{w\in W}\sum_{l\in L}\sum_{t\in T} u_{wlt}\right\} \end{aligned} \tag{6}$$

subject to Constraints (1), (2), (4), and (5) where vector $\boldsymbol{u}$ (with component $u_{wlt}$) is the non-negative Lagrangean multiplier vector. Problem (Dual_P) in Eq. 6 can be decomposed into $|K|$ independent sub-problems (one for each call $k$). Problem (Dual_P) is then expressed as $Z_{\text{dual}}(\boldsymbol{u}) = \sum_{k\in K} Z_k^{sub}(\boldsymbol{u}) + \sum_{w\in W}\sum_{l\in L}\sum_{t\in T} u_{wlt}$, where $Z_k^{sub}(\boldsymbol{u})$ is as follows.

$$Z_k^{sub}(\boldsymbol{u}) = \max\left\{ r_k y_k - \sum_{p\in P_k}\sum_{w\in W}\sum_{l\in L}\sum_{t\in T} u_{wlt} x_{pw}\delta_{pl}\sigma_{kt} \right\}$$

subject to:

$$y_k = \sum_{p\in P_k}\sum_{w\in W} x_{pw} \quad \text{(s1)}$$

$$\sum_{p\in P_k}\sum_{w\in W} x_{pw} \le 1 \quad \text{(s2)}$$

$$x_{pw} = 0 \text{ or } 1 \qquad \forall p \in P_k, w \in W \quad \text{(s3)}$$

$$y_k = 0 \text{ or } 1 \quad \text{(s4)}$$

The above sub-problem for call $k$ is to determine the decision variable, $y_k$ and $x_{pw}$ for all $p \in P_k$ and $w \in W$. By carefully observing the problem, one could find that it includes a shortest path problem. We propose the following algorithm to solve the problem optimally. For each wavelength $w$ on link $l$, we assign cost to be $\sum_{t\in T} u_{wlt}\sigma_{kt}$, then we apply Dijkstra's algorithm to obtain the shortest path $p^*$ and the best wavelength $w^*$. Let $c_k$ denote the cost of path $p^*$. If $r_k - c_k$ is non-negative, then $y_k$ is set to 1 and $x_{p^*w^*}$ is 1; otherwise, $y_k$ and all $x_{pw}$ are 0 for every $p \in P_k$ and $w \in W$. The computational complexity for each $Z_k^{sub}(\boldsymbol{u})$ is O($m$+$nlog$ $n$), where $m = |L|, n = |N|$.

By solving all the $|K| Z_k^{sub}(\boldsymbol{u})$ subproblems, we can obtain the value of $Z_{\text{dual}}(\mathbf{u})$. According to the weak Lagrangean duality theorem [9], $Z_{\text{dual}}$ in Eq. 6 is an upper bound of the original Problem (P) for any non-negative Lagrangean multiplier vector $\boldsymbol{u}$. Clearly, we are to determine the lowest upper bound. Equation 6 can be solved by the subgradient method, as shown as a part of the LGR approach delineated in Fig. 2, as which shows that the algorithm is run for a fixed number of iterations (*Iteration_Number*). In every iteration, the sub-problems are solved (as described above), resulting in the generation of a new Lagrangean multiplier vector value. Then, according to Eq. 6, a new upper bound is generated. If the new upper bound is tighter (lower) than the current best achievable upper bound (UB), the new upper bound is designated as the UB. Otherwise, the UB value remains unchanged. Significantly, if the UB value does not improve for a number of iterations that exceeds a threshold, called *Quiescence_Threshold* (QT), the step size coefficient $\lambda$ of the subgradient method is halved, in an attempt to reduce oscillation possibility. Specifically, in the update-step-size and update-multiplier procedures in Fig. 2, the Lagrangean multiplier vector $\boldsymbol{u}$ is updated as $\boldsymbol{u}_{k+1} = \boldsymbol{u}_k + \theta_k \boldsymbol{b}_k$, where $\theta_k$ is the step size, determined by $\theta_k = [\lambda_k(Z_{\text{dual}}(u) - \text{LB})]/\|b_k\|^2$, in which $\lambda_k$ is the step size coefficient, LB is the current achievable largest lower bound obtained from the primal heuristic algorithm described next, and $\boldsymbol{b}_k$ is a subgradient of $Z_{\text{dual}}(\boldsymbol{u})$ with vector size $|L + W + T|$.

### 3.2 Primal heuristic algorithm and upper bound

The primal heuristic algorithm in the LGR approach is used to find a near optimal solution. Since our problem is a maximization problem, a near optimal solution is clearly also a lower bound solution. Similar to the upper bound case, as given in Fig. 2, if the new lower bound *(lb)* is tighter (larger) than the current best achievable upper bound (LB), the new lower bound is designated as the LB.

To obtain a near-optimal solution that is the highest lower bound, at the end of a subgradient iteration, the LGR solution is verified whether or not it satisfies those relaxed constraints. If it does, the solution is feasible and is thus used to calculate a lower bound of the primal problem (P). If the solution is infeasible, we employ the following LGR-based heuristic algorithm, which takes advantage of Lagrangean multipliers. As shown in Fig. 3, the LGR algorithm sequentially accepts connections based on the $r_k - c_k$ values. Calls with higher $r_k - c_k$ hold higher priority in the sequence. The

**begin**
  initialize Lagrangean multiplier vector $\boldsymbol{u} := \boldsymbol{0}$
  $UB := \sum_{k\in K} r_k$ /* upper bound */
  $LB := 0$ /* lower bound */
  *quiescence_age* := 0
  *step size coefficient* $\lambda := 2$
  **for** each $k := 1$ **to** *Iteration_Number* **do**
  **begin**
    **solve** sub-problem for each $k \in K$
    $Z_{dual} = \sum_{k\in K} Z_k^{sub}(\boldsymbol{u}) + \sum_{w\in W}\sum_{l\in L}\sum_{t\in T} u_{wlt}$ /*Eq. (6)*/
    **if** $Z_{dual} < UB$ **then**
    **begin**
      $UB := Z_{dual}$
      *quiescence_age* := 0
    **end**
    **else** *quiescence_age* := *quiescence_age* + 1
    **if** *quiescence_age* ≥ *Quiescence_Threshold* **then**
    **begin**
      $\lambda := \lambda/2$
      *quiescence_age* := 0
    **end**
    **run** Primal Heuristic Algorithm to get *lb*
    /* Sec. 3.2 */
    **if** *lb* > *LB* **then**
      *LB* := *lb* /* *lb* is the new lower bound */
    **run** update-step-size
    **run** update-multiplier
  **end**
**end**

**Fig. 2** Lagrangean relaxation algorithm (LGR)

```
begin
  Sorting Z_k^sub(u) for all calls k and put their index in
  priority Q
 /* Q[1] is the call with the largest Z_k^sub(u) value*/
 /* Q[|K|] is the call with the smallest Z_k^sub(u)
   value*/
  for each link l ∈ L, w ∈ W
    a_lw := 1 /*all wavelength channels available*/
 for (i = 1; i ≦ K; i++)
 begin
   k = Q(i) /*DeQueue the highest priority call from
   Q*/
   c_k :=∞
   accept := False
   for each wavelength w ∈ W do
   begin
     for each link l∈L do
     if a_lw = 1 then
       link cost cost_l := Σ_{t∈T} u_wlt σ_kt
     else
       cost_l :=∞
     src = source(k)
     dest = destination(k)
     p' := Dijkstra-shortest-path(cost, src, dest)
     if p' is a feasible path then
     begin
       accept := True;
       /* denote c_wk as path cost of p' */
       If c_wk < c_k then
       begin
         c_k := c_wk
         p* := p'
         w* := w
       end
     end
   end
   If accept = True
   begin
     Accept call k and p* is the routing path,
     w* is the wavelength
     a_lw* := 0 for those links used by path p*
   end
   else
     Reject call k
   end
  end
  update total revenue and return as a lower bound lb
end
```

**Fig. 3** Primal heuristic algorithm

routing is determined by Dijkstra's shortest path algorithm based on the link cost, $\sum_{t\in T} u_{wlt}\sigma_{kt}$, as those used in the previous section except that those links cost are set to infinite for wavelengths are taken by previous calls. It prevents those calls with lower priority to use the wavelength channel taken by previous high priority one. If there are not enough resources for the request, the call is rejected. The algorithm run repeatedly until all requests are satisfied or rejected.

## 4 Experimental results

We have carried out a performance study on the LGR approach, and drawn comparisons between LGR and some heuristic algorithms via experiments over the well-known NSFNET Network. In the simulations, the start time and end time of call requests are generated randomly following uniform distribution in one day. Each time slot is five minutes in the experiments. Consequently, the mean call duration is 450 min. The call revenue $r_k$ is set exactly equal to the call duration. Therefore, a call with longer duration receives more revenue than those with shorter durations.

In the computation using our LGR approach, we adopted *Iteration_Number* = 3000 and *Quiescence_Threshold* = 50. The LGR algorithm can obtain near optimal results within 10 min of computation time operated on a PC running Windows XP with a 2 GHz CPU power.

Three other heuristics are also considered in the study. The Greedy method sequentially allocates lightpaths according to connection's $r_k$ value. Calls with larger revenues hold higher priority in call setup process. We also consider two timing related heuristics in our experiments. The First Come First Serve (FCFS) method schedule the requests according to call arrival time while the Deadline First (DF) method schedule the requests according to call finish time instead. The numerical results on NSFNET ranging from 150 to 275 calls are plotted in Fig. 4. Figure 4b shows the total revenue. The LGR achieves highest total revenue followed by the Greedy method. The FCFS method and the DF method results in lower output due to lack of taking call revenue into account. We use *Percentage Gap* (Gap%) to be the performance metric to evaluate the quality of those algorithms to a legitimate upper bound. The *Percentage Gap* (Gap%) is defined as the percentage of (Lagrangean UB—total revenue of the considered algorithm)/Lagrangean UB. As shown in Fig. 4c, the percentage gap between the LGR and the UB are within 7% for all cases.

We further make comparisons of performance with respect to call blocking. As shown in Fig. 4d, the LGR outperforms the other three methods. It is interesting that the Greedy heuristic algorithm is the one with largest number of call

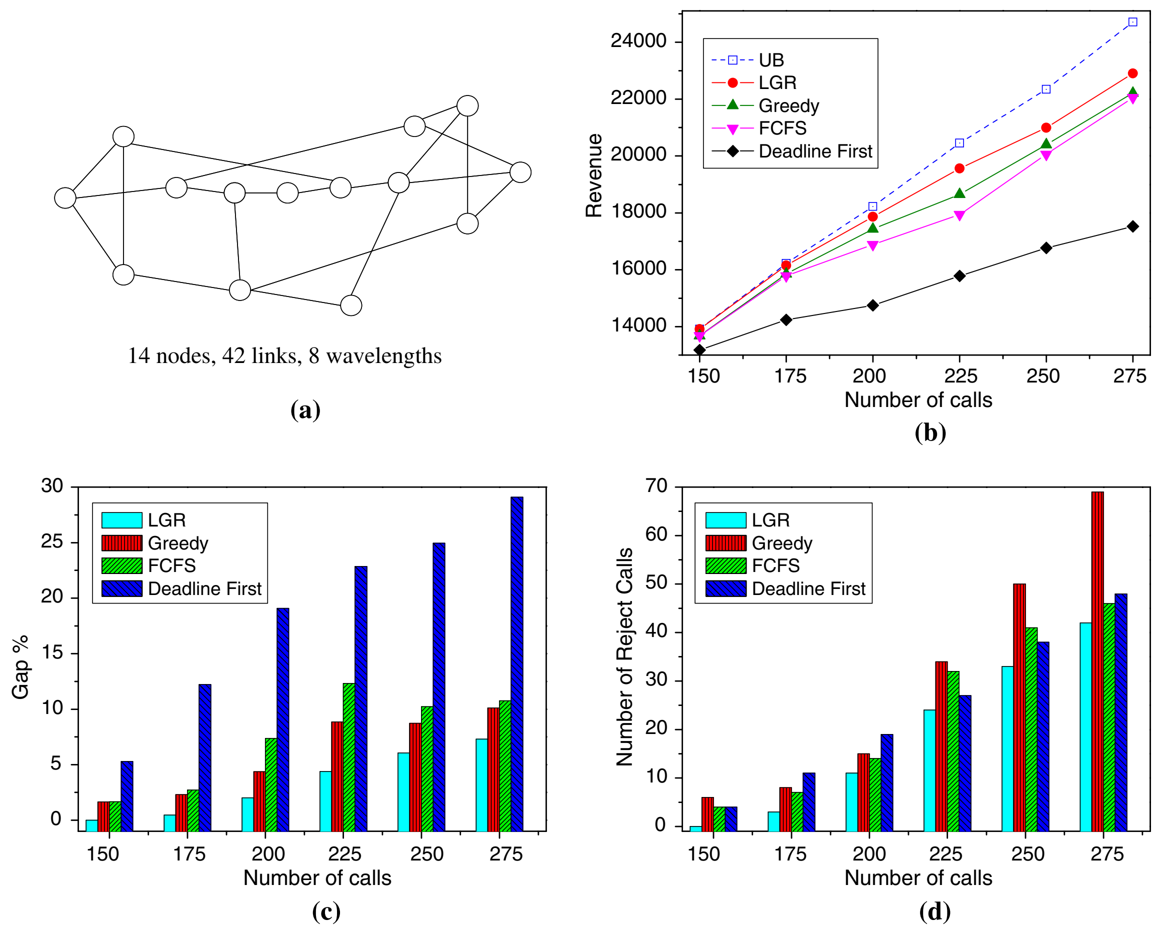



**Fig. 4** Experimental Results. **a** NSFNET network. **b** Performance comparisons—Revenue. **c** Performance Comparisons—Percentage Gap. **d** Performance Comparisons—Call blocking

rejection. By closely examining the results we find that those calls rejected by the Greedy algorithm are with small call durations.

## 5 Conclusions

In this paper, we have resolved an ALR problem using a LGR based approach augmented with an efficient primal Heuristic algorithm. The primal heuristic algorithm of LGR achieves a near-optimal lower-bound solution. With upper and lower bounds, we assess the performance of LGR with respect to solution accuracy. We have drawn comparisons of accuracy among LGR, Greedy, FCFS, and DF algorithms. Experimental results demonstrate that LGR outperforms the other three heuristic approaches in gaining more revenue on receiving more call requests over the widely-used NSFNET Network.

## References

[1] Zheng, J., Zhang, B., Mouftah, H.T.: Toward automated provisioning of advance reservation service in next-generation optical Internet. IEEE Commun. Mag. **44**(12), 68–74 (2006). doi:10.1109/MCOM.2006.273102

[2] Wallace,T.D., Shami, A.: Advanced lightpath reservation in WDM networks. In: Proceedings of IEEE INFOCOM, 2006. doi:10.1109/INFOCOM.2006.30

[3] Miyagi, H., Hayashitani, M., Ishii, D., Arakawa, Y., Yamanaka, N.: Advanced wavelength reservation method based on deadline-aware scheduling for lambda grid network. IEEE/OSA J. Lightwave Technol. **25**(10), 2904–2910 (2007). doi:10.1109/JLT.2007.904416

[4] Naiksatam, S., Figueira, S., Chiappari, S.A., Bhatnagar, N.: Analyzing the advance reservation of lightpaths in lambda-grids. IEEE CCGrid **2**, 985–992 (2005). doi:10.1109/CCGRID.2005.1558668

[5] Mukherjee, B.: Optical Communication Networks. McGraw-Hill, New york (1997)

[6] Banerjee, D., Mukherjee, B.: A practical approach for routing and wavelength assignment in large wavelength-routed optical networks. IEEE J. Select. Areas Commun. **14**(5), 903–908 (1996). doi:10.1109/49.510913

[7] Zheng, J., Mouftah, H.T.: Routing and wavelength assignment for advance reservation in wavelength-routed WDM optical networks. Proc. IEEE ICC. **5**, 2722–2726 (2002). doi:10.1109/ICC.2002.997338

[8] Lee, S., Yuang, M., Tien, P.: A Lagrangean relaxation based approach for routing and wavelength assignment in multi-granularity

optical WDM networks. IEEE J. Select. Areas Commun. **22**(9), 1741–1751 (2004). doi:10.1109/JSAC.2004.835523

[9] Ahuja, R., Magnanti, T., Orlin, J.: Network Flows: Theory, Algorithms, and Applications. Prentice-Hall, Englewood Cliffs, NJ, USA (1993)

## Author Biographies

**Steven S. W. Lee** received his Ph.D. degree in Electrical Engineering from National Chung Cheng University, Taiwan, in 1999. From 1999 to 2008, he was with Industrial Technology Research Institute (ITRI), Taiwan, where he was the leader of Intelligent Optical Networking project and a section manager of Optical Communications Department. He was also a Research Associate Professor of National Chiao Tung University, Taiwan, during 2004–2007. In 2008, he joined National Chung Cheng University, Taiwan, where he is currently an Associate Professor of the Department of Communications Engineering. His research interests include optical and broadband networking, network planning, and network optimization.

**Alice Chen** received her B.S. degree in Electronics Engineering from the National Chiao Tung University, Taiwan in 1984 and the M.S. degrees in Computer Science and Information Engineering from the National Chiao Tung University, Taiwan in 1992. Currently, she is the deputy director of Optical Communication Division at Information and Communications Research Laboratories of Industrial Technology Research Institute, Taiwan, where she works on network control and management of optical networks.

**Maria C. Yuang** received her Ph.D. degree in Electrical Engineering and Computer Science from the Polytechnic University, Brooklyn, New York, in 1989. From 1981 to 1990, she was with AT&T Bell Laboratories and Bell Communications Research (Bellcore), where she was a member of technical staff working on Broadband Networks and Protocol Engineering. In 1990, she joined National Chiao Tung University (NCTU), Taiwan, where she is currently a Professor of the Department of Computer Science. Prof. Yuang has served as a Guest Editor for a Special Issue of IEEE Journal of Selected Areas in Communications on Next-Generation Broadband Optical Access Network Technologies in 2009. She has served on the technical program committee of many technical conferences including *IEEE ICC* and *GLOBECOM*, and has been invited to give invited talks at many technical conferences. Her main research interests include broadband optical networks, wireless networks, multimedia communications, and performance modeling and analysis. She is a senior member of IEEE, and a member of OSA. She holds 17 patents in the field of broadband networking, and has over 100 publications, including a book chapter.