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Genetic algorithm and tabu search algorithm for solving the static	Giải thuật di truyền và tìm kiếm tabu (tìm kiếm vùng cấm) để giải

manycast RWA problem in optical networks	bài toán RWA manycast tĩnh trong các mạng quang học
Abstract The static routing and wavelength assignment (RWA) problem in Optical Networks is a combinatorial optimization problem fit to iterative search methods. In this paper we deal with the static manycast RWA problem in optical networks and solve it by maximizing the number of manycast request established for a given number of wavelengths. In this article, we implement and compare the performance of two meta- heuristics namely the GA "Genetic Algorithm" and the TSA "Tabu Search Algorithm". The proposed algorithms solve, approximately, the wavelength assignment problem and a backtracking approach is used to solve the routing problem. We first introduce our algorithms. We then evaluate and compare their performance. We corroborate our theoretical findings through extensive simulations. Representative empirical results show the accuracy of our GA and TSA.	Tóm tắt Bài toán định tuyến và gán bước sóng (RWA) trong các Mạng Quang Học là một bài toán tối ưu hóa tổ hợp thích hợp với các phương pháp tìm kiếm lặp. Trong bài báo này, chúng tôi xét bài toán RWA manycast trong các mạng quang học và giải nó bằng cách tối đa hóa số yêu cầu manycast được thiết lập cho một số bước sóng nhất định. Trong bài báo này, chúng tôi triển khai và so sánh hiệu quả của hai giải thuật meta- heuristics cụ thể là "Giải thuật di truyền" GA và Giải Thuật tìm kiếm Tabu" TSA. Những thuật toán đề xuất giải một cách gần đúng bài toán gán bước sóng và phương pháp quay lui được dùng để giải bài toán định tuyến. Trước hết chúng tôi trình bày các thuật toán. Sau đó, chúng tôi đánh giá và so sánh hiệu quả của chúng. Chúng tôi củng cố thêm các phát hiện lý thuyết thông qua các mô phỏng mở rộng. Các kết quả thực nghiệm khẳng định độ chính xác của giải thuật GA và TSA của chúng tôi.
1 Introduction To take full advantage of the potential of flber, the use of wavelength division mul- tiplexing (WDM) technology has become the option of choice (Ramaswami 2006). The reason for utilizing WDM is because the bandwidth demand from average	[redacted]

users is increasing at an unprecedented rate. Additionally, aiming for higher speed, it has the potential to be the dominant technology choice for near future Tera-bit communication infrastructure. In fact, WDM can provide unprecedented bandwidth, reduce processing costs, and enable efflcient failure handling (Ramaswami and Sivarajan 1995). An end-to-end lightpath has to be established prior to the communication between any two nodes in optical networks. A sequence of lightpath requests arrive over time, each lightpath having a random holding time.

These should be set up dynamically by determining a route across the network connecting the source to the destination and assigning a free wavelength along the path.

Existing lightpaths cannot be rerouted to accommodate new lightpath requests until they are released, so some of the lightpath requests may be blocked if there is no free wavelength along the path (Skorin-Kapov 2007). Therefore, Anding a physical route for each lightpath demand and assigning to each route a wavelength, subject to a set of constraints, is known as the routing and wavelength assignment (RWA) problem (Kharroubi et al. 2013; Ramamurthy and Mukherjee 1998; Khar- roubi 2014).

There are two variants of the RWA problem: static RWA, where the traffic require- ments are known in

[redacted]

[redacted]

advance, whenever a lightpath request arrives, the RWA algorithms assign the pre-allocated route and wavelength for that request. In the dynamic RWA whereby connection requests arrive in some random fashion, a dynamic RWA algo- rithm uses the current state of the network to determine the route for a given lightpath request. The concept of a lightpath was generalized into that of a light-tree (Sahasrabuddhe and Mukherjee 1999; Watel et al. 2015), which unlike a lightpath, a light-tree has multiple destination nodes; i.e it is a point-to-multipoint communication. Thus a light-tree forms a tree rooted at the source node need to be established rather than a path in the physical topology.

[redacted]

Generally, the bulk of the communication established in a network is unicast, where a single source node sends data to a single destination node. In our work, we consider a new type of communication termed Manycast (Cheung et al. 1994; Bathula and Vokkarane 2010; Charbonneau and Vokkarane 2010a). The manycast is a generalization of the multicast communication paradigm (Singhal et al. 2006). Indeed, manycast is the transmission of information from one source to multiple destinations simultaneously. The key difference between multicast and manycast is that in multicast, the destinations are specifled ahead of time, whereas in manycast the

[redacted]

destinations must be chosen. The future of many services such as video con- ferencing, Grid Computing, e-Science and peer-to-peer are employing manycasting for data delivery. The support of manycast in the WDM networks of the future is therefore essential for these applications. This necessarily makes manycast a power- ful communication framework that is important for next-generation applications (Jain 2006).

The objective of solving the manycast RWA problem can be either, given a flxed number of wavelengths and a set of manycast requests, to maximize the total number of manycast requests admitted, or to minimize the number of wavelengths used, provided that wavelength availability is sufflcient to route all the requests (Charbonneau and Vokkarane 2010a). As far as we know, there has been no work addressing the manycast RWA problem speciflcally for maximizing the number of established manycast requests. Given the hard computations of the linear integer program (Krishnaswamy and Sivarajan 2001), we study the problem using meta-heuristics. Our objective, given a flxed number of wavelengths is to maximize the number of manycast requests to be established in a given session or traffic matrix.

The next section reviews the previous

[redacted]

work. In Sect. 3, problem deflnition and formulation is given. Section 4 suggests two different assignment algorithms GA and TSA. In Sect. 5, experimental results and a comparison between the proposed approaches are presented. Section 6 discusses the empirical results obtained for the suggested metaheuristics. The paper is concluded in Sect. 7.

2 Previous work

The RWA problem can be divided into two sub-problems, the path from source to destination—this is the routing part—and the wavelength along the path, which is the wavelength assignment part. Both of these sub-problems are NP complete (Jue 2001), and tightly linked together. The manycast RWA issue is therefore NP complete since it contains the RWA problem as a special case.

Manycast is a special case of multicast, in which from a single resource we must reach k destination nodes. These destination nodes are to be selected instead of being given. In fact, there are many previous works that investigate the multicast problem. This static multicast RWA was flrst studied in Sahin and Azizoglu (2000) and He et al. (2011) targeting the objective of minimizing the blocking probability. Manycast is also a generalization of unicast where the message needs to be delivered to any

[redacted]

[redacted]

one of the group. Indeed, there is a wealth of recent work (Kharroubi et al. 2013; Kharroubi 2014; Dzongang et al. 2005; Qin et al. 2002; Kharroubi et al. 2014), that has proposed a tabu search metaheuristic and a genetic algorithm to solve RWA prob- lem in the unicast case. While in the manycast case, in numerous previous works, the manycast problem was flrst presented as quorumcast (Cheung et al. 1994; Low 1998; Wang et al. 2001). In quorumcast, messages are sent to a subset of destinations (quo- rum pool), which are selected from a set. The authors in Charbonneau and Vokkarane (2010a,b) have proposed three heuristics to solve the manycast problem. One of these heuristics is a tabu search metaheuristic. The objective was to minimize the num- ber of wavelengths required to satisfy all the manycast requests. In the work (She 2009), an ILP and several heuristics have been proposed for solving multi-resource manycast in mesh networks. Few studies, however, tackled the manycast service over optical burst-switched networks (Huang et al. 2007; She et al. 2007; Bathula et al. 2009).

[redacted]

3 Problem definition and

formulation

3.1 Problem detìnition

Let a networkbe represented as agraph G(V, E), where V denotes the set of network nodes and E represents the set of unidirectional fibers. Assume that lightpath requests are unidirectional, each carrying W wavelengths. A manycast request is represented as MR {s, Dc, k} where s, D and k denote the source, the set of candidate destination nodes, and k <\Dc \ = m is the number of destination nodes needed to be reached out of m. If we change the parameters of the manycast request, we can also perform unicast (k=m= 1). Therefore, any algorithm that solves the static manycast RWA problem, in general, should respect these following constraints:

(1) Wavelength continuity constraint: The wavelength continuity constraint implies that a particular request for a source-destination pair must follow a single lightpath (Qin et al. 2002).

(2) Wavelength conflict constraint: The wavelength conflict constraint states that a wavelength may be used only once per fiber. Thus no two signals can traverse along the same wavelength in a particular fiber (Skorin-Kapov 2007).

3.2 Problem formulation

The notation and variables used in our proposed mathematical formulation is given as follows:

NLPG Number of all lightpaths

[redacted]

in G.

R = (Ri) Vectorthatcontainstherequestnumberto whichalightpathbelongs.

NR Number of all requests in G.

multiplicity(n) Number of connection requests desired to be set up for one request. Let Ịì be the sum of all used traffic by all requests. Such as:

NR
ịì = multiplicity (n). V n e{1, 2... Nr}
n = 1

Let D = (dij) be the NLPG X NLPG matrix, i.e.,
1, iflightpaths i and j share a physical link,
0, otherwise

Let T = (Ti) be the 1 X NR vector, i.e.,

1, VẰ e{1, 2 ...W}, ifthe wavelength Ằ is assigned to the lightpath - tree i,
0, otherwise

Let P = (Pi) be the 1 X NLPG vector, i.e.,
1, VẰ e{1, 2. ..W}, ifthe wavelength Ằ is assigned to the lightpath i, 0, otherwise

Mathematical formulation

Our problem can be mathematically formulated as follows:

NR
Maximize: F = f (ộ) = ệi i = 1

Our objective is to maximize the number of manycast requests that can be established for a given number of wavelengths in a given physical

[redacted]

topology.
Constraints:
In (1), wavelengths assigned must be such that no two lightpaths that share a physical link, belonging to different requests, use the same wavelength on that link.

NR
In (2), the sum X ệi of the elements of the vector P that are not equal to zero, cannot, i=1 under any circumstances, exceed the number ịì.

3.3 Network assumptions

We assume that splitting capabilities and wavelength converters are not adopted in our case. Actually, many research approaches have been proposed to solve the manycast and mostly the multicast problems by splitting capability for different nodes in the network i.e. whether or not equipped with multicast-capable optical cross connect (MC-OXC) (Cao and Yu 2006). However, these methods are costly in both fabrication and power consumption (Le et al. 2015).

Figure 1 shows an example of a manycast request where node S is the source and nodes one through four are some of the destinations of the session.
As node 2 does not have the splitting capability as shown in Figure 1, node 2 can only forward one copy (e.g. to node 3). Therefore, a separate path from S to node 4 is needed.

[redacted]

[redacted]

4 Our proposed GA and TSA for solving the manycast RWA problem

Previous research has offered a variety of solutions, from simple to complex meta- heuristic algorithms for solving the RWA complication. Here, we extended the same

12n

Fig. 1 An example of manycasting routing and wavelength assignment. Node 2 has no wavelength conversion and splitting capabilities

Fig. 2 Crossover phase

Fig. 3 Mutation phase

genetic algorithm (GA) and Tabu search algorithm (TSA) presented in (Kharroubi et al. 2013; Kharroubi 2014; Kharroubi et al. 2014) based on a backtracking approach but this time to solve the Static Manycast RWA problem.

4.1 Genetic algorithm (GA)

The GA is a search technique originally invented by Holland (1992) and used in computing to flnd true or approximate solutions to optimization and search problems. Indeed this metaheuristic belongs to the larger class of evolutionary algorithms which is inspired on process of natural selection and is routinely used to generate useful solutions. Genetic algorithms use biologically-derived techniques such as inheritance, mutation, natural selection, and crossover (or recombination). The key concepts of the GA explained below:

[redacted]

[redacted]

Initial population In this phase, each gene in a chromosome solution represents one of the paths generated through a backtracking algorithm so that we can explore all the candidate paths between the origin and the destination pairs. These candidate solutions are usually called chromosomes (or genomes) which take, in our implementation, the

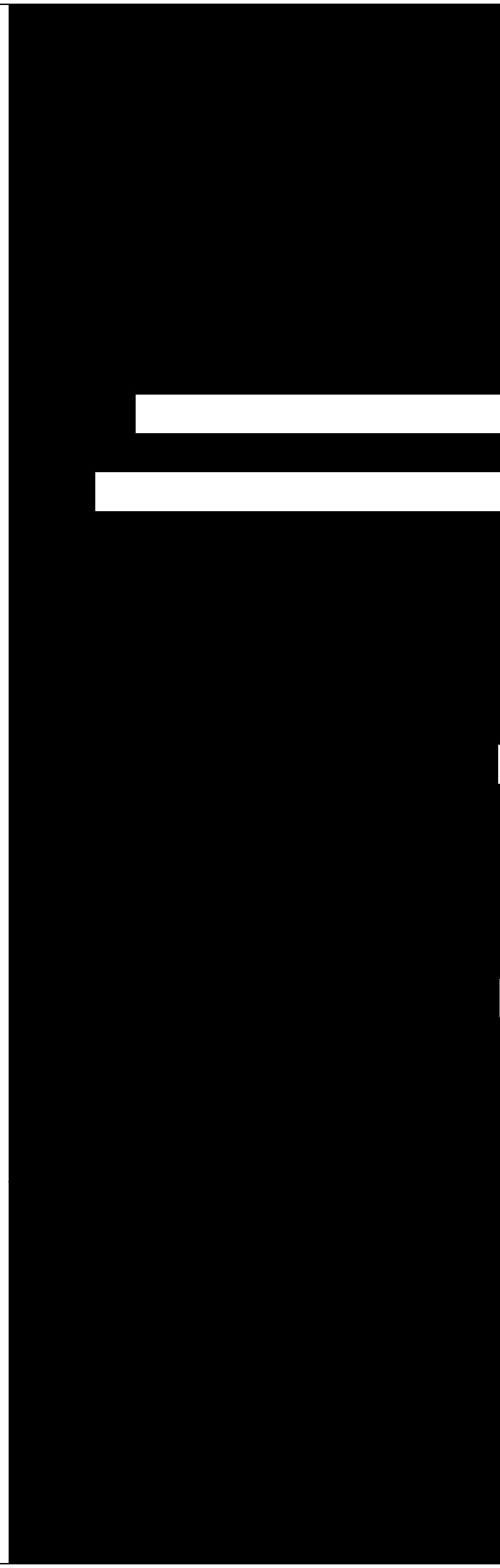

Fig. 4 Genetic algorithm flow chart

form of bit strings, each bit position (refer to as locus) in the chromosome has Å possible values (called alleles), such as Å e {1, 2. ..W - 1}. During this step, we initialize the variables that will be used namely: n, P, Pmax and Fmax.

Selection in this step, the chromosomes of the next generation are selected from the current population by evaluating all the chromosomes using a Atness function choosing the best individual.

Crossover at this stage, the selected generation, with a certain crossover probability a chromosome is asked for mating with another chromosome. In other world, two parent chromosomes (i.e. two random vectors P) are chosen to reproduce and their crossover results in two new child chromosomes, which are added to the second generation of the search space. In fact, this crossover site will take place between the source destination pairs of paths rather than inside paths that belong to the same source-destination pair. Thus, paths that belong to the same source-destination pair will maintain their identity during the crossover process. Hence, the constraint (2) will not be violated in this phase. The process is repeated until we get an appropriate number of candidate solutions in the second generation of the pool. The crossover process is shown in Fig. 2.

Mutation This operator randomly flips some of the bits in a chromosome which is con- sidered as a random mutation of the new pool. Thus, some randomly chosen elements of the vector P (P contains the best-found solution in terms of the assigned wavelength

Fig. 5 Tabu search metaheuristic flow chart

to the chosen paths for a manycast request) containing the value Å which represents the wavelength that the lightpath will use, will be randomly replaced by another value of Å. In this phase of mutation the created chromosome replaces itself regardless of the Atness function. This concept is shown in Fig. 3.

More details about GA can be found in Kharroubi et al. (2013), Kharroubi (2014), Kharroubi et al. (2014), Melanie (1996) and Oliveira and Pardalos (2011). The main working steps of our proposed GA are shown above in the general flow (Fig. 4).

[redacted]

[redacted]

4.2 Tabu search algorithm (TSA)

The TSA is often used for combinatorial optimization problems (Oliveira and Pardalos 2011). It explores the solution space for a number of iterations from an initial random solution to another better solution in the neighborhood of the former one. The best solution from the neighborhood is then chosen as the current solution and the process continues. In order to avoid getting stuck in the same set of solutions, a tabu list is implemented. This tabu list maintains the moves for the last visited solutions that will not be selected again as long as they are on the tabu list. Another two important steps of tabu search are intensiflcation and diversiflcation. The diversiflcation step is executed when no improvement is achieved on the best solution after a number of iterations. The purpose of intensiflcation is to perform a more thorough search of the neighborhood for an optimal solution. The key concepts of the TSA explained below:

Fig. 6 The NSF network used for performance evaluation

Initial solution Every tabu search starts with an initial solution. This step will be performed after the backtracking algorithm is operated. In our case, during this step, we initialize the variables that will be used namely: n, P, Pmax and Fmax, then we implement and initialize an empty tabu list. We create in each iteration

[redacted]

flve random initial solutions (i.e. flve vectors P) and evaluate their current solutions.

Tabu list The tabu list is a list containing the last several moves carried out and that will not be selected again as long as they are on the tabu list.

Neighborhood A move from the current solution produces a new solution. A number of such new solutions compose a neighborhood. This move operation is performed randomly to generate the neighborhood. Once it’s generated a new non-tabu solution will be added to the tabu list to become the current solution to become the current solution in the next iteration.

Finally, our TSA will start from the candidate solutions and until the maximum number of iterations is reached, the algorithm will test a new solution by updating the vector Pmax. Therefore, each time the constraint (1) is met then the current solution F will be replaced by the best-found solution Fmax until the end of the algorithm. More details about TSA can be found in Kharroubi et al. (2013), Kharroubi (2014), Dzongang et al. (2005), Qin et al. (2002), Kharroubi et al. (2014), Oliveira and Pardalos (2011), Glover and Laguna (1997) and Wang et al. (2005). The main working steps of our proposed TSA are shown in Fig. 5.

[redacted]

[redacted]

4.3 Backtracking algorithm

In the work (Kharroubi et al. 2013, 2014; Kharroubi 2014) the authors haveproposed a backtracking algorithm for routing unicast demands. This algorithm can be extended for manycast if a path search is done for every destination one-by-one, using this method we will be able to explore all the candidate paths between the origin and the destination pairs of the trees.

All work in this paper focuses on extension of the work done on static unicast RWA problem in using the backtracking algorithm which has been proposed in Khar- roubi et al. (2013). Previous studies have focused on k-shortest path (Ramaswami and Sivarajan 1995; Dzongang et al. 2005; Chamberland et al. 2005), which has been widely used in the literature to flnd alternative paths. Hence by using the backtracking approach our initial search space will contain not only the k-shortest paths between each source-destination pair, but also all the possible candidate lightpaths. More details about the backtracking can be found in Kharroubi et al. (2013, 2014) and Kharroubi (2014). We reiterate our proposed backtracking as below, with its pseudo-code.

Algorithm backtracking()

[redacted]

5 Numerical results

In this section, we present numerical results from simulations to demonstrate the performance of our proposed solution approaches. We ran extensive simulations on the 14-node NSF network shown in Fig. 6.

Fig. 7 Satisfied manycast requests for D = 4 and k=2 as well as the time taken versus the number of manycasts and wavelengths on the 14-node NSF network for both GA and TSA algorithms

We carried out an experiment that consisted of 144 extensive tests. The experiment is executed for 8 manycast groups consisting of 10, 20, 30, 40, 50, 60, 70 and 80 requests, running each test on two different algorithms with the same initial population and parameters. The number of wavelengths, W, chosen for network simulation, is 64, 160, and 320, which are practical values today (Singhal et al. 2006). Moreover, we used three different destination set sizes (4, 6 and 8). For each request MR, we used three different sizes of Dc, and k = Dc/2. The maximum number of iterations is fixed at 5000.

The hardware used for our experiments is an Intel(R) Core(TM) i7- 4790k CPU 4 GHZ processor with 8 GB RAM, running under Ubuntu 14.04.2. All algorithms were compiled

[redacted]

by GCC compiler of Qt Creator 3.4 (based on Qt 5.4 “64Bit”). As it can be seen from the performance results, we noticed that the number of established sets of manycast sessions increases with the increase of W . Manycast sessions decrease when the set of destination is larger:	[redacted]
• When D = 4 (Fig. 7), the proposed TSA gives better results compared to GA tech- nique especially when W = 320. However, for other wavelengths, TSA approach	[redacted]
Fig. 8 Satisfied manycast requests for D = 6 and k=3 as well as the time taken versus the number of manycasts and wavelengths on the 14-node NSF network for both GA and TSA algorithms	[redacted]
performs better for small manycast group sizes, but for larger sizes TSA satisfies up to 12 % and GA achieves up to a 10 % improvement over TSA. • When D = 6 (Fig. 8), we noticed that GA outperformed TSA, specifically when the manycast group sizes is more than 40, this out- performance goes up to 30 %.	[redacted]
• When D = 8 (Fig. 9), GA has shown a decent performance that is close to the TSA method when W = 64. Otherwise, we observed that GA has a better improvement over TSA.	[redacted]

• The time spent by GA or TSA to solve the manycast problem increases rapidly depending on the number of manycasts groups as well as the number of the wave- lengths. However, the time spent using the TSA is ten times higher than GA. This is the only disadvantage of using TSA. In fact, since we were dealing with the static case, computations were done offline.	[redacted]
• GA performs very efficiently in terms of speed. • We should remark that TSA has shown sufficient performance to solve the many- cast RWA problem in many cases. Nevertheless, it takes a while to reach its end even if the solution has already been found after only a few iterations from the	[redacted]
Fig. 9 Satisfied manycast requests for D = 8 and k=4 as well as the time taken versus the number of manycasts and wavelengths on the 14-node NSF network for both GA and TSA algorithms	[redacted]
beginning. Thus, we considered the time and minimum number of iterations of the best found solution for the future work.	[redacted]
6 Discussion In small manycast group sizes TSA largely performs better than GA. In terms of a solution, however, TSA has a higher run time than GA. GA run times are very low compared to the TSA approach. The TSA can still be	[redacted]

optimized to reduce the run time, since the best solution can be found after only a few iterations from the beginning. Indeed, this run time issue doesn’t affect the optimal solution since these computations are done offline. Conversely, GA has shown it can perform better than TSA by up to 20 %, especially for large manycast group sizes. This can be explained by the crossover operator used by GA which maintains diversity in the solution space. Related to the wavelength variation, the results are somewhat predictable, since it is easier for small size manycast requests to be nearly accepted, most notably when the wavelength number is large. In contrast, large-sized requests often require a high amount of network resources, affecting the number of requests that could be satisfled.

Regarding the fairness issue, we have observed that GA achieves better fairness among the manycast groups in terms of satisfying groups of connections, whereas the TSA have shown low fairness, speciflcally when the manycast groups increase. For the wavelength reuse issue, we have noticed that the probability of the reuse of exciting wavelengths is higher only if the frequency of occurrence of a common physical link is very low, seeing that lately the number of wavelengths has been increasing, so this wavelength reuse problem will be nonexistent.

Our proposed TSA and GA

[redacted]

[redacted]

[redacted]

approaches reach an acceptable solution. Our perfor- mance evaluation of 144 tests has conflrmed that, although much research has been proposed to solve the multicast RWA problem, only a few studies have tried to deal with the manycast RWA issue specially using the backtracking algorithm. It is, there- fore, important to develop more new metaheuristics for solving the manycast RWA problem.

7 Conclusion

In this article wehave implemented and compared two metaheuristics to solve the static manycast RWA problem, with a special focus on maximizing the number of manycast requests established for a given number of wavelengths. The problem was studied for the static case only. We proposed two metaheuristics to compute the approximated solutions, in which GA works best when the manycast group sizes are larger. This is when we increased the manycast set size. TSA has shown good performance for small manycast group sizes. The routing sub-problem was solved using a backtracking algorithm. The proposed GA and TSA in this paper were applicable to a real NSF network. A relevant comparison, including the performance and the time involved, was made between the two algorithms, making a total of 144 experiments. The time spent by TSA, on average, is 10 times higher than GA.

[redacted]