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An Adaptive Switcher Mechanism of Integrated Two-Stage Multi-Neighbourhood Tabu Search for University Examination Timetabling Problems

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Abstract: The method of focusing only on intensification or diversification within a Tabu Search algorithm may jeopardize the possibility in finding better quality of solutions. Thus, the decision to switch between intensification and diversification during solving process may enhance the overall performance of the search. This research proposes an adaptive switcher mechanism in Integrated Two-stage Multi-neighbourhood Tabu Search (ITMTS) to decide when to switch from intensification to diversification. The trigger value is calculated from the mean plus the standard deviation of the qualities of some recently accepted solutions. When the search consecutively generates bad (or same) quality solutions, it will automatically switch from intensification to diversification. The search will switch back to intensification phase after performing the shaking process. The technique is tested on examination timetabling datasets and demonstrates the effectiveness of adaptive switcher mechanism.

Key words: Metaheuristics, Tabu search, intensifaction, diversification, search strategies

INTRODUCTION

Tabu Search (TS) is a single solution based local search technique where its search strategies are important in finding better solution (Osman and Kelly, 1996; Yang, 2008; Lewis, 2008; Talbi, 2009). According to Glover and Laguna (1997), this technique has been clarified as a memory based dynamic neighbourhood technique that intelligently controls its search strategies, intensification and diversification search, in improving the quality of solutions. They also emphasized the importance of these search strategies application within Tabu Search algorithm which would directly increase the effectiveness of the overall technique's performance. These strategieshave been defined as:

- Intensification is focused on the finding the best improved neighbourhood through intensified searching process
- Diversificationis concentrated more on to diverting the search mechanism's focus from the saturated search space area into the new search space region in searching the best improved solution

Based on the literatures on the technique's implementation particularly on examination/course timetabling problems, only several researchers had utilized directly on these components such as Di Gaspero (2002), Paquete and Stuzle (2002), White *et al*. (2004) and Lu and Hao (2010). But none of them discussed and justified in depth their research implementation on these search strategies particularly on the transition of the search process from intensification to diversification or vice versa.

Several search variation strategies of Tabu Search had been used by researchers. For example, White *et al*. (2004) they applied the shifting policy mechanism in their OTTABU procedure that vigorously changed the profile of the objective function which might stimulate the similarity of diversification approach within the search space. This mechanism was applied by adaptively adjusting the objective function with the intention to reroute the search mechanism into the new search space.

In the meantime, Paquete and Stutzle (2002) applied the constraint priority ordering strategies in enhancing

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the quality of the solution. In this technique, the selection consideration was made based on either one constraint with highest priority first at a time or all constraints at a time. Lextie and Lexseq strategies were applied in this technique where the earlier strategy is concentrated on comparing the solution's objective function value of the higher priority objective subject to better function values. If the compared value is tie then the evaluated solution will be compared to the next lesser priority objective. The latter strategy can be seen as a diversification mechanism of this technique where it's main concentration is to satisfy the constraints that linked to the decreasing of objective's priority order in a sequentially search region. The solution is required firstly to fulfill the highest priority constraints hierarchy and continuously required to satisfy the next lesser priority constraint hierarchy with regards to no violation condition of the constraints.

Recently, Lu and Hao (2010) used Adaptive Tabu Search (ATS) to solve ITC2007 course timetabling datasets where Tabu Search was applied as intensification strategy and hybridized Iterated Local Search (ILS) component as a diversification strategy. They implemented two approaches to control the behavior of ATS by using the intensification depth of TS and the perturbation strength of ILS for diversification. They obtained comparable results on this dataset (and outperformed other approaches on several instances). In their method of application, ILS technique had been hybridized as a diversification mechanism into their original method (Tabu Search). This hybridized ILS technique would require some parameters to be defined and tested.

Most of these Tabu Search (TS) implementation can be either fully technique application or full/partially applied TS hybridization with other techniques by researchers to solve this problem. However, most of the reported TS based literatures did not state or discuss clearly about the utilization of these search strategies.

As in a case study on the ITMTS technique of Malik *et al*. (2009), these search transitions issues are considered very important. Its search mechanism totally depends on the mechanisms's performance during the intensification phase in finding the best solution improvement. Once the qualities of the accepted solutions by ITMTS are deteriorating the search mechanism needsto switch its mode into diversification procedure for solution shaking process. Thus, it may allow the solution to be restructured with the objective to create a new search landscape of the solution.

Unfortunately, this diversification process will drastically change the current state of the solution and may jeopardize the future possible neighbourhood options of the current intensification process. The outcome of this process may not guarantee better solution quality compared to the earlier intensified solution quality. Thus, it may also force the search mechanism to restartits intensification process at the worse quality level of the diversified solution.

In contrast, the search mechanism should be allowed to prolong the intensification process for certain iterations in order to evaluate any non-improving neighbour before a major restructuring of the neighbourhood (diversification process) can be executed. Positively if this situation will allow some minor changes on the current neighbourhood's search space area. The changes were meant to find the improved neighbours among the non-improving accepted solutions which may then used to change the overall quality of the current solution. All accepted solutions of ITMTS's intensification search are based on a merit of best improved results but under certain circumstances the second or the third best neighbourhood option will be accepted by the technique. However, the option would be subjected to the Tabu restriction and unavailability of non-Tabu status neighbourhood. The acceptance of the non-improved solution during the intensification phase will allow the intensification search to be continued within this stage.

Instead of this scenario, it may also give negative effect to the solution quality if the search mechanism continuously is acceptingthe non-improving solutions in longer period of intensification process. Thus, it will directly further deteriorate the quality of current solution. Even though, a counter based switche rwas used in this technique, its number size of counter was static and not adaptive to the current nature of acceptance pattern. The switching decision of this counter will not consider any future good potential of the neighbourhood options which possibly may get during this deterioration situation.

In order to overcome this problem there is a need to have an adaptive mechanism to controland decide when is the most suitable transition period for the search to switch to diversification stagewithout ignoring anygood potential possibility of the current search stage (intensification stage). As a result, it will indirectly allow ITMTS's search mechanism to become more tolerant to the non-improving neighbourhoods while in intensification phase.

Several issues need to be given more attention when enhancing the ITMTS's search mechanism particularly on decision making process. The issues are:

- Searching period of ITMTS's search mechanism to find the best improving move (s)
- The premature switching by the search mechanism

Therefore, in this study, researchers introduce a search switching mechanism that can utilize adaptively the search operation of the technique. As compared to the ITMTS of Malik *et al.* (2009) this proposed strategy method is based on the utilization of adaptive evaluation subject to a set of window recently accepted solution groups.

PROBLEM DEFINITION OF UNCAPACITATED UNIVERSITY TIMETABLING PROBLEMS

Examination timetabling problemsarea part of the educational timetabling problems that have been studied by researchers until today (Lewis, 2008; Qu *et al*., 2009). The main goal of these problemsis to produce a feasible and accepted timetable to all involved stakeholders, subject to some restrictions (Romero, 1982) by accommodating the student-exam requirement. Depending on the institutions'definition of the examination timetable requirements the classification of these constraints are varies. They may fall either under hard constraints or soft constraints categories (Carter *et al*., 1996; Burke *et al*., 1996; Schaerf, 1999; Qu *et al*., 2009). The hard constraint (s) are mandatory to be satisfied in order to produce a feasible timetable and its common constraint is to ensure no student can sit more than one exam in any period of time (Qu *et al*., 2009). The soft constraints are preferable to be satisfied if possible without jeopardizing the hard constraint (s). For example, to schedule the multiple exams based on the same duration length in one exam hall (Malik *et al*., 2007).

The quality of a timetable is based on the minimization cost subject to the soft constraint violations (Sabar *et al*., 2009). The more soft constraints can be fulfilled the lower quality of a timetable and the better solution. Burke *et al*. (2004a, b) defined several inputs of this problem as:

- N is the number of exams
- E_i is the ith exam where $i \in \{1,..., N\}$
- e^i is the number of student population that involve with the examination
- K is the set of all N exams, $K = \{E_1,..., E_N\}$
- T is the number of available timeslots
- M is the number of students
- T_j specific the assigned timeslot for exam E_i where $t_j \in \{1,..,T\}$ and $i \in \{1,..., N\}$
- $C = (c_{ij})_{N \times N}$ is the conflict matrix where each element denoted by c_{ij}
- $i, j \in \{1,..., N\}$ is the number of students taking both exams E_i and E_j where $c_{ij} = 0$ for $i = j$
- $\Delta t = |t_i - t_j|$ is the timeslot different between exam E_i and E

Minimise:

$$F = \frac{\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} C_{ij}.\text{Penalty}(t_i, t_j)}{M}$$

$$\text{Penalty}(t_i, t_j) = \begin{cases} 2^5/2^{\Delta t} & \text{if } 1 \le |\Delta t| \le 5 \\ 0 & \text{otherwise} \end{cases}$$

INTEGRATED TWO MULTI NEIGHBOURHOOD TABU SEARCH

The main idea of this technique (Malik *et al*., 2009) is to separate the search strategies of Tabu Search into two separate stages with several independent Tabu lists. This technique's workflow uses two-stage optimization: construction phase and optimization phase. The earlier stage applies a graph colouring with constructive heuristic approaches that based on Ayob *et al*. (2007)'s technique that utilize a combination of heuristic strategies such as least saturation degree, largest degree and largest enrolment. This phase is responsible to produce a feasible initial solution (as an input) for the second phase of the ITMTS. The ITMTS's second phase is concentrated on the optimization procedure where the two-stage search strategies of Tabu Search technique are applied. The manipulation of the search strategies of intensification (VNhS) stage and diversification (HNhS) stage are iteratively applied with regards to the neighbourhood and memory management strategies.

ITMTS begins with HNhS diversification phase where the newly generated initial solution will be briefly refined. The purpose of this refinement process is to find the best improved solution's structure before a specific refinement in intensification phase of VnhS stage can be carried out. Subject to a predefined number of counteriterations the search will switch into intensification search strategy for further search. In the VNhS stage, the search mechanism's concentration is to intensively improve the quality of solution subject to the multi-neighbourhood structure options strategy. All the recently accepted solutions of this stage will be evaluated accordingly basedon their quality status subject to the static counter of non-performing accepted solutions.

Subject to this counter's limitation size, the search mechanism will divert to the diversification phase (HNhS) once it reaches the limit and will be reset every time the improving neighbor is found. This diversification will happen when the ITMTS is showing the trend to continuously accept non-improving results during the intensification phase (VnhS stage). The aim of this procedure is to reshake the current saturated solution's neighbourhood search space to be used in the next intensification stage. For the details procedures of ITMTS and its neighbourhood structures strategies please refer to Malik *et al.* (2009).

Adaptive switcher mechanism of ITMTS: In this research, researchers introduce a switcher mechanism for ITMTS that can work adaptively based on current pattern of the recently accepted solutions during the intensification procedures. This switcher's role as an adaptive decision mechanism that calculates a trigger value (level) to be used as a guide for the search mechanism whether to switch into diversification stage or stick in the intensification stage for further intensification process. The search will only swap its modes into diversification (HNhS) if the recently evaluated solution quality exceeded this trigger value.

Figure 1 shows ITMTS with an adaptive switcher mechanism of ITMTS. The VNhS stage is mainly focused on the Tabu Search's intensification strategy. The aim is to find the best improving neighbours (subject to the quality of solution cost). On the other hand, HNhS is for diversification strategy. The concept of this switcher mechanism is derived and adapted from the central tendency of standard deviation formulation for data description pattern (Sekaran, 2003; Salkind, 2003).

For this strategy, a small number of recently accepted solutions will be selected and updated in short-term memory. The trigger value of switcher mechanism will be adaptively calculated, based on this information for every recently accepted solution and will be used as a limitation value for the next acceptance solution of VNhS stage (intensification process).

With regards to the ITMTS's intensification stage operation some of the non-improving solutions will be allowed to be accepted by the search mechanism subject to the trigger value. The intention of this strategy is to create some minor changes on search space area which may indirectly influence the current accepted solution quality pattern. Thus, it may allow ITMTS to be more tolerance with some non-improving solutions to be accepted. The acceptance tolerance in evaluating and accepting some of the non-improving neighbours in VNhS should be given to the search mechanism before it can switch to the next stage for major restructuring process (diversification). Thus, it may allow for some future neighbourhood structure options to be evaluated. This may possibly produce better results although the search's acceptance tendency to accept the un-improving neighbour options is high.

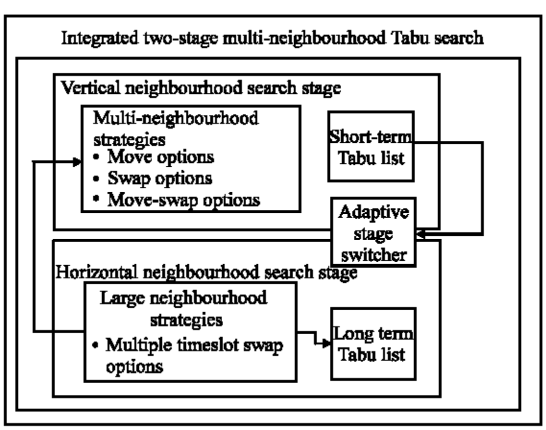

Fig. 1: Adaptive switcher mechanisms of ITMITS

Ideally, the proposed mechanism works based on the pattern of a window of recently accepted solution qualities. This is done by monitoring the acceptance progress subject to its trigger value. This value is continuously updated, based on a window of recently accepted solution qualities of VNhS stage. Once the recently solution quality is detected to be worse than the trigger value the search mechanism will switch to the next stage for diversification process of HNhS stage.

This switcher mechanism acts as a barometer that is very sensitive to any changes of solution quality acceptance made by the search mechanism. The formulation of this trigger value, T, for this switcher is derived from Sekaran (2003) and Salkind (2003) and can be defined as follow:

- X = A set of recently accepted solutions where i = {1,..., n}
- n = Number of accepted solution quality costs
- i = A recently accepted solution; $X_i \in X$
- T = A trigger value of switcher
- δ = Standard deviation of a set of accepted solution costs
- $\bar{X}$ = Mean of a set of accepted solution costs

Where:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n}(X_i) \tag{1}$$

And:

$$\delta = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2} \tag{2}$$

Therefore:

$$T = |\delta| + \bar{X} \tag{3}$$

Table 1: An example of simulation evaluation for adaptive switcher mechanism

Num	X_{i+1}	$X_{i+1} - \overline{X}$	$(X_{(i+1)} - \overline{X})^2$	δ
1	157.60	-0.331	0.109561	
2	157.70	-0.231	0.053361	
3	158.90	0.969	0.938961	$\sqrt{2.205487} - 17$
4	158.70	0.789	0.591361	
5	157.50	-0.431	0.185761	
6	157.72	-0.211	0.044521	
7	157.40	-0.531	0.281961	
	$\overline{X}$=157.931		$\sum = 2.205487$	$\delta = \pm\, 0.367581$

The switching conditions of this mechanism is subjected to two rules: if T value is lesser than the recently accepted trial cost then the search will switch to HNhS stage (for diversification stage) and if T value is bigger than the recently accepted trial cost, no-switch action will be taken by the search mechanism which means the search will remain in VNhS stage. Based on the formulation earlier, a simulation example of the switch mechanism evaluation for sta-f-83 instance of Carter datasets subject to a set of the latest solution costs is given as in Table 1. The process of evaluating the trigger value for the switcher mechanism started by selecting a set of predefined number of the latest accepted solutions and calculate the distribution of central tendency for these solution quality costs. The mean of these quality costs is 157.931 is calculated by using the function of (1). The selection of a window of quality costs is reflected to the current evaluation progress of the search mechanism. If the number of quality costs of the earlier accepted number is too big it may not imitate to the actual central tendency acceptance of the current solutions acceptance pattern.

Through the mean value, the standard deviation of these costs can be calculated by using function (2) where the value of δ is equivalentto the approximation of ± 0.367581. The range of the trigger value are from -0.367581 to $+0.367581$ based on central tendency value of $\overline{x} = 157.931$. Since, ITMTS is minimization optimization approach the negative value of δ will be ignored because the lower the trial solution quality cost the better this solution option will be accepted. The trigger value for the switcher mechanism to switch to another stage (HNhS) will be a value of positive δ plus $\overline{x}$ as in (4). Any trial solution cost that below than the trigger value, this solution will be accepted by the search mechanism and no switching process will be executed by the search mechanism. Through this strategy, the search of VNhS will allow any unimproving neighbour option to be accepted as long as they do not exceed the trigger value. If the trial neighbour option quality cost is bigger than the trigger value, the switch mechanism will allow the search to switch to the next stage of ITMTS.

```
While S witch is not true
    calculate X̄ for these solution costs within window
    calculate δ
    compare the trial neighbour cost with trigger value
    iftrial neighbour cost lower than trigger value
        accept the trial neighbour
        break
        continue in intensification stage
    else
        switch is true
        break;
    end of if
end of while
```

Fig. 2: Pseudo-code of adaptive switcher mechanism

The pseudo-code of the ASM of ITMTS as in Fig. 2 and the full pseudo-code of ITMTS can be referred to Malik *et al*. (2009). This enhanced ITMTS Method has been named as EITMTS.

EXPERIMENTS AND RESULTS

Two experiments were conducted for the EITMTS technique and they are: window size for Adaptive Switcher Mechanism (ASM) and a comprehensive test for the EITMTS. In both experiments, the uncapacitated Carter datasets Version I (Qu *et al*., 2009) were used with the proximity cost function as by Carter *et al*. (1996). Several personal computers (Intel Duo Core2 2 Ghz 3 Gb memory) were used to implement these experiments.

Window size of ASM test: This experiment was conducted with the objective to identify the suitable number of accepted solution to be considered (i.e., the value of n) in determining the trigger value of ASM, T. Several instances of Carter datasets (Version I) were used for this test subject to their conflict density. They were: car-f-92, hec-s-92, kfu-s-93, rye-s93 and uta-s-92. This experiment was executed for 10 runs of 10,000 iterations or 12 h.

In deciding the number of n size for window size, a preliminary test was conducted on a number <5 and the overall quality results of the testwas not very impressive. From this preliminary test, it can be concluded that if the window size of n is too small (<5) the search mechanism to stay in intensification search stage for a very short period (or iterations) will force the search to switch into diversification search stage for solution reshaking procedure. The search mechanism will not be given the opportunity to further evaluateany potential neighbourhood options including the non-improving

Table 2: The results of ASM's window size n tests

Dataset	Conflict density	Number of latest solution cost for ASM evalution (n) 5	7	10	15	20
car-f-92	0.13	5.56	6.09	5.82	5.58	6.37
hec-s-92	0.42	10.86	11.29	10.90	10.97	11.27
kfu-s-93	0.06	14.49	19.04	17.14	17.62	16.53
rye-s-93	0.07	11.11	12.96	12.92	12.77	13.63
uta-s-92	0.13	4.36	4.87	4.85	5.01	5.43

neighbourhood options while in the current intensification stage. Thus, it will force the current solution to be restructured again. The possibility of getting poor quality newly produced solution may be high due to the switch to solution reshaking procedure. Apart from that the possibility of getting the search mechanism entrapped in non-improvement solution situation is also very high and some potential of recursive exams selection could even occur. Therefore, the method could be very costly and could not promise any positive progress on solution quality.

Through, the application of ASM's strategy, the ITMTS will be able to avoid a premature switching (from VNhS's intensification search strategy into diversification search strategy). By identifying the suitable n size of ASM window, it will give some spaces for the search mechanism to continuously stay in the current mode of intensification. Thus, it will also adaptively force the search mechanism to be more tolerance with any possibility of non-improving solutions by accepting them during its searching process. Some minor restructuring on the solution search space area will happen during this process due the acceptance of non-improving solutions. The restructuring may recreate some potential improvement neighbourhood on the current solution andthe major restructuring exercise of HNhS's diversification process can be avoided. Unless the situation of solution quality is worsen and no potential to be further improved in the near future then a major solution restructuring procedure of diversification stage should be implemented.

Table 2 presents the best test's results for the window size (n) of 5, 7, 10, 15 and 20. The window size of 5 has emerged as the best performed window size for this test and can be seen as the best size of window size for the ITMTS's Adaptive Switcher Mechanism (ASM). Based on these results, it can be concluded that the bigger the window size of n is applied the worse results of the technique will be produced. In general, the results performance among n that is >5 can be considered as not stable because some of the results regardless the size of n can are better than others and vice versa.

Table 3: A comparison between EITMTS and Standard ITMTS

Dataset	EITMITS	Standard ITMITS	Different	Difference percentage (%)
car-f-92	5.25	8.72	3.48	39.90
car-s-91	5.97	10.79	5.97	55.32
ear-f-83	40.12	38.58	-1.54	-4.00
hec-s-92	11.48	11.63	0.15	1.29
kfu-s-93	15.38	28.29	12.92	45.63
lse-f-91	11.07	20.75	9.68	46.70
rye-s-93	15.24	22.16	6.92	31.20
sta-f-83	157.61	157.91	0.30	0.19
tre-s-92	9.41	11.42	2.01	17.60
uta-s-92	4.08	6.77	2.69	39.73
ute-s-92	26.37	29.19	2.82	9.70
york-f-83	40.71	41.99	1.28	3.05

Comprehensive test for EITMTS: In this test, 12 instances of Carter datasets had been tested for 25 runs with 100,000 iterations or 12 h. The aim of this testing is to investigate the performance of EITMTS compared to ITMTS (standard method).

Comparisons of the EITMTS against ITMTS: In Table 3, the overall performance of the EITMTS shows an improvement of the technique's results to all datasets compared to the standard ITMTS's results except for ear-f-83. Four instances' results (car-f-92, car-s-91, kfu-s-93, lse-f-91 and uta-s-92) have improved >35% from the best reported results of the standard ITMTS. Although, the EITMTS cannot outperform the basic ITMTS's result of ear-f-83 the variance between these results is <5%. All of these results have demonstrated the effectiveness of applying the Adaptive Switcher Mechanism (ASM) in EITMTS.

A comparison of the EITMTS with other Tabu Search Methods: Table 4 shows the EITMTS has produced several best results particularly on kfu-s-93, lse-f-91 and ute-s-92 instances compared to the other Tabu Search methods and become the second best method from seven compared techniques. By referring to the ranking status of overall compared methods the results of ear-f-83, sta-f-83 and uta-s-92 can be classified as comparable. Most of the EITMTS's results show positive achievement as other compared methods and have some future potential to be further improved in order to produce much better results.

Comparison EITMTS with other local search state of the art methods: Table 5 shows the ability of this enhanced technique to produce some good and comparable results against other state of the art techniques although Caramia *et al.* (2001) had dominated the overall compared techniques. Relatively, EITMTS's overall performance on all tested instances (except sta-f-83) can be considered as moderate and under-performed.

Tble 4: A comparison between EITMTS with other Tabu Search based methods

Dataset	EMITS	Di Gaspero (2002)[1]	Di Gaspero (2002)[2]	Paquete and Stuztle (2002)[3]	White *et al.* (2004)[4]	Kendall and Hussain (2005)[5]	Sabar *et al.* (2009)[6]	Rank
car-f-92	5.97	5.2	-	-	5.73	4.67	4.09	5/5
car-s-91	5.24	6.2	5.2	-	4.63	5.37	4.00	4/6
ear-f-83	40.12	45.7	39.2	38.2	45.80	40.18	41.21	3/7
hec-s-92	11.48	12.4	10.2	11.2	12.90	11.86	12.34	3/7
kfu-s-93	15.38	18.0	-	16.2	17.10	15.84	16.46	1/6
lse-f-91	11.07	15.5	12.2	13.2	14.70	13.67	14.50	1/7
rye-s-93	15.24	-	-	-	11.60	-	12.00	3/3
sta-f-83	157.61	160.8	157.2	168.2	158.00	157.38	159.20	3/7
tre-s-92	9.41	10.0	-	9.2	8.94	8.39	7.89	5/6
uta-s-92	4.08	4.2	4.2	-	4.44	3.92	3.19	3/6
ute-s-92	26.37	29.0	-	29.0	29.00	27.60	28.76	1/6
york-f-83	40.71	41.0	39.2	38.2	42.30	39.42	36.19	5/7

[1]Selection Strategies Methods with dynamic Tabu list (160); [2]TS with token ring search (11); [3]Costraint prioritization ordering (12); [4]OTTABU-4 phases; [5]Tabu search hyper-heuristic; [6]EMCQ with tabu list (18)

Table 5: A comparison between EITMTS with other state of the art local search methods

Dataset	EITMITS	Carter *et al.* (1996)[1]	Caramia *etal.* (2001)[2]	Bark *et al.* (2004)[3]	Asmuni *et al.* (2005)[4]	Abdullah *et al.* (2007)[5]	Yang and Petrovic (2005)[6]	Burke *et al.* (2006)[7]	Burke *et al.* (2007)[8]	Abdullah *et al.* (2007)[9]	Rank
car-s-91	5.97	7.10	6.6	4.20	5.19	5.20	4.50	3.90	4.600	4.42	8/10
car-f-92	5.24	6.20	6.0	4.80	4.51	4.40	3.93	4.60	4.000	4.80	8/10
ear-f-83	40.12	36.40	29.3	35.40	36.64	34.90	33.71	32.80	37.920	34.92	10/10
hec-s-92	11.48	10.80	9.2	10.80	11.60	10.30	10.83	10.00	12.025	10.73	8/10
kfu-s-93	15.38	14.00	13.8	13.70	15.34	13.50	13.82	13.00	15.200	13.00	10/10
lse-f-91	11.07	10.50	9.6	10.40	11.35	10.20	10.35	10.00	11.330	10.01	8/10
rye-s-92	15.24	7.30	6.8	8.90	10.05	8.70	-	-	-	9.65	7/7
sta-f-83	157.61	161.50	158.2	159.10	160.79	159.20	158.35	159.90	158.190	158.26	1/10
tre-s-92	9.41	9.60	9.4	8.30	8.47	8.40	7.92	7.90	8.920	7.88	9/10
uta-s-92	4.08	3.50	3.5	3.40	3.52	3.60	3.14	3.21	3.900	3.20	10/10
ute-s-92	26.37	25.80	24.4	25.70	27.55	26.00	25.39	24.80	28.010	26.10	8/10
york-f-83	40.71	40.70	36.2	36.70	39.79	36.20	36.35	37.28	41.370	36.22	8/9

[1]Constructive heuristic with backtracking; [2]Greedy constructive heuristic with an optimiser; [3]Great Deluge Algorithm; [4]Fuzzy multiple ordering criteria; [5]Ahuja-Orlin's large neighbourhood search; [6]Similarity measure for heuristic selection; [7]Hybrid variable neighbourhood approaches; [8]Graph based hyper-heuristic; [9]Hybrid Kreat Deluge Algorithm

DISCUSSION

With the introduction of Adaptive Switcher Mechanism (ASM) in ITMTS technique (EITMTS) it has indirectly contributed to the performance improvement for ITMTS. The function of the switcher as a decision making mechanism in deciding has helped the technique to be more reliable compared to the switch's static counter of the standard ITMTS. In this strategy, it has made the switching process become more justifiable and tolerance to non-improved solutions to be accepted by the search mechanism and at the same time, creating some minor restructuring on the solution's search region. It also will give some flexibilities and independence for the search mechanism to accept the non-improving solutions (within an adaptive limitation range depending on the aspiration criteria and tabu list) which possibly creates some neighbourhood potentials in searching better solution quality during the intensification process. It also could avoid any premature diversification switching that may cause prolong the next intensification process of the technique.

Instead of using the arbitrary technique (switch static counter) to decide the switching process, this adaptive switcher could also solve a problem of auto-switching mechanism by using the concept that can adapt the current environment of the solution before making any decision to execute any action.

CONCLUSION

Rooted from the accomplishment of this adaptive switcher mechanism concept as a part of ITMTS's component, some further enhancement can be implemented on ITMTS technique especially in maximizing its search capability and neighbourhood structure options including hybridization with other methods. This ASM concept can also be applied in many areas of the search's decision making procedure where some adaptive justification processes are needed on group of decision options.

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