Tabu Search
Part 2: Advanced Strategies

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Outline

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- Diversification
- Allowing Infeasible Solutions
- Surrogate and Auxiliary Objectives
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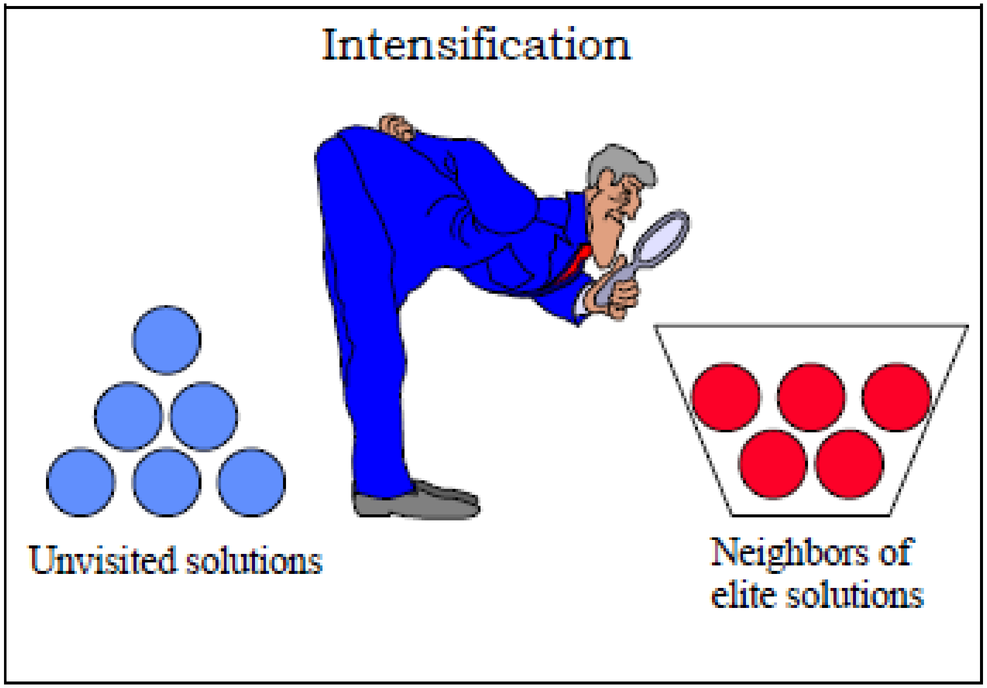
Intensification

Intensification

- Intensification
  - is to spend time exploring **more carefully** the portions of the search space that have already been visited
- **The idea behind of Intensification**
  - one should explore more thoroughly the portions of the search space that seem **promising** in order to make sure that the best solutions in these areas are found.
- Intensification is based on some intermediate-term memory or recency memory.
- From time to time, one would thus stop the normal searching process to perform an intensification phase.

Intensification

- Intensification strategies are based on neighbors of elite solutions



Intensification

- Method 1:
  - They may also initiate a return to attractive regions to search them more thoroughly.
- Method 2:
  - in which one records the number of **consecutive iterations** that various **solution components** have been present in the current solution without interruption.
- Method 3:
  - Another technique that is often used consists in **changing the neighborhood structure** to one allowing more powerful or more diverse moves.

Intensification

- Method 2: In the CPLP application,
  - Option 1:
    - one could record how long each site has had an open facility.
    - A typical approach to intensification is **to restart** the search from the **best currently known solution** and to **freeze** (**fix**) in it the components that seem more attractive.
  - Option 2:
    - one could thus freeze a number of facilities in the sites that have had them for the largest number of iterations and perform a restricted search on the other sites.

Intensification

- Method 3: **changing the neighborhood structure**
  - In the CVRP:
    - one could therefore allow **more complex insertion** moves or switch to an ejection chain neighborhood structure.
  - In the CPLP:
    - if Add/Drop moves were used, Swap moves could be added to the neighborhood structure.
    - In probabilistic TS, one could increase the sample size or switch to searching without sampling.

Intensification

- Intensification is used in many TS implementations, but it is not always necessary.
- This is because there are many situations where the search performed by the normal searching process is thorough enough.

Diversification

Diversification

- One of the main problems of all methods based on Local Search approaches, is that they tend to be **too local**, i.e., they tend to spend most of their time in a restricted portion of the search space.
- The negative consequence of this fact is that one may fail to explore the most interesting parts of the search space and thus end up with solutions that are still pretty far from the optimal ones.

Diversification

- **Diversification** is an algorithmic mechanism that tries to force the search into unexplored areas of the search space.
- Diversification is usually based on some form of **long-term memory** of the search, such as a **frequency memory**, in which one records the total number of iterations (since the beginning of the search) that various "solution components" have been present in the current solution or have been involved in the selected moves.

Diversification

- In CPLP:
  - one could record during the number of iterations during which each site has had an open facility.
- In CVRP:
  - one could note how many times each customer has been moved from its current route.
- In cases where it is possible to identify useful **regions of the search space**, the frequency memory can be refined to track the number of iterations spent in these different regions.

Diversification

- Diversification involves forcing a few rarely used components in the current solution and restarting the search from this point.
- **In CPLP**
  - one could thus open one or a few facilities at locations that have seldom had them up to that point and resume searching from that plant configuration.
  - one could also close facilities at locations that have been used the most frequently.
- **In a CVRP**
  - customers that have not yet been moved frequently could be forced into new routes.

Diversification

- The diversification is possibly **the most critical issue** in the design of TS heuristics.
- It should be addressed with extreme care fairly early in the design phase and revisited if the results obtained are not up to expectations.

Allowing Infeasible Solutions

Allowing Infeasible Solutions

- Accounting for all problem constraints in the definition of the search space often restricts the searching process **too much**.
- Example,
  - in CVRP instances where the **route capacity** or **duration constraints** are too tight to allow moving customers effectively between routes
- In such cases, constraint relaxation is an attractive strategy, since it creates a larger search space that can be explored with **simpler neighborhood structures**.

Allowing Infeasible Solutions

- Constraint relaxation is easily implemented by dropping selected constraints from the search space definition and adding to the **objective weighted penalties** for constraint violations.
- This raises the issue of finding correct weights for constraint violations.
- To solve this problem is to use self-adjusting penalties, i.e., weights are adjusted dynamically on the basis of the recent history of the search:
  - weights are increased if only infeasible solutions were encountered in the last few iterations, and decreased if all recent solutions were feasible

Allowing Infeasible Solutions

- Penalty weights can also be modified systematically to drive the search to cross the feasibility boundary of the search space and thus make diversification.
- This technique, known as **strategic oscillation**.

Surrogate and Auxiliary Objectives

Surrogate and Auxiliary Objectives

- There are many problems for which the true objective function is quite costly to evaluate
- Example:
  - In the CPLP when one searches the space of location variables
  - In this case, computing the objective value for any potential solution entails solving the associated transportation problem.
  - When this occurs, the evaluation of moves may become **too expensive**, even if sampling is used.

Surrogate Objectives

- An effective approach to handle this issue is to evaluate neighbors using a **surrogate objective**,
  - i.e., a function that is correlated to the true objective, but is less computationally demanding, in order to identify a (small) set of promising candidates (potential solutions achieving the best values for the surrogate).
  - The true objective is then computed for this small set of candidate moves and the best one selected to become the new current solution.

Auxiliary Objectives

- Another frequently encountered difficulty is that the objective function may not provide enough information to effectively drive the search to more interesting areas of the search space.
- Example:
  - When the fleet size is not fixed in the CVRP, but is rather the primary objective (i.e., one is looking for the minimal fleet size allowing a feasible solution).

Parameter Calibration

Parameter Calibration

- Parameter calibration and computational experiments are key steps in the development of any algorithm.
- The first step is to select a good set of benchmark instances (either by obtaining them from other researchers or by constructing them), preferably with some reasonable measure of their difficulty and with a wide range of size and difficulty.

Parameter Calibration

- This set should be split into two subsets:
  - the first one being used at the algorithmic design and parameter calibration steps, and
  - the second reserved for performing the final computational tests that will be reported in the paper(s) describing the heuristic under development.
- The reason for doing so is quite simple:
  - When calibrating parameters, one always run the risk of **overfitting**, i.e., finding parameter values that are excellent for the instances at hand, but poor in general, because these values provide too good a "fit" (from the algorithmic standpoint) to these instances.

Parameter Calibration

- Methods with several parameters should thus be calibrated on much larger sets of instances than ones with few parameters to ensure a reasonable degree of robustness.

Recent Trends in Tabu Search

Recent Trends in Tabu Search

- Recent Trends in TS:
  - Making the search more effective
  - Hybridization
  - Moving to new application areas

Recent Trends in Tabu Search

- A large part of the recent research in TS deals with various techniques for making the search **more effective.**
- These include:
  - Methods for exploiting better the information that becomes available during search
  - Creating better starting points
  - More powerful neighborhood operators and parallel search strategies.

Recent Trends in Tabu Search

- The numerous techniques for making better use of the information are of particular significance since they can lead to dramatic performance improvements.
- Many of these rely on elite solutions (the best solutions previously encountered) or on parts of these to create new solutions, the rationale being that “fragments” (elements) of excellent solutions are often identified quite early in the searching process,
- but that the challenge is to complete these fragments or to recombine them

Recent Trends in Tabu Search

- Another important trend in TS (this is, in fact, a pervasive trend in the whole meta-heuristics field) is hybridization, i.e., using TS in conjunction with other solution approaches such as Genetic Algorithms

Recent Trends in Tabu Search

- TS research has also started moving away from its traditional application areas (graph theory problems, scheduling, vehicle routing) to new ones:
  - continuous optimization,
  - multi-criteria optimization,
  - stochastic programming,
  - Mixed integer programming
  - real-time decision problems
- with new challenges that, in turn, call for novel and original extensions of the method.

Terminology

Terminology

- **Search Space**
  - The search space of an LS or TS heuristic is simply the space of all possible solutions that can be considered (visited) during the search.
- **Neighboring Solutions**
  - At each iteration of LS or TS, the local transformations that can be applied to the current solution (denoted ***S***), define a set of **neighboring solutions** in the search space, denoted ***N(S)*** (the neighborhood of S).
- **Move**
  - A move is changing current solution to a **neighboring solutions**

Terminology

- **Tabus**
  - Tabus are used to prevent cycling when moving away from local optima through non-improving moves.
- **Tabu Tenure**
  - The number of iterations that some moves are disallowing
- **Short-Term Memory / Tabu List**
  - Tabus are stored in a **short-term memory** of the search (the **tabu list**) and usually only a fixed and fairly limited quantity of information is recorded.

Terminology

- **Aspiration Criteria**
  - The tabus may in fact prevent the search to visit solutions that have not been examined yet.
  - **Aspiration Criteria** are the strategies that will allow one to **revoke** (cancel) tabus to avoid missing good solutions.
- **Intensification**
  - A mechanism that exploring more carefully the portions of the search space that have already been visited that seem “promising” in order to make sure that the best solutions in these areas are indeed found.
- **Diversification**
  - An algorithmic mechanism that tries to forcing the search into unexplored areas of the search space.

Terminology

- **Surrogate Objective**
  - A function that is to evaluate neighbors.
  - It is correlated to the true objective, but is less computationally demanding in order to identify a (small) set of promising candidates.
  - The true objective is then computed for this small set of candidate moves and the best one selected to become the new current solution.

References

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