

Optimal Sensor Network Design and Upgrade using Tabu Search

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Abstract

In this work a Tabu Search heuristic is proposed to solve the optimal design and upgrade of sensor structures that satisfy both economic criteria and specific requirements on key variable estimates. The heuristic is based on the Strategic Oscillation Technique around the feasibility boundary, a procedure that has good intensification and diversification capabilities. Comparative performance studies between stochastic solution strategies are performed for two industrial process networks.

Keywords: Sensor Network Design, Tabu Search, Meta-heuristics, Data Reconciliation

1. Introduction

Basic and high-level plant activities, such as monitoring, regulatory and supervisory control, real-time optimisation, planning and scheduling, etc., provide valuable results only if a reliable and complete knowledge of current plant state is at hand. The quality and availability of variable estimates strongly depend on the structure of instruments installed in the process and the software tools applied to enhance its precision.

The design and upgrade of sensor structures consists in selecting the type, number, accuracy, failure rate, and location of new sensors that provide the quantity and quality of information required from the process. To solve this combinatorial problem different deterministic and stochastic strategies have been presented.

The existing deterministic algorithms are only efficient for solving specific problems of small to medium size (Bagajewicz and Cabrera, 2002). Consequently stochastic optimisation methods arise as an alternative to tackle the design of large-scale plant sectors subject to complex function constraints.

There exist stochastic procedures based on Genetic Algorithms (GA) to design general sensor structures. Recently Chao-An et al. (2003) presented a methodology to maximize the network availability subject to cost and precision constraints on key variables, but they solve the problem for a small size network using the classical approach. In contrast, a hybrid novel procedure is developed by Carnero et. al (2004) to minimize the

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instrumentation network cost during its life cycle subject to precision and availability constraints. Furthermore parallel techniques based on GA are proposed by Gerkens and Heyen (2004).

The Tabu Search (TS) is a memory-based stochastic optimisation strategy (Glover, 1986), that has shown to be effective for solving hard problems such as The Travelling Salesman Problem, the global optimisation of Artificial Neural Networks and telecommunication networks. Recently some applications to chemical engineering problems have appeared (Lin and Miller (2004a-b), Teh and Rangaiah (2003), Cavin et al. (2004)).

It was reported that TS has a more flexible and effective search behaviour than other stochastic methods (Glover, 1986) as consequence of the use of adaptive memory. Thus it was investigated how TS could be used to solve the open sensor network design and upgrade problem.

Within the framework of TS, the Strategic Oscillation Technique was applied to develop a solution procedure and its performance was compared with other existing techniques. This paper reports the results of this study and is structured as follows. In Section 2 the design problem is briefly introduced. The new strategy is described in Section 3. Application results are provided in Section 4 for two case studies and, conclusions are addressed in Section 5.

2. Sensor Network Design and Upgrade Problem

The minimum cost sensor network design and upgrade problem that satisfies precision and estimability constraints for a set of key variable estimates is formulated as follows

$$\begin{aligned}
 & \text{Min} \quad \mathbf{c}^T \mathbf{q} \\
 & \text{s.t.} \\
 & \quad \hat{\sigma}_j(\mathbf{q}) \leq \sigma_j^* \quad \forall j \in S_J \\
 & \quad E_k(\mathbf{q}) \geq 1 \quad \forall k \in S_K \\
 & \quad q_i = 1 \quad \forall i \in I_0 \\
 & \quad \mathbf{q} \in \{0,1\}^{n-|I_0|}
 \end{aligned} \tag{1}$$

where $\mathbf{q}$ is a $(n - I_0)$ dimensional vector of binary variables such that: $q_i = 1$, if variable i is measured and $q_i = 0$ otherwise; $\mathbf{c}^T$ is the cost vector; $\hat{\sigma}_j$ is the standard deviation of the j -th variable estimate after a data reconciliation procedure is applied and E_k stands for the degree of estimability of variable k (Bagajewicz and Sánchez, 1999). For this formulation E_k is set equal to one, consequently only a variable classification procedure run is needed to check its feasibility. Furthermore S_J and S_K are the set of key process variables with requirements in precision and estimability respectively, I_0 is the initial set of instruments that is empty at the network design stage and, n is the total number of measurable variables.

For large-scale processes, the dimension of the search-space for Problem (1) increases significantly; consequently the design turns out to be a huge combinatorial optimisation problem.

3. A Tabu Search Heuristic based on Strategic Oscillations

Tabu Search is a meta-heuristic optimisation technique, which makes use of historical information about the solution process to explore the entire solution space and escape from local optima. The historical information is maintained in the form of Tabu lists that record the recency and frequency of solutions.

At each iteration a neighbourhood of possible solutions $N(\mathbf{q})$ is defined by modifying the current solution $\mathbf{q}$ through a sequence of moves. The new neighbours are examined to determine the best one, $\mathbf{q}'$, which is absent from a Tabu list. This is selected as starting point for the new iteration even it is worse than $\mathbf{q}$. Also the best solution ever found, $\mathbf{q}^*$, is saved.

New solutions are incorporated to the Recency based Tabu list and maintained there, as forbidden moves, until the Tabu tenure (pr) period is elapsed. This prevents solution cycling and being entrapped in local optima. The tabu property can be invalidated, for example, if the best neighbour is in the tabu list but it is better than $\mathbf{q}^*$.

Frequency based Tabu list records the solutions that have been found more often. This memory enables TS to examine regions that have not been previously explored and others that have historically given good solutions.

In this work the Strategic Oscillation Technique around the feasibility boundary is used to solve Problem (1) with the framework of TS. This technique provides a good balance between intensification and diversification over the intermediate to long term (Glover and Laguna, 1997). It consists of a sequence of destructive and constructive phases. Given a feasible solution, the search is strategically driven to cross the feasibility boundary and to continue in the infeasible region (destructive phase) until certain depth is reached, then the search changes the direction towards the feasible region where it continues until the same depth (constructive phase). The process of repeatedly crossing the feasibility boundary from different directions originates an oscillatory behaviour. Standard TS mechanisms are applied to avoid going back over previous trajectories.

For the sensor structure design problem the procedure progress as follows. Given a feasible set of instruments $\mathbf{q}$, the destructive phase consists in eliminating one measurement per iteration, consequently the quantity of null elements in the members of $N(\mathbf{q})$ increases. The search crosses the feasibility boundary and proceeds in the infeasible region until the evaluation function reaches the bound L_0 . Then it turns around and the constructive phase is initiated by incorporating measurements. In contrast to the previous phase, the quantity of null elements in the members of $N(\mathbf{q})$ lowers and the search returns to the feasible region. The constructive phase finishes when the number of measurements is greater than the bound L_1 . In the rest of the section implementation details of the proposed strategy are provided.

3.1 Initial Solution

The procedure used to generate the initial population in the GA based strategy developed by Carnero et al. (2004) is applied. It provides a set of solutions satisfying the condition that the variables in S_J and S_K are estimable (measured or unmeasured but observable). The best individual that satisfies precision constraints is selected as the initial solution for the TS procedure. This allows to compare the evolution of both strategies using the same base.

3.2 Neighbourhood Search

Given a solution $\mathbf{q}$, its neighbourhood $N(\mathbf{q})$ is defined as the set of solutions obtained by adding to (constructive phase) or eliminating from (destructive phase) $\mathbf{q}$ one measurement. The neighbourhood $N(\mathbf{q})$ comprises a set of new solutions, $\mathbf{q}_N$, that are at a Hamming distance of one with respect to $\mathbf{q}$, that is

$$N(\mathbf{q}) = \{\mathbf{q}_N / q_{Ni} \neq q_i \text{ and } q_{Nj} = q_j \quad \forall j \neq i\} \quad (2)$$

3.3 Evaluation Function

As a move can originate an infeasible solution, a member of the neighbourhood is evaluated using a function, F , that takes into account constraint violations as follows:

$$F = \begin{cases} \mathbf{c}^T \mathbf{q} & \text{if } \mathbf{q} \text{ is feasible} \\ CT_{\max} + Q(\mathbf{q}) & \text{if } \mathbf{q} \text{ is infeasible} \end{cases} \quad (3)$$

where

$$Q(\mathbf{q}) = \begin{cases} (CT_{\max} - \mathbf{c}^T \mathbf{q}) \left(\frac{ncu}{nr} \right) & \text{if } \mathbf{q} \text{ not satisfy estimability constraints} \\ \mathbf{c}^T \mathbf{q} \left(\frac{1}{R} \sum_{r=1}^R \frac{\sigma_r - \sigma_r^*}{\sigma_r} \right) & \text{if } \mathbf{q} \text{ satisfy estimability but not precision constraints} \end{cases} \quad (4)$$

$CT_{\max}$ is the cost of measuring all variables, nr is the number of variables in S_K and, R and ncu stand for the number of variables in S_j and S_K whose constraints are unsatisfied respectively.

3.4 Short and Long Term Memories

The Recency based Tabu list is a vector $\mathbf{t}$ of dimension $(n-I_0)$. A non-zero element of $\mathbf{t}$ indicates that this variable move is forbidden because it was performed to obtain a recent solution. Furthermore its value is the number of remaining iterations until the Tabu tenure period for this move is elapsed.

The Frequency based Tabu list is represented by a vector $\mathbf{h}$ of dimension $(n-I_0)$. The i -th component of $\mathbf{h}$ reports the number of moves of variable i used to generate the next solution during ph iterations. The evaluation function corresponding to the i -th allowable move is penalized in proportion to h_i in order to direct the search to unvisited areas or regions visited less frequently. After ph iteration vector $\mathbf{h}$ is reset.

3.5 Aspiration and Termination Criterion

If the best neighbour is in a tabu area but has a better evaluation function value than $\mathbf{q}^*$ then its tabu property is invalidated.

Termination on convergence criterion has been implemented. If the improvement after T iterations is no larger than a threshold, the search is stopped.

3.6 Bounds for the Strategic Oscillations

The value for bound L_0 is the instrumentation cost if all variables are measured plus the cost of the most expensive measurement. For bound L_1 , the 80% of the length of $\mathbf{q}$ is assumed.

4. Application Examples

The procedure described previously is applied to the instrumentation design of two process flowsheets. Design problems are selected as application examples because the search space for this type of problems is higher than for instrumentation upgrade.

Three solution strategies are run to solve each case: 1) Classic TS (CTS), 2) Strategic Oscillations (SO), 3) the procedure based on GA, developed by Carnero et al. (2004). The last one combines the benefits of a structured population in the form of neighbourhoods with a local search method, and takes advantage of process knowledge at different stages. The performance of the three methods is analysed in terms of the objective function value at the solution, that is the total cost CT , and the number of calls to the Evaluation Function (#FE).

4.1 Case 1

The selection of flowmeters for the steam metering network (SMN) of a methanol production plant is performed. The process consists of 11 units interconnected by 28 streams. It is assumed there is no restriction for the location of sensors on any stream. Data of cost and standard deviation for measurement errors are obtained from Sen et al. (1998).

The following constraints are imposed on the estimates of flowrates: $\sigma_2^*=0.025$, $\sigma_6^*=1.7851$. Furthermore the flowrate of stream 1 should be measured or unmeasured but observable.

Parameters pt and ph are set equal to 5 and 25 respectively.

Table 1 shows SO solves efficiently the design. Although the three methods obtained the same solution, SO requires only 7% of the #FE of GA and 17% of the #FE of CTS.

4.1 Case 2

The flowmeter network design for a simplified ethylene plant (EP) is conducted. The process involves 82 streams and 47 units. It is assumed that the standard deviation of a flowmeter is 2.5% of the corresponding true flowrate.

The following constraints are imposed on the precision of variable estimates: $\sigma_{10}^*=1584.2$, $\sigma_{17}^*=1359.6$, $\sigma_{35}^*=200.7$, $\sigma_{39}^*=1580.6$, $\sigma_{56}^*=122.72$, $\sigma_{69}^*=1284.4$. The lower bound for the flowrate degree of estimability of streams [5 12 14 35 37 44 62 70 77] is set equal to 1.

Parameter pt is 9 and, $ph=60$ for TS and $ph=80$ for SO.

Table 2 shows the proposed strategy outperforms CTS and GA. It obtains the best solution using 41% of the #FE of GA and 50% of the #FE of CTS.

Table 1. Application Results for SMN Flowsheet

Procedure	Measurements	CT	# FE
CTS	1 2 6 7 9 10 13 20 26 28	533.56	4100
SO	1 2 6 7 9 10 13 20 26 28	533.56	717
GA	1 2 6 7 9 10 13 20 26 28	533.56	10000

Table 2. Application Results for EP Flowsheet

Procedure	Measurements	CT	# FE
CTS	1 2 5 10 12 15 21 30 33-35 37 43 44 50 54-56 60 62 64-68 74-78 82	50885.9	16400
SO	1 2 5 10 12 15 21 30 33-37 44 50 55 56 60 62 64-68 74-78 82	50845.3	8298
GA	1 2 5 9 13 15 21 30 33-35 37 44 45 52 54-56 60 62 64-68 74 -78 82	50856.4	20000

5. Conclusions

In this work a new strategy for the design and upgrade of sensor networks is presented. A Tabu Search heuristic based on the Strategic Oscillation Technique around the feasibility boundary is proposed, and its performance is compared to other existing procedures.

Results indicate the strategy has good diversification capabilities because it obtains the best solution for the design problems analysed during our investigation. Furthermore, it efficiently searches the solution space, allowing to reduce significantly the number of required calls to the Evaluation Function.

In future works alternative intensification and diversification techniques, such as path relinking, will be analysed.

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