IMPROVED MOGA-TUNING AND VISUALIZATION FOR A HYBRID CONTROL SYSTEM

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Abstract: A hybrid controller is developed for a solar-thermal power plant using a gain-scheduled controller with feedforward to control the more linear operating regimes and a fuzzy PI incremental controller for the highly nonlinear operating region of the plant. An enhanced method of MOGA-tuning is employed by first optimizing the number of input/output membership functions using neuro-fuzzy data clustering. Enhancements to the visualization properties of the MOGA's graphical user interface are evaluated to improve the decision maker's choice when deciding between non-dominated solutions or potential fuzzy controller inference systems.

Keywords: Solar Thermal Power Plant, Multiobjective Genetic Algorithm (MOGA), Gain Schedule Control, Fuzzy Logic Control, Adaptive Neuro-Fuzzy Inference System, Evolving Trade-off.

1. INTRODUCTION

Recent research has demonstrated that a gain scheduling approach, Johansen, *et al*. (2000), can be used to control a solar power generation plant successfully over a large part of its operating range. However, the results of this type of control deteriorate somewhat when the plant is operated in its more nonlinear regimes. This work therefore combine this gain scheduled type of controller with controllers that better suit the more nonlinear part of the operating space, in particular the fuzzy PI incremental controller of Loebis (2000). Fuzzy controllers are well suited to design using a multiobjective genetic algorithm (MOGA) approach, Fonseca and Fleming (1998). These designs can be improved upon by optimizing the number and parameters of its input membership functions using data clustering and adaptive neuro-fuzzy inference system (ANFIS) techniques, e.g. Stirrup and Chipperfield (2003). This can be shown to reduce complexity and the size of the fuzzy rule-base while affording acceptable control along with the possibility of a simple hardware realization. The overall effect of this enhancement is to reduce the search space by reducing the number of membership functions and the rule-base required for fine-tuning. This greatly improves the processing time when tuning the fuzzy controller, and improves control within the plant's nonlinear region.

In this work an evolving conflict sensitivity technique, Stirrup and Chipperfield (2002), is also employed to automatically adjust goal information to help improve the decision support provided within the MOGA's graphical user interface (GUI). This intends to give improved trade-off visualization for better non-dominating solution or controller choice, while maintaining the quality of non-dominating solutions within the solution set.

2. PLANT DESCRIPTION

The solar power plant or ACUREX-field to be controlled is a pilot scheme situated at the Plataforma

Solar de Almeria (PSA) site in the Taberna Desert, southern Spain. The field is composed of 480 distributed solar parabolic collectors, arranged in 10 parallel loops and is outlined in schematic in Fig. 1. A collector uses the parabolic surface to focus the solar radiation onto a receiver tube, which is placed in the focal line of the parabola. The heat-absorbing oil is pumped through the receiver tube, causing the oil to collect heat, which is transferred through the receiver tube walls. The thermal energy developed by the field is pumped to the top of the thermal storage tank, whereupon the oil from the top of the storage tank can be fed to a power-generating system, a desalination plant, detoxification plant or to an oil-cooling system if needed. The oil outlet from the storage tank to the field is at the bottom of the tank.

For the initial start-up of the plant, the system is provided with a three-way valve, which allows the oil to be circulated in the field until the outlet temperature is adequate to enter the storage tank. The oil pump, which pumps the oil from the storage tank, through the collector tubes and into the top of the storage tank is located at the field inlet. To ensure that the collectors give optimum solar absorption, every collector row has a sun tracking system fitted to it.

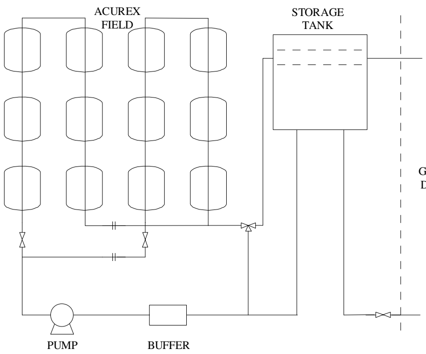

Fig. 1: Schematic representation of the solar plant

A data acquisition system for the plant, described by Camacho, *et al*., (1997) provides the following data: the solar intensity, inlet temperature to the field, outlet temperature of each loop and two other outlet temperatures between the field and storage tank, the current oil pump flow and requested value, and the tracking status of the collectors. The plant can generate 1.2 MW of peak power with beam solar radiation of 900 Watts m^{-2}. The oil-storage tank has a capacity of 140 m^3, which allows for storage of 2.3 thermal MWh for an inlet temperature of 210 °C and an outlet temperature of 290 °C.

The operation limits for the oil pump are between 2.0 and 10.0 litres/sec.. The minimum value is there for safety and to reduce the risk of the oil being decomposed, which happens when the oil temperature exceeds 305°C. The consequence of exceeding the maximum oil temperature, is that all the oil may have to be changed leading to plant down time and loss of Power generation. Another important restricting element in this system is the difference between the field's inlet and outlet oil temperatures. A suitable, or normal, difference is around or less than 70°C. If the difference is higher than 100°C, then there is a significant risk of causing oil leakage due to high oil pressure in the pipe system.

A control system for this plant has the objective of maintaining the outlet temperature (in this case the average outlet temperature of all the parallel loops) at a desired level in spite of disturbances like solar irradiation (clouds and atmospheric phenomena), mirror reflectivity and inlet oil temperature. The oil flow rate is manipulated by the control system through commands to the pump. It should be noted that the primary energy source, solar radiation, couldn't be manipulated. The performance measures of the control system are to keep the oil outlet temperature close to its set point, and to avoid oscillations in the oil pump flow rate.

3. GAIN-SCHEDULED CONTROL

In previous work, Johansen, *et al.,* (2000), employed a gain-scheduling approach for the solar plant. This used a set of local linear controllers, each designed by pole-placement, based on local linear ARX models that were identified using the methods and software described in Hunt and Johansen (1997). A feed-forward block was also placed in the controller from the solar radiation input (I), to improve disturbance rejection. The linear models were designed for control in the more linear regions of oil-flow (q) i.e., above 5 l/s^{-1}. The decomposition of the proposed hybrid controller was carried out in the operating range of $0 \leq I \leq 1000$ W m^{-2} and $5 \leq q \leq 10$ $l\ s^{-1}$ as shown in Fig. 2.

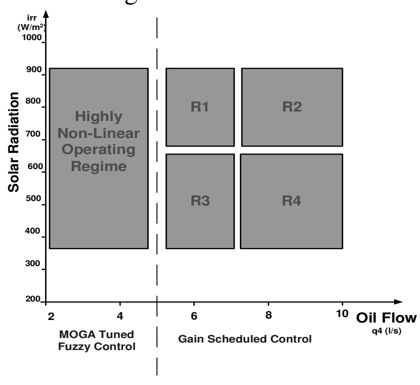

Fig. 2: The plant's operating regimes

Two local linear models presented by Hunt and Johansen (1997), were identified from experimental data, using locally weighted regression. These correspond to the operating points with oil flow rates at 6 and 8 $l\ s^{-1}$ respectively. Also, the gain of the local linear models was corrected using the average solar radiation during each PRBS test such that they corresponded to a solar radiation of 800 W m^{-2}. Furthermore, by reducing the gain by a factor of 5/8 generated two new local models corresponding to a solar radiation of 500 W m^{-2} giving a total of four local models corresponding to the operating regimes.

In Johansen, *et al.* (1998), it was also shown that the performance of the gain-scheduled controller was not ideal at the lower flow rate of 4 l s^{-1} producing significant overshoot and some oscillation of the control signal. Johansen *et al.* (1998) suggest that this may be improved by refining the models in this regime with an improved PRBS test signal. Furthermore, the non-lineararities were more pronounced at low flow rates. Thus, a finer decomposition into operating regimes may be desirable as q becomes smaller. In view of the uncertainties and difficulties of control at low flow rates, the method chosen in this study was to use a MOGA-tuned fuzzy incremental PI controller to improve these flow rates.

4. FUZZY PI INCREMENTAL CONTROL

In a study by (Loebis, 2000), a fuzzy PI controller, Fig. 3, was designed for better control of the solar plant's low flow rates. This offered an improved overall performance compared with the standard PI controller. In this work the MOGA will be used to optimise the output rule-base and membership functions against four objectives: Overshoot, Rise time, Settling Time and Error Variance.

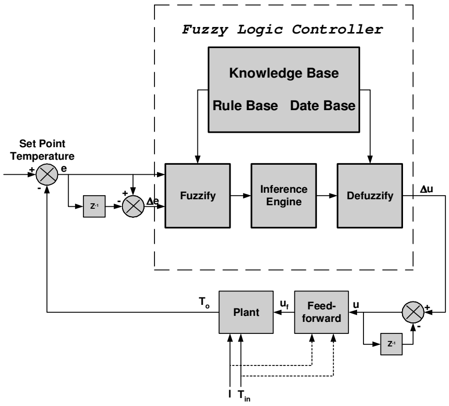

Fig. 3: A Fuzzy Incremental Controlled Solar Plant.

The fuzzy logic incremental controller (FLC) defines the error (e) as the difference between the plant's output temperature (T_o) and the set point signal (T_r). The error and its increment (Δe) were considered to be the inputs for the fuzzy controller and the output variable (Δu) was the increment to the control signal. A feedforward term was also added after the FLC to improve the disturbance rejection caused by changes in the solar radiation.

5. INPUT DATA MODELLING FOR IMPROVED MOGA TUNING

To aid the MOGA tuning of the number and positions of input membership functions, the error (e) and its increment (Δe) were pre-optimized. The fuzzy inference generation function `genfis2` (Matlab 2002) builds on the subtractive clustering function to generate a Sugeno-type Fuzzy Inference System (FIS) that models the system behaviour from the input training data. The model FIS was then tested with different data (see Fig. 4), using an evaluation function to find the optimal cluster radius.

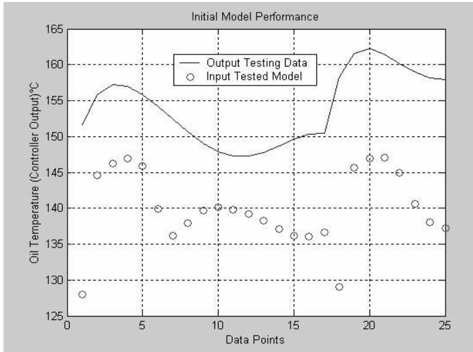

Fig. 4: Poor performance of model output using input checking data compared with output checking data.

This radius was then input into a clustering tool (Matlab, 2002) to identify natural groupings of the training data, Fig. 5, and hence give an initial idea of the number of input membership functions used by MATLAB's ANFIS tool.

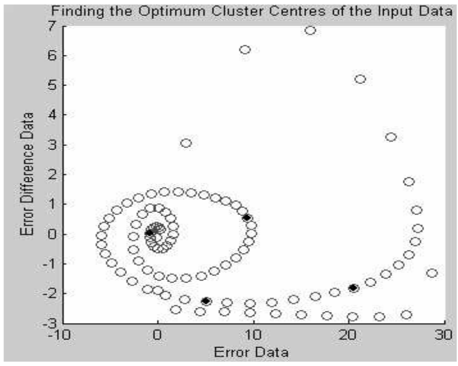

Fig. 5: Optimum Clusters and cluster radius influence.

Due to the poor performance of the FIS, Fig. 4, an ANFIS was chosen to tune (adjust) its membership functions, using a combination of a back-propagation algorithm and a least squares method. This allows the fuzzy system to learn from the input/output data set, adjusting the FIS parameters (parameter estimation) to reduce the error, defined as the sum of the squared difference between the actual and desired outputs.

The FIS model was run initially under two hundred epochs of ANFIS training to create a new FIS model. This model was then checked for over-fitting of the fuzzy system to the training data by comparing the training input/output data with the checking input/ output data. Fig. 6 illustrates how a system can be over-fitted (the model's ability to generalise the test data) when too many epochs are used. Here the training error settles at about the sixty-fifth epoch with no further improvement in the checking data error.

The ANFIS was then run for sixty-five epochs to give the improved results of Fig. 7. This gives a reduction of fuzzy membership functions from 7x7x11 (49 rules) to 4x4x11 (16 rules), thus reducing the decision variable search space to improve MOGA efficiency, see section 6. The input membership functions are also optimized on real data instead of relying on *a posteriori* knowledge, which will add to the accuracy of the final results.

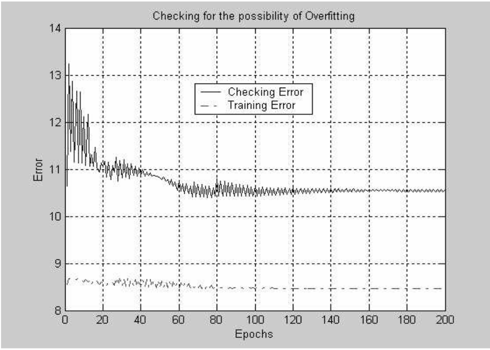

Fig. 6: Over-fitting the Fuzzy System.

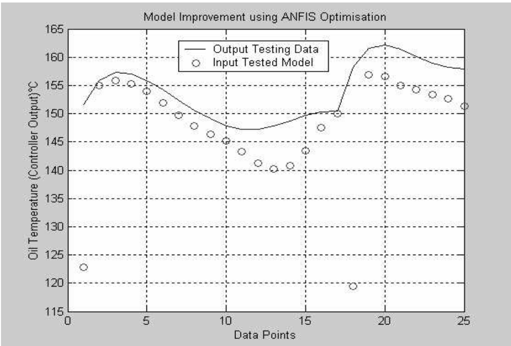

Fig. 7: Improved fit using ANFIS Optimisation.

6. REDUCING THE SYSTEM SEARCH SPACE

The search space can be reduced by allowing the fuzzy incremental controller to operate only in the higher nonlinear areas of the system. This permits a wider choice of objectives, such as overshoot and settling time, because the set point change into this area has only one portion. Also having optimised the number and parameter positions, this helps the MOGA to quickly search for optimum output parameter sets.

The MOGA uses the Pareto-optimality developed by Fonseca and Fleming (1998), to determine fitness based on non-dominance of the individuals. The objectives used to assess the performance of the potential fuzzy controllers are: overshoot; rise-time; settling time; and error variance. A standard binary coded representation was employed with a chromosome length of 27 decision variables (11 for the parameters of the output membership functions and 16 for the rules), each with 8 bit precision and a 20 bit decision variable bound. This compares well to the original controller, (Loebis, 2000) which required 60 decision variables. A rank fitness value of 2.22 was also used; hence exponential ranking was assumed indicating selective pressure.

7. ENHANCED DECISION SUPPORT

Here a novel enhancement to the MOGA decision support system is introduced, by using evolving tradeoff sensitivity information to automatically adjust the goal weighting. This is carried out to improve the visualisation and reduce the number of solutions in the non-dominated set, while at the same time maintaining the quality of those solutions.

As described in (Fonseca and Fleming, 1998), the population based nature of the standard GA makes it the ideal vehicle for the development of a Multi-objective Genetic Algorithm (MOGA) where several possibly competing objectives must be optimised simultaneously. Towards this end, goal and priority information are made available to the design objectives to make it possible to differentiate between some non-dominated solutions (best performers). These and other criteria form the basis of the decision support system that allows the decision maker to interactively control the final outcome of the simulation. The method of goal and priority change (manually via a GUI) is called Progressive Preference Articulation.

Methods for progressive articulation of preferences require that trade-off information be communicated to the decision maker in a form, which can be easily comprehended. When there are only two objectives, non-dominated solutions can be represented in objective space by plotting the first objective component against the second. For three and more objectives, a different representation is required. A common approach, known as the method of parallel coordinates, Fig. 8 (top), consists of associating an integer index i to each objective and representing each non-dominated point by the line connecting the points (i, $f_i^*(x)$), where $f_i^*(x)$ represents a normalisation of f_i to a given interval, e.g., [0,1]. With such a representation, competing objectives with consecutive indices result in the crossing of lines, whereas lines that don't cross indicate non-competing objectives, where the cost values equate to $f_i^*(x)$ and the objective numbers equate to $f_1 - f_4$.

The development of the decision support system was initiated by computing the minimum cost solution – to be used later as a benchmark. The minimum cost solution was obtained by summing the objective costs for each individual in the non-dominated set, sorting them to obtain the minimum then extracting the minimum for display, see Fig. 8.

Study of the trade-off graph, Fig. 8 (top left) can lead to a greater understanding of the trade-offs inherent in the system. Although it is difficult to see the trade-off information clearly as the number of non-dominating solutions is often too large. A tool, developed by (Schroder, 1999), allows a quantitative analysis of the amount of trade-off between objectives. This measures the amount of competition between objectives by computing the distance by which the lines cross as a percentage of the maximum distance that they could cross by. It uses a partitioning of the objective space to normalise with respect to the density of solutions so as not to allow highly populated parts of the objective space to artificially dominate. The results of applying this tool to the graph of Fig. 8 (top left) are shown directly below. The ranges are those between the maximum and minimum values of each objective. These represent the 'true' competition on the Pareto surface and each cell in the matrix represents the percentage trade-off between objectives. The figures on the diagonal are the sum of the trade-offs for that objective divided by the total number of objectives. This shows that the objective that caused the most amount of competition was objective two, which is reasonable when comparing it with the other objectives. The bar charts of Fig. 8 highlight the overall trade-off per objective for each objective on view. It gives an instant visual assessment of what is happening within the multi-criteria system being analysed.

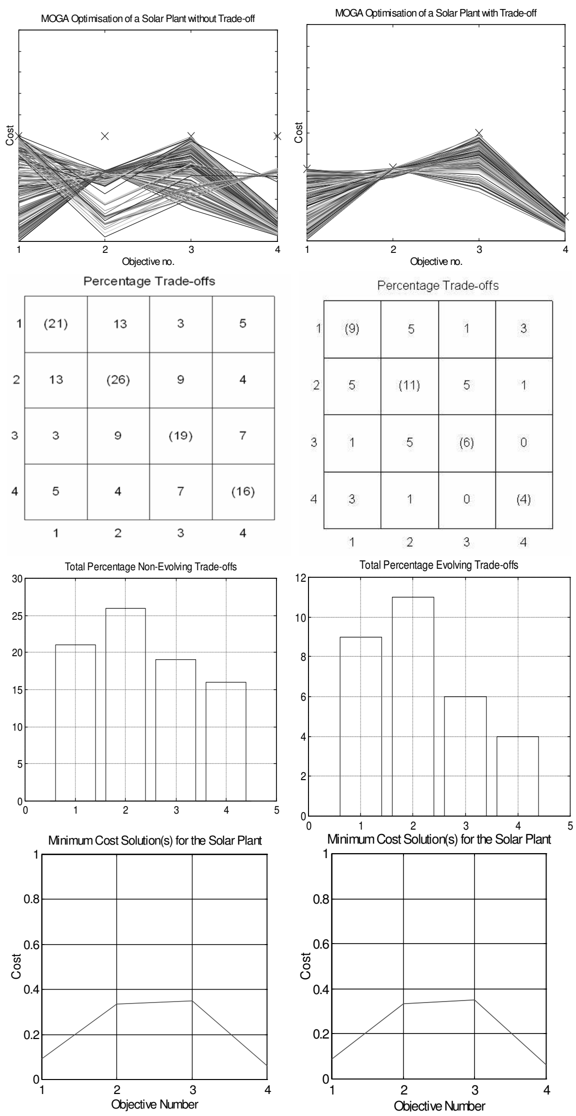

Fig. 8: Results of the enhanced visualisation: without evolving trade-off (left); and with (right).

An evolving goal weighting method is used here to adjust the goals automatically in relation to trade-off information, which is only included if there are a minimum number of solutions in the non-dominated set. After each generation, this technique re-positions the goals to the initial maximum cost of each objective before it includes the trade-off information. The trade-off information tightens the goals on the objectives with conflict sensitivity below the halfway or overall average objective sensitivity, and reduces the goals for the objectives that have conflict sensitivity above the overall average (Fig. 9).

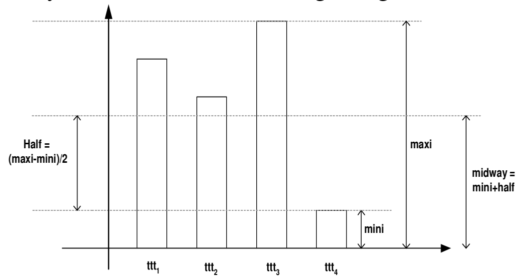

Fig. 9: Goal weighting to average trade-off sensitivity.

9. RESULTS

The active controller is determined by the oil flow rate, where the MOGA-tuned Fuzzy PI controller is implemented only at flow rates below 5 litres per second, Fig. 10.

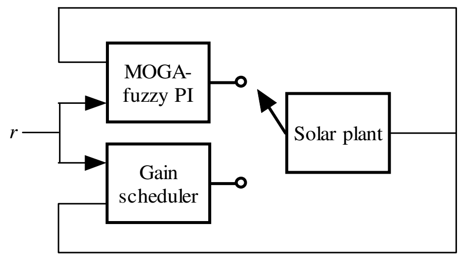

Fig. 10: The combined controller.

The enhanced decision support and visualisation improves the trade-off between the non-dominating solutions in the set while conserving the quality of the set Fig. 8 (right). The diagram shown in Fig. 11 illustrates how a particular solution (in this case the benchmark) represents a particular fuzzy controller.

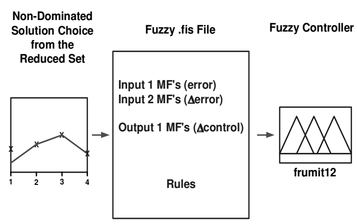

Fig. 11: Benchmark solution choice

The results of the conflict sensitivity between the solutions within the non-dominated set, before and after evolving trade-off, are shown in Table 1.

Table 1. Simulation without/with evolving trade-off

	OBJECTIVES			
	O.shoot	R.Time	S.Time	Variance
Initial Goals	5	20	315	10
Final Goals	3.3	14.1	69.5	9.8
Min cost	0.3334	0.3513	0.1130	0.4913
Total Minimum Cost: Without: 1.2911 With: 1.2890				
Number of Initial Individuals: 40				
Total Percentage Trade-off: Without: 83% With: 30%				
Number of Generations: 100				
Stochastic Universal Sampling				
Single Point Crossover Rate 0.7				
Mutation Probability 0.007				
Reinsertion 0.04				
Minimum number of potential solutions found before trade-off initiated: 5				
Number of near nptimum solutions in the non-dominated set: Without: 356 With: 351				

A typical response for the outlet oil temperature tracking for the new improved fuzzy controller is shown in Fig. 12, along with the oil flow and radiation. In the figure, the single operating region facilitates the use of more design objectives. The design of the final controller is therefore a compromise that offers good performance across the highly non-linear operating range and also minimises the task-oriented nature of the set point tracking error.

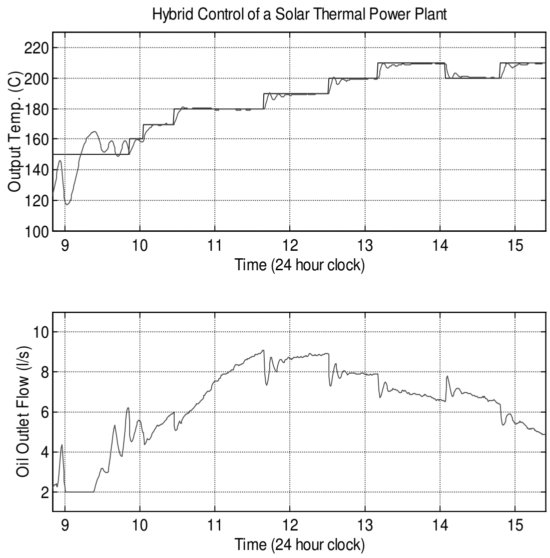

Fig. 12: Typical simulation results for the combined fuzzy PI incremental/gain schedule controller.

10. CONCLUDING REMARKS

This work developed a hybrid controller that uses a gain scheduler to control the more linear regions of a solar thermal power plant, in combination with a MOGA-tuned fuzzy PI controller to control the plant's highly nonlinear operating areas. MOGA-tuning and visualization enhancements were also implemented which led to:

- a reduction of the rule base and search space, which in turn permitted the MOGA to produce a set of sub-optimal solutions at a much faster rate,
- improved control by allowing a wider choice of performance criteria,
- improved decision support,
- an increase in the operating range at low oil flow rates, which allows the plant to function in environments where local solar radiation conditions have always been regarded as marginal.

The reduction in the size of fuzzy controllers is attractive because they are simpler to both understand and validate, and also easier to implement in hardware. The work here also improved the visualisation techniques required for a deeper understanding of the system. Allowing the trade-off, and hence goal information to evolve automatically gives the decision maker a solid foundation to work from if further alterations to the goal information are required manually. A benchmark solution was also provided in the form of an overall standard minimum cost solution from the non-dominated set.

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