Immune Procedure for Optimal Scheduling of Complex Energy Systems

Enrico Carpaneto[1], Claudio Cavallero[1], Fabio Freschi[1] and Maurizio Repetto[1]

Dept. of Electrical Engineering,
Politecnico di Torino, Torino, Italy
{enrico.carpaneto, claudio.cavallero, fabio.freschi, maurizio.repetto}@polito.it
http://www.polito.it/cadema

Abstract. The management of complex energy systems where different power sources are active in a time varying scenario of costs and prices needs efficient optimization approaches. Usually the scheduling problem is is formulated as a Mixed Integer Linear Programming (MILP) to guarantee the convergence to the global optimum. The goal of this work is to propose and compare a hybrid technique based on Artificial Immune System (AIS) and linear programming versus the traditional MILP approach. Different energy scheduling problem cases are analyzed and results of the two procedures are compared both in terms of accuracy of results and convergence speed. The work shows that, on some technical cases, AIS can efficiently tackle the energy scheduling problem in a time varying scenario and that its performances can overcome those of MILP. The obtained results are very promising and make the use of immune based procedures available for real-time management of energy systems.

1 Introduction

Distributed energy generation systems are becoming more and more widespread in the power grid. This increase is driven by the growing demand of energy for industrial and civil purposes and by energy market deregulation. In this way, the classic passive electric grid with few power plants is overcome by an active network where dispersed nodes can generate power on their own and, possibly, they offer power to the grid. This solution has many advantages, some drawbacks and certainly it requires an accurate energy management. Design and optimization of the energy local network is, in fact, quite different from the one of the classical energy grid.

In particular, starting from the fact that loads very often requires both electric and thermal power, the local system can be of Combined Heat and Power (CHP) type. The combined production of electric and thermal energy leads to the use, in a positive way, of the thermal energy usually wasted in the thermodynamic cycle. This energy can be efficiently employed to satisfy the requirements of thermal loads both domestic and or industrials. Since heat cannot be efficiently transferred to far sites, its source must be located close to the load and thus also this characteristic requires that energy is produced in a distributed way all over the network. The energy management of this system needs to take into account local loads and generators, with different nominal powers, reliability and pollution levels and the possible presence of energy storage units. In addition, all these characteristics and requirements change with time: for instance load profiles, price of energy bought from or sold to the electrical network etc.. An accurate scheduling of the system must ensure the use of the most economical power sources, fulfilling operational constraints and load demand.

The management of the energy system requires the definition of the on/off status of the machines and the identification of their optimal production profile of them. When the start-up/shut-down profile is set, the problem can be approached by means of Linear Programming (LP). The definition of the on/off status of the sources is referred to as *scheduling* and it requires the introduction of logical variables, which define in each time interval (e.g. one hour, one quarter of an hour etc.) the power source availability. As a consequence, the complete problem must deal with both continuous (power levels) and integer (on/off status) variables. This problem can be stated as a Mixed Integer Linear Programming problem (MILP) [1]. Even if this approach guarantees to find out the global minimum of the cost function, the use of MILP needs a branch and bound, or similar approaches, whose computational cost is shown to exponentially increase with the number of branches. Instead of a full LP approach, an heuristic optimization algorithm can be used to define the on/off status of the power sources, leaving to an inner LP module the optimization of a particular configuration. An Artificial Immune System (AIS) algorithm can be efficiently employed in this phase and its use is shown to be quite efficient if all operational constraints are embedded inside the scheduling interval definition [2].

In this paper, a comparison of the two techniques, MILP and AIS-LP is presented, both approaches are described and comparisons are carried out in terms of results accuracy and convergence speed to the optimum.

2 Definition of energy management problem

The outline of the system under study is represented in Fig. 1, where:

- P_e is the electrical power produced by the CHP;
- P_t is the thermal power produced by the CHP;
- B_t is the heat produced by a boiler which fulfills the thermal load when production of electric power is neither needed nor economically convenient;
- D_t is the heat produced in the thermodynamic cycle which is not used by the thermal load and it is thus released into the atmosphere;
- P_p and P_s are the electrical power purchased from or sold to the external network respectively;
- S_t is the stored thermal energy;
- U_e and U_t are the electrical and thermal power required by the load;

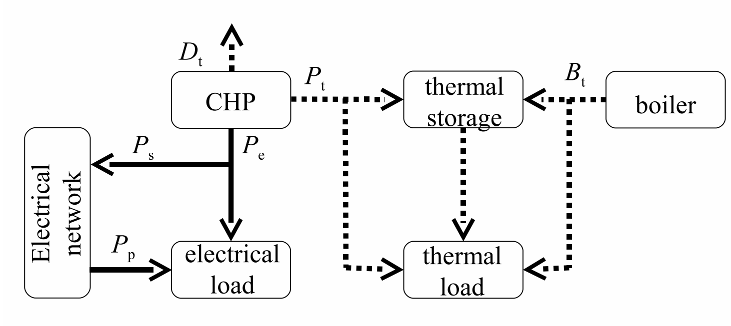

Fig. 1. Structure of a CHP. Straight lines: electrical power fluxes, dotted lines: thermal power fluxes.

In each time interval (i), thermal and electrical power of a CHP are linked by a linear relation

$$P_t(i) = k_t P_e(i) \tag{1}$$

The energy management problem of the CHP system regards the definition of the best arrangement of production levels of the power unit to minimize the management costs and fulfilling all loads requirements. The problem is defined over a scheduling period (e.g. one day, one week etc.) where loads, costs, fares etc. can change. The scheduling period is subdivided in $N_{\text{intervals}}$ time intervals of length Δt. During each interval all CHP characteristics and load data are assumed to be constant.

Besides plant data, some operational constraints have to be imposed on the power source like:

- *Minimum On Time* (MOT): minimum time interval during which CHP must be on when it is switched on;
- *Minimum Shut-down time* (MST): minimum time interval which CHP must be off since it was turned off;
- *Maximum ramp rate*: maximum power rate of the source

The unit production costs of the node, expressed in €/kWh, are:

- c_e: cost coefficient of electric energy produced by the CHP;
- c_t: cost coefficient of thermal energy produced by the boiler;
- $c_p(i)$, $c_s(i)$: prices of purchased and sold energy at i-th time interval.

By using the previous definitions it is possible to write a global cost function (in €) over the scheduling period

$$f_{\text{CHP}} = \sum_{i=1}^{N_{\text{intervals}}} \left[c_e P_e(i) + c_p(i) P_p(i) - c_s(i) P_s(i) + c_t B_t(i) \right] \Delta t \tag{2}$$

The optimization problem can be stated as

$$\text{minimize } f_{CHP} \tag{3}$$

subject to operational constraints

1. electrical balance: $P_e(i) + P_p(i) - P_s(i) = U_e(i)$;
2. thermal balance: $P_t(i) + B_t(i) - D_t(i) + \dfrac{S_t(i-1) - S_t(i)}{\Delta t} = U_t(i)$;
3. dissipation of thermal power produced by CHP: $D_t(i) - P_t(i) \leq 0$;
4. thermal and electrical CHP characteristic (1): $k_t P_e(i) - P_t(i) = 0$;
5. MOT, MST and ramp limit satisfaction.

Variables are bounded by their upper and lower bounds

$$\begin{array}{lll} P_e^{\min} & \leq P_e(i) & \leq P_e^{\max} \\ 0 & \leq B_t(i) & \leq B_t^{\max} \\ 0 & \leq P_s(i) & \\ 0 & \leq P_p(i) & \\ 0 & \leq D_t(i) & \\ 0 & \leq S_t(i) & \leq S_t^{\max} \end{array} \tag{4}$$

The first bounds do not hold during the starting-up and shutting-down phases.

3 Mixed Integer scheduling approach

The scheduling problem can be directly formulated as a MILP [1, 3]. This means that the problem is still linear, but it has both continuous and integer variables. This class of problems can be solved by exact methods like Branch and Bound technique [4]. The MILP approach requires to define the on/off status of the CHP as a logical variable $\delta(i)$ defined for all i-th time interval. Moreover, two additional sets of logical variables must be considered to take into account MOT/MST constraints and up/down ramps [5] (see Fig. 2)

$$y(i) = \begin{cases} 1 \text{ if CHP turns on at } i-\text{th time interval} \\ 0 \text{ otherwise} \end{cases} \tag{5}$$

$$z(i) = \begin{cases} 1 \text{ if CHP turns off at } i-\text{th time interval} \\ 0 \text{ otherwise} \end{cases} \tag{6}$$

The complexity of the problem hardly depends on time discretization, because the finer the discretization the higher the number of integer variables. Besides, the model of ramp limits, MOT and MST limits introduce several additional constraints which must be explicitly added to the model. In [5] it is shown that it is possible to model start-up and shut-down power trajectories with eleven

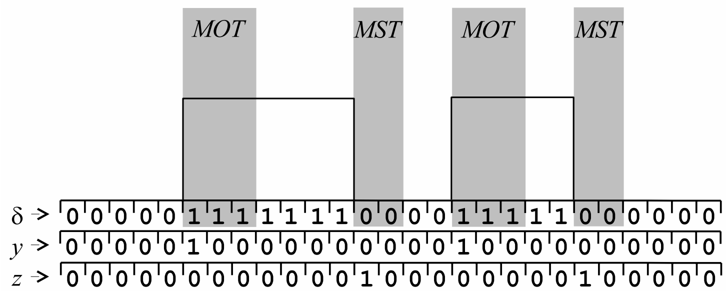

Fig. 2. Binary variables of MILP approach.

constraints. Finally, it is common to define an upper limit to the number of turns on and off during the scheduling period $N_{\text{on}} = N_{\text{off}} = N_{\text{change}}$.

$$\begin{aligned} \sum_{i=0}^{N_I} y(i) &\leq N_{\text{change}} \\ \sum_{i=0}^{N_I} z(i) &\leq N_{\text{change}} \end{aligned} \tag{7}$$

For instance, for a one-day scheduling period with the CHP in one day, and $N_{\text{on}} = N_{\text{off}} = 1$, this means that CHP can be turned on and off just once.

4 Immune scheduling approach

The second approach is based on the opt-aiNet version [6] of the clonal selection algorithm. The optimization procedure (AIS-LP) is divided into two nested stages: the inner one is the LP problem derived in Section 2 which defines the optimal production levels at each time interval once the on/off profiles are defined. The outer stage is responsible defining the on/off status of the generation units.

It is useful to use as degrees of freedom of the optimization the time amplitudes of the on and off intervals τ_j of the CHP (Fig. 3). These values are treated as integer variables representing the number of on and off intervals of each control period. The variables are then decoded in terms of 0-1 strings representing, for each utility, its on/off status. This assumption drastically simplify the optimization search. The number of available solutions is in fact equal to M^N, where N is the number of degrees of freedom and M the number of possible values assumed by each variable. A fine discretization does not affect the number of variables but only their range of values M, thus the overall complexity of the problem is polynomial. With a MILP approach, M is always equal to 2, because the problem is modeled by binary variables. The time discretization affects the value of N, giving rise to an exponential complexity of the problem. Moreover, in AIS-LP approach, the value of M is restricted when including MOT/MST constraints. Thus the modeling of technical constraints reduces the search space allowing a faster convergence to the optimal solution. Table 1 The definition of

Table 1. Number of available configurations for two time discretizations

	$\Delta t = 1$ hour		$\Delta t = 0.25$ hour	
	MILP	AIS-LP	MILP	AIS-LP
M	2	24	2	96
N	24	2	96	2
M^N	16.8×10^6	576	79.2×10^{27}	9216

on/off intervals τ as optimization variables requires an algorithm without complex operators. This consideration is due to the fact that it is not easy to keep the feasibility of solutions. Thus algorithms with crossover and recombination operators, like Genetic Algorithm and Evolution Strategy must be excluded *a priori*. The AIS has the advantage of using the mutation operator only, and its memory capability will be exploited in a future work to handle the time varying scenarios in real time optimization. The AIS-LP performances can be enhanced

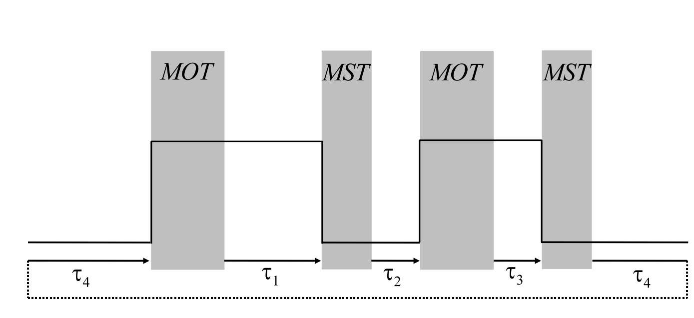

Fig. 3. Representation of the variables for the AIS-LP approach: intervals τ_j.

by using problem-specific information:

– creation of feasible initial population which satisfies the equality constraints

$$\sum_i \tau_i = N_{\text{intervals}} - N_{\text{on}}\text{MOT} - N_{\text{off}}\text{MST} = N_{\text{free}} \qquad (8)$$

– modified mutation operator to generate of feasible-only clones.

For these reasons some immune operators must be customized to solve the specific problem. In particular the mutation operator is not related to the actual fitness of the parent cell. Algorithms 1 and 2 report the pseudocodes of the generator of new cells and mutation operator, respectively.

The use of problem-specific information drastically decreases the dimension of the search space [2], making the AIS-LP approach more suited for high dimensional or fine discretized problems [7].

Algorithm 1 New cells generation

```
for all newcells do
    sum ← 0
    for i ← 1, N_intervals do                          ▷ Random initialization
        cell(i) ← random()
        sum = sum + cell(i)
    end for
    for i ← 1, N_intervals do                          ▷ Normalization and interization
        cell(i) ← INT(N_free × cell(i)/sum)
    end for
end for
```

Algorithm 2 Mutation

```
for all clones do
    for i ← 1, N_intervals do
        mutaz(i) ← random()
        if 0 ≤ mutaz(i) ≤ 1/3 then mutaz(i) ← −1
        if 1/3 ≤ mutaz(i) ≤ 2/3 then mutaz(i) ← 1
        if 2/3 ≤ mutaz(i) ≤ 1 then mutaz(i) ← 0
    end for
    for i ← 1, N_intervals do
        clone(i) = parent(i) + mutaz(i) − mutaz(i − 1)      ▷ Feasible mutation
        if clone(i) ≤ xlow(i) then                         ▷ Fix mutation to the lower bound
            clone(i) ← xlow(i)
            mutaz(i) ← 0
        end if
        if clone(i) ≥ xup(i) then                          ▷ Fix mutation to the upper bound
            clone(i) ← xup(i)
            mutaz(i) ← 0
        end if
    end for
end for
```

5 Proof of principle test case

MILP and AIS-LP are tested on a simple but effective energy management problem. The structure of the CHP node is the one of Fig. 1; the operational data of the devices are reported in Table 2. The thermal storage unit is considered to have a maximum capacity of 300 kWh. Energy price profiles are shown in Fig.

Table 2. Main operational data used in the test case

	$P_e^{\min}$ kW	$P_e^{\max}$ kW	MOT hour	MST hour	Ramp limit $\frac{\text{kW}}{\text{h}}$
CHP	200	600	5	4	170
Boiler	0	800	none	none	none

4. Several scheduling instances are solved with a quarter of hour time sampling

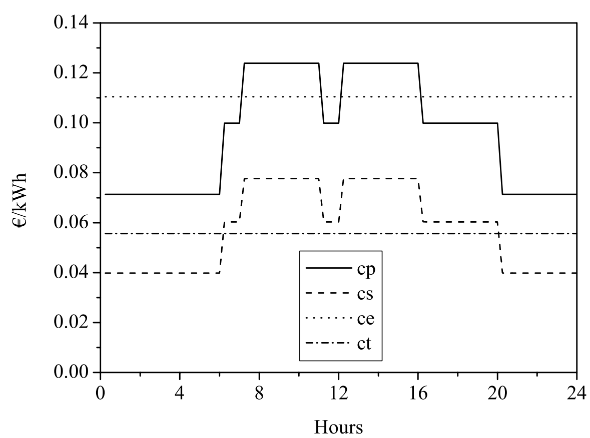

Fig. 4. Profile of costs purchased (c_p) and sold (c_s) electrical power.

($\Delta t = 0.25$ hours), thus a one day scheduling period has $N_{\text{intervals}} = 96$, two days scheduling $N_{\text{intervals}} = 192$ etc. Results are compared in terms of convergence time and number of objective function calls. It must be remarked that a comparison in terms of the mere number of objective function calls can be misleading because the linear problem solved by MILP and AIS-LP are different. These differences can be explained by noting that the number of variables, number of constraints and number of non zero elements in coefficients matrix are not the same for two formulations. The main differences in the LP formulation between AIS-LP and MILP are summarized in Table 3. The larger MILP

Table 3. Comparison of dimensions of different LP problems (N_{MOT}: number of minimum on time intervals, N_{MST}: number of minimum shutdown time intervals, N_{up}: number of time intervals needed to reach, $P_e^{\min}$ during start-up phases, N_{dw}: number of time intervals needed to reach zero power during shut-down phases)

	AIS-LP	MILP
nr. of constraints	$6N_{\mathrm{intervals}}$	$21N_{\mathrm{intervals}} + 2$
nr. of variables	$7N_{\mathrm{intervals}}$	$10N_{\mathrm{intervals}}$
matrix elements	$35N^2_{\mathrm{intervals}}$	$210N^2_{\mathrm{intervals}}$
non zeros	$14N_{\mathrm{intervals}}$	$(48 + N_{\mathrm{MOT}} + N_{\mathrm{MST}} + 8N_{\mathrm{dw}} + 8N_{\mathrm{up}})N_{\mathrm{intervals}}$

model is due to the fact that operational constraints (ramp limits and MOT and MST constraints) have to be taken into account directly in the linear model whereas AIS-LP approach manage these limits in the external loop, as described in Section 4.

The parameter setting of AIS-LP is:

- population cardinality: 10;
- number of clones: 5;
- number of inner iterations: 5;
- convergence criterion: the search ends if the objective function value does not improve for more than ten external generations.

Results are averaged on 10 independent runs to take into account the statistical variation of performances due to the stochastic nature of the algorithm.

6 Discussion

In Fig. 5 MILP and AIS-LP are compared with respect to the computational time (in seconds) to converge to the optimal value on a Pentium IV 2.8 GHz. These data are displayed versus dimension of problem, represented by the value of $N_{\mathrm{intervals}}$.

Fig. 5 shows two important properties. Firstly, there is a crossover between the two curves of MILP and AIS-LP. This fact leads to the consideration that the computational time of MILP approach becomes impracticable for large instances, i.e. for fine discretization and/or long period managements.

Secondly, by analyzing each curve, it is possible to find that MILP has an exponential dependence of the computational time on the cardinality of the problem, while AIS-LP has a quadratic rule. The previous considerations are confirmed by the analysis of Fig. 6 which shows the number of LP problems solved by the two techniques. In this case the number of LP problem is linearly

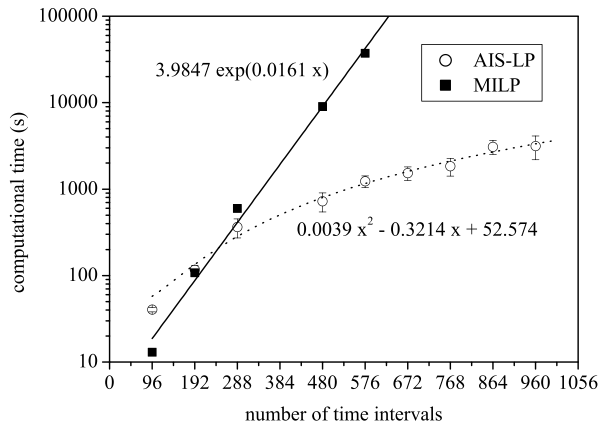

Fig. 5. Computational time of the two procedures vs number of time intervals. AIS-LP computational time has a quadratic dependence on the cardinality of the problem.

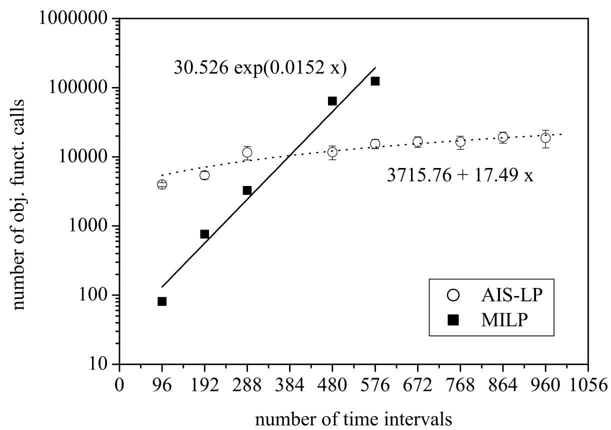

Fig. 6. Number of objective function calls of the two procedures vs number of time intervals. The number of LP problems solved by AIS-LP is linearly dependent on time discretization.

dependent on the cardinality of the problem. It is also worth noting that the solutions found by AIS-LP and MILP models share the same objective function values, or are slightly different. This fact shows that AIS-LP procedure converges to the exact solution.

Figs. 7, 8 and 9 show the electrical and thermal power and energy storage profiles of a one day scheduling. The following remarks can be made:

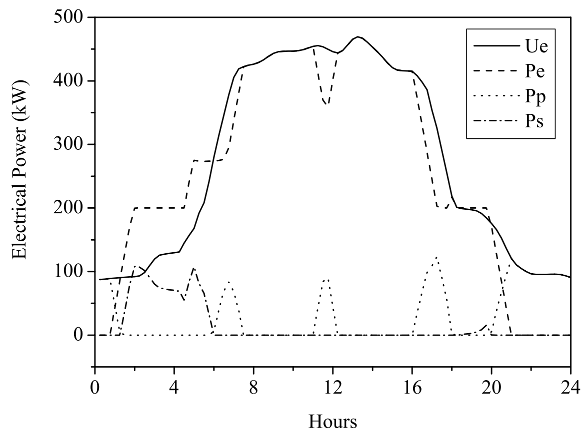

Fig. 7. One day electrical power profiles.

a) the CHP starts early in the morning in order to store heat energy and satisfy the first thermal load peak of the day. Excess electrical power is sold to the external network;
b) the electrical load is always supplied by the CHP except for few time intervals; by looking at Fig. 8 it is possible to note that CHP production never follows thermal load. This fact is explained by the role of thermal storage;
c) the boiler is requested to produce thermal power only during night hours, when the CHP electrical production is neither needed nor economical;
d) during night hours, thermal storage reaches its upper limit for some time intervals. This fact means that the possibility of storing more thermal energy would be useful to reduce costs.

The effectiveness of the optimal scheduling is evidenced by referring the optimal objective function to the cost of a non cogenerative system, where the electrical load is supplied by the external network and the thermal power is

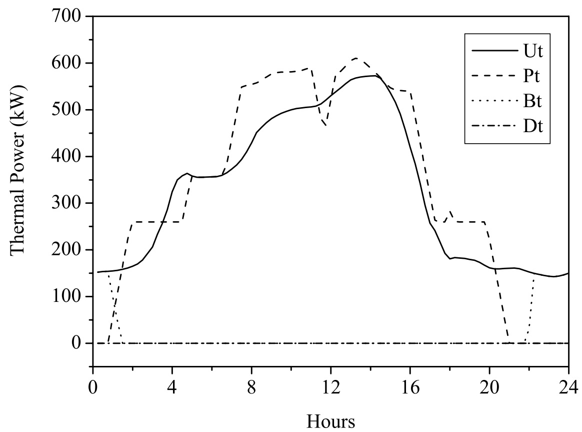

Fig. 8. One day thermal power profiles.

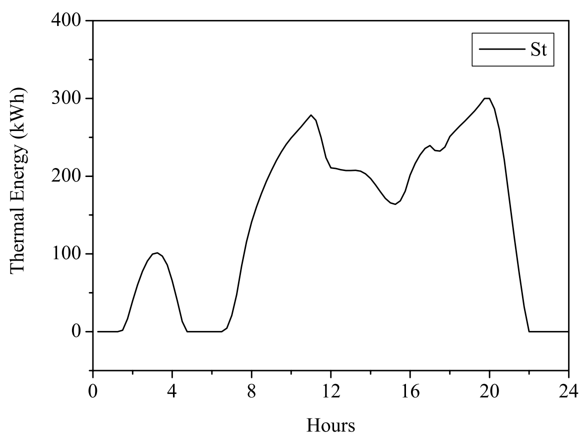

Fig. 9. One day thermal storage energy profile.

produced by the boiler only. In this case

$$f_{\text{noncogenerative}} = \sum_{i=1}^{N_{\text{intervals}}} \left[c_p(i) U_e(i) + c_t U_t(i) \right] \Delta t \tag{9}$$

$$f_{\%} = \frac{f_{\text{CHP}}}{f_{\text{noncogenerative}}} 100. \tag{10}$$

The one day scheduling allows to save money of about 34% ($f_{\%} = 66\%$)

7 Acknowledgments

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