Use of Evolutionary Algorithms in Electric Bill Optimisation

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Abstract

Sustainability is strongly related to the appropriate use of available resources, being an important cornerstone in any company's administration due to the direct influence on its efficiency and ability to compete in the global market. Therefore, the intelligent and proper management of these resources is a pressing matter in terms of cost savings; especially in times of economic crisis. Among the possible alternatives for optimisation, the one regarding electricity consumption stands out due to its strong influence on the expenses account. In general, this type of optimisation can be carried out from two different perspectives: one that concerns the efficient use of energy itself and the other related to the proper adjustment of the electricity contract so that it meets the infrastructure needs while avoiding extra costs derived from poorly sized bills. This paper describes the application of an artificial intelligence based methodology for the optimisation of the parameters contracted in the electricity tariff. This technique is able to adjust the power term needed so that the global economic cost derived from energy consumption is significantly reduced.

Introduction

The economic crisis has motivated the need to audit all expenses in order to identify the key areas where saving techniques can be applied to reduce global costs. Nowadays, most of these techniques focus on minimising costs within the electric scope, not only in terms of reducing the overall consumption, but also in configuring an specific electric contract that meets the energy needs of the infrastructure while avoiding overruns.

The knowledge on how the energy is consumed within an infrastructure provides a great advantage when negotiating contracts with the electricity supplier. For this, most companies turn to *energy managers* whose labour is to regulate and monitor energy consumption with the aim of improving its efficiency by implementing new policies and changes where necessary. They are responsible for knowing in detail all the variables that come into play within the electric market such as the methodology for the calculation of electricity prices and the advantages and disadvantages of the current electric tariffs.

In this sense, electricity contracts can be challenging to understand. With so many new electric companies entering the market and unclear terms and conditions, residential consumers and businesses alike need to carefully understand what type of service they need and how to get the best rates. The billing concepts are not always understandable for an average user, which together with the inclusion of several taxes of different kind hinders its comprehension. The result of this misinformation is that most companies choose contracts based on what a sales representative from the electric company advised them rather than taking into account their own energy needs. Therefore, the optimisation of the energy bill requires a technical and thorough analysis of both the parameters that influence it and the facility's consumption patterns, as well as the possibilities of negotiation within the electric market.

0.1 Tariff model

In Spain, the concepts defined in any electricity bill are classified under two main components: regulated and non-regulated. Regulated components refer to those concepts which price or methodology of calculus is defined in the Boletín Oficial del Estado (BOE), the official gazette of the Government of Spain, and they are applicable to every supply contract regardless of the electricity supplier. Non-regulated components include those concepts which price can be negotiated with the electricity supplier and, therefore, can vary among contracts. In general, the most common terms that appear on every electricity bill are as follows:

Regulated

Power term: When negotiating an electric contract, companies choose the type of tariff depending on the voltage of their electric infrastructure and the amount of power they expect to consume. The available tariffs are summarised in Table 1. Some of these tariffs split the days in *periods* which are assigned an annual power term price by the BOE. In order to calculate the monthly bill, the amount of contracted power in every period is multiplied by the proportional price for the days invoiced.

Power excess: Penalty applied each time the company demands more power than the amount originally contracted.

Rental of equipment: Amount paid to the electricity supplier for the use of the measurement and control equipment. This is a fixed rate so it cannot be optimized.

Electricity tax and VAT: Tax that applies to the total of the power term, the energy term and the supplement for reactive energy. Obviously, this term cannot be optimized so it would no be taken into account in this paper.

Non-Regulated

Energy term: It is important to select when energy consumption is necessary and when it is superfluous. Energy prices are different depending on the time of the day and month, so it is not irrelevant to consume at night than during daylight. The energy term of the monthly bill is calculated by multiplying the price of energy negotiated with the electricity supplier by the amount of energy measured by the meter.

Complement for consumption of reactive energy: The billing of high electricity consumption in industrial sectors includes a charge for the generation of reactive energy. Its purpose is to promote energy efficiency by issuing an economic penalty for inefficient consumption and is billed according to the power factor, an indicator that quantifies an entire electric infrastructure regarding the total active energy consumed in comparison to the global consumption. The complement for reactive energy is calculated by multiplying the values of reactive energy measured by the meter by the cost negotiated with the electricity supplier. The easiest form to avoid this penalization consist on installing a capacitor bank. This measure have a typical short pay-back and the distributed utility usually inform and offer this type of services so this term will not be consider in this paper.

Based on the aforementioned parameters and the type of contracted electricity tariff, energy optimisation can be achieved in three different ways:

Optimisation of the power term: Adjust the contracted power to the real amount of power expected to be demanded by the infrastructure so as to minimise the penalty for power excesses.

Optimisation of the reactive term: Compensate the generation of this type of energy, derived from the use of some electrical and mechanical devices, by installing capacitor batteries.

Reduction of power and energy consumed: Implement policies and best practices such as replacing lighting fixtures and electric equipment with more efficient alternatives.

The configuration of an appropriate electricity contract is as important as knowing the specific needs and energy capabilities of the infrastructure. The BOE establishes the voltage steps, power ranges and billing characteristics that define each of the available tariffs. As shown in Table 1, these tariffs are classified into two groups: low voltage rates ($v \leq 1\,\mathrm{kV}$), oriented to small and medium energy consumers, and high voltage rates ($v > 1\,\mathrm{kV}$) for large industrial consumers with high energy needs. The selection of the proper tariff is determined by the amount of voltage on which the infrastructure is connected to the electric grid and the minimum and maximum power to be demanded.

The study presented in this article focuses on the optimisation of the regulated cost of the energy bill in terms of power for 6.1 high voltage electric tariffs, though the same methodology can be applied to other tariffs. The 6.1 tariff splits the hours of the days in periods, as shown in Figure 1. When contracting energy supply under this type of tariff, the energy manager has to estimate the global power expected to be demanded p_i on each period P_i, configuring them in ascending order:

$$p_1 \leq p_2 \leq p_3 \leq p_4 \leq p_5 \leq p_6. \tag{1}$$

The definition of the hours belonging to each period depends on the global energy demand within the country. For example, the hours belonging to P_1 are the ones in which the global demand reaches its maximum peak and so the cost of demanding power or consuming energy on this period has a higher cost than doing so on P_6.

Nowadays, the power optimisation technique most commonly used by energy managers consists on analysing the power consumption of the installation and identifying the maximum amount of power demanded on each one of the six periods. These values are then modified so as they the fulfil the Inequality (1) and conform the power term of the electric contract. This approach reduces the cost derived from the power term significantly, however there is a great margin of improvement since the existence of a power peak can overstate the power requirements of the facility, incurring in penalties for power excesses. This paper proposes the use of evolutionary algorithms as a technique to optimise the regulated part of the electricity bill by finding the best combination of power values and therefore, minimise the annual electricity cost.

The rest of the paper is divided as follows: Section 1 provides a mathematical analysis of the tariff, Section 2 provides a brief introduction to the purpose and characteristics of evolutionary algorithms, Section 3 presents experimental background and methodology used in the development of the study, Section 4 discusses the results and finally and, finally, Section 5 summarises the conclusions and future lines of work.

1 Analytical optimisation of the 6.1 electric tariff

This section analyses the mathematical properties defined by the regulated components of the 6.1 tariff. As stated in the previous section, this function only takes into account the power term and power excesses.

Let $p := (p_1, \ldots, p_6)$ denote the power limit assigned to every period P_i. Please note that p is a vector of integers in which at least one of the values must be greater than 450 kW and should also fulfil Inequality 1. On the other hand, let $\pi_j^{i,m}$ denote the maximum power demanded in j quarter (which corresponds to an hour in the period P_i on month m). Now, for every month m, the cost function ϕ_m of the power term and excesses would be:

$$\phi_m(p) := \sum_{i=1}^{6} \left(c_i p_i + 1.4064 k_i \sqrt{\sum_{j \in J} (\pi_j^{i,m} - p_i)^2} \right),$$

where c_i denotes the power cost of the period P_i, $k := (1, 0.5, 0.37, 0.37, 0.37, 0.17)$ is a vector of coefficients used to assign importance to power excesses on the most critical periods (please note that these two latter quantities are defined in the BOE) and J denotes the set of quarters where the power measured $\pi_j^{i,m}$ is higher than the power limit p_i contracted for this period. Namely, J is the set of quarters j such that:

$$p_i < \pi_j^{i,m}. \tag{2}$$

This function can have as much as 35 040 jump discontinuities depending on the cardinality of J. This results in a highly non-continuous non-linear integer optimization problem in which the use of classical integer programming algorithms is nearly impossible. However, a more graphical approach can give us additional information (see Figure 2 for help in following the next statements). As can be seen, $\phi_m(p_i)$ is a monotonic increasing linear function until one p_i fulfils Inequality (2) (α label in Figure 2). In this situation we have the first jump discontinuity. Now, $\phi_m(p_i)$ could be monotonic decreasing or increasing depending on whether c_i is bigger or not than $1.4064k_i$. The latter case means that the minima has been reached and the process can stop . In the former case, however, the process should continue until a quarter (or a discontinuity jump) $k \in J$ is found so that (β label in Figure 2):

$$c_i \leq 1.4064k_i \frac{\sum_{k \geq j}(\pi_k^{i,m} - p_i)}{\sqrt{\sum_{k \geq j}(\pi_k^{i,m} - p_i)^2}}.$$

Please note that this process only finds the best set of p_i for a single month. Since these coefficients are shared among the twelve months, the problem becomes combinatorial. A brute-force approach would help in testing all the possibilities, however, this would be better accomplished by using more efficiency techniques such as evolutionary algorithms.

2 Evolutionary algorithms: basic concepts

Evolutionary algorithms are artificial intelligence techniques that have gained great importance over the last decade since they are capable of coping with difficult to characterise [2], large search spaces which purpose is to optimise complex functions (non-linear, non-differential, etc.). This type of algorithms provide a solution where other methods are not feasible, too complex or a solution can not be found within a reasonable amount of time. Currently, the application of these algorithms covers different fields, from the design of the optimal placement of windmills in a wind farm in order to produce the maximum amount of energy at the lowest infrastructure cost [3], to delivering an adequate job-schedule that reduces energy costs while meeting delivery dates in a foundry [4]. Other applications are also focused on the provision of lighting on motorways [5], optimisation of food packaging [6], structural optimisation design of wind turbine blades [7], configuration of power distribution systems [8], optimal operation of a multi-reservoir system [9], short-term power forecasting model for photovoltaic plants, operation and power flow Control of multi-terminal DC Networks for grid integration of offshore wind farms [10], optimal charging scheduling of electric vehicles in Smart Grids linearisation and input-output decoupling for non-linear control of proton exchange membrane fuel cells [11].

This type of algorithms work with populations of individuals where each individual represents a candidate solution. In this paper, an individual is equivalent to the definition of 6 power values that meet the problem constraints, i.e., the values are between the minimum and maximum set by the chosen tariff and are sorted in ascending order. Individuals undergo an iterative process that applies a series of operations, combining them together and creating new individuals. Each transformation and selection cycle constitutes a generation, so that after a certain number of generations the best individual is close to the optimum solution. The main components of the evolutionary algorithms are:

Individual codification: Representation of a candidate solution.

Population of individuals: Set of individuals on which to apply the genetic operators in order to build new and better candidate solutions.

Fitness function: Involves the definition of an objective against which each individual is tested for suitability for the environment under consideration. In this study, the fitness function is equivalent to the replication of the electric bill, which evaluates whether a particular combination of power values maximises or minimises the annual electricity cost.

Selection procedure: Mechanisms that determine how to choose the individuals, which will later act as operands for the transformation procedures, in such a way that the best candidate solutions are kept within each iteration and the genetic diversity of the population is maintained.

Transformation procedures: Operations that allow to build new individuals from old ones.

Genetic algorithms are a particular type of evolutionary algorithms. These algorithms try to simulate the process of natural selection as a process optimiser by defining a set of operations that can be applied to the population of candidate solutions. The operations available are as follows:

Selection procedure: Depending on the characteristics of the problem, there are several types of selection techniques:

- ***Elitist:*** ensures the selection of the fittest individuals of every generation.
- ***Roulette:*** the probability of selecting an individual is proportional to the difference between its ability and its competitors'.
- ***Tournament:*** constructs population subgroups which members compete against each other. Only the best individual of each tournament is selected.
- ***By rank:*** each individual in the population is assigned a numerical rank according to its fitness defining its selection priority among the rest.

Transformation procedures: Genetic algorithms use two procedures to evolve the population:

- ***Mutation:*** involves the alteration, at random, of a portion of the structure of the individual.
- ***Crossover:*** combines the structure of two individuals to produce an artificial offspring, simulating the recombination process that takes place during sexual reproduction. Common forms of crossovers techniques include:
  - *Single point:* one crossover point is selected, code from the beginning of the individual to the crossover point is copied from one parent, the rest is copied from the second parent.
  - *Two point:* two crossover points are selected, code from the beginning of the individual to the first crossover point is copied from one parent, the part from the first to the second crossover point is copied from the second parent and the rest is copied from the first parent.
  - *Uniform:* each equivalent element of both individuals is compared and exchanged based on a fixed probability, typically 0.5.

There are several ways in which genetic algorithms can be implemented. The most common, which covers the use of the most important operators is described in Algorithm 1.

Algorithm 1: Pseudocode of genetic algorithm

```
Data: size a of population, rate b of crossover, rate c of mutation, number d of
      iterations
Result: A population of possible solutions X
for i = 1 to a do
    Create a random candidate solution i;
    Assign a fitness value to candidate solution i;
    Introduce candidate solution i in the population X
end
j = 0;
while j ¡ d do
    [Selection] Select two candidate solutions from population X;
    [Crossover] With crossover probability b, combine the parents to form a
    new offspring;
    [Mutation] With mutation probability c, mutate new offspring;
    [Accepting] Place new offspring in new population;
    [Replace] Use new generated population for a further run of algorithm;
    j = j + 1;
end
```

The selection of the operators and methodology used to construct a genetic algorithm strongly affects the process and its ability to find a solution close to the global optimum. In fact, the following are the most important aspects that should be taken into account when designing a genetic algorithm:

Range of variables: It is important to note that the algorithm will not be able to find a good solution if the range of variables is not correctly defined and/or the initial population is not properly distributed.

Variability of candidates: The heterogeneity of the individuals within the population is a key for the "goodness" of the final solution. A higher genetic diversity increases the possibility of combining and generating new solutions, allowing a better exploration of the search space and coming up with solutions that are closer to the global optimum.

Final local search: Once the algorithm has come up with an optimal solution, a local search can be carried out to improve the final result.

3 Experimental Section

3.1 Datasets

The public infrastructure which electricity consumption was evaluated is comprised of six buildings: five located in Bilbao and one in Donosti; both cities situated on the north of Spain. Currently, each building feeds electricity from its own supply point and therefore is managed under a particular electric contract. Five of the buildings (four in Bilbao and the one in Donosti) have a 6.1 tariff (six periods) while the remaining one has a 3.1 tariff (three periods).

As seen in Figure 3, the behaviour of the demand curves of four of the buildings with the 6.1 tariff is quite similar:

- There are three day-types, weekdays, Saturdays and holidays.
- The highest energy consumption takes place on weekdays.
- The peak hours being between 10:00 and 18:00.
- On Saturday, the demand curve follows a similar pattern, with lower consumption and the peak hours finishing at 14:00.
- On holidays, the curve is almost flat.

The only difference of the fifth building with the previous ones is the existence of a fourth day type, bank holidays, where the shape of the load profile is similar to a weekday but the peak load is similar to a Saturday.

Based on this configuration, two case studies are proposed:

Individual case: Analyse the electric consumption per building and apply a power term optimisation algorithm to each dataset separately.

Joined case: Simulate that the buildings with the 6.1 tariff located in Bilbao are all connected to a single supply point and are all managed under the same electric contract. This means that the consumption values of the four buildings will be added together to generate a global dataset on which to apply the genetic algorithm.

In both case studies, the purpose of applying the genetic algorithm to the consumption datasets is to find the best combination of power values that meets the demand of the infrastructure while minimising the economic cost derived from a contract configured with higher power values than what the facility needs. The analysis of the best solution will depend not only on the degree of optimisation achieved in each case, but also on the possibility of modifying the current electric configuration if the best optimisation is given by a different layout regarding the supply points.

Please note that buildings A, B, C and E have already been manually optimised using the technique explained in Section while building D is yet to be optimised since an extension that will be electrically attached is still under construction. It is expected for the optimisation of the latter building to be much larger than the others.

The energy consumed by the whole infrastructure is monitored by an automated system, which periodically collects the data recorded by the buildings' meters and stores it in a centralised database. The monitoring module manages all aspects of telemetering, from the identification of missing or corrupted data up to the management of events in case of meter malfunction or communication failure. The centralised database also stores additional data regarding the electricity contracts associated with each building, the definition of the tariff's periods, the cost of the power term established by the BOE, and the distribution of bank holidays within the year. All this information feeds the system's optimisation module, which replicates the annual bills in order to simulate scenarios with different sets of contracted power values to find the combination that meets the infrastructure needs while minimising the global cost.

In addition, the historical evolution of electric consumption in the six buildings is accessible via the visualisation module which provides a web interface to interact with the functionalities provided by the automated system. Users can monitor the status of meters and demand curves, query information regarding the electricity contracts of each building, analyse monthly bills and run simulations for power optimisation.

4 Results and Discussion

The implementation of the genetic algorithm and the bill replication module altogether called for a deep study of the parameters and characteristics influencing the electricity contract of each building in order to identify common and particular aspects. The process of optimisation performed by the algorithm in both case studies is as follows:

- The system collects data from the database regarding the annual consumption, contracts, and tariff parameters per building.
- A partial calculus of the annual billing is done for those concepts that do not influence the power term such as cost of active energy, reactive energy and equipment rental. This partial invoice is added as input to the core of the optimisation algorithm. It is important to note that in the joined study use case, in which all buildings are evaluated as a single facility, the values of energy consumption are added together to form a single dataset.

- The genetic algorithm then generates a set of candidate solutions, i.e, combinations of six power values that satisfy the constraints set by the type of tariff (upper and lower limit values of power that can be demanded; in the case of the 6.1 tariff, one of the values must be higher than 450 kW).
- The candidate solutions undergo a series of transformation through the use of genetic operators.

Using the previous approximation, it was carried out three different experiments in order to asses the quality of the proposed method.

4.1 Tariff Optimisation

The first experiment assesses the percentage of reduction achieved in the electricity bill using the traditional method (TM), i.e. the optimisation technique explained in Section in comparison with the proposed method (GA), i.e. the method explained in Section 2. Namely, the objective is to look for the power limits $p_1, \ldots, p_6$ of every period that minimises the electric bill of the previous year. The results can be seen in Table 2. Columns $\Delta\, T\ PM$ and $\Delta\, T\ GA$ show the *percentage of reduction* on the period of time comprised by the dates in columns *From* and *To* for the traditional algorithm and the proposed method respectively. Please note that negative values denote an increment in the electric bill while positive values denote reductions.

As can be seen, the proposed method almost always finds a better combination of parameters that minimises the annual cost than the traditional procedure. As expected, the improvement is scarce, except in building D. However, please note that these results imply that a simple phone call represent more than 1000 € of savings. Finally, the savings can be particularly important if all the loads are combined. In this case the savings could be up to 30 %. Please note that this situation can not be always possible to contract due to physical or legal restrictions but should always be considered in the design phase of a complex of buildings such as a university campus.

4.2 Savings Forecasting

We tried to asses the ability to forecast future savings for the two methods. Namely, in this experiment we suppose that we have changed the power limits using the data comprised between *From* and *To* dates for the period comprised between the *To* date until 2014-03-31. Columns $\Delta\, V\ PM$ and $\Delta\, V\ GA$ of Table 2 contain the percentage of reduction over this period for the traditional algorithm and the proposed method respectively. Please note that, just like before, negative values denotes an increment in the electric bill while positive values denote reductions.

As can be seen, the proposed method achieves a reduction in the annual electricity cost and, moreover, this improvement is bigger in all cases. Please note that the results suggest that the savings of the proposed method are kept during long periods.

4.3 Convergence

Since the proposed method is stochastic by nature, its convergence properties have to be tested empirically. Please note that, in this context, convergence refers to the ability of the proposed method to find a local minima. In order to measure this ability, the previous experiment was repeated 100 times for each period of time defined by the *From* and *To* columns. The variability of the results was examined by using the Coefficient of Variation [12] which normalises the standard deviation with respect to the mean value of the sample. In this sense, it represents the percentage of central variation of the sample. Namely, a low value would mean that the method always finds the same local minimum which suggests it gets the absolute minimum. On the other hand, high variability may mean that the function has several different local minima or that the method fails to converge. Column *Conv* of the results in Table 2 suggest that in all cases the method converges to the same local minimum so it is likely that this is also the absolute one.

5 Conclusions

The optimisation of the electricity bill is a secure alternative in terms of cost savings given the high energy consumption in which business and particulars alike incur today. Of the possible alternatives for optimisation, the one that equilibrates contracted power values is the most affordable, since its application does neither involve a change in the electric system nor a change of supplier, and is of immediate application when renewing electric contracts. This paper proposes an artificial intelligence based methodology, namely evolutionary algorithms, to find the best combination of power values that minimizes the annual electricity cost while meeting the infrastructure needs, in this case a public infrastructure comprised of several buildings.

In this sense, two case studies were proposed to evaluate the degree of optimisation achieved within each building separately in comparison to the results obtained by simulating that all the buildings are connected to the same single supply point. The results show that the optimisation achieved with the evolutionary algorithm is greater than that obtained with the traditional method.

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Author Contributions

Cruz E. Borges conceived the idea of using evolutionary algorithms for the optimisation of the electric tariff. Oihane Kamara-Esteban implemented the algorithm, conducted the experiments and together with Cruz E. Borges analyzed the data. Julio Manuel Revilla Ocejo provided expert knowledge on the electric infraestructure of the buildings and the tariffs contracted as well as the middleware to access the data in real time.

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Figure Legends

Figure 1. Distribution of annual hours within the 6-period tariff.

Figure 2. Outline of the cost function $\phi_m(p_i)$.

Figure 3. Mean load over a year for all buildings. Errors bar denote $\pm\sigma$.

Tables

Table 1. Electric tariffs defined by the Spanish BOE [1].

Tariff	Voltage (v)	Power (p)	Periods
2.0A	$v < 1\,\mathrm{kV}$	$p < 10\,\mathrm{kW}$	1
2.0DHA	$v < 1\,\mathrm{kV}$	$p < 10\,\mathrm{kW}$	$2^{\dagger}$
2.0DHS	$v < 1\,\mathrm{kV}$	$p < 10\,\mathrm{kW}$	$3^{\dagger}$
2.1A	$v < 1\,\mathrm{kV}$	$p < 10\,\mathrm{kW}$	1
2.1DHA	$v < 1\,\mathrm{kV}$	$10\,\mathrm{kW} \leq p < 15\,\mathrm{kW}$	$2^{\dagger}$
2.1DHS	$v < 1\,\mathrm{kV}$	$10\,\mathrm{kW} \leq p < 15\,\mathrm{kW}$	$3^{\dagger}$
3.0	$v < 1\,\mathrm{kV}$	$15\,\mathrm{kW} \leq p < 450\,\mathrm{kW}$	$3^{\ddagger}$
3.1	$1\,\mathrm{kV} \leq v < 36\,\mathrm{kV}$	$15\,\mathrm{kW} \leq p < 450\,\mathrm{kW}$	$3^{\ddagger}$
6.1	$1\,\mathrm{kV} \leq v < 36\,\mathrm{kV}$	$450\,\mathrm{kW} \leq p$	$6^{\S}$
6.2	$36\,\mathrm{kV} \leq v < 72.5\,\mathrm{kV}$	$450\,\mathrm{kW} \leq p$	$6^{\S}$
6.3	$72.5\,\mathrm{kV} \leq v < 145\,\mathrm{kV}$	$450\,\mathrm{kW} \leq p$	$6^{\S}$
6.4	$145\,\mathrm{kV} \leq v$	$450\,\mathrm{kW} \leq p$	$6^{\S}$

† Each period is assigned an equal number of hours per day in summer and in winter. The power limit contracted is the same for all periods.
‡ Each period is assigned an equal number of hours per day in summer and in winter. The power limit contracted for every period can vary, the only condition is that these amounts have to be configured in ascending order.
§ Each period is assigned different hours and days throughout the year. The power limit contracted for every period can be different, though at least one of those values should be greater than 450 kW and they have to be configured in ascending order.

Table 2. Comparison or the results achieved by PM and GA optimisation methods.

Building	From	To	ΔT TM (%)	ΔT GA (%)	Days	ΔV PM (%)	ΔV GA (%)	Conv (%)
A	2012-09-01	2013-08-31	−1.68	0.03	211	−1.69	0.59	0.03
A	2012-10-01	2013-09-30	−1.66	0.09	181	−1.95	0.88	0.03
A	2012-11-01	2013-10-31	−1.51	0.18	150	−1.78	1.01	0.04
A	2012-12-01	2013-11-30	−1.24	0.22	120	−1.50	1.61	0.03
A	2013-01-01	2013-12-31	−0.63	0.91	89	−0.47	2.44	0.04
A	2013-02-01	2014-01-31	0.06	1.47	58	−1.23	1.23	0.04
A	2013-03-01	2014-02-28	0.10	2.09	30	6.49	6.95	0.03
B	2012-09-05	2013-08-31	1.56	3.02	211	5.92	9.54	0.04
B	2012-10-01	2013-09-30	1.97	3.45	181	6.52	10.18	0.04
B	2012-11-01	2013-10-31	2.25	3.88	150	6.39	10.49	0.05
B	2012-12-01	2013-11-30	2.54	4.43	120	6.34	10.31	0.04
B	2013-01-01	2013-12-31	3.82	5.69	89	7.39	11.86	0.04
B	2013-02-01	2014-01-31	4.37	6.61	58	8.01	13.62	0.03
B	2013-03-01	2014-02-28	5.76	8.18	30	15.79	26.04	0.04
C	2012-09-01	2013-08-31	−1.18	0.31	211	−0.31	2.48	0.05
C	2012-10-01	2013-09-30	−1.06	0.45	181	0.29	3.66	0.05
C	2012-11-01	2013-10-31	−0.69	0.76	150	0.62	3.90	0.03
C	2012-12-01	2013-11-30	−0.87	0.95	120	−0.35	4.07	0.03
C	2013-01-01	2013-12-31	−0.41	1.62	89	0.19	4.59	0.03
C	2013-02-01	2014-01-31	0.03	2.18	58	−0.57	3.78	0.03
C	2013-03-01	2014-02-28	0.33	2.88	30	3.34	11.22	0.03
D	2012-09-10	2013-08-31	10.40	12.68	211	9.36	10.39	0.09
D	2012-10-01	2013-09-30	10.80	13.03	181	7.79	9.50	0.07
D	2012-11-01	2013-10-31	11.25	13.35	150	5.16	8.22	0.07
D	2012-12-01	2013-11-30	11.46	13.54	120	1.45	6.69	0.09
D	2013-01-01	2013-12-31	9.77	12.83	89	2.72	10.52	0.08
D	2013-02-01	2014-01-31	9.59	13.03	58	5.77	12.70	0.09
D	2013-03-01	2014-02-28	9.09	12.94	30	34.00	29.11	0.09
E	2012-09-10	2013-08-31	−2.26	0.48	211	−6.06	3.38	0.03
E	2012-10-01	2013-09-30	−1.91	0.74	181	−4.64	4.73	0.03
E	2012-11-01	2013-10-31	0.33	1.22	150	0.90	5.18	0.05
E	2012-12-01	2013-11-30	0.37	1.50	120	0.92	4.99	0.03
E	2013-01-01	2013-12-31	0.41	1.75	89	0.95	6.44	0.03
E	2013-02-01	2014-01-31	0.52	2.19	58	1.27	8.10	0.05
E	2013-03-01	2014-02-28	0.57	2.53	30	1.95	12.50	0.03
JOIN	2012-09-10	2013-08-31	38.91	39.53	211	35.30	37.87	0.03
JOIN	2012-10-01	2013-09-30	38.38	39.05	181	37.05	39.42	0.05
JOIN	2012-11-01	2013-10-31	36.80	28.61	150	40.04	33.65	0.03
JOIN	2012-12-01	2013-11-30	36.22	28.55	120	42.47	35.69	0.03
JOIN	2013-01-01	2013-12-31	36.08	28.72	89	43.45	36.87	0.05
JOIN	2013-02-01	2014-01-31	35.76	28.88	58	44.26	37.45	0.03
JOIN	2013-03-01	2014-02-28	35.48	29.09	30	47.37	42.50	0.03