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Abstract (for dissemination)	This deliverable contains the description of a non-linear optimization model for the behavior of an energy provider and a set of customers (or classes of customers) in a deregulated energy market. The model can be used by an energy provider to obtain suggestion for Time-Of-Use base prices (at district or building level), and by a policy maker to identify the customer behavior that leads to the lowest energy costs, or to asses the likely response of an energy provider to changes in the customer behavior. The deliverable describes also a set of prototype decision support tools the rely on the optimization model.					
Keywords	Optimization, Dynamic pricing, Energy customer behavior					

***Nature:** **R** = Report, **P** = Prototype, **D** = Demonstrator, **O** = Other

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Glossary

Table 3 Glossary

Acronym	Meaning
DR	Demand Response
ToU	Time Of Use
RTP	Real Time Pricing
CPP	Critical Peak Pricing
DLC	Directly Controllable Loads
I/C Services	Interruptible/Curtainable Services
EDR	Emergency Demand Response
CAP	CAPacitated Market Programs
DB	Demand Bidding
AS	Ancillary Services
LP	Linear Programming
MINLP	Mixed Integer Non-Linear Programming
KKT	Karush-Kuhn-Tucker
API	Application Programming Interface
REST	REpresentational Sate Transfer
JSON	JavaScript Object Notation
GUI	Graphical User Interface

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1 Executive Summary

Global energy demand is expected to grow by 37% by 2040, with a consequent increase of polluting emissions[1] (data from the International Energy Agency) and electricity is the form of energy whose use is growing the fastest. Therefore, it has become important to re-organize the management of electrical energy to change its trends for the better.

Demand Response (DR) mechanisms can potentially lead to economical and environmental advantages. One of the main research objectives in this field is the design and experimentation of new mechanisms for the efficient use of energy with the implementation of technologies to *lower* electricity consumption, and to *better* electricity consumption via demand shifting. Increasing energy efficiency requires to obtain of a reduction of energy demand during peaks through a shifting of energy consumption. This can be done via demand response mechanisms and load control, which have become important topics of research at international level.

DR mechanisms can also lead to economic advantages compared to flat energy tariffs. In particular, they can provide end-users with the opportunity to reduce their electricity costs by responding to market pricing. However, both devising (from the energy provider point of view) and exploiting (from the consumer point of view) effectively a DR scheme is a challenging task, and one of the major barriers for fully utilizing the potential of DR programs.

With the aim to overcome these barriers, we developed set of software tools to support political and economic decision makers in the definition of new business models and policies based on a specific (and very common) form of DR scheme, namely Time-Of-Use (ToU) pricing.

All our tools are based on mathematical programming technology, and in particular on a **non-linear optimization model**. In the complex and heterogeneous context of the electricity market, we aimed at creating a comprehensive model, which collects the main variables and parameters that are relevant in the study and analysis of sustainable ToU based tariffs. In particular, we take into account: 1) the existence of multiple tariffs, possibly offered by multiple energy providers; 2) the elasticity of the electricity demand w.r.t. price variations; 3) cognitive aspects of the customer behavior (risk aversion and accuracy of the consumption estimation). To the best of our knowledge, this is the first optimization approach to take into account such a variety of factors into a single model.

Our optimization model can be employed by a utility company to **define optimal ToU prices**, and to compare alternative scenarios in terms of user behavior and demand shift. Policy makers (e.g. local municipalities) can employ the model to **identify possible changes in the customer behavior** that lead to a more efficient use of energy: this information can be very valuable in the definition policy goals, in the design of campaigns to improve the energy usage efficiency, or in shaping incentive schemes.

In particular, we use our optimization model as the basis to design **four decision support tools**. The first two tools are addressed to energy providers and allow one respectively to 1) identify optimal ToU prices for

[1] See http://www.iea.org/textbase/npsum/weo2014sum.pdf

a target district, or 2) identify tailored ToU tariffs for a set of large customers (i.e. companies or public buildings). These prices will be optimal from the point of view of a single energy provider, and beneficial for the customers as long as the presence of competitor providers is taken into account. The remaining two tools are addressed to policy makers and enable respectively 1) the identification of an "ideal" customer behavior (in terms of elasticity, risk aversion, and accuracy of perception), and 2) a quick assessment of how an energy provider is expected to react to changes in the customer behavior.

As a first case study, we have employed our approach to obtain an approximate model for the Lizzanello pilot in the DAREED project. The results for this case study should be considered preliminary (the main validation will be done as part of the WP7 activities). The main goal of the use case at this stage is showcasing how the developed tools could be used in practice.

The deliverable is organized as follows: Section 2 provides an analysis of the current state of the art on demand response mechanisms, showing the innovating aspects and the focus of this work. Section 3 describes the proposed optimization model. Section 4 discusses the design and implementation of the four decision support tools, while Section 5 presents our simple use case. Finally, Section 6 provides some concluding remarks.

2 Related Work on Optimization and Demand Response

Demand Response can be defined as the occurrence of deviations from the usual consumption pattern in response to stimuli, such as dynamic prices, incentives for load reductions, tax exemptions, or subsidies. Demand response programs studied in literature can be divided in two main groups: price-based and incentive-based mechanisms.

Price-based demand response is related to the changes in energy consumption by customers in response to the variations in their purchase prices. This group includes DR mechanisms like Time-of-Use (ToU) pricing, Real Time Pricing (RTP) and Critical-Peak Pricing (CPP) rates. If the price varies significantly, customers can respond with changes in their pattern of energy use. They can reduce their energy costs by adjusting the time of the energy usage by increasing consumption in periods of lower prices and reducing consumption when prices are higher.

ToU mechanisms define different prices for electricity usage during different periods (typically with a weekly pattern): the tariffs usually reflect the average cost of generating and delivering power during those periods. *For RTP* the price of electricity is defined for shorter periods of time (usually 1 h) reflecting the changes in the wholesale price of electricity. *CPP* is a hybrid of the ToU and RTP programs. This mechanism is based on the real time cost of energy in peak price periods, and has various methods in implementation.

Incentive-based demand response consists in programs with fixed or time-varying incentives for customers in addition to their electricity tariffs. Incentive-Based programs (IB) include Direct Load Control (DLC), Interruptible/Curtailable service (I/C), Emergency Demand Response programs (EDR), Capacity Market Programs (CAP), Demand Bidding (DB) and Ancillary Service (AS) programs. Classical IB programs include DLC and I/C programs. Market-Based IB programs include EDR, DB, CAP, and the AS programs.

In classical IBP, customers receive participation payments (e.g. discounted rates) for their participation in the programs. In Market-Based programs, participants receive money for the amount of their load reduction during critical conditions. In *I/C programs*, participants are asked to reduce their load to fixed values and participants who do not respond can pay penalties based on the program conditions. *DB* are programs in which consumers are encouraged to change their energy consumption pattern and reduce their peak load in return for financial rewards and to avoid penalties. In *EDR* programs, customers are paid incentives for load reductions during emergency conditions. *Capacity Market Programs* offer to customers pre-specified commitments (e.g. providing load reductions) in case of system contingencies. While other programs aim to reduce energy peak consumption, another form of DR is emerging to improve the reliable transmission of electricity. *AS* programs allow customers to bid load curtailment in the spot market as operating reserve. The need for Ancillary Services is growing as energy operators face new challenges (e.g. transmission congestion and the intermittent renewable power generation).

A more detailed overview of demand response schemes can be found in [1], [2] and [3]. The main Demand Response programs are also summarized in Figure 1. The position of our work w.r.t. the relevant state of the art is summarized in Figure 2.

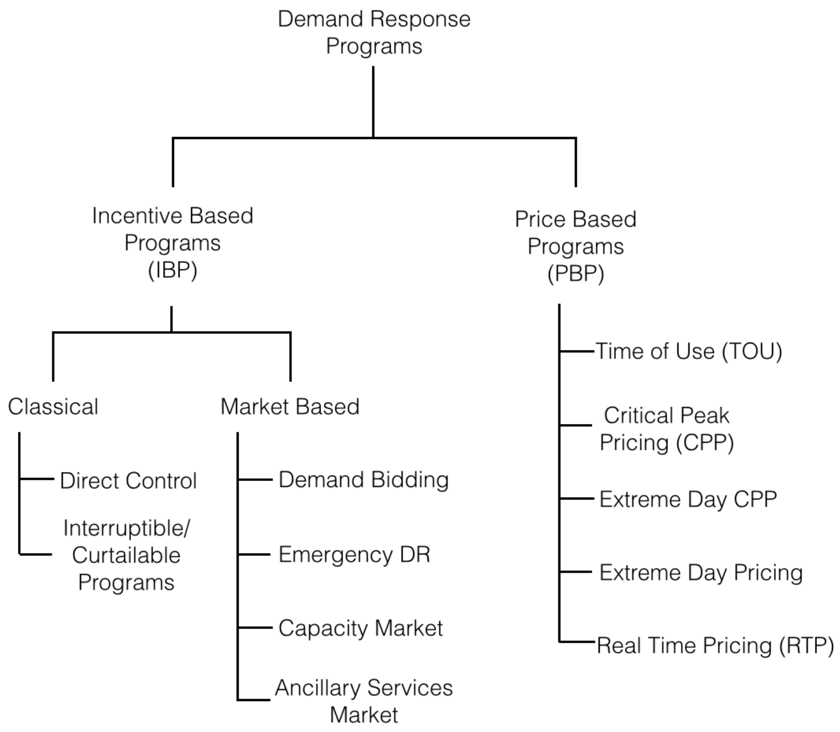

Figure 1: Classification of Demand Response programs, based on [2] .

2.1 Optimization approaches for Electricity Market actors

A survey of DR potentials and benefits in smart grids is presented in [4] where also innovative enabling technologies and systems are described and discussed. A very important aspect observed by the scientific literature analyzing the electricity market is the trend towards competition and market liberalization. This has led to the development of decision models and analytical support tools adapted to the new market environment. It is important to identify, classify and characterize the different approaches that can be found in the technical literature on the electricity market modeling. It is possible, in the current state of the art, to identify three major trends: optimization models, equilibrium models, and simulation models. A survey of the literature on electricity market models can be found in [5].

Another important aspect in the electricity market modeling is the definition of energy prices and provider tariffs: a survey on demand response pricing methods and optimization algorithms is presented in [6]. Optimization approaches to define dynamic prices have been proposed in [7], and [8]. All such works focus on the definition of day-ahead prices for a period of 24 hours and for a single customer (or a single group of homogeneous customers), and consider multiple DR schemes. Our approach is focused on ToU pricing, but we take into account multiple customers and reason over a dramatically longer time period (one year).

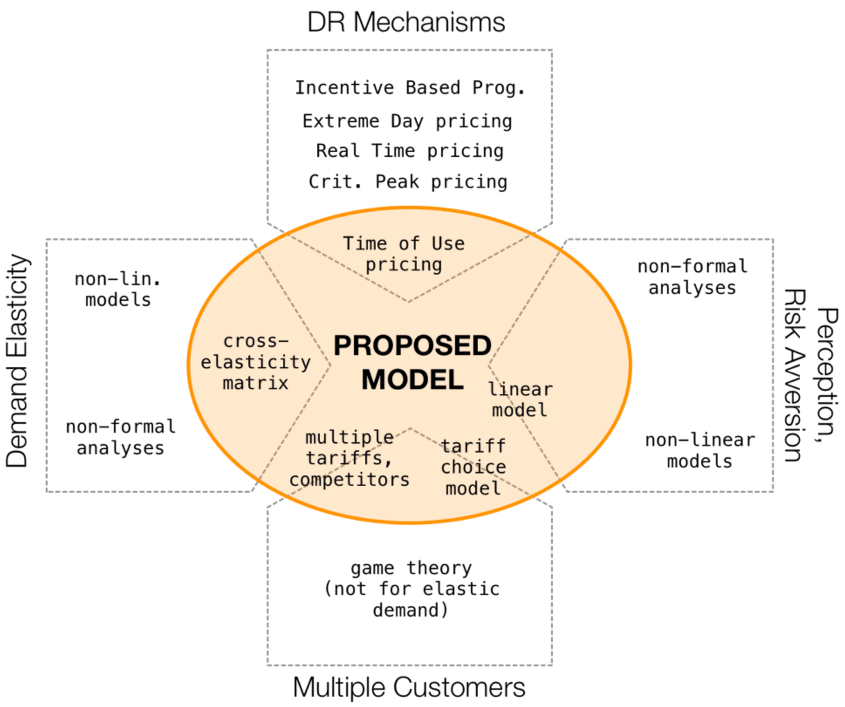

Figure 2: Position of our approach w.r.t. the state of the art (partial overlapping text = novel or partially novel pieces of model)

Probably the most widespread demand response mechanism in practice is given by Time of Use (ToU) based tariffs, where the price of electricity is dynamic and follows a weekly pattern. Usually, in this mechanism, peak periods have higher prices than off-peak periods; this is expected to push users to changing their use of electricity. This type of DR program is particularly easy to apply for residential users [9]. Concerning the study of Time of Use (ToU) mechanisms and load management for residential users, [10] shows an optimal load management strategy for residential consumers and studies how end-users can adjust their load level according to a determined DR program.

2.2 Elastic Model for Residential User consumption

Under dynamic pricing, consumers may decide to modify their load profile to reduce their electricity costs. For this reason, it is important to analyze the effect that price variations have on the elasticity of the electricity demand. One influential approach is given in [11], which proposes an elastic model to characterize the demand-response behavior and load management, and describes in particular how the consumer behavior can be modeled using a *matrix of self and cross-elasticities*. The same elastic demand-response model is employed in [7] and [8], which take into account a variety of DR programs.

[12] assesses the impacts of ToU tariffs on a dataset of residential users from the province of Trento in northern Italy in terms of changes in electricity demand, price savings, peak load shifting and peak electricity demand at sub-station level. The paper shows that a significant level of load shifting takes place for morning peaks but not for evening peaks. In [13], the response of a non-linear mathematical model is analyzed for the calculation of the optimal prices for electricity, assuming default customers under different scenarios over a 24h period.

A model of an electric energy service provider in the environment of the deregulated electricity market is also defined in [14]. The paper studies the impact on the profits of several factors, such as the price strategy, the discount on tariffs and the elasticity of customer demand, once again over a 24h period.

In our paper, we have adapted the elastic demand-response model form [11] to ToU based prices *over an year-long period,* which is better suited for the purpose of defining a new commercial tariff. This is a major difference w.r.t. the existing literature, and it allows us to better identify trends, and to assess how the characteristics of the market and the customers affect the annual consumption profiles.

2.3 Customer behavior and perceived consumption

Consumption and cost awareness have an important role for the effectiveness of demand response schemes. [15] describes a system architecture for monitoring the electricity consumption and displaying consumption profiles to increase awareness. [16] and [17] study how customers respond to price changes, and which price indicators are more relevant on this respect.

[18] shows how real-time price elasticity contains important information on the demand response of consumers to the volatility of peak prices, and provides a quantification of the real-time relationship between total peak demand and spot market prices. The authors of this work find a low real-time price elasticity, which may partly be explained with the fact that not all users observe the spot market price. This shows the necessity to define corrective measures for this phenomenon (e.g. monitoring and feedback systems).

One of the most common measures undertaken by residential customers to adjust their behavior is the use of domestic appliances in off-peak periods. However, many customers do not understand how to lower electricity costs and call for a device that displays the current power output [19]. The authors of [16] try also to account for misperception of energy consumption, which are further analyzed in [20]. The latter work in particular attempts to design a model for the relationship between real and perceived consumption via regression techniques (i.e. function fitting). The conclusion is that customers tend to slightly overestimate low-energy activities and significantly underestimate activities with high energy consumption.

In our work, we take into account the effect of perception accuracy in the consumer behavior, based on the insights from [20]. However, we model the relation using a simpler (linear) function, which is inserted into a richer and more complex model that already takes into account demand elasticity and ToU based prices.

2.4 Multiple and Risk Averse Residential Users

In this work, we aim to show how multiple, different, consumers react to electricity prices. Only a few papers have considered multiple customers or intermediate actors: for example, [21] developed an investment model for renewable energy (solar parks) through crowdfunding. In particular, the paper presents a game theory approach that takes into account interactions between crowd-funders, the owner of the solar park, and a power company that buys renewable energy generated from the solar farm itself.

The consumer participation has become more and more important for energy market growth, but to reap the benefits of market liberalization, consumers need to be aware and engaged, and they need access to clear and transparent information. Usually, consumer choices are marked by personal proclivities, risk aversion and ignorance of their consumption. Consumers do not seem to be able to gain the best from a competitive market; in many cases they obtain just a slightly more advantageous offer, without obtaining the maximum possible gain from switching to a new operator. In our approach, we model *multiple groups of homogeneous customers* and we take into account some cognitive aspects of the customer behavior to differentiate these groups. In particular, our model analyzes a market situation where the users exhibit some *risk aversion* when they consider switching to a new tariff, which is natural in this type of markets.

2.5 Modeling of a Competitive Market

Although demand response is not a new concept, it can have a much more relevance in the context of competitive electricity markets. Technical and economic issues have to be considered, and new approaches are required in order to take full advantage of demand response for electricity market operation and electricity market actors [22].

Under this new situation of deregulation and competition, electric firms assume more risk and are more responsible for their own decisions. Utilities need original models that satisfy these new requirements: for example, models for the competitive behavior of the energy generation market, built by incorporating a set of constraints (namely the market equilibrium constraints) into a traditional production cost model. In our approach, we take into account the existence of (static) competitors by providing support for multiple tariffs.

3 The Proposed Modeling Approach

The main actors considered in our model are *one energy provider* and *multiple "customers"*, which may represent either individual large customers, or customer classes (i.e. groups of homogeneous customers). The semantic depends on how the model is used. In particular, we distinguish three main possible configurations:

- **Configuration A:** In this case the model is solved to obtain recommended ToU prices for a tariff *at district level*. The "customers" represent large group of homogeneous customers, and the problem objective is to maximize the provider profit. The tariffs suggested by the model will be beneficial for the customers only if the presence of competitors is taken into account.

- **Configuration B:** In this case the model is solved to obtain recommended ToU prices for a group of *individual, large electricity users*. The "customers" represent either different actual individual customers, or several buildings with the same owner (e.g. public buildings owned by the local municipality). The tariffs suggested by the model will be beneficial for the customers only if the presence of competitors is taken into account.
- **Configuration C:** In this case the model is solved to identify the customer behavior (in terms of elasticity, risk aversion, and accuracy of perception) that leads to the lowest electricity costs. Since the cost of electricity tends to be lower in the price bands when power generation is more efficient, this configuration will also likely lead to a more efficient use of energy.

Our model consists of several components that take into account: (1) the existence of multiple tariffs with ToU based prices; (2) the demand-response behavior of customers; (3) some cognitive aspects of the customer behavior, in particular their ability to correctly estimate their consumption, and their risk aversion when switching to a new tariff. We consider a year-long time horizon. To the best of our knowledge, this is the first approach that tries to take into account multiple tariffs and cognitive aspects of the customer behavior.

We will start by presenting each component of our model for configuration A. In Section 3.2 and Section 3.3 we will discuss the changes that are necessary to switch to configuration B and C.

3.1 Configuration A (ToU prices at district level)

This is probably the configuration of our model that is easiest to understand. The goal is finding the prices for a set of ToU based tariffs that maximize the profit of an energy provider over a target district. The presence of competitors is taken into account by assuming that some fixed, non-owned, tariff exist.

3.1.1 Set of Tariffs

We consider a set T of ToU based tariffs τ_i, defined over a common price band scheme. The scheme specifies a set P of pre-defined price bands π_j: the exact configuration (e.g. start, end) of each price band is left unspecified, but we assume that for each band π_j the total number of hours $|\pi_j|$ over a period of one year is available.

Each ToU based tariff is defined by a price value $p_{i,j}$ for each band, which takes value over a bounded range, i.e. $p_{i,j} \in \left[\underline{p}_{i,j}, \overline{p}_{i,j}\right]$. As long as the bounds are large enough, this assumption is sufficiently general to handle practical scenarios. We assume that the tariffs in a subset $T_f \subseteq T$ are *fixed*, i.e. they cannot be altered by the energy provider: for each $t_i \in T_f$, the prices are constant values. The remaining tariffs are *variable*, and their prices are decision variables in our model. Finally, we assume that a subset T_o of tariffs is *owned* by the energy provider, i.e. the provider earns profit (and pays the cost) for the electricity consumed under such tariffs. All variable tariffs are owned.

This setup is sufficient to handle a number of interesting cases. Variable tariffs are those for which we wish to obtain price recommendations. Tariffs that are both fixed and owned represent pre-existing contracts that cannot be altered. Tariffs that are fixed and not owned are those offered by competitor providers. To the best of our knowledge, our approach is the first to provide support for multiple tariffs and for modeling the existence of competitors.

3.1.2 Tariff Choice and Customer Risk Aversion

We take into account the behavior of a set C of "customers". Each customer $\kappa_k \in C$ is associated to an original tariff $\tau(\kappa_k)$, which must be fixed (i.e. $\tau(\kappa_k) \in T_f$). Customers may switch to a new tariff, based on its economical benefits. In particular, we assume that each customer in a group can switch tariff with a probability that depends on the obtained savings. Formally, let $c_{k,i}$ be the electricity cost for customer κ_k under tariff τ_i. The $c_{k,i}$ term is a constant if τ_i is fixed, and a decision variable if τ_i is variable: the computation of such cost values will be discussed in Section 3.1.5. The cumulative savings for class κ_k under tariff τ_i are given by:

$$s_{k,i} = max(0, c_{k,\tau(\kappa_k)} - c_{k,i})$$

The equation does not take into account the fact that staying with the current tariff is in practice more convenient and less risky than switching. Technically, we say that the customers are likely to exhibit a certain degree of *risk aversion*. We take this into account by adjusting the equations as follows:

$$s_{k,i} = \begin{cases} \rho_k\, c_{k,\tau(\kappa_k)} & if\ \tau_i = \tau(\kappa_k) \\ max\left(0, c_{k,\tau(\kappa_k)} - c_{k,i}\right) & otherwise \end{cases}$$

where $0 < \rho_k < 1$ is a risk aversion coefficient. In practice, *staying with the current tariff is considered equivalent to saving a factor ρ_k of the current cost*: this provides an intuitive approach to define the value of ρ_k based on questionnaires or existing data.

As we mentioned, we model the tariff switching as a stochastic process. In particular, we assume that all tariff choices for a given customer class are independent and identically distributed. Formally, we introduce a set of stochastic binary variables $Y_{k,i}$ that are equal to 1 if a customer in class κ_k adopts tariff τ_i. Each variable has a discrete probability distribution, given by:

$$P(Y_{k,i} = 1) = \frac{s_{k,i}}{\sum_{\tau_i \in T} s_{k,i}} \qquad\qquad P(Y_{k,i} = 0) = 1 - P(Y_{k,i} = 1)$$

i.e. the probability is proportional to the savings. Let us assume that $|\kappa_k|$ represents the number of customers in class κ_k. The number of customers of class κ_k that adopt tariff τ_i can then be obtained by summing $Y_{k,i}$ for $|\kappa_k|$ timesThe expected value of this expression is given by:

$$E\left[\sum_{h=0}^{|\kappa_k|-1} Y_{k,i}\right] = |\kappa_k| E\left[Y_{k,i}\right] = |\kappa_k| \frac{s_{k,i}}{\sum_{\tau_i \in T} s_{k,i}}$$

And the expected *fraction of switching customers* is given by:

$$\frac{s_{k,i}}{\sum_{\tau_i \in T} s_{k,i}}$$

Therefore, on average the customers in each class spread over the available tariffs proportionally to the value of $s_{k,i}$ (i.e. the cumulative savings). We use this information to define the *tariff selection (and risk aversion) component of our model*, which is given by:

$$y_{k,i} = \frac{s_{k,i}}{\sum_{\tau_i \in T} s_{k,i}} \qquad\qquad \forall \kappa_k \in C, \tau_i \in T$$

$$s_{k,i} = \begin{cases} \rho_k \, c_{k,\tau(\kappa_k)} & if\ \tau_i = \tau(\kappa_k) \\ max\left(0, c_{k,\tau(\kappa_k)} - c_{k,i}\right) & otherwise \end{cases} \qquad \forall \kappa_k \in C, \tau_i \in T$$

$$y_{k,i} \in [0,1] \qquad \forall \kappa_k \in C, \tau_i \in T$$

$$c_{k,i} \in \mathbb{R}^+ \qquad \forall \kappa_k \in C, \tau_i \in T$$

The $y_{k,i}$ variables represent the fraction of customers of class κ_k that adopt tariff τ_i. Due to the presence of "max" operators in the savings equation, this model component is non-smooth (it is piecewise linear in particular). The "max" operators can however be linearized by using Special Ordered Sets of type 2, which require the addition of binary variables: this is the technique that we employ in our implementation.

3.1.3 Demand Response Behavior

We assume that customers can shift their consumption depending on the energy prices, i.e. they are capable of a demand response behavior.

Many demand response programs (including ToU based prices) have been considered in the literature and a few mathematical models have been provided. We have developed a variant of one of the most widely employed approaches, which was proposed in [11] and is based on a *cross-elasticity matrix*. Essentially, the approach uses a linear transformation to map variations of prices to variations of demand:

$$\tilde{d} = \epsilon \, \tilde{p}$$

where $\tilde{d}$ is a vector of demand variations over multiple time periods, $\tilde{p}$ is a vector of (normalized) price variations, and ϵ is called cross-elasticity matrix. The original approach by [11] and employed in [7], [8], [23] is designed for time periods of homogeneous duration and day-ahead prices.

We adapted the model to ToU based tariffs with price bands of non-uniform duration, over a year-long time period. The main idea is simply to introduce variables to represent the variation in the yearly electricity demand of an individual customer, *for each price band* π_j. Since we consider multiple customer classes and tariffs in our model, we need separate variables $\tilde{d}_j^{(k,i)}$ for each class κ_k and tariff τ_i. The demand variation is therefore connected to the tariff prices by:

$$\tilde{d}_j^{(k,i)} = \sum_{\pi_h \in P} \hat{d}_h^{(k)} \, \epsilon_{j,h}^{(k)} \, \tilde{p}_h^{(k,i)}$$

where the $\tilde{p}_h^{(k,i)}$ variables represent normalized price variations. The term $\hat{d}_h^{(k)}$ is a problem parameter, representing the original demand for an individual customer of class κ_k, in price band π_h.

The terms on the diagonal of $\epsilon^{(k)}$ are always *non-positive* and are called *self-elasticity coefficients*. The other terms are always *non-negative*. For normalizing the price variations, we use the average price under the original tariff, i.e.:

$$\tilde{p}_j^{(k,i)} = \frac{p_{i,j} - p_{\tau(\kappa_k),j}}{p_{avg}^{(k,i)}}$$

With:

$$p_{avg}^{(k,i)} = \frac{1}{|P|} \sum_{\pi_h \in P} p_{\tau(\kappa_k),h}$$

Our choice is based on insights from [16] and [17], which show how customers tend to reason in terms of average prices.

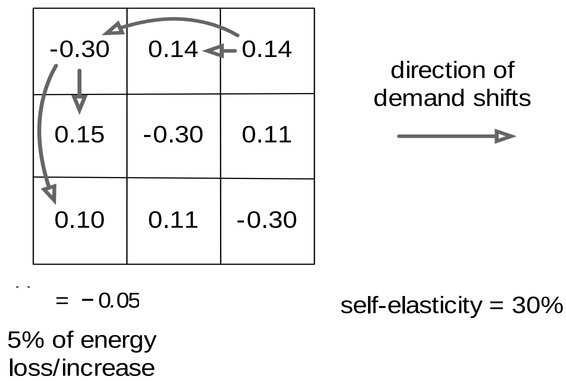

Figure 3: Example of a cross-elasticity matrix

Having weighted the contributions by $\hat{d}_j^{(k)}$ and normalized the prices provides us with a way to intuitively interpret the $\epsilon_{j,h}$ coefficients. In particular, if the price in band π_h roughly doubles (i.e. the normalized variation is 1), then:

- The demand in band π_h (the same band) *decreases* by a factor $|\epsilon_{h,h}^{(k)}|$ of the original demand (we recall that self-elasticity coefficients are non-positive)
- A factor $\epsilon_{j,h}^{(k)}$ of the original demand of band π_h *shifts* to band π_j

Intuitively, the self-elasticity coefficients describe how the demand within each band depends on the prices. The other terms in the matrix represent how the demand shifts *from* price bands (columns to rows) and *to* price bands (rows to columns). The sum of the coefficients *on each column* corresponds to the *net increase/decrease of consumption* when the normalized prices increase/decrease: we refer to such quantity as *loss factor*. If the loss factor is zero, changing the prices may alter the distribution of the demand between the price bands, but not its total value. Figure 3 reports an example of cross-elasticity matrix, with a visual depiction of the demand flows. Overall, the demand-response component of our model is given by:

$$\tilde{d}_j^{(k,i)} = \sum_{\pi_h \in P} \hat{d}_h^{(k)} \epsilon_{j,h}^{(k)} \tilde{p}_h^{(k,i)} \qquad \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P$$

$$\tilde{p}_j^{(k,i)} = \frac{p_{i,j} - p_{\tau(\kappa_k),j}}{p_{avg}^{(k,i)}} \qquad \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P$$

$$\tilde{d}_j^{(k,i)}, \tilde{p}_j^{(k,i)} \in \mathbb{R} \qquad \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P$$

3.1.4 Simplified configuration of the elasticity coefficients

Assigning a meaningful value of all the $\epsilon_{j,h}^{(k)}$ coefficients in the elasticity matrix of a customer is a complex operation. Therefore, with the aim to provide the users of our tools with an intuitive way to setup the optimization model, we devised a simplified configuration method. In particular, all the $\epsilon_{j,h}^{(k)}$ coefficient are defined by specifying only two parameters, namely an *elasticity index* $\eta_k$and a *conservation index* δ_k, both taking values in the range $[0,1]$.

The elasticity index corresponds directly to the self elasticity coefficients in the matrix, i.e.:

$$\epsilon_{j,j}^{(k)} = -\eta_k$$

while the conservation index defines the sum of the coefficients on each column in the matrix:

$$\sum_{\pi_j \in P} \epsilon_{j,h}^{(k)} = -\eta_k + \eta_k \delta_k = (1 - \delta_k)\, \eta_k$$

Intuitively, η_k represents the relative amount of the change in the original demand due to a change of price. Then, δ_k defines how much of such demand change is shifted to other price bands. If $\eta_k = 1$ the customer is very flexible, while if $\eta_k = 0$ the customer is completely rigid. If $\delta_k = 1$ the demand is only shifted around (there is no net increase/decrease), while if $\delta_k = 0$ there is no demand shift between bands (the consumption is increased/decreased) in each band separately.

The value of the remaining coefficients of the $\epsilon^{(k)}$ matrix is computed based on the η_k and δ_k parameters and on the original consumption profile of each user. In particular, we start by computing the usage density during each price band, i.e.

$$dens(\kappa_k, \pi_j) = \frac{\hat{d}_j^{(k)}}{|\pi_j|}$$

intuitively, the higher the usage density, the higher the preference for a price band. However, there is chance that the distribution of the original consumption is affected by the prices of the original tariff: in particular, the customer may have shifted some consumption from a favorite, but expensive, price band to a cheaper one. With the aim to take this behavior into account, we compute a set of elasticity-adjusted prices for each customer:

$$nprice(\kappa_k, \pi_j) = 1 + \left(\frac{p_{\tau(\kappa_k),j}}{p_{avg}^{(k,i)}} - 1\right)\eta_j$$

The $nprice(\kappa_k, \pi_j)$ terms do not depend on decision variables and are therefore always constant. Based on the usage density and the adjusted prices we obtain a preference score for each price band:

$$pref(\kappa_k, \pi_j) = \ nprice(\kappa_k, \pi_j)\, dens(\kappa_k, \pi_j)$$

The idea is that if a large usage density is associated to a large adjusted price, then the customer has a very strong preference for a price band.

The preference scores are used to deduce the value of the coefficients of the elasticity matrix that are not on the main diagonal. On this purpose, it is useful to normalize the preference values over the non-diagonal element of each column. In practice, we obtain the normalized preferences as:

$$npref_h(\kappa_k, \pi_j) = \begin{cases} 0 & if\ h = j\ (i.e.\ on\ the\ diagonal) \\ \dfrac{pref(\kappa_k, \pi_j)}{\sum_{q \neq h} pref(\kappa_k, \pi_q)} & otherwise \end{cases}$$

Where the h index refers to the considered column. As an example, assuming that we have three price bands, the normalized preferences will be:

$$\begin{pmatrix} 0 & \dfrac{pref(\kappa_k, \pi_0)}{pref(\kappa_k, \pi_0) + pref(\kappa_k, \pi_2)} & \dfrac{pref(\kappa_k, \pi_0)}{pref(\kappa_k, \pi_0) + pref(\kappa_k, \pi_1)} \\ \dfrac{pref(\kappa_k, \pi_1)}{pref(\kappa_k, \pi_1) + pref(\kappa_k, \pi_2)} & 0 & \dfrac{pref(\kappa_k, \pi_1)}{pref(\kappa_k, \pi_0) + pref(\kappa_k, \pi_1)} \\ \dfrac{pref(\kappa_k, \pi_2)}{pref(\kappa_k, \pi_1) + pref(\kappa_k, \pi_2)} & \dfrac{pref(\kappa_k, \pi_2)}{pref(\kappa_k, \pi_0) + pref(\kappa_k, \pi_2)} & 0 \end{pmatrix}$$

The computation is done so that, for each column, the sum of the normalized preferences is equal to 1. Now we observe that, for each column on the cross-elasticity matrix, the sum of the coefficients that are not on the diagonal must be equal to $\eta_k \delta_k$. This ensures that the sum for the full column is:

$$\sum_{\pi_j \in P} \epsilon_{j,h}^{(k)} = -\eta_k + \eta_k \delta_k$$

As per the definition of δ_k. The coefficients of the cross-elasticity matrix can therefore be computed as follows:

$$\epsilon_{j,h}^{(k)} = \begin{cases} -\eta_k & if\ j = h \\ \eta_k \delta_k\, npref_h(\kappa_k, \pi_j) & otherwise \end{cases}$$

This approach saves the user of our model from having to specify the value of all the $\epsilon_{j,h}^{(k)}$ coefficients individually.

3.1.5 Energy Demand, Cost and Perception Accuracy

There is a growing awareness that a correct perception of the electricity consumption may be a key factor to enable energy savings and make demand response schemes more effective: this is shown by the increasing diffusion of smart-meters and energy monitoring systems in general. However, only a limited number of works have tried to characterize the dynamics of consumer perception: a few papers, e.g. [16] [17] have focused on perceived prices, and even fewer, e.g. [20] on the accuracy of the consumption estimates.

In particular, the authors of [20] propose to relate perceived and real consumption via a polynomial model in logarithmic scale. The model is calibrated over the estimates provided by a group of users for the consumption of some electric appliances. The authors conclude that people tend to slightly over-estimate low consumption value and considerably under-estimate large values.

In this paper, we take into account the perception accuracy in the demand response behavior. We do not use the model from [20] because it is optimized for interpolation (i.e. prediction on the range of the original training data) and has poor predictive ability when used for extrapolation. Therefore, we opted for a simpler (linear) model *with a bias toward underestimation* of the real consumptions.

The main idea is to view the $\tilde{d}_j^{(k,i)}$ variables from Section 3.1.3 as *perceived variations*. We then introduce a second set of variables $\tilde{r}_j^{(k,i)}$ to represent the corresponding *real variations*. The two sets of variables are related by a linear relation:

$$\tilde{d}_j^{(k,i)} = (1 - \alpha_k)\, \tilde{r}_j^{(k,i)}$$

The α_k parameter is in the range $]0,1]$ and represent the *degree of underestimation* for customer κ_k. We can then use the real variation variable to compute the total electricity demand for each individual customer of class κ_k, in each price band, and for each tariff. Formally, we have:

$$d_j^{(k,i)} = \hat{d}_j^{(k,i)} + \tilde{r}_j^{(k,i)}$$

where the $d_j^{(k,i)}$ represents the total demand. For the original tariff, i.e. $\tau_i = \tau(\kappa_k)$, the total demand will be the same as the original demand, i.e. $d_j^{(k,i)} = \hat{d}_j^{(k,i)}$, because a zero perceived variation corresponds to a zero real variation.

The demand variables $d_j^{(k,i)}$ can be used to compute the *cost of energy* for each individual customer under each tariff: this is the value of the $c_{k,i}$ variables employed in Section 3.1.2 for the tariff selection component of our model. In detail the cost is given by:

$$c_{k,i} = \sum_{\pi_j \in P} p_{i,j}\; d_j^{(k,i)}$$

Overall, the perception and demand component of our model is given by:

$$\begin{aligned}
\tilde{d}_j^{(k,i)} &= \alpha_k\, \tilde{r}_j^{(k,i)} && \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P \\
d_j^{(k,i)} &= \hat{d}_j^{(k,i)} + \tilde{r}_j^{(k,i)} && \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P \\
c_{k,i} &= \sum_{\pi_j \in P} p_{i,j}\; d_j^{(k,i)} && \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P \\
\tilde{r}_j^{(k,i)} &\in \mathbb{R} && \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P \\
d_j^{(k,i)} &\in \mathbb{R}^+ && \forall \kappa_k \in C, \tau_i \in T, \pi_j \in P
\end{aligned}$$

3.1.6 Provider Profit

The total revenue for the energy provider is given by the sum of the energy cost for the customers that adopt an owned tariff. To this quantity we need to subtract the cost that the utility company itself needs to pay in order to provide the energy. Overall, we get:

$$G = \sum_{\kappa_k \in C} \sum_{\pi_j \in P} profit\,(\kappa_k, \pi_j)$$

Where we have:

$$profit(\kappa_k, \pi_j) = \sum_{\tau_i \in T_o} y_{k,i}\, d_j^{(k,i)}\, (p_{i,j} - o_j)$$

For each owned tariff (i.e. $\tau_i \in T_o$), the product $y_{k,i}\, d_j^{(k,i)}$ denotes the total demand of the customers that adopt the tariff. For each unit of consumed energy the provider will earn $p_{i,j}$ units of money, and will need to pay a cost. This cost is given by the o_j term, which represents an overhead value capturing costs due to (e.g.) energy distribution services, taxes, and the wholesale price of electricity.

3.2 Configuration B

Configuration B is similar to configuration A in that the goal is still to find ToU prices that maximize the provided profit. As a major difference, however, in this case the tariff is addressed to a set of *individual, larger customers*, or to a set of buildings managed by a single customer (e.g. public buildings owned by the local municipality). In this context, using a stochastic model for the tariff selection sub-problem is no longer suitable, since each customer will pick a single tariff. As a consequence, the model for the tariff selection sub-problem must be replaced by a deterministic counterpart. All the other model components remain unchanged.

3.2.1 Deterministic Tariff Selection Model

In configuration B each "customer" corresponds to an individual user, who is expected to choose its electricity tariff based on the assessed economical benefits. In practice, each user picks a tariff by solving an optimization model whose objective is in contrast with that of the energy provider. The presence of such conflicting objectives, each pursued by a different agent, is typical of game theory approaches, and it can be difficult to incorporate into an optimization model. In this work, it has been possible to correctly model the user behavior by converting such an optimization problem into a constraint *satisfaction* problem. This is done by formulating the Karush-Kuhn-Tucker (KKT) conditions for the tariff selection sub-problem of each customer.

Karush Kuhn Tucker Conditions: The Karush-Kuhn-Tucker conditions (see for example [24]) are general first order necessary conditions for a point to be a *local* optimum of a *constrained* minimization problem. Under certain circumstances the KKT conditions are both necessary and sufficient to define a global optimum. For example, this happens if both the objective function and the feasible space are convex, because in such case the problem is guaranteed to have a single, global, minimum (assuming that the problem parameters have non-degenerate values). As a consequence, in such case the KKT conditions can be employed to convert an optimization problem into a satisfaction problem.

In this paragraph we present a brief overview of the KKT conditions to better explain their use in our work. The objective function and all constraints of the problem for which the KKT conditions need to be specified must be continuously differentiable over $\mathbb{R}^n$: this is the case for the sub-problem we consider, which will be presented in the following subsection.

The optimality conditions are specified through the use of a Lagrangian Function by introducing a multiplier $\mu_i \geq 0$ for each inequality constraint and a multiplier ν_j for each equality constraint. The KKT conditions state that if x^* is an optimal solution of a problem, then there exist Lagrange multipliers $\mu^* = (\mu_1^*, \dots, \mu_m^*) \geq 0$ and $\nu^* = (\nu_1^*, \dots, \nu_p^*)$ that satisfy certain constraints (here we will not report their general form). Hence, the existence of such multipliers is a necessary condition for a point x^* to be an optimal solution.

In the following paragraph, we will define the tariff selection sub-problem for each customer and then cast it to a constraint satisfaction problem by means of the KKT conditions.

Application of the KKT Conditions to Our Model: Residential users are expected to choose their own tariff (mainly) with the aim to minimize their energy costs. In other words, each user k chooses the tariff by solving an optimization problem, which can be formulated in the following way:

$$\begin{aligned} \min z = & \sum_{\tau_i \in T} y_{k,i} c'_{k,i} \\ & \sum_{\tau_i \in T} y_{k,i} = 1 \\ & y_{k,i} \in \{0,1\} \quad \forall \tau_i \in T \end{aligned}$$

Where we assume that:

$$c'_{k,i} = \begin{cases} c_{k,i} & if\ i = \tau(\kappa_k) \\ (1+\rho_k) c_{k,i} & otherwise \end{cases}$$

The problem is defined so that $y_{k,i}$ variables are defined so that $y_{k,i} = 1$ for the selected tariff and $y_{k,i} = 0$ for all other tariffs. All tariffs except the original are perceived as being more expensive than they actually are by a ρ_k factor, due to the risk aversion. We have therefore obtained (simple) Integer Linear Programing (ILP) problem, which each customer κ_k needs to solve in order to choose a tariff. In the following discussion, we will focus on a single customer, so that the k indices appearing in the equations can be considered constant.

Our aim is to use the KKT conditions to characterize the optimal solution to this problem. This approach requires the objective function and the constraints to be convex, so that the KKT conditions are both necessary *and sufficient*. ILP problems are not convex in general, which poses in principle a difficulty. However, in our case it is possible to replace the original ILP problem with its Linear Programming (LP) relaxation:

$$\begin{aligned} \min z_R = & \sum_{\tau_i \in T} y_{k,i} c'_{k,i} \\ & \sum_{\tau_i \in T} y_{k,i} = 1 \\ & y_{k,i} \geq 0 \quad \forall \tau_i \in T \end{aligned}$$

Where it should be noticed that the integrality constraint has been removed. We have also dropped the explicit upper bound on the $y_{k,i}$ variables, because this is implied by the constraint on the summation. The replacement is possible since for this specific problem we can prove that: 1) the original ILP formulation and its LP relaxation have the same cost, i.e. $z^* = z_R^*$; and more importantly that the optimal LP solution is integer, as long as there the is a only one tariff having minimal cost $c_{k,i}$. A proof of this results is provided in the Appendix of this document.

Now, let μ_i is the multiplier associated with constraints $y_i \geq 0$, and ν_i the multiplier associated with equality constraints ; with these notation, we can define for the problem the following Lagrangian function:

$$\mathcal{L}(y,\mu,\nu) = \sum_{\tau_i \in T} y_{k,i} c'_{k,i} + \nu \left(\sum_{\tau_i \in T} y_{k,i} - 1 \right) - \sum_{\tau_i \in T} \mu_{k,i} y_i \qquad \mu_{k,i} \geq 0, \nu \in \mathbb{R}$$

The KKT conditions for our LP problem state that, if there exist y_i, μ_i and ν values such that:

$$
\begin{aligned}
&c'_{k,i} + \nu - \mu_{k,i} = 0 && \forall \kappa_k \in C, \tau_i \in T \\
&\sum_{\tau_i \in T} y_{k,i} = 1 && \\
&\mu_{k,i}(-y_{k,i}) = 0 && \forall \tau_i \in T \\
&y_{k,i} \geq 0 && \forall \tau_i \in T \\
&\mu_{k,i} \geq 0 && \forall \tau_i \in T \\
&\nu_k \in \mathbb{R} &&
\end{aligned}
$$

then the assignment of $y_{k,i}$ is an optimal solution for the original problem. It is possible to rewrite these conditions by eliminating $\mu_{k,i}$, since:

$$\mu_{k,i} = c'_{k,i} + \nu_k$$

By taking into account all the classes κ_k, we can finally introduce the following constraints in our model:

$$
\begin{aligned}
&\sum_{\tau_i \in T} y_{k,i} = 1 && \forall \kappa_k \in C \\
&y_{k,i} \geq 0 && \forall \kappa_k \in C, \tau_i \in T \\
&c'_{k,i} + \nu_k \geq 0 && \forall \kappa_k \in C, \tau_i \in T \\
&(c'_{k,i} + \nu_k) y_{k,i} = 0 && \forall \kappa_k \in C, \tau_i \in T
\end{aligned}
$$

Provided that there is a single tariff with minimal cost $c'_{k,i}$, the constraints ensure that the $y_{k,i}$ variables are a solution for the original ILP, i.e. that the cheapest tariff is selected. However, in our case some of the the $c'_{k,i}$ terms are decision variables that can be modified by changing the tariff prices. As a consequence, having multiple tariffs with the same, minimal, cost is a real possibility. In such scenario the $y_{k,i}$ variables will be assigned so as to optimize the objective function of the main model (e.g. maximizing the provider profit). For this reason, it is recommended that the risk aversion factor ρ_k is *strictly greater than 0* for all customers: this ensures that a tariff is selected only if it provides a real advantage compared to the original tariff.

3.3 Configuration C

In configuration C, the goal is to identify the customer behavior parameters (in terms of elasticity, risk aversion, and perception accuracy) that lead to the lowest overall electricity cost *at district level*. This operation may allow municipalities to prioritize the goals for local energy policies, or to plan an effective campaign to improve the energy behavior of the citizens. Moving from configuration A to configuration C requires several adjustments to the model, which are discussed in the following sections.

3.3.1 Decision Variables

In configuration C, *all tariffs are assumed to be fixed*. The main decision variables are instead the elasticity index η_k, the conservation index δ_k, the risk aversion factor ρ_k, and the overestimation factor α_k. For each such terms, we assume to have access to an original value, representing the baseline behavior of the customer, and to a range. We refer to the original values as $\eta_k^{(o)}$, $\delta_k^{(o)}$, $\rho_k^{(o)}$, and $\alpha_k^{(o)}$, and to the ranges as

$[\underline{\eta}_k, \overline{\eta}_k]$, $[\underline{\delta}_k, \overline{\delta}_k]$, $[\underline{\rho}_k, \overline{\rho}_k]$, and $[\underline{\alpha}_k, \overline{\alpha}_k]$. We assume that all bounds are consistent with the hypothesis that are necessary for our mode to have physical sense, i.e. $\eta_k \in [0,1]$, $\delta_k \in [0,1]$, $\rho_k \in]0,1]$, $\alpha_k \in [0,1[$.

3.3.2 Cross-Elasticity Matrix

The coefficients of the cross-elasticity matrix $\epsilon_{j,h}^{(k)}$ are computed with an approach similar to the one presented in Section 3.1.4 for configuration A. As a main difference, the *original* elasticity index is used in the computation of the normalized prices, i.e.

$$nprice(\kappa_k, \pi_j) = 1 + \left(\frac{p_{\tau(\kappa_k),j}}{p_{avg}^{(k,i)}} - 1\right)\eta_j^{(o)}$$

The rationale is that the normalized prices are used to infer the user preferences, and this operation should be done by reasoning on the original elasticity rather than on the one suggested by the model. The final value of the elasticity coefficients in the matrix is instead computed based on the decision variables η_k and δ_k:

$$\epsilon_{j,h}^{(k)} = \begin{cases} -\eta_k & if\ j = h \\ \eta_k \delta_k\, npref_h(\kappa_k, \pi_j) & otherwise \end{cases}$$

3.3.3 Inferred Baseline Demand Profile

Adjusting the behavior of a customer may change the corresponding consumption profile, even if there is no tariff switch. On the other hand, if the behavior is not modified than the profile should remain the original one. In order to satisfy both these properties, in configuration C we change the meaning of the $\hat{d}_h^{(k)}$ variables, which in configuration A and B used to represent the original demand. In configuration C, the $\hat{d}_h^{(k)}$ represent an *inferred baseline consumption profile*, which is computed so that if no change of behavior occurs, then the original profile arises.

In practice, we start by obtaining a set of (constant) values for the cross-elasticity matric coefficients corresponding to the original elasticity and conservation index, i.e.:

$$\epsilon_{j,h}^{(k,o)} = \begin{cases} -\eta_k^{(o)} & if\ j = h \\ \eta_k^{(o)} \delta_k^{(o)} npref_h(\kappa_k, \pi_j) & otherwise \end{cases}$$

Then, let $\hat{d}_h^{(k,o)}$ denote the original demand profile. The $\hat{d}_h^{(k)}$ terms are computed by solving the following set of linear equations:

$$\hat{d}_h^{(k,o)} = \hat{d}_h^{(k)} + (1 - \alpha_k^{(o)}) \sum_{\pi_h \in P} \hat{d}_h^{(k)}\, \epsilon_{j,h}^{(k,o)}\, \tilde{p}_h^{(k,\tau(\kappa_k))}$$

This ensures that if the values of η_k, δ_k, α_k found by optimizing the model are identical to the original ones, then we have:

$$d_j^{(k,\tau(\kappa_k))} = \hat{d}_h^{(k,o)}$$

i.e. the demand profile for the original tariff is unchanged. On the other hand, if some behavior parameters are changed, then also the profile with the original tariff is modified accordingly. This allows to assess the effect of behavior changes, even if no tariff switch occurs.

3.3.4 Total Customer Cost

The problem objective in configuration C is minimizing the total customer cost, which is given by:

$$Q = \sum_{\kappa_k \in C} \sum_{\pi_j \in P} cost\,(\kappa_k, \pi_j)$$

with:

$$cost(\kappa_k, \pi_j) = \sum_{\tau_i \in T_o} y_{k,i}\, d_j^{(k,i)} p_{i,j}$$

Since the electricity prices tend to be lower in the band where producing energy is more efficient, by minimizing the cost it is likely that the update demand profile is also more environmentally friendly.

4 Design and Implementation of the DS Tools

Our optimization model is the basis for four decision support tools, addressed to energy providers and local policy makers. Figure 4 shows the role and location of the decision support tools within the main DAREED architecture: the tools are grouped based on the target user (i.e. energy providers and policy makers), and, once the integration will be completed, they will rely on information supplied from the Knowledge Manager to provide high-level functionalities to the end users. In detail, the tools are as follows:

- **Tool 1, for energy providers:** *"Obtain Price Suggestions for a District". Acronym: STD (Suggest Tariff District).* This tool allows one to obtain recommendation for ToU prices over a district, and it is based on the solution of our model in configuration A.
- **Tool 2, for energy providers:** *"Obtain Price Suggestions for Groups of Buildings". Acronym: STB (Suggest Tariff Buildings).* This tool allows one to obtain recommendation for ToU prices tailored for a group of large sources of consumption (e.g. a group of public buildings), and it is based on the solution of our model in configuration B.
- **Tool 3, for policy makers:** *"Identify Ideal Customer Behavior". Acronym: SOB (Suggest Optimal Behavior)*. This tool allows one to identify the customer behavior parameters that lead to the lowest electricity consumption cost. The tool is designed to operate at district level and it is based on the solution of our model in configuration C.
- **Tool 4, for policy makers:** *"Simulate Energy Provider's Behavior". Acronym: SPB (Suggest Provider Behavior)*. This tool allows to make a quick assessment of how an energy provider would likely respond to changes in the behavior of the customers. This is intended as a complement to the SOB tool, with the aim to evaluate the robustness of the advantages the customers may obtain via changes

of behavior. The tool is based on the solution of our mode in configuration A, and will output the optimal (from the point of view of the provider) prices for a single ToU based tariff, plus consumption and cost information for all the customers.

For the development of the tools we have adopted a three tier approach. In particular, we have chosen to expose (web) services that allow one to solve our model in configuration A, B, and C: this conforms to one of the main design guidelines for the DAREED platform, which envisions a service layer that provides the foundation for the platform functionalities. In detail, for the decision support tools we have that:

- **Tier 1** corresponds to a back-end for the basic functionalities offered by our tools. In particular, Tier 1 includes the non-linear optimization solver that we use for our model, plus a Database Management System (DBMS) that we use to store data specific to the tools.
- **Tier 2** consists of a set of web services that rely on Tier 1 to expose a REST-like API. The services allow one to access the local datable, and to solve the optimization model in configuration A, B, C.
- **Tier 3** consists of a four single-page web applications that provide the GUI of our four tools.

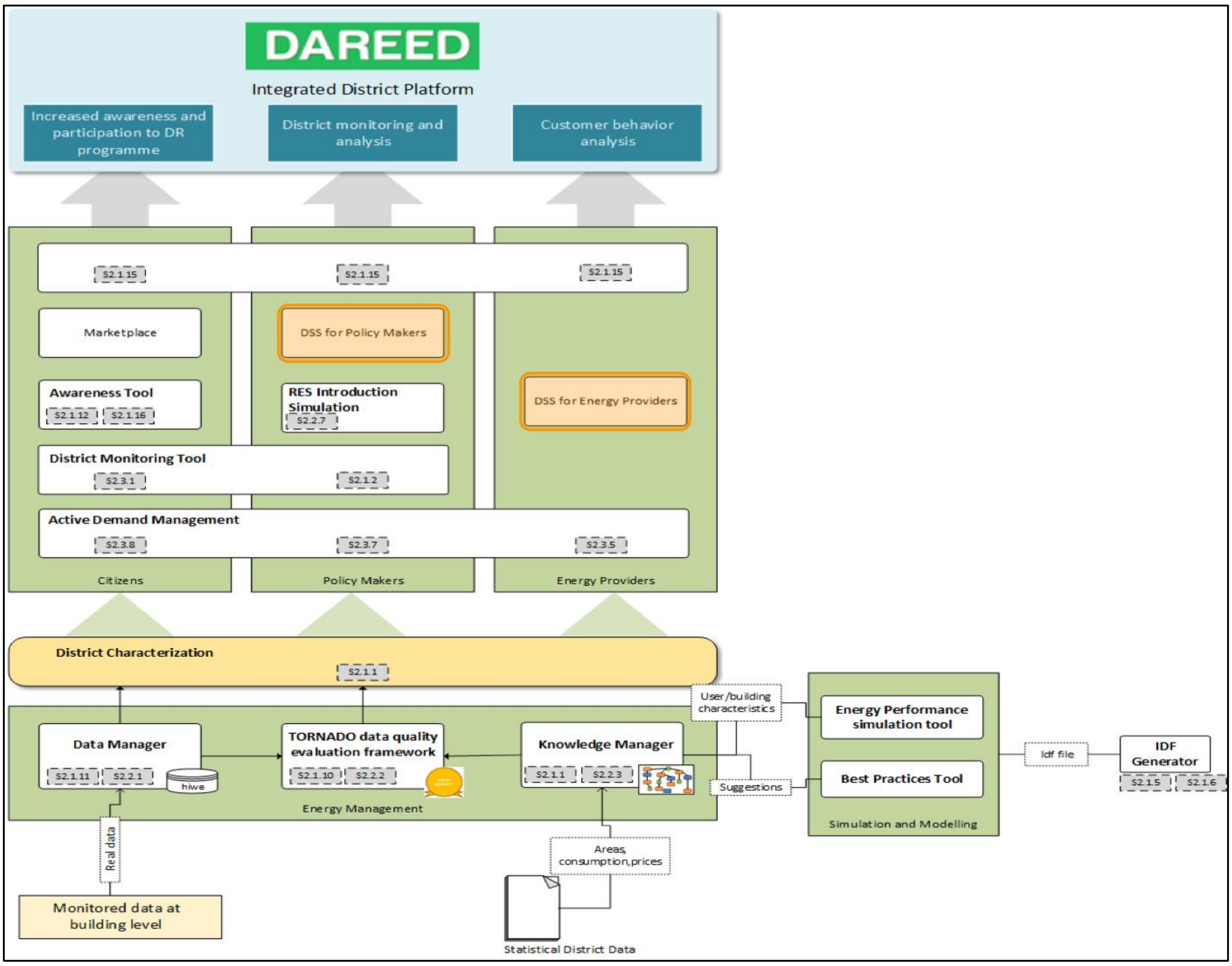

Figure 4: Location of the Decision Support Tools within the main DAREED architecture

All the tools and services should be considered as prototypes at this stage. The local DBMS is currently used to store all the necessary data, but a lot of information will be moved in the DAREED Knowledge manager as part of the integration process in the next few months.

In the following sections, we will discuss the content of each tier, providing and overview of their design and implementation. The discussion will be kept as brief as possible, while at the same time attempting to provide all the most important pieces of information.

4.1 Tier 1: Solver and DBMS

We perform optimization via the SCIP solver (Solving Constraint Integer Problems), developed at the Zuse Institute, in Berlin[2]. SCIP is currently one of the best performing solvers for Linear and Non Linear mathematical optimization problems, and can be employed for free for research purpose.

We input an instantiation of our model to the SCIP solver by means of a text file written in the ZIMPL language. ZIMPL is a modeling language designed by people from the Zuse Institute, and suitable for describing both linear and non-linear optimization problems.

As a DBMS, our prototypes are employing MongoDB[3], which is also free to use for research purpose. Since we rely on a database only for simple operations (namely: storing the description of optimization problems and solutions) MongoDB could be easily replaced by another document based DBMS.

4.2 Tier 2: Web Services

Tiers 2 consists of a collection of web services with a RESTful or REST-like API (depending on the service). The web services provide in particular: (1) access to collection of problem descriptions (i.e. scenarios) and solutions for the four tools; and (2) access to the optimization services for the three model configurations.

All the services are implemented using the *express.js* module for *node.js*, which was chosen because of its efficiency and its ability to handle easily asynchronous operations. In particular, all the solution services are implemented by spawning SCIP as an external process, and then collecting the solver output from text files once the execution is over.

In the following sections we will present the interface (input/output) of each service.

4.2.1 DBMS Access Services

We have developed a DBMS access service for each of the four tools. Each service allows to store descriptions of specific optimization problems, referred to as “scenarios” in the remainder of this document. Each scenario is stored as an object, described in JSON format, and may include a description of its solution (if one has been obtained via the optimization services).

All DMBS services expose a RESTful API, designed according to the guidelines from http://jsonapi.org. In particular, POST requests add a new scenario, GET requests return either a single scenario (if an id is

[2] See the product web site: http://scip.zib.de
[3] See the product web site: https://www.mongodb.org

provided) or the list of all scenarios, PUT requests can be used to replace an existing scenario. POST and PUT requests should contain as payload the JSON description of the scenario to be added/updated.

The content of a scenario object differs slightly for tools 1, 2, 4 and for tool 3. The format is designed to be used by the web GUIs and does not match the format used by the optimization services (which will be discussed later).

4.2.1.1 DBMS Access for Tool 1 (STD), Tool 2 (STB), and Tool 4 (SPB)

The services are available at the addresses:

- `[server]/api/stdscenarios`
- `[server]/api/stbscenarios`
- `[server]/api/spbscenarios`

Tools 1, 2, and 3 employ the same scenario description. A scenario in this case is an object with the following JSON representation:

```
{
  “description”: <string>,
  “priceBands”: <PriceBand object>,
  “fixedTariffs”: [<FixedTariff object>],
  “variableTariffs”: [<VariableTariff object>],
  “fixedCosts”: [<Number object>],
  “price_lb”: <number>,
  “price_ub”: <number>,
  “customers”: [<Customer object>]
}
```

Where “description” is a string that describes briefly the scenario, while “price_lb” and “price_ub” correspond the value of the $\underline{p}_{i,j}$ and $\overline{p}_{i,j}$ bounds in the model. Note that for simplicity in the prototypes we employ a single lower bound and a single upper for all prices, despite the model allows for customized bounds on each price. The “fixedCosts” fields specifies (as a list of Number objects) the value of the cost of electricity for each price band, i.e. the value of the o_j parameters in the model.

Most of the elements in the description are secondary objects or lists of secondary objects. In particular, a PriceBand object has the following JSON description:

```
{
  “name”: <string>,
  “hourCount”: [<number>],
  “priceBandNames”: [<string>]
}
```

Where “name” is the name of the considered price band system, and “hourCounts” is a list containing all the $|\pi_j|$ values that are necessary for the model. Finally, “priceBandNames” is just a list with the names of all price bands. The number of price bands is specified implicitly via the length of the lists.

FixedTariff objects have the following description:

```
{
  “name”: <string>,
  “prices”: [<Number object>],
  “owned”: <boolean>
}
```

Where “prices” is a list of Number objects that specify the value of the prices for the fixed tariff. The “owned” field is “true” if the tariff is owned by the provider, and “false” for tariffs offered by competitors. Number objects are in the form:

```
{
  “val”: <number>
}
```

Number objects are sometimes used instead of simple numbers because that simplifies the implementation of the web GUIs. VariableTariff objects correspond to the tariffs whose prices are decided by solving the model. They are in the form:

```
{
  “name”: <string>
}
```

I.e. they specify simply the name of the tariff. Finally, Customer objects are in the form:

```
{
  "name":<string>,
  "originalTariff": <number>,
  "originalDemand": [<Number object>],
   "elasticityIndex": <number>,
   "conservationIndex": <number>,
   "riskAversionIndex": <number>,
   "perceptionAccuracyIndex": <number>
}
```

The “originalTariff” field is an integer that specified which of the fixed tariffs is originally used by the customer: it corresponds to the the $\tau(\kappa_k)$ parameter in the model. The “originalDemand” field specifies the values of the $\hat{d}_h^{(k)}$ parameters in the model (i.e. the original demand in each price band). For the remaining fields we have:

- “elasticityIndex” corresponds to the η_k parameter in the model. It is specified as an integer percentage and should range over {0..100}
- “conservationIndex” corresponds to the δ_k parameter in the model. It is specified as an integer percentage and should range over {0..100}
- “riskAversionIndex” corresponds to the ρ_k parameter in the model. It is specified as an integer percentage and should range over {1..100}
- “perceptionAccuracyIndex” corresponds to the $-\alpha_k$ term in the model. It is specified as a negative integer percentage and should range over {-99..0}. A negative value is used here for reason of

compatibility with earlier versions of the code: it is possible that a modification will be done in the future to make the API more consistent.

4.2.1.2 DBMS Access for Tool 3 (SOB)

The service is available at the address:

- `[server]/api/sobscenarios`

A scenario for the SOB tool is an object with the following JSON representation:

```
{
   “description”: <string>,
   “priceBands”: <PriceBand object>,
   “fixedTariffs”: [<FixedTariff object>],
   “customers”: [<SOBCustomer object>]
}
```

There are several differences w.r.t. the scenario object used by the STD, STB, and SPB tool (i.e. STDScenario). The variable tariffs are missing (since all tariffs are assumed to be fixed when the model is used in configuration C), no price bounds are specified (since all tariffs are fixed), and the fixed costs of electricity are not provided.

Customers are described using a specialized SOBCustomer object, in the form:

```
{
   “name”: <string>,
   “originalTariff”: <number>,
   “originalDemand”: [<Number object>],
    "elasticityIndex": <number>,
    "conservationIndex": <number>,
    "riskAversionIndex": <number>,
    "perceptionAccuracyIndex": <number>,
    "elasticityIndexVar": <number>,
    "conservationIndexVar": <number>,
    "riskAversionIndexVar": <number>,
    "perceptionAccuracyIndexVar": <number>
}
```

All fields that we already appearing in Customer objects are defined as before, except that “elasticityIndex”, “conservationIndex”, “perceptionAccuracyIndex”, “riskAversionIndex” now specify the *original* values of the behavior parameters, i.e. the value of $\eta_k^{(o)}$, $\delta_k^{(o)}$, $-\alpha_k^{(o)}$, $\rho_k^{(o)}$.

The new fields in the form “_IndexVar” define the ranges for all η_k, δ_k, $-\alpha_k$, ρ_k (i.e. the main decision variables of the model in configuration C). In particular, the ranges are computed as:

```
lower bound = (_Index - _IndexVar)/100
upper bound = (_Index + _IndexVar)/100
```

This also implies that the variations are always expressed as a (integer) percentages, taking value over the range {0..100}.

4.2.2 Optimization Services

We have designed an implemented an optimization service for each of the model configurations. In particular, we have that:

- The service for configuration A is available at `[server]/api/suggest-tariff-district`
- The service for configuration B is available at `[server]/api/suggest-tariff-buildings`
- The service for configuration C is available at `[server]/api/suggest-optimal-behavior`

All services are invoked via POST requests. The request content is essentially a scenario, although the format is different from that used by the DBMS services.

All the optimization services can be called by specifying a time limit for the solver, via the query string parameter “timelimit”. If an explicit time limit is not provided, then a default value of 10 seconds is assumed. The largest possible time limit is 300 seconds (larger values are simply capped at 300). If the solver has not proved optimality when the time limit is reached, then a solution will (usually) still be returned, typically together with an optimality gap that allows one to estimate the solution quality.

All the optimization services can be called by specifying a starting solution: this allow to boost the optimization process via a warm start.

By combining time limits and warm starts it is possible to control the response time of the optimization services. In particular, all our GUIs start by calling the service with a time limit of 2 seconds. If optimality is not proved, the GUIs make further calls: each time the time limit is doubled and the best solution found so far is used for a warm start. The last call happens when the time limit reaches 60 seconds.

4.2.3 Request and Response format for Configuration A and B

The optimization services for configuration A and B share the same format for the request and the response. The only difference is that configuration A employs our stochastic tariff selection sub-problem, so that customers will “spread” over the available tariffs. Conversely, configuration B employs the deterministic tariff selection sub-problem, and each customer will adopt a single tariff.

The request should have the following format:

```
{
  “scenario”: <STDScenario object>,    // The scenario to be solved
  “solution”: <STDSolution object>     // The solution for a warm start
}
```

Where STDScenario should have the format (descriptions are provided next to the field name):

```
{
  “n_price_bands”: <number>,           // |P| in the model
  “n_customers”: <number>,             // |C| in the model
  “n_tariffs”: <number>,               // |T| in the model
  “hour_count”: [<number>]             // Value of |π_j| for each price band
  “owned_tariffs”: [<number>],         // Values of T_o (integer indices)
```

```
  "fixed_tariffs": [<number>],          // Values of $T_f$ (integer indices)
  "fixed_cost": [<number>],             // Values of $o_j$ in the model
  "price_lb": <number>,                 // A unique value for all $\underline{p}_{i,j}$
  "price_ub": <number>,                 // A unique value for all $\overline{p}_{i,j}$
  "fixed_price": <number>,              // Values of $p_{i,j}$ for the fixed tariffs
  "original_tariff": [<number>]         // Value of $\tau(\kappa_k)$ for each customer
  "original_demand":[[<number>]]        // Value of $\hat{d}_h^{(k)}$for each cstm. and price band
  "risk_aversion": [<number>]           // Value of $1 + \rho_k$ for each customer
  "perception_accuracy": [<number>]     // Value of $\alpha_k$ for each customer
  "elasticity": [<number>]              // Value of $\eta_k$ for each customer
  "conservation": [<number>]            // Value of $\delta_k$ for each customer
}
```

Note that "risk_aversion" should specify the value of the expressions $1 + \rho_k$ rather than simply the value of ρ_k. This is done for compatibility with earlier version of the code and may be modified in the future to make the API more consistent. It is also assumed the indices of the fixed tariffs are lower than those of the variable tariffs.

STDSolution objects are returned by the optimization services, and can be passed with the POST request to make the solver perform a warm start. The format for the object is:

```
{
  "status": <string>,              // "optimal", "feasible", "infeasible", "unknown"
  "objective": <number>,           // Value of the total profit $G$
  "switch_ratio": [[<number]],     // Value of $y_{k,i}$ for each customer and tariff
  "price": [[<number>]],           // Value of $p_{i,j}$ for each tariff and band
  "dmd_real": [[[<number>]]],      // Value of $d_j^{(k,i)}$ for each tariff, cstm., and band
  "dmd_perc": [[[<number>]]],     // Value of $\hat{d}_j^{(k,i)} + \tilde{d}_j^{(k,i)}$ for each tariff, cstm., and band
  "rawdata": <string>,             // Solution in raw format (returned by the solver)
  "bound": <number>,               // Best available upper bound for $G$
}
```

In terms of the API, the only difference between the configuration A service and the configuration B service is that in the former the "switch_ratio" fields will contain fractional values, while in the latter only integer values will be provided (either 0 or 1, depending on whether a customer adopts a tariff).

4.2.4 Request and Response format for Configuration C

The optimization service for configuration C employs a slightly different format for the request and the response. In particular, a request should be in the format:

```
{
  "scenario": <SOBScenario object>,    // The scenario to be solved
  "solution": <SOBSolution object>     // The solution for a warm start
}
```

Where a SOBScenario object is described instead as:

```
{
   "n_price_bands": <number>,            // $|P|$ in the model
   "n_customers": <number>,              // $|C|$ in the model
   "n_tariffs": <number>,                // $|T|$ in the model
   "hour_count": [<number>]              // Value of $|\pi_j|$ for each price band
   "fixed_price": [<number>],            // Values of $p_{i,j}$ for the fixed tariffs
   "original_tariff": [<number>]         // Value of $\tau(\kappa_k)$ for each customer
   "original_demand":[[<number>]]        // Value of $\hat{d}_h^{(k)}$for each cust. and price band
   "risk_aversion": [<number>]           // Value of $1+\rho_k^{(o)}$ for each customer
   "perception_accuracy": [<number>]     // Value of $\alpha_k^{(o)}$ for each customer
   "elasticity": [<number>]              // Value of $\eta_k^{(o)}$ for each customer
   "conservation": [<number>]            // Value of $\delta_k^{(o)}$ for each customer
   "risk_aversion_var": [<number>]           // Variability for $\rho_k$
   "perception_accuracy_var": [<number>]     // Variability for $\alpha_k$
   "elasticity_var": [<number>]              // Variability for $\eta_k$
   "conservation_var": [<number>]            // Variability for $\delta_k$
}
```

Where all variability values are in the range $[0,1]$ and are used to obtain the bounds on the behavior parameters, i.e. the main decision variables for the model in configuration A. For example, the bounds for ρ_k are obtained as:

$$\underline{\rho}_k = \rho_k^{(o)} - variability(\rho_k)$$

$$\overline{\rho}_k = \rho_k^{(o)} + variability(\rho_k)$$

If the bounds exceed the feasible range for the behavior parameter, then the value is capped.

The form for the SOBSolution objects returned by the optimization service for configuration C is:

```
{
   "status": <string>,              // "optimal", "feasible", "infeasible", "unknown"
   "objective": <number>,           // Value of the total cost $Q$
   "switch_ratio": [[<number]],     // Value of $y_{k,i}$ for each customer and tariff
   "price": [[<number>]],           // Value of $p_{i,j}$ for each tariff and band
   "dmd_real": [[[<number>]]],      // Value of $d_j^{(k,i)}$ for each tariff, cstm., and band
   "dmd_perc": [[[<number>]]],    // Value of $\hat{d}_j^{(k,i)} + \tilde{d}_j^{(k,i)}$ for each tariff, cstm., and band
   "elasticity": [<number],         // Value of $\eta_k$ for each customer
   "conservation": [<number],       // Value of $\delta$ for each customer
   "risk_aversion": [<number],      // Value of $\rho_k$ for each customer
   "perception_accuracy": [<number], // Value of $\alpha_k$ for each customer
   "rawdata": <string>,             // Solution in raw format (returned by the solver)
   "bound": <number>,               // Best available lower bound for $Q$
}
```

The format is identical to that of STDSolution, but there are additional fields to contain the optimized values of the behavior parameters.

4.3 Tier 3: Web GUIs

Tier 3 contains four web GUIs (one for each tool), developed using the Ember[4] framework for single-page web applications. Each GUI allows to define and edit scenarios for the STD, STB, SOB, or SPB tools, to solve the scenarios and to inspect the solutions. From the main DAREED GUI, the decision support tools appear as icons in the “tools panel”, under the “decision support and energy awareness” label (see Figure 5). As for the other platform functionalities, access to the tools is restricted, depending on the role/class of the user (e.g. only energy providers will be able to access the STD and STB tools)

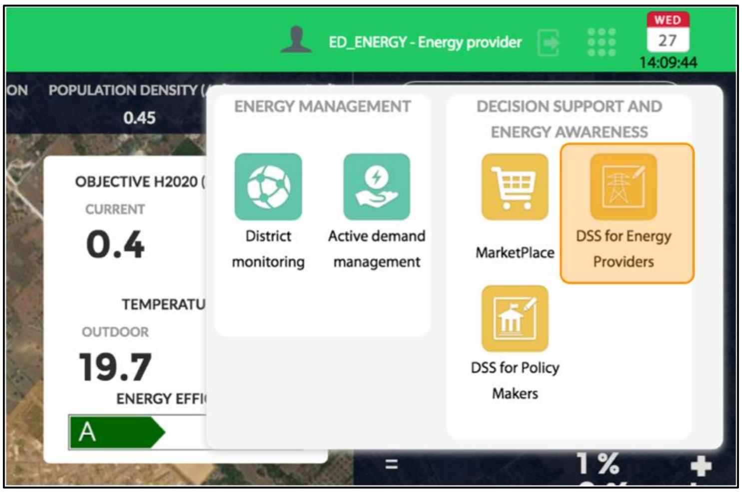

Figure 5: Decision support tools in the main DAREED GUI

In this section, we present, as examples, the main GUI for the STD tool.

Adding a new scenario: Adding a new scenario requires to input a minimal amount of information. In particular, the user has to specify a name and a price band scheme. The price bands are currently selected from a pre-populated list, but future versions of the tools will use a central repository stored on the DAREED Knowledge Manager. A screenshot for the scenario addition form is reported in Figure 6.

Figure 6: Screenshot for the scenario addition form (STD tool)

[4] See the product web site: http://emberjs.com

Populate a scenario: Next, the user has to configure the scenario by providing some general information and then adding fixed tariffs, variable tariffs, and customers. Each of these entities can be configured using a specialized GUI element: the information to be provided matches that of the DBMS services, and therefore will not be described in details. Scenarios can be “cloned” using the corresponding button, to facilitate experimentations with different parameter values.

Currently, all information must be provided manually. Once the tool integration is over, however, the scenario will be automatically pre-populated based on information from the DAREED knowledge base. Some data will still need to be provided manually, however (e.g. all behavior parameters), and the user will be able to adjust the configuration according to his/her needs (e.g. by adding or modifying customers and tariffs).

Screenshots of the main GUI elements are provided in Figure 7, Figure 8, and Figure 9.

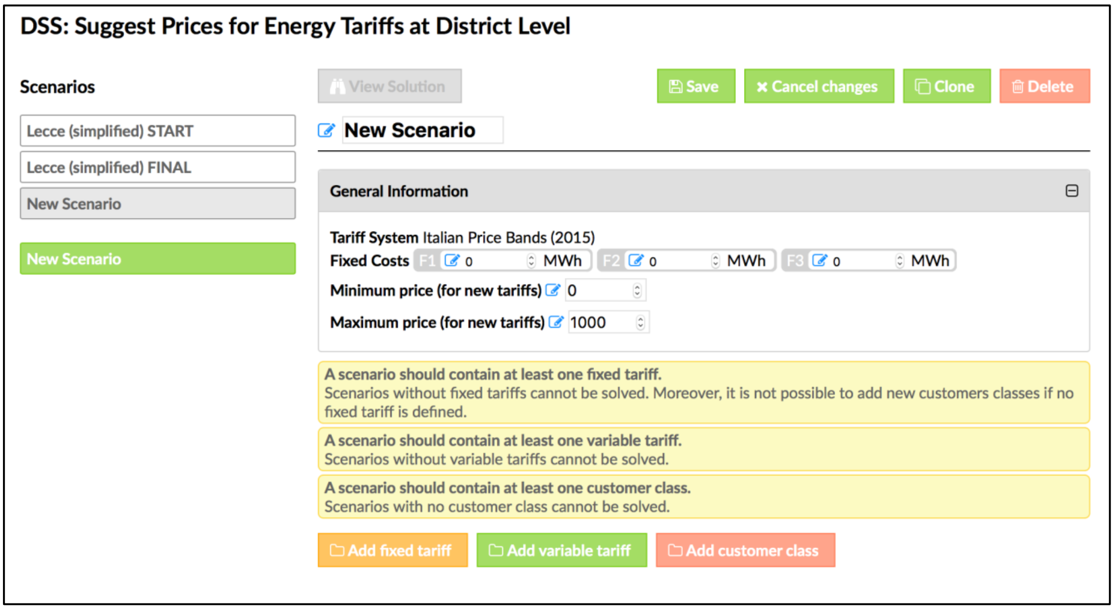

Figure 7: GUI element for editing general scenario information (STD tool)

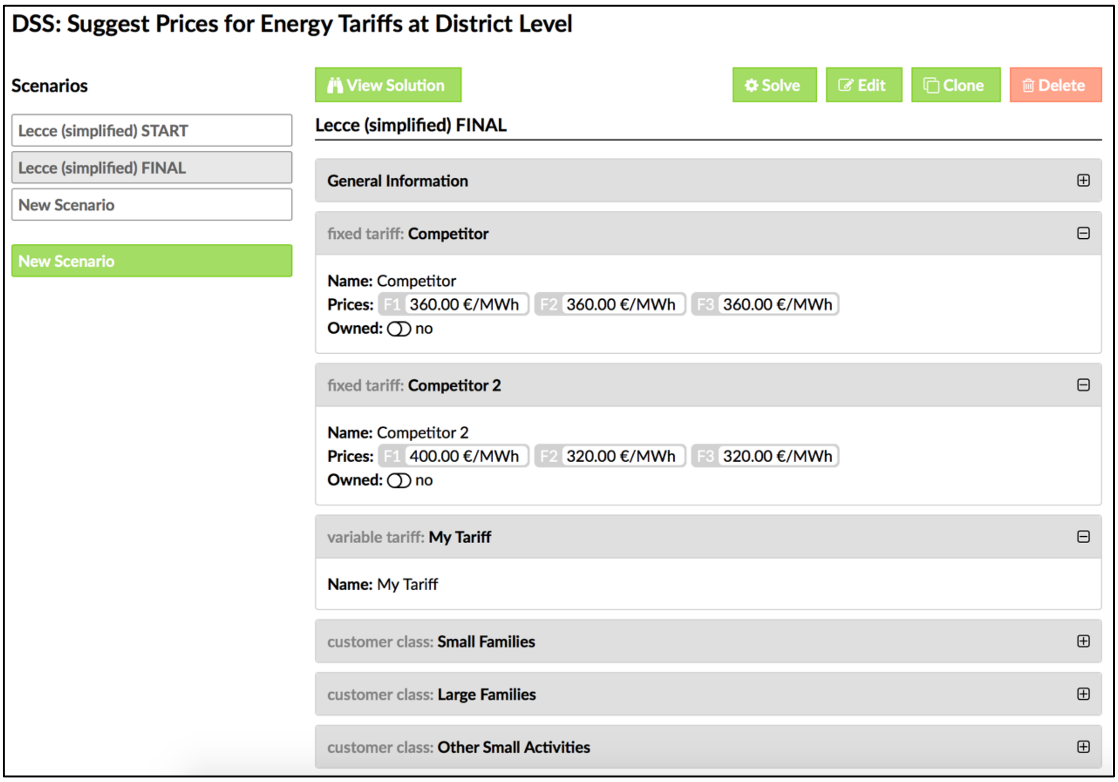

Figure 8: GUI elements to configure fixed and variable tariffs

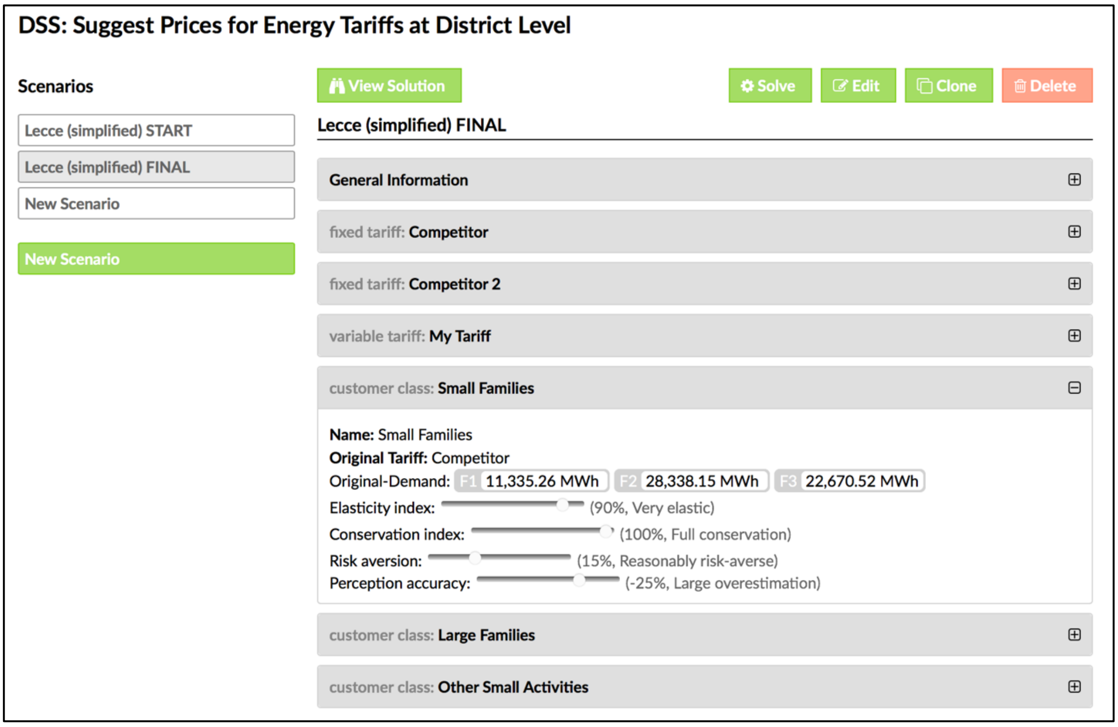

Figure 9: GUI element for configuring a customer (STD tool)

Solving a scenario: A scenario can be solved by clicking on the corresponding button. This will start the solution process, that can be stopped at any time by clicking another button. By clicking the "View Solution" button the user can access a set of GUI elements that allow one to explore the solution. In particular, for the STD tool it is possible to inspect:

- The solution state and the optimality gap (0% if the solution is proven optimal)
- The optimized prices for the variable tariffs
- The expected customer costs, revenues, and profit
- The *overall* distribution of the electricity demand in each price band
- The fraction of each customer class that switched to each tariff
- The distribution of the electricity demand *of each customer* over the price bands
- The electricity cost for each customer in each price band
- The total cost of electricity for each customer, with each tariff

Some of the GUI elements for inspecting an STD solution are visible in the screenshot from Figure 10.

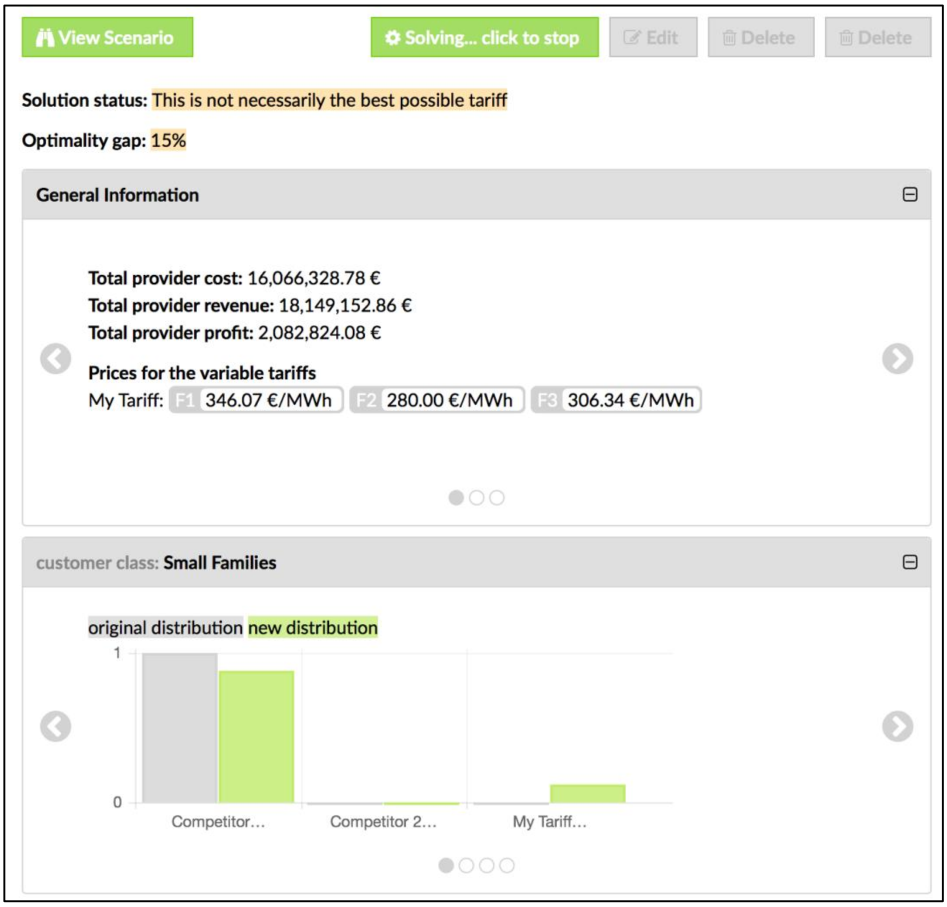

Figure 10: Some GUI elements to inspect a solution (STD tool)

5 A Small Use Case for the Lizzanello Pilot

We conclude the deliverable with a small use case for the Lizzanello pilot. The use case has been defined using approximate data and cannot be considered part of the project validation: rather, it is provided to give an idea of how our decision support tools can be used obtain some useful information. We have chosen to present examples for the STD and SOB tools.

5.1 Case Study for the STD Tool

All Italian electricity tariffs must be defined on a standard scheme including three price bands, corresponding roughly to (1) working days, (2) evenings and Saturdays, and (3) nights and Sundays.

We have chosen to define three "customers" based on two of the consumption classes that are taken into account in the DAREED platform. Since the data for the Lizzanello district in the platform is still incomplete, we have estimated the demand of each customer in each price band based on publicly available energy and census data. In detail, based on the "Residential" and "Care" consumption classes we have defined the customers:

Residential (small groups): this customer represents households with a small number of people, which are expected to have relatively high flexibility, but lower overall consumption, and therefore probably a non negligible degree of risk aversion. The configuration for this group is as follows:

Demand:	**F1:** 1,192.62 MWh **F2:** 1,700.82 MWh **F3:** 1,942.62 MWh
Elasticity index:	90%
Conservation index:	100% (full conservation)
Risk aversion:	10% (at least 10% savings to consider a tariff switch)
Perception accuracy:	-25% (large overestimation)

Residential (large groups): this customer represents households with a larger number of people, which are expected to have lower flexibility, but larger overall consumption, and therefore (probably) lower risk aversion. The configuration for this group is as follows:

Demand:	**F1:** 2,816.29 MWh **F2:** 3,755.05 MWh **F3:** 2,816.29 MWh
Elasticity index:	80%
Conservation index:	100% (full conservation)
Risk aversion:	5% (at least 5% savings to consider a tariff switch)
Perception accuracy:	-25% (large overestimation)

Care: this customer represents sports and assistance centers, and similar service buildings. Mixing this type of customers with residential ones in a real setting is probably not a good idea, but for sake of demonstration this gives the possibility to consider a quite different type of electricity consumer. In particular, in this case the demand will be concentrated in the F1 and F2 bands. The configuration for this group is as follows:

Demand:	**F1:** 3,129.21MWh **F2:** 3,129.21 MWh **F3:** 853.42 MWh
Elasticity index:	65%

Conservation index:	100% (full conservation)
Risk aversion:	5% (at least 10% savings to consider a tariff switch)
Perception accuracy:	-10% (reasonable overestimation)

We assume the existence of **two tariffs offered by competitors**. The first one is a flat tariff with a price of 360 K€/MWh (i.e. 0.360 €/KWh) in all price bands. The second tariff has a larger price in F1 (400 K€/MWh), but a lower price in F2 and F3 (300 K€/MWh). All customer classes are originally with the flat tariff.

We assume that the cost of electricity is 300 K€/MWh in F1 and 280 K€/MWh in F2 and F3: these values have been estimated based on public data on energy price, energy distribution costs, and energy taxes.

By **solving the model** for a single variable tariff we obtain recommended prices of 425.15 K€/MWh in F1, 280 K€/MWh in F2, and 289.47 K€/MWh in F2. The estimated profit is 278 K€.

The new tariff is especially appealing for larger residential customer, which exhibit the largest amount of savings and (thanks also to the lower risk aversion) the largest number of tariff switches (see Figure 11 and Figure 12). The savings are less significant for smaller residential customers, which leads to fewer tariff switches (see Figure 13). The number of switches for the “Care” class is larger than expected, thanks to the low price of the new tariff for F2 (where the “Care” consumption is significant) and to the low risk aversion (see Figure 14).

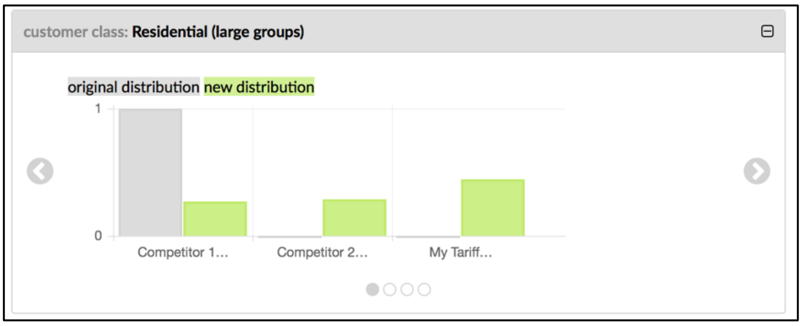

Figure 11: Distribution of larger residential customers (STD use case)

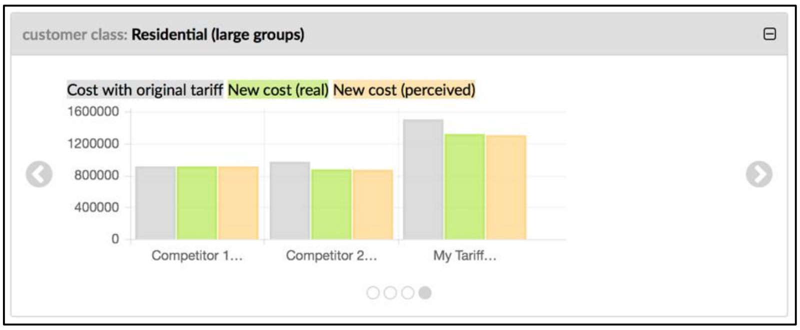

Figure 12: Costs with the three tariffs for larger residential customers (STD use case)

Figure 13: Distribution of smaller residential customers (STD use case)

Figure 14: Distribution of smaller residential customers (STD use case)

5.2 Case Study for the SOB Tool

For our case study with the SOB tool we use a setup similar to that of the STD case. In particular, we have the same set of customers with the same demand profile and the same baseline value of the behavior parameters.

We assume the existence of two (fixed) tariffs. The first one has a price in F1 of 370 K€/MWh, and 350 K€/MWh in F2 and F3. The second tariffs has a larger discrepancy, with a price in F1 of 400 K€/MWh, and 300 K€/MWh in F2 and F3. All customer classes are originally with the first tariff.

Initially we allow no variability on the behavior parameters, in order to evaluate the baseline demand and cost profiles of the customers. We solve the problem and we observe that the smaller residential groups, who have a high flexibility, do not switch to the second tariff, despite it intuitively should provide some savings (see Figure 15).

Figure 15: Initial distribution of smaller residential customers (SOB use case)

We therefore decide to investigate if increasing the accuracy of perception or decreasing the risk aversion of this customer could lead to a different behavior. If we find that this is the case, it may be worthwhile to run an information campaign to increase the awareness that savings can be obtained by switching, or to encourage the installation of consumption monitoring systems.

With the aim to investigate this hypothesis we allow up to 5% variations on the risk aversion (e.g. because larger values are deemed unrealistic) and up to 20% variations on the accuracy of perception (because installing a monitoring system would dramatically improve the quality of the consumption estimates).

We solve the problem again, and the system suggest that indeed the risk aversion should be decreased and the accuracy of perception should be increased as much as possible (see Figure 16). If the smaller residential customers could be encourage to take this behavior, then some tariff switches would occur (see Figure 17) and the total cost of electricity would decrease.

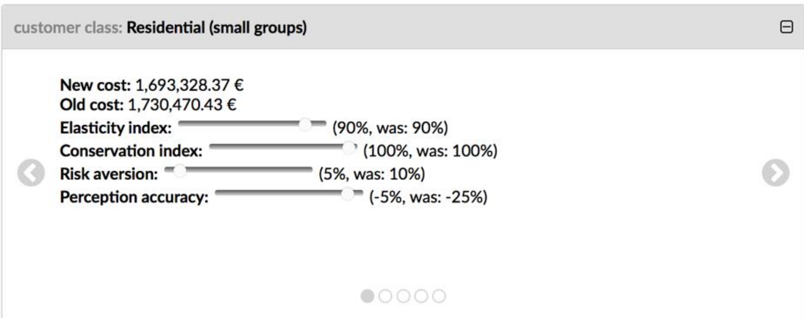

Figure 16: Optimal values of the behavior parameters for smaller residential customers (SOB use case)

Figure 17: Final distribution of the smaller residential customers (SOB use case)

6 Concluding Remarks

In this deliverable we have described the current outcome of the activities of tasks T5.2 and T5.3 in WP5. The goal of the tasks was to design software tools to support energy providers in the definition of new business models, and policy makers in the definition of new policies.

On this purpose, we have devised a complex and flexible non-linear optimization model, and we have shown how it can be adapted to provide suggestions on a number of tasks. The most innovative aspects of the model are the support for multiple tariffs (useful to consider competitors), and the ability to take into account some cognitive aspects of the customer behavior (elasticity, risk aversion, accuracy of perception).

We have devised two tools that allow energy providers to obtain price recommendations for ToU based tariffs at district level, or specifically tailored ToU based tariffs for large customers (e.g. public buildings owned by local municipalities). Since we can model the presence of competitors, the tariff suggested by the system need to be beneficial for the customers, or they won’t adopt them and the provider will get not profit.

For policy makers, we have devised a second pair of tools. The first one allows local municipalities to quickly identify how the behavior of the customers could be adjusted so as to minimize the total cost of electricity (which usually results also in a more environmentally friendly consumption). This information will likely prove valuable in the definition of incentive schemes or campaigns to encourage specific actions (e.g. the installation of monitoring systems). The second tool is a complement to the first one and allows a policy maker to assess the likely response of an energy provider to a change of the customer behavior.

For the rest for project, our efforts will be directed toward: (1) the integration of the developed tools with the main DAREED platform, mainly by relying on the Knowledge Manager to obtain and export useful information; and (2) on the validation of the results via tests on the pilot data.

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8 Appendix

Let the integer version of the deterministic tariff selection sub-problem be referred to as (ILP):

$$\begin{aligned} \min z_I = & \sum_{\tau_i \in T} y_{k,i} c'_{k,i} \\ & \sum_{\tau_i \in T} y_{k,i} = 1 \qquad (1) \\ & y_{k,i} \in \{0,1\} \quad \forall \tau_i \in T \end{aligned}$$

And let the corresponding LP relaxation bet referred to as (LP):

$$\begin{aligned} \min z_L = & \sum_{\tau_i \in T} y_{k,i} c'_{k,i} \\ & \sum_{\tau_i \in T} y_{k,i} = 1 \qquad (1) \\ & y_{k,i} \geq 0 \quad \forall \tau_i \in T \end{aligned}$$

We want to prove that (banning degenerate cases) the optimal solution of the LP relaxation is integer and therefore feasible for the original problem.

Let z_I^* and z_L^* be the optimal solutions of (ILP) and (LP). Since in (LP) we are minimizing the same objective function over a larger set of solutions, we have:

$$z_L^* \leq z_I^* \quad (2)$$

Moreover, because of Constraint (1), z_L is a convex combination of the $c_{k,i}$ values, i.e. a linear combination where all coefficients are non-negative and sum up to 1. We therefore have that:

$$\min(c'_{k,i}) \leq z_L \leq \max(c'_{k,i}) \quad (3)$$

Now, it is possible to observe that the optimal solution of (ILP) is obtained by assigning to 1 the $y_{I,i}$ variable associated to the smallest cost. As a consequence, we have:

$$z_I^* = min(c'_{k,i}) \quad (4)$$

By combining Equation (3), and (4) we obtain:

$$z_L^* \geq min(c'_{k,i}) = z_I^* \quad (5)$$

And finally, by combining Equation (2) and (5) it is possible to derive that:

$$z_L^* = z_I^* \quad (6)$$

i.e. the relaxed problem has the same optimal cost as the original problem.

In order to satisfy condition (6) and have $\sum_{\tau_i \in T} y_{k,i} = 1$, it is necessary in (LP) to have all $y_{k,i} = 0$, to the exclusion of the $y_{k,i}$ variables associated to the minimal $c'_{k,i}$, i.e. to the optimal cost of (ILP). Unless there are multiple $c'_{k,i}$ values equal to $\min(c'_{k.i})$, this means that a single $y_{k,i}$ will be assigned to 1 in (LP), and hence that the solution is integer.