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Individualized time-dependent water pricing for residential consumers

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We consider a water supplier that provides water to residential consumers. The supplier desires the ability to control the consumption and the funds to protect, maintain, upgrade and expand the available infrastructure. To do so, the supplier implements individualized dynamic pricing that maximizes the weighted sum of the total supplier profits and the total consumer convenience. The supplier has the constraint of providing water cheap enough to allow consumers to fulfill their basic needs, but expensive enough to discourage them from consuming too much, depleting the reserves and congesting and deteriorating the available infrastructure. Our work contributes to the literature by providing the mathematical formulation and solution of an individualized time-dependent pricing problem, so the supplier can determine the optimal individualized time-dependent pricing for any given consumer group and any given time interval. This work integrates the allocated reserve and unit cost of the supplier, the ideal consumption, minimum required consumption and price sensitivity of each consumer and the price cap imposed by the government. The behavior of the results to parameter value deviations is observed through computational experiments and explained. The ideal consumption and price sensitivity of each consumer for these experiments are provided by the largest water supplier of Greece. An increase of up to 3225 % in the objective function the supplier wishes to maximize is achieved, compared to uniform pricing.

JEL: D12, Q25

Keywords: Time-dependent pricing, individualized pricing, residential water, water utilities

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1 Introduction

Clean water is a fundamental resource for residential consumers. However, the supply of clean water decreases due to droughts and pollution (United Nations, 2025b), while the demand for clean water increases due to population growth and economic growth (United Nations, 2025a). Figure 1 depicts the increasing trends in the water consumption of Athens, the population of Athens and the GDP of Greece as functions of time. European Commission (2025)'s Water Resilience Strategy highlights that by 2030, global water demand is projected to exceed available resources by 40%, necessitating urgent action to ensure water availability and quality. This dynamic leads to the depletion of the reserves and the congestion and deterioration of the available infrastructure, which is already insufficient due to age (McKinsey &Company, 2025). Water suppliers are forced to adapt to this reality by managing to control the consumption and to fund the protection, maintenance, upgrade and expansion of the available infrastructure.

One example of a water supplier that has begun to adapt on the funding front is EYDAP, a state-controlled monopoly water utility serving the Athens region. EYDAP is majority-owned by the Greek state, operates under a long-term concession, and is fundamentally treated as a public service provider rather than a purely profit-driven firm (though it is listed on the stock exchange). At the same time, it generates revenue within a regulated framework, meaning it must balance social obligations with financial sustainability. Changes in EYDAP's prices must first be approved by the relevant regulatory body. In recent years, EYDAP has modestly increased charges (mainly through fixed fees) to finance a €2–2.5 billion infrastructure program, including network upgrades, digital systems, and drought resilience projects (Kathimerini, 2025). This reflects a broader shift: even as a public monopoly, EYDAP is increasingly expected to recover costs and fund long-term investment through tariffs, rather than relying solely on direct state support. EYDAP and other regulated monopolies are a prime candidate to utilize new pricing approaches as they can be designed without competition as a factor and can focus on whichever goal the company has at the current time, while regulators ensure the consumers are not overburdened.

Notably, the use of the term "profit" for water utilities is fully justified when examining entities structured as corporate, publicly traded enterprises such as EYDAP. EYDAP explicitly reports financial metrics such as pre-tax profits and after-tax profits in compliance with international accounting standards. Similarly, major news journals such as Reuters use the term profit when reporting on the American Water Works Company (Reuters, 2026). Because these regulated utilities operate under corporate financial frameworks and trade on public markets, employing standard profitability terminology is both empirically accurate and essential for conveying their economic performance to a wider audience.

Suppliers can achieve these goals by utilizing time-dependent pricing, where the price increases during periods of high demand discouraging consumption (Marzano et al., 2020) and increasing revenue (by consumers who ignore the price and keep consuming) and decreases during periods of low demand making the demand curve more uniform and manageable over time. Alghamdi et al. (2024) demonstrate that time-dependent pricing leads to reductions in demand and infrastructure energy consumption. However, time-dependent pricing that is uniform among all consumers is flawed as it does not

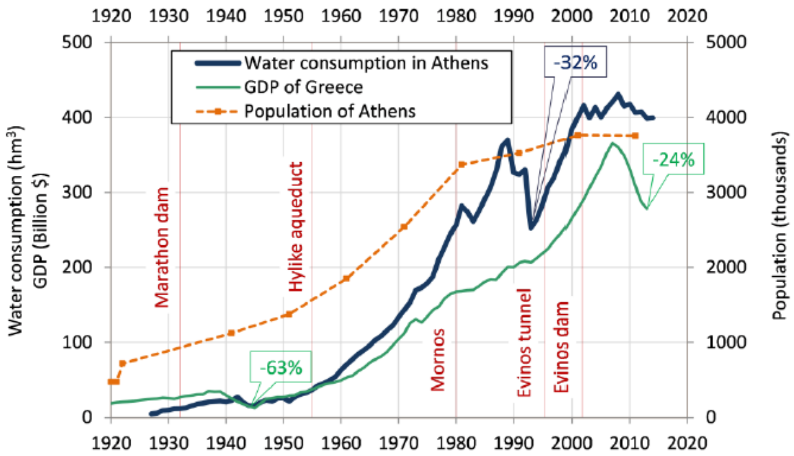

Figure 1: Water consumption of Athens, population of Athens and GDP of Greece as functions of time (Koutsoyiannis and Mamassis, 2015).

account for the differences between each consumer's characteristics that affect demand such as the behavior, family status, economic conditions and residence (Kostakis, 2021). Certain consumers may pay a large share of their living budget to fulfill their basic needs, while other consumers may be indifferent to the price and small changes in it, thus over-consuming or wasting water. Costa et al. (2024) found clear evidence that higher household income correlates with higher water consumption. Their findings highlight that lower-income households face strict budgetary pressures that force them to actively restrict their daily water usage. Higher-income households are largely unconstrained by the cost of water utilities, leading to higher baseline consumption and an expansion of non-essential water use (such as larger outdoor spaces, pools, or a higher density of water-consuming appliances).

Suppliers can tackle these problems by utilizing individualized pricing, where the price is lower for the former consumers and higher for the latter consumers, thus ensuring fairness in the allocation of clean water. Smith (2022) demonstrates that individualized pricing leads to more equitable consumption patterns by aligning price with consumer characteristics. Though this type of pricing may raise questions, even now with tiered uniform pricing each consumer already pays a different average price per quantity of water when they exceed the basic tier. Even if two consumers consume the same amount of water and pay a different price, that is already a well-established and highly common practice across many heavily regulated utility and service sectors. For example, telecommunications and energy providers routinely charge different prices for the exact same amount of data or electricity based on factors such as customer loyalty, contract length, enrollment timing, or demographic subsidies (e.g., low-income discounts). Therefore, while a uniform tariff seems intuitively "fair," market segmentation where identical consumption yields different costs is already a reality of modern consumer infrastructure. So, individualized pricing is the next step to ensure fairness in water distribution.

While suppliers are interested in maximizing their total profits (to the extent allowed by the entity overseeing them that ensures there is a valid goal to achieve with these profits) to fund the protection, maintenance, upgrade and expansion of the available infrastructure they are also interested in minimizing their consumers' inconvenience to ensure their satisfaction. Thus, maximizing profits is not the goal itself, but merely the means to ensure consumer prosperity. Moving from traditional tiered flat pricing that is common for all consumers to individualized time-dependent pricing provides the suppliers with greater flexibility to address these challenges compared to tiered flat pricing due to the increased number of decision variables available. In conclusion, the implementation of individualized time-dependent pricing represents a promising solution to several difficulties suppliers and consumers face and is a relatively uncharted field for further research.

1.1 Background

The relevant literature on water pricing has developed into three streams, with no work explicitly examining the joint role of time-dependent and individualized pricing. While recent contributions have advanced our understanding of each dimension independently, their integration remains largely unexplored.

A first stream of research examines optimal tariff design and pricing structures in water resource systems. This literature analyzes how different pricing mechanisms affect consumption, welfare, and resource sustainability. For instance, Caravaggio et al. (2023, 2024) model supplier–consumer interactions through differential game frameworks, comparing linear and increasing block tariffs under dynamic resource constraints. Their findings highlight the importance of tariff structure and demand fluctuations in shaping both consumption patterns and long-term basin dynamics, with linear pricing often outperforming more complex tariff schemes in terms of efficiency and welfare. More broadly, this line of work provides important insights into how pricing can balance economic and environmental objectives, but typically assumes homogeneous or aggregated demand responses rather than explicitly accounting for heterogeneity across individual users.

A second stream focuses on time-dependent pricing mechanisms, which aim to improve efficiency by aligning prices with temporal variations in demand, supply conditions, and system costs. Chu and Grafton (2021) introduce the concept of Risk-Adjusted User Cost (RAUC) to capture the opportunity cost of water use, showing that incorporating such dynamic considerations into pricing can substantially enhance long-term welfare. Similarly, Vidal Lamolla et al. (2022); Alghamdi et al. (2024); Marlim and Kang (2025) demonstrate how time-of-use and hourly pricing can reduce peak demand, improve system efficiency, and lower operational costs, particularly when combined with detailed consumption data and behavioral modeling. Despite these advances, this literature generally applies uniform pricing schedules across users, without differentiating prices at the individual level.

In contrast, a more limited body of work explores individualized pricing, enabled by the increasing availability of high-frequency consumption data from smart metering technologies. Atwater et al. (2022); Smith (2022) show that tailoring prices to individual consumption patterns can improve both efficiency and equity, for example by better reflecting cost causation or by designing rates based on household-specific usage benchmarks. However, these approaches are typically implemented in static settings and do not explicitly incorporate variation in pricing with regard to time.

Taken together, these streams highlight important perspectives on water pricing.

Existing models either allow prices to vary over time or across individuals, but rarely both. As a result, the potential interactions between temporal demand fluctuations and user heterogeneity remain largely unexplored. This limitation is particularly relevant in modern water systems, where both dimensions are increasingly observable and actionable due to advances in data collection and monitoring technologies.

This paper addresses this gap by developing a framework that jointly incorporates time-dependent and individualized pricing, allowing prices to vary both across users and over time. By combining these two dimensions, we provide new insights into the design of pricing mechanisms that can better balance efficiency, equity, and sustainability objectives.

1.2 Contribution and structure overview

Our work advances existing research by providing the mathematical formulation and solution of an individualized time-dependent pricing problem. To the best of our knowledge, no other work in the literature tackles this problem. Thus, this work is a valuable tool for suppliers to determine the optimal individualized time-dependent pricing for any given consumer group and any given time interval. It takes into account the following parameters: the allocated reserve and unit cost of the supplier, the ideal consumption, minimum required consumption and price sensitivity of each consumer and the price cap imposed by the government. The behavior of the results to parameter value deviations is observed through computational experiments and explained. The ideal consumption and price sensitivity of each consumer for these experiments are provided by the largest water supplier of Greece.

The rest of the paper is organized as follows: Section 2 provides the mathematical formulation and solution of the problem. Section 3 presents computational experiments using the results of Section 2 and discusses them. Section 4 summarizes our work and proposes future research directions to extend it.

2 Mathematical formulation and solution

A supplier wants to provide individualized time-dependent pricing for I consumers for period t. All functions, variables and parameters in this section are specific to period t. A function, variable or parameter that is associated with consumer $i \in 1, 2, 3, \ldots, I$ is denoted by the subscript i. The supplier decides the $Ix1$ vector P that contains each unit price p_i for consumer i. Each p_i is non-negative and is measured in €$/m^3$. Then, knowing their p_i, each consumer i decides their consumption q_i, which depends on p_i. Each q_i is non-negative and is measured in m^3.

2.1 Utility function and demand function of consumer i

The utility function for consumer i is measured in € and is (Caravaggio et al., 2024)

$$U_i(p_i, q_i) = \begin{cases} \dfrac{b_i}{a_i} q_i - \dfrac{1}{2a_i} q_i^2 - p_i q_i, & \text{if } 0 \le q_i \le b_i, \\ \dfrac{b_i^2}{2a_i} - p_i q_i, & \text{if } b_i \le q_i < \infty. \end{cases}$$

where a_i is non-negative and is measured in $m^6/€$, and b_i is non-negative and is measured in m^3.

The utility function indicates that consumer i has no incentive to consume more than b_i because they will pay more but receive no additional utility. So, $0 \leq q_i \leq b_i$ and b_i can be interpreted as the ideal or maximum consumption for consumer i if $p_i = 0$. At the end of this subsection an interpretation for a_i and simple approximations of a_i and b_i if consumer i's past consumption data are given.

The supplier knows the utility function for each consumer and chooses the following non-negative price vector which maximizes the supplier's objective function

$$P = \begin{bmatrix} p_1 \\ \vdots \\ p_I \end{bmatrix}.$$

Given p_i, consumer i maximizes their utility function by choosing q_i that satisfies

$$\frac{\partial U_i(p_i, q_i)}{\partial q_i} = 0,$$
$$\frac{\partial^2 U_i(p_i, q_i)}{\partial q_i^2} < 0.$$

Thus, consumer i chooses

$$q_i(P) = q_i(p_i) = \begin{cases} b_i - a_i p_i, & \text{if } 0 \leq p_i \leq \dfrac{b_i}{a_i}, \\ 0, & \text{if } p_i \geq \dfrac{b_i}{a_i}, \end{cases}$$

which is the demand function for consumer i. Note that q_i is always non-negative and less than or equal to b_i because p_i is non-negative. q_i is made up of two terms. The first is b_i, which, as mentioned, can be interpreted as the ideal or maximum consumption for consumer i. The second term is $a_i p_i$ which can be interpreted as the deviation due to price from the ideal consumption for consumer i. Because a_i is the multiplier of p_i it can be interpreted as the sensitivity to price for consumer i.

If q_i and p_i are given through a smart meter for the same period t of a previous year k and a previous year l then a_i and b_i can be approximated (though note that this is not a guaranteed way to calculate highly accurate values) by solving the 2×2 linear system

$$q_{i,k} = b_i - a_i p_{i,k},$$
$$q_{i,l} = b_i - a_i p_{i,l},$$

so they can be used in the computational experiments of Section 3.

Of course, data from a single previous year are not enough to calculate the parameter values for a consumer for period t with high accuracy. To do so would require:

- the consumer's consumption data for that period for multiple previous years to make an initial estimate
- adjusting the estimate to the consumer's consumption trends of immediately previous periods

- adjusting the estimate to external conditions such as temperature etc.

Still, it is rather difficult to account for substitution between periods. For example, if a consumer needed a larger amount of water than expected in a certain period (perhaps due to a change in how they schedule their activities which may be caused by a low water price or other factors in their life) then it is likely that their ideal consumption in a future period will be lower than previously expected. This can be reflected in the parameter b_i if it is updated using its immediate previous values. However, when that lower consumption will take place is difficult to predict. So, the highly accurate calculation of these parameters is outside the scope of this paper and would require a separate work delving into prediction techniques dedicated to it.

On the consumer rationality front our model does not require rational consumers but predictable ones. The supplier should also ensure the chosen period is not small enough to cause increased mental load to consumers. If the prices change too often it is difficult for consumers to follow these changes and act accordingly.

2.2 Objective function and constraints of the supplier

The consumers' total consumption is measured in m^3 and is

$$\mathrm{CON}(P) = \sum_i q_i(P)$$

The supplier's total cost is measured in € and is (Caravaggio et al., 2024)

$$\mathrm{COS}\,(P) = x\mathrm{CON}(P)^2 + y\mathrm{CON}(P) + z,$$

where x is the quadratic cost coefficient, is non-negative and is measured in $€/(m^3)^2$, y is the linear cost coefficient, is a real number and is measured in $€/m^3$, and z is the constant cost coefficient, is non-negative and is measured in € This is a more complex form than the linear one proposed by Caravaggio et al. (2024) to ensure broader application of our work.

The supplier's total profit PRO is measured in € and is equal to

$$\mathrm{PRO}\,(P) = \sum_i p_i q_i(P) - \mathrm{COS}\,(P)$$

The supplier's profit percentage PER is measured in % and is equal to

$$\mathrm{PER}(P) = \frac{100\mathrm{PRO}(P)}{\mathrm{COS}(P)}$$

The consumers' total inconvenience INV has no unit and is equal to

$$\mathrm{INV}\,(P) = \sum_i \frac{b_i - q_i}{b_i} = \sum_i \frac{a_i p_i}{b_i}.$$

A similar measure of the deviation of individual allocations from their ideal / fair scenario has been used in Steriotis et al. (2019) for an energy setting. Due to the similarity to our setting, its simplicity and its intuitiveness, we choose this function to represent consumer interests.

The supplier's objective function for maximization OBJ is measured in € and is equal to

$$\mathrm{OBJ}\left(P\right) = \mathrm{PRO}\left(\left(P\right)\right) - w\mathrm{INV}\left(P\right),$$

where w is the convenience factor, is non-negative, is measured in € and the higher it is the more the supplier is interested in total consumer convenience compared to total profit. Because this is an optimization problem and z is a constant in the objective function it can be omitted . When $w = 0$ the supplier focuses exclusively on maximizing the first term. As w increases the supplier focuses more on maximizing the second term. For very large values of w the supplier focuses exclusively on maximizing the second term as the value of the first term becomes insignificant compared to the second.

The supplier faces three additional constraints

First, each consumer's q_i should exceed m_i, which is the amount consumer i consumes to fulfill their basic needs, is non-negative and is measured in m^3. Because determining m_i is extremely complex and depends on several factors (e.g. household members) each consumer is assumed to have $m_i = mb_i$, where m is the minimum consumption factor, is non-negative and has no unit:

$$q_i = b_i - a_i p_i \geq m_i = mb_i. \tag{1}$$

Second, each consumer's p_i should not exceed the price cap c_i, which is non-negative and is measured in $\frac{€}{m^3}$. This price cap may be imposed by the government and apply to all consumers or may be used by the supplier to ensure vulnerable consumers have access to affordable water. This price cap that applies only to some consumers is required because even though the model is incentivized to assign higher prices to low sensitivities to price there must be a way to ensure all vulnerable consumers get sufficiently low prices regardless of the consumer dataset:

$$p_i \leq c_i. \tag{2}$$

Third, the total consumption $CON(P)$ should not exceed the supplier's allocated reserve E, which is non-negative and is measured in m^3. E depends on several factors such as the current and past weather, the current reserves and the current state of the infrastructure:

$$CON\left(P\right) = \sum_i q_i\left(P\right) \leq E. \tag{3}$$

From (1), we have

$$p_i \leq \frac{b_i(1-m)}{a_i}.$$

From (1) and (2), we have

$$p_i \leq \min\left(c_i, \frac{b_i(1-m)}{a_i}\right).$$

Equation (2) becomes redundant if $c_i \geq \frac{b_i(1-m)}{a_i}$. This is because $q_i \geq mb_i$, so $p_i \leq \frac{b_i(1-m)}{a_i}$ already. Equation (3) becomes redundant if $E \geq \sum_i b_i$. This is because $q_i \leq b_i$, so $CON = \sum_i q_i\left(p_i\right) \leq \sum_i b_i$ already. Equation (3) becomes unfeasible if $E < \sum_i(b_i - a_i \min\left(\left(c_i, \frac{b_i(1-m)}{a_i}\right)\right))$. This is because $p_i \leq \frac{b_i(1-m)}{a_i}$ and thus $CON = \sum_i q_i\left(p_i\right) \geq \sum_i(b_i - a_i min\left(\left(c_i, \frac{b_i(1-m)}{a_i}\right)\right))$ so (3) cannot be true.

2.3 Optimization problem of the supplier

The supplier determines P^* for each period by solving the quadratic programming optimization problem (through rewriting $OBJ\,(P)$ and omitting constant terms)

$$\max(\text{OBJ}\,(P)) = \max\left((\frac{1}{2}P^T HP + f^T P) \right),$$

where

$$H = -2x \begin{bmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_I \end{bmatrix} \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_I \end{bmatrix} - 2 \begin{bmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_I \end{bmatrix}$$

$$f^T = [b_1 \ldots b_I] + 2x \left(\sum_i b_i \right) [a_1 \ldots a_I] + y\,[a_1 \ldots a_I] - w \left[\frac{a_1}{b_1} \cdots \frac{a_I}{b_I} \right]$$

subject to (through combining and rewriting (1)–(3))

$$\begin{gathered} 0 \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \leq P \leq \begin{bmatrix} c_1 \\ \vdots \\ c_I \end{bmatrix} \\ AP \leq B \end{gathered} \tag{4}$$

where

$$\begin{aligned} A &= \begin{bmatrix} A_1 & A_2 \end{bmatrix}, \\ A_1 &= \begin{bmatrix} a_1 & \cdots & 0 & \vdots & \ddots & \vdots & 0 & \cdots & a_I \end{bmatrix}, \\ A_2 &= -\begin{bmatrix} a_1 & \cdots & a_I \end{bmatrix}, \\ B &= \begin{bmatrix} B_1 & B_2 \end{bmatrix}, \\ B_1 &= \begin{bmatrix} b_1 - m_1 & \vdots & \cdots & \vdots & b_I - m_I \end{bmatrix}, \\ B_2 &= \begin{bmatrix} E - \sum_i b_i \end{bmatrix}. \end{aligned}$$

The supplier can consider P a 1×1 vector and follow similar steps to determine the optimal uniform price p for all consumers. Note that in this case only a common price cap c is necessary and (4) reduces to $0 \leq P \leq c$.

The supplier can set, for the constraints to be non-redundant,

$$0 \leq c \leq \min_i \left\{ \frac{b_i(1-m)}{a_i} \right\},$$

since $q_i \geq mb_i$, so

$$0 \leq p_i \leq \min_i \left\{ \frac{b_i(1-m)}{a_i} \right\}$$

already.

Since $q_i \leq b_i$,

$$CON = \sum_i q_i(p_i) \leq \sum_i b_i$$

already.

For (3) to be feasible, the supplier must set c such that

$$0 \leq p_i \leq \min\left\{c, \frac{b_i(1-m)}{a_i}\right\}.$$

Thus,

$$CON(P) = \sum_i q_i(p_i) \geq \sum_i \left[b_i - a_i \min\left\{c, \frac{b_i(1-m)}{a_i}\right\}\right],$$

so (3) cannot be true.

The mathematical formulation and solution are for a single period. However, they are meant to be used for multiple sequential periods where the parameters for each period depend not only on current period data but also on previous period data (as is the case for a and b). Also, the consumers that will experience this pricing will observe pricing that changes with time (different price for a different period). For the above reasons this pricing is time-dependent instead of static.

Pricing on a per-period basis (whether that is an hour, day, week, month, etc.) is a deliberate design choice that allows the model to dynamically adapt to the specific conditions of each period while directly incorporating consumer behavior from previous periods. However, the supplier's true goal is to maximize the sum of objective functions of all periods, not merely one period. If it is assumed that the consumption of each period does not affect the consumption of future periods and that parameters a and b can be accurately predicted and capture substitution, then the problem reduces to maximizing the objective function of each period and adding them. Indeed, let us assume that a higher value of the sum of objective functions for all periods (than the sum of the maximized objective functions for each period) was possible. Then, at least one period would have an objective function value higher than the maximized objective function for that period which is impossible. So,

$$\max\left(\sum_{\text{all periods}} \mathrm{OBJ}(P)\right) = \sum_{\text{all periods}} \mathrm{OBJ}(P).$$

That said, the consumption of each period affects the consumption of future periods due to substitution and the accurate prediction of a and b and the incorporation of substitution in them is outside the scope of this paper (and there will always be deviations from the real values regardless of how sophisticated the methods are). In this case, sequentially maximizing the objective function for each individual period to maximize the sum across all periods is a greedy algorithm and good approximation but not necessarily 100 % accurate. Still, this greedy approach provides a highly robust, computationally efficient, and sufficient solution within these practical forecasting constraints. If instead of optimizing for only one period at a time it was attempted to optimize for all periods (a single execution gave prices for all periods as output) that would require writing the a and b parameters of all but the first period as functions of the consumptions of the previous periods and would also be very computationally inefficient compared to the current approach.

The quadratic programming optimization problem for a single period can be solved through the interior-point method (Potra and Wright, 2000) utilized by the MATLAB software. For example, the flowchart for individualized time-dependent pricing for one day split into 24 periods (1-hour period for each iteration) is presented in Figure 2.

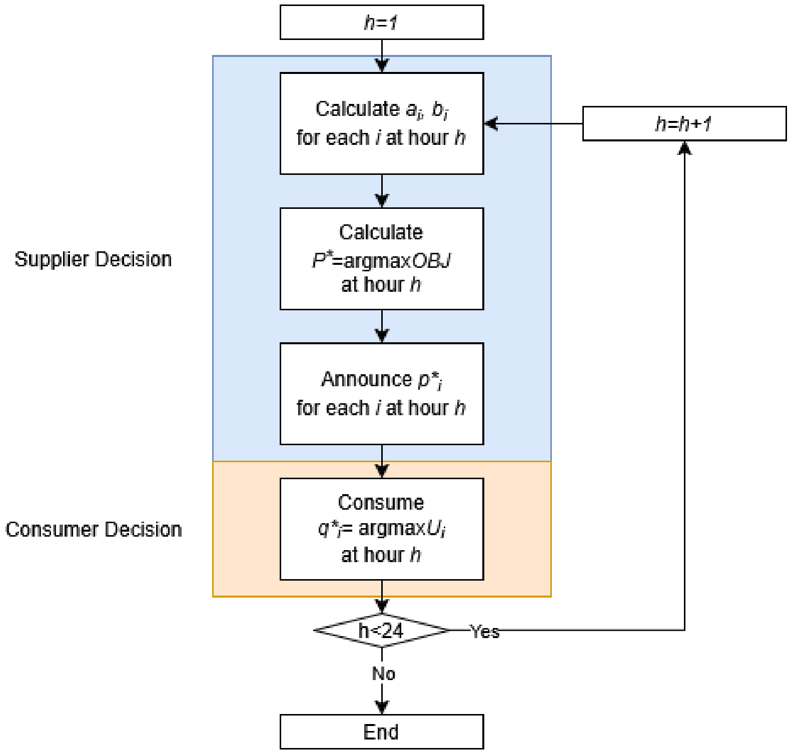

Figure 2: Flowchart for individualized time-dependent pricing for one day split into 24 periods (1-hour period for each iteration)

Note that instead of INV (P) the consumer surplus could be used to represent consumer interests. The consumers' total surplus SUR is measured in € and is equal to

$$\mathrm{SUR}\,(P) = \sum_i \frac{(b_i - a_i p_i)^2}{2a_i}$$

In that case, w is the surplus factor, is non-negative, has no unit and

$\mathrm{OBJ}(P) = \mathrm{PRO}(P) + w\mathrm{SUR}(P),$

$$H = -2x \begin{bmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_I \end{bmatrix} \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_I \end{bmatrix} - 2 \begin{bmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_I \end{bmatrix} + w \begin{bmatrix} \frac{a_1}{2} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{a_I}{2} \end{bmatrix},$$

$$f^T = [b_1 \ldots b_I] + 2x \left(\sum_i b_i \right) [a_1 \ldots a_I] + y\,[a_1 \ldots a_I] - w\,[b_1 \ldots b_I]\,.$$

The implementation cost of the proposed model is primarily determined by data integration, which scales predictably depending on a supplier's existing metering infrastructure. If the pricing is adopted, as intended, by suppliers that have already deployed Advanced Metering Infrastructure, the necessary data collection systems are already in place. In these environments, implementation is limited to establishing a standard data pipeline to feed existing database records into the optimization algorithm. Because the quadratic programming model operates as an independent optimization layer that receives standard consumption metrics as inputs and outputs a deterministic price, it can be integrated into existing supplier databases without requiring a structural rewrite of core billing software.

3 Results

3.1 Input data

Period t is assumed to be a certain hour of the year. The consumer data for that hour were provided by the largest water supplier of Greece. The data consisted of the values for the parameters a and b of 100 consumers for a certain hour. These values were derived by the supplier from consumption data by solving the appropriate 2×2 linear system for each consumer. No other data personal or otherwise was made available to respect consumer privacy. The supplier has $x = 0$ and a common price cap c for all consumers so

$$0[1:1] \leq P \leq c[1:1] = c[1:1],$$

and the consumer data have the following properties:

$$\begin{aligned} \sum_i a_i &= 5.28, \\ \sum_i b_i &= 4.17, \\ \min_i \frac{b_i}{a_i} &= 0.02, \\ \max_i \frac{b_i}{a_i} &= 2. \end{aligned}$$

3.2 Experiment design

In this section, computational experiments are performed to investigate the effect of each parameter on CON, PRO, PER and INV for both uniform and individualized pricing. During each experiment only one parameter varies from its minimum to its maximum value, while the others remain constant at their baseline value. In this way, the effects of changes in a parameter's value on CON, PRO, PER and INV for both uniform and individualized pricing can be plotted and observed. The parameters examined along with their baseline, minimum and maximum value are presented in Table 1.

The baseline parameter values are the most beneficial for the supplier as they provide the most relaxed constraints and thus more flexibility. The minimum value for y is 0.01 (very close to 0), while its maximum value is 0.35, which is equal to the lowest water price tier of the water supplier of Athens (EYDAP, 2025), so the supplier is never forced to sell at a loss. The minimum value for c is 0.01 (equal to the minimum value for y so the supplier is never forced

Table 1: Baseline value for each parameter and the minimum and maximum value it reaches when it is the one varied.

Parameter	Unit	Meaning	Value		
			Baseline	Minimum	Maximum
c	€$/m^3$	price cap	1.98	0.01	1.98
E	m^3	allocated reserve	4.17	4.06	4.17
m	-	minimum consumption factor	0.01	0.01	1
w	€	convenience factor	0	0	0.1
y	€$/m^3$	unit cost	0.01	0.01	0.35

to sell at a loss), while its maximum value is max $\left(\frac{b_i(1-m)}{a_i}\right)$ =1.98, (see Section 2.2, if the computational experiments were only for uniform pricing min $\left(\frac{b_i(1-m)}{a_i}\right)$ would be chosen instead). The value of c is assumed the same for all consumers so $C = c\begin{bmatrix}1 & \cdots & 1\end{bmatrix}$. The minimum value for E is $\sum_i \left(b_i - a_i\left(c, \frac{b_i(1-m)}{a_i}\right)\right)$ =4.06 (see Section 2.3, if the computational experiments were only for individualized pricing $\sum_i \left(b_i - a_i\left(c_i, \frac{b_i(1-m)}{a_i}\right)\right)$ would be chosen instead), while its maximum value is $\sum_i b_i$ =4.17 (see Section 2.2). The minimum value for m is 0.01 (very close to 0), while its maximum value for m is 1 (each consumer must consume exactly their ideal consumption b_i). The minimum value for w is 0 (the supplier does not take consumer inconvenience into account), while its maximum value is 0.1 (the supplier almost exclusively takes consumer inconvenience into account). Higher values than 0.1 lead to little change in results.

3.3 Baseline scenario

Before proceeding with the computational experiments, it is useful to solve the problem with the baseline parameter values. For optimal uniform pricing

$$\begin{aligned} p = p_i &= 0.02, \\ \min_i \frac{q_i}{b_i} &= 0.01, \\ CON &= 4.06, \\ OBJ = PRO &= 0.04, \\ PER &= 98, \\ INV &= 5.14, \end{aligned}$$

and for optimal individualized pricing

$$\begin{aligned}
\min p_i &= 0.02, \\
\max p_i &= 1.01, \\
\min_i \frac{q_i}{b_i} &= 0.25, \\
CON &= 2.06, \\
OBJ = PRO &= 1.29, \\
PER &= 6290, \\
INV &= 51.29.
\end{aligned}$$

3.4 Computational experiments

This section includes Figures 3–7. Each figure contains 4 graphs that show the behavior of CON, PRO, PER, INV as a parameter varies from its maximum to its minimum value, while the others retain their value. In Figure 3 c is varied, in Figure 4 E is varied, in Figure 5 m is varied, in Figure 6 w is varied and in Figure 7 y is varied. Regarding the computational experiments, because w's baseline is equal to 0 the objective function of the supplier is equal to PRO when a parameter other than w is varied. As such, individualized pricing always yields an equal or higher $OBJ = PRO$ compared to uniform pricing when a parameter other than w is varied. This is because individualized pricing has more independent variables available for the supplier and at worst the supplier can consider them equal and solve the uniform pricing optimization problem.

Our results demonstrate the effectiveness of individualized pricing in comparison to uniform pricing in maximizing the supplier's objective function. That effectiveness is demonstrated through computational experiments and is achieved through a very straightforward methodology that considers an objective function and a parameter combination not included in the existing literature. Though the experiments confirm individualized pricing's superiority compared to uniform pricing, they also give other useful insights. These insights are mostly aligned with intuition though that does not detract from their importance as they are proven through a rigorous mathematical approach.

3.4.1 Constant value of a result in an interval

In each of the following figures sometimes the results of either uniform or individualized pricing (or both) remain constant in an interval that either starts with the minimum value of the varied parameter or ends with the maximum value of the varied parameter. It is useful to explain why that happens. As mentioned, the baseline scenario has the most relaxed constraints as far as the supplier is concerned. So, if for a value of the varied parameter the optimal uniform pricing P^* becomes equal to the optimal uniform pricing $P^*_{baseline}$ of the baseline scenario then any change in that value that relaxes the constraint further, leads to no change in the optimal solution and each result (since each result depends exclusively on that solution). This can easily be proven by contradiction. If by relaxing the constraint the optimal uniform pricing P^* changed from that of the baseline scenario $P^*_{baseline}$ (i.e. P^* resulted in a higher objective function than $P^*_{baseline}$) then P^* would also be the optimal uniform pricing instead of $P^*_{baseline}$ for the baseline scenario, which has more relaxed constraints (so, P^* is sure to be a valid solution that satisfies the baseline constraints as it satisfied stricter constraints). The same is true for the individualized pricing.

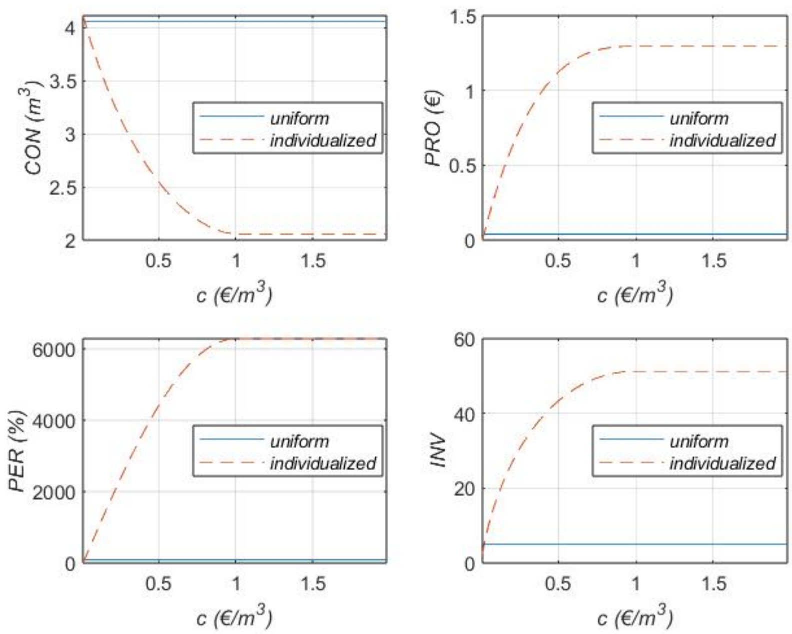

Figure 3: Results as functions of c.

Regarding Figure 3 and individualized pricing, as c increases from its minimum value the supplier can set higher prices that were previously prohibited due to the price cap. As a result, total consumption decreases, while total profits, profit percentage and total inconvenience increase.

Regarding Figure 4, we believe this is a non-intuitive result as one would believe that profits would increase as the quantity available for sale increased. This does not happen here because the consumer sample under study does not consume enough even if prices are lowered and cannot absorb the extra quantity of water.

Regarding Figure 5, as m increases from its minimum value the supplier is forced to lower prices to ensure each consumer consumes at least mb_i. As a result, total consumption increases, while total profits, profit percentage and total inconvenience decrease.

Regarding Figure 6, as w increases from its minimum value, the supplier is forced to decrease prices as the supplier is more concerned with satisfying the consumers by providing affordable water. As a result, total consumption increases, while total profits, profit percentage and total inconvenience decrease. This happens until w reaches a certain value for the uniform pricing. After it reaches that value, the INV factor of the objective function becomes fully dominant over the PRO factor. Further increasing w does not meaningfully alter the optimal uniform price found and the results. The individualized pricing also has this behavior but the value of w to achieve almost constant pricing and results is a bit higher (close to 0.1).

Regarding Figure 7, as y increases from its minimum value the supplier is forced to increase prices to keep up with the increase in cost. As a result, total consumption, total

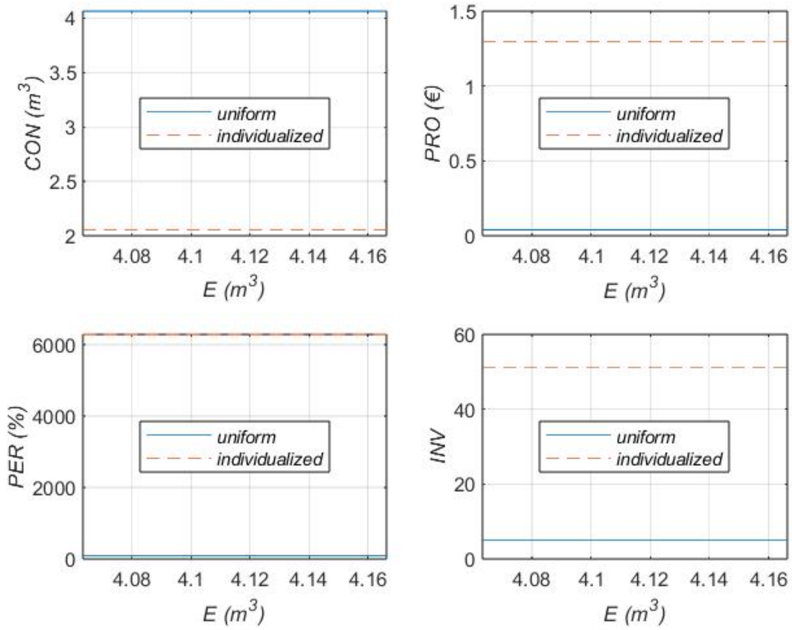

Figure 4: Results as functions of E.

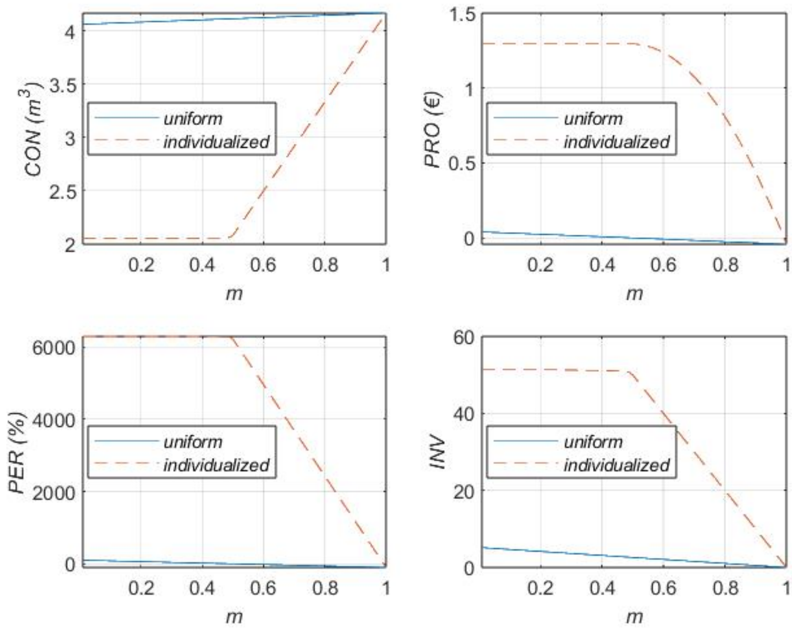

Figure 5: Results as functions of m.

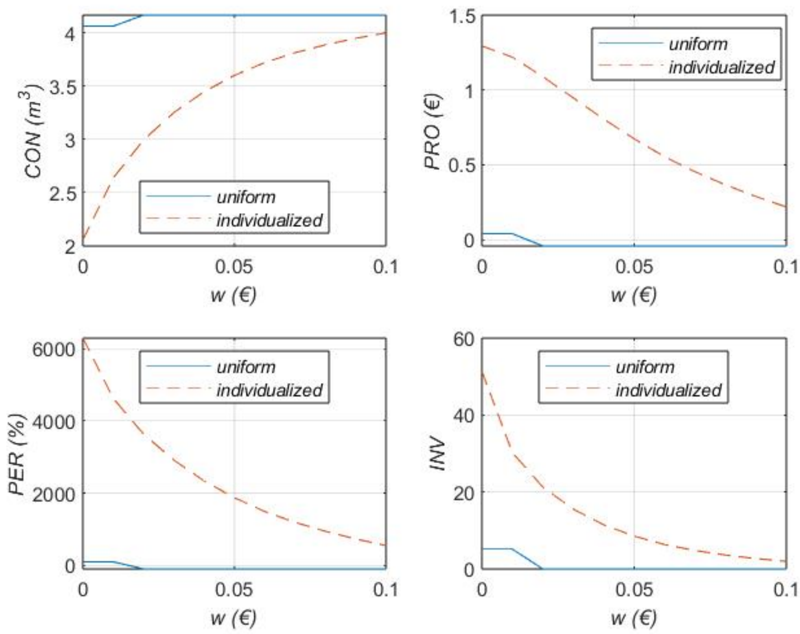

Figure 6: Results as functions of w.

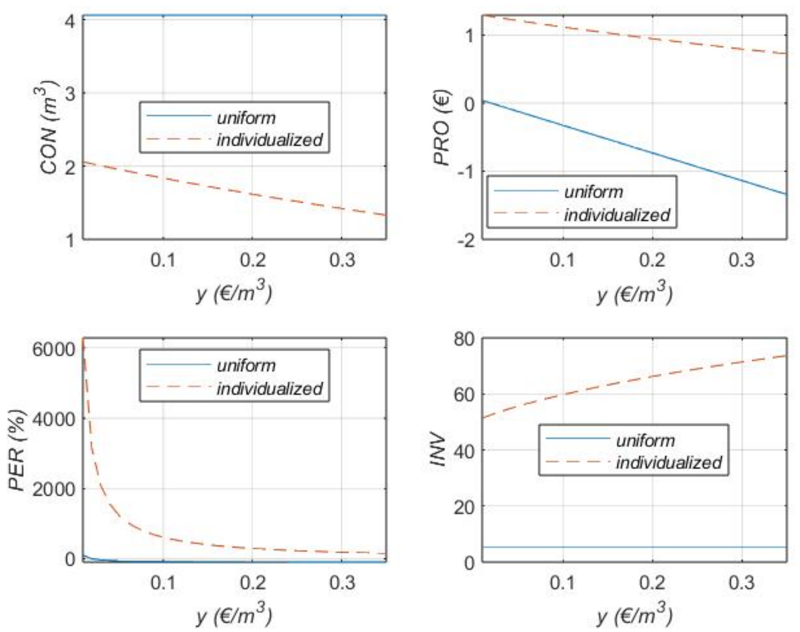

Figure 7: Results as functions of y.

profits and profit percentage decrease, while total inconvenience increases.

Looking at all figures, the following patterns can be extracted. First, individualized pricing leads to higher INV than uniform pricing, though as the value of w increases INV for both pricing methods converge to zero. This is because the supplier prioritizes profit at the expense of consumer convenience unless the value of w is high. Second, CON exhibits opposite behavior to INV, an expected result as an increase in CON will be distributed among consumers (though that distribution is not guaranteed to be uniform) lowering INV. Third, PRO exhibits a similar behavior to PER, which is not a given for all industries. It appears that for this consumer data as CON and thus COS increase, PRO increases more rapidly than them causing an increase in their ratio PER. Fourth, PRO exhibits similar behavior to INV and opposite behavior to CON, an expected result as an increase in PRO is derived from higher prices to consumers who consume less and are less satisfied as a result. The increasing unit water cost in Figure 7 disrupts this pattern as the supplier strives to maintain profits for individualized pricing and minimize losses for uniform pricing while satisfying the minimum consumption of each consumer.

4 Conclusion

We contribute to operational research related to the water sector through the mathematical formulation and solution of an individualized time-dependent pricing problem. Our work aspires to help suppliers face the modern challenges of the sector. First, we formulate a model for consumption that includes a supplier and multiple consumers. The functions related to the supplier and the consumers are based on the literature. We derive the demand function of each consumer from their utility function and proceed to derive the consumers' total consumption and total inconvenience and the supplier's total profits, profit percentage and objective function. We also propose a way to calculate two of the model's parameters that are different for each consumer using the consumer's historical consumption data. Through manipulation of the involved functions, we convert the initial problem into a quadratic programming optimization problem with a known solution. Though some of our model's functions, variables and parameters already exist in the literature, we innovate by combining them and providing suppliers with an optimization tool that achieves higher objective function values than uniform pricing as expected due to a higher number of independent variables. However, note that this work does not claim that individualized pricing is universally better than uniform pricing, it only claims that dynamic pricing is better for the goals (maximization of objective function) set in this paper.

We proceed to test our approach by giving the parameter values for 100 consumers, provided by the largest supplier of Greece, as inputs to it. Then, we perform various computational experiments on four functions that are integral to our approach. During each experiment the value of one parameter is varied while the values of all other parameters are kept constant. We observe the behavior of each function through this process and give an explanation for it. Additionally, we identify correlations among the behaviors exhibited by the four functions. While the mathematical formulation and solution of an individualized time-dependent pricing problem are the main innovations of our work, the fact that the intuitive behavior of these functions when submitted to parameter value variations is confirmed through a rigorous mathematical approach constitutes, in our opinion, another contribution to the literature.

However, our work has limitations that emanate from the assumptions made for the mathematical formulation of the problem and the rather simple way that the parameter values were calculated. In our work, the utility function of each consumer has the same form and only differs from the utility functions of other consumers through different parameter values. The minimum consumption of each consumer is a fixed percentage of their ideal consumption and the parameters a and b of each consumer were simple approximations using data from a single previous period. Finally, substitution can be taken into account only to a limited degree using our model because we cannot predict in which future period the consumer will change their consumption to balance previous increased or decreased consumption. Future research can use this work as a starting point and address these limitations.

Rather than assuming a uniform utility function for each consumer, subsequent works could introduce heterogeneous utility functions to better capture diverse consumer behaviors. Additionally, instead of the minimum consumption of each consumer being a fixed percentage of their ideal consumption it could be determined on a household-by-household basis by creating a function that receives household characteristics and external conditions as inputs and minimum consumption as output. Furthermore, the parameters a and b of each consumer can be much more accurately calculated by taking into account the consumer's consumption data for that period for multiple previous years, the consumer's consumption trends of immediately previous periods and the external conditions of the current period. Finally, devising a way to account for substitution between periods (perhaps through communication with each consumer via an app) can further improve our model.

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