A Fuzzy Logic Expert System for Pricing Digital Services: The Case of Price Adjustment for a Mobile Service Provider

Adeolu Olukorede Dairo and Krisztián Szűcs

Faculty of Business and Economics, University of Pecs, Hungary

Ijfis

Abstract

As connected smart devices and terminals continue to grow along with digital content, data traffic of mobile service providers is also growing, and the price war in mobile markets is driving traffic growth without a commensurable increase in revenue. As a result, network capital expenditure (CAPEX) investment, quality of experience, and customer experience are under enormous pressure. In a competitive mobile market, strategic pricing may play an essential role in managing this pressure only if appropriate tools are available for the service providers. In this paper, a fuzzy knowledge-based expert pricing system was developed with a focus on solving network traffic, price war, and business revenue challenges in a competitive mobile market. Its core lay in its ability to recommend digital- and data services-related price points within a competitive and price war mobile environment. The proposed pricing system was experimentally evaluated through a pilot conducted on a few segments of a mobile service provider's customer base in an emerging market and later scaled up to a broader base. Upon implementation, data services revenue increased, and overall gross margin increased with a reduction in data traffic, resulting in better throughput and network quality and, consequently, better customer experience with improved net promoter score.

Keywords: Pricing adjustment, Data services, Digital services, Fuzzy expert, Knowledge-based

1. Introduction

Pricing is an integral part of the marketing function and one that is critical to a firm's overall survival. It is an aspect of the marketing mix that a firm cannot afford to get wrong [1, 2]. The increase in awareness on the part of the consumers and the emergence of smart shoppers have made the pricing of products and services more complex and critical within marketing functions [3–5]. Moreover, the strategy behind pricing is crucial due to different customer behavior—hence the need to price products and services for different target segments in the market appropriately.

In a competitive market where a pricing decision, if wrong, can be catastrophic for a brand due to a lack of evidence of how the market would react to the price change, experts can leverage fuzzy linguistic terms to navigate the problem [6, 7]. The ability of fuzzy logic to associate the ambiguity characterizing pricing decision with the application of imprecise data motivates its usage in this study on price adjustment. For the pricing of mobile and digital-

Received: May 26, 2020
 Revised : Sep. 2, 2020
 Accepted: Sep. 12, 2020

Correspondence to: Krisztián Szűcs
 (szucsk@ktk.pte.hu)
 ©The Korean Institute of Intelligent Systems

©This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (<http://creativecommons.org/licenses/by-nc/3.0/>) which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

related services, a pricing objective is fundamental, being the motivation for the change in price points of the existing product or for assigning a price point to a new product [8–10]. For example, if a market leader makes a price move in a competitive mobile environment, other players may need to adjust their prices in order to protect their market share across value and volume. The motivation behind the price move determines the strategy that is used in bringing the price change to the consumer. When commercial managers consider the right price point, factors such as marketing strategy, competition, and the associated value that consumers perceive to be suitable for the product top the list for consideration [11, 12], though they carry much ambiguity rather than certainty. This is where human and expert judgments come to play in decision-making, since human understanding and ability can pierce through imprecise or obscured data that cannot be easily modeled. Through the means of linguistic terms, experts assign scores such as high and low to events when it is difficult to make a definite or specific measurement of possibility, or when they lack evidence on the situation. These circumstances are characterized by vague and imprecise data such that assigning a crisp (non-fuzzy) value to a seemingly subjective judgment becomes difficult [13]. The ability of fuzzy logic to capture and wave the associated ambiguity by making judgments out of imprecise data motivates its use for the pricing model of digital and data-related services of mobile telecommunication service providers in this study.

Generally, an expert system is a computer-based system with enhanced components that are knowledge-based such that it may give advice or help make intelligent decisions; the system conducts this intelligent act based on underlying rules. The main constituent of the fuzzy expert system is fuzzy logic. The pattern that fuzzy logic uses is a synonym of human thinking. As for the human brain, a decision can be made with incomplete and uncertain information, but computers can only manage exact judgment. Data having “0” and “1” can only be understood by computers; therefore, fuzzy logic provides an intermediary in the form of an interface between human thinking, which is the brain, and computers. The application of expert systems, which deal with uncertainty by leveraging fuzzy information processing through fuzzy rules, stretch across many industries such as medicine, space, engineering, and management [14]. In this study, a fuzzy knowledge-based expert pricing system is developed with a focus on solving network traffic, price war, and business revenue challenges in a competitive mobile market. This expert knowledge-based pricing tool is named the Fuzzy Digital Pricing System (FDPS). The tool is implemented

on a few segments of a mobile service provider’s customer base in an emerging market as a pilot and later scaled up to a more significant segment of it. The summary of this paper contribution is as follows: (1) FDPS uses historical customer data across the network elements, market research information, competitors’ data, and experience of commercial and network professionals of a service provider to build its knowledge base; (2) through price adjustment and recommended price points for data and digital-related services that are powered by FDPS, issues of cost estimation, demand estimation, and competitive issue (price war), which are critical strategic pricing issues facing mobile service providers in a competitive and large market environment are addressed; (3) we develop and implement a fuzzy knowledge-based pricing system through a pilot that is later extended to a large customer base. Performance is measured along with the underlying strategic constraints, and price adjustment decisions are made through the recommended price points from data traffic reduction (CAPEX savings), data, and digital revenue growth, with improvement in gross margin and net promoter score. Section 2 of this paper discusses fuzzy logic, the application of expert systems, and related studies. Section 3 presents a fuzzy expert pricing system and pricing dynamics in the mobile market environment. Section 4 outlines the development of the FDPS as well as its implementation, results, and discussions through a case study of a mobile operator with a large customer base in an emerging market. Section 5 is the conclusion.

2. Background

2.1 Related Work

Price adjustments are tools used by firms to remain competitive amidst a turbulent and fiercely competitive market. Firms may need to adjust prices due to cost, regulatory, competition, or some other factors. Regardless of the element that influences price adjustment, a price move will have an impact on business performance [15]. Ensuring that the impact is positive on the bottom line without backlash from the customers is what makes pricing decisions a sensitive and challenging task for the firms [6]. In practice, managers are confronted with pricing-related decision-making with enormous consequences on business performance if the products are not well priced. In such a situation, when managers lack enough evidence, or when experts lack all the relevant data to make an informed judgment, experts leverage fuzzy linguistic terms [16]. Fuzzy logic draws its strength from its ability to absorb ambiguity and apply vague-

ness and imprecise data to make a sound judgment, such as pricing decisions; this motivates its use in this study.

Several applications of fuzzy expert systems have been highlighted in literature across different domains. By leveraging fuzzy inference theory, an agent-based price system for online auction was proposed by Li et al. [17]. Mediator, seller, and buyer were the three agents used in the study, and its output was a convenient and customizable system for both buyer and seller through underlying fuzzy rules for their pricing and negotiation strategies. In the healthcare sector, Djam et al. [18] developed a fuzzy expert system for malaria sickness and management. By making use of the inputs in the form of symptoms indicated by the patient, the system detected the presence of malaria parasites. For the fuzzification process, a triangular-shaped fuzzifier was used to define a set of symptoms that were relevant to the parasites. The authors applied a fuzzy value to each symptom, and weighting factors were also applied to the symptom sets. From a fuzzy set (mild, 1; moderate, 2; severe, 3; very severe, 4), they selected values along with the membership of each by leveraging a triangular fuzzifier. According to the system, IF “headache = severe” and “vomiting = severe” and body “weakness = severe” and “dizziness = severe” and “joint pain = mild” and loss of appetite are severe, THEN “malaria = severe?”.

Gupta and Celtek [19] built a fuzzy expert system for automating the processing of a small business loan. The system determined who, among the applicants, qualified for a loan. Several variables, such as the ability to repay, credit history, owner investment, and management ability, were considered as inputs in the system. The membership functions in this system overlapped triangles and trapezoids consisting of names of functions and membership values, and the aggregation operator calculated the degree of fulfillment. With about 109 rules, the system provided the output to either lend or not lend loans to customers.

A web-based fuzzy expert system was developed and implemented by Goodarzi and Rafe [20] as a career advisor within the educational setting. Passed courses, course grades, GPA, and student’s rank across different parameters were used as input variables. Categorization of the student’s GPA along different groups was represented in linguistic terms such as *Excellent*, *Weak*, and *Very Weak*, which formed a Gaussian (exponential) membership function after selecting the numeric equivalent of the linguistic terms that carried the maximum degree of membership. This fuzzy expert system is a robust educational adviser system with several fuzzy rules. It was also used for the development of a generic medical system for cardiac disease

diagnosis by using symptoms for heart diseases as inputs. The authors [21] divided the input variables into linguistic variables such as “low”, “medium”, “high”, and “very high”. The system used triangular and trapezoid type fuzzifiers, and the aggregated weighted decision value determined the risk of cardiac disease according to the defined fuzzy rules. In this fuzzy expert system, the centroid method was used for the defuzzification of the aggregate result into the crisp value. The overall output of the system determined whether a patient was at risk for heart disease or not.

Nolan [22] developed a fuzzy logic application for assessment in the education environment. The system leveraged samples and assigned scores to students for their write-ups and essays. Severable variables, such as student understanding and reading comprehension scores [23] were used as inputs, and linguistics variables such as “insightful” and “thoughtful” were derived from the crisp inputs; fuzzy rules such as “IF understanding is high, and character recognition is high, THEN reading comprehension is high” were considered the underlying rules. In the transformation of the fuzzy set into a usable crisp output through the defuzzification process, the centroid method was applied.

Razak et al. [24] developed a career path recommendation system for students with fuzzy logic and evaluation. Moreover, faculty performance within technical institutions was modeled by the fuzzy expert system by Jyothi et al. [25]. The authors [26] combined fuzzy logic pricing steps with an adaptive search procedure to set reserve prices in an online ad auction. The method outperformed a similar algorithm in experiments involving real ad auction data and proved to aid better decision-making in price reservations.

When a brand enters the market with a product, one of the most critical items that connect all the go-to-market activities with the customer is price; therefore, setting the right price point for a product is a vital decision for pushing a product or service into the market [11]. Price is a visible component of any service or product and determines consumers’ encouragement toward a buying decision. Cost naturally plays a significant role in setting the price point; however, the associated value that the customer attaches to the product or service is also a critical factor that must be considered when pricing the item. This is the worth of the product or service to the consumer in monetary terms, and it is referred to as *customer value* [27]. The cost of a product or service is not visible to the consumer, whereas this is a significant factor for price point consideration from the service provider’s end. Pricing managers are challenged to

determine a price point that takes care of the cost and that meets the consumers' perception of the product or service in terms of value [28].

2.2 Pricing of Mobile Telecommunication Products and Services

Traditionally, the pricing of products and services in the mobile telecommunication industry is one of the most complex to model due to the complexity associated with the delivery of network services. However, the industry has developed standard approaches that form the basis for the pricing of their products and services [29, 30].

In the telecommunication market, a customer compares prices using online catalogs, specialized search tools, and collaborative platforms. In a predominantly prepaid market, where many mobile customers have the SIM cards of two or more service providers, price comparison is more pronounced [31]; therefore, mobile operators have no choice but to pay close attention to several parameters when setting prices [31]. Factors such as competition, market positioning, servicing costs, and customer management costs play a crucial role for mobile service providers in making the right price move. However, operators have developed algorithms that can learn patterns from data, continuously integrate new information and detect emerging trends or changes in demand. In this way, mobile operators benefit from predictive models that allow them to determine the best price for each product or service, i.e., the optimized price (See Figure 1).

Prices are set for products and services through price optimization and are revised regularly due to the constant change in

customer behavior and quality of service. Customer preferences are often analyzed through automatic conjoint analysis while monitoring competition in real time to keep track of competitors' actions. In doing so, mobile operators try to understand customers' reactions to different pricing strategies while finding the best prices that are favorable to their gross margin and yield at the product level [32].

In the process of developing price points for products and services, several data are gathered as input. A sales history that includes the list of products purchased along with customer usage at the individual or segment level is considered. Relevant information about each product and the information on past promotions and marketing campaigns are data inputs. Moreover, reviews and feedback given by customers about product mechanisms and business rules along market dynamics of the geographical location and other competitors are among relevant data that operators would consider during their pricing process [33].

Usually, strategic goals and constraints are defined when considering a pricing move. Some clear objectives to pursue may be profit maximization, reaction to competition move, or regulatory decision to either increase or reduce prices across the market. In the model development and training of models, mobile operators rely on a variety of models for price optimization. Historically, they have used generalized linear models (GLMs), especially logistic regression; however, more complex models have been developed in recent times [34]. For instance, depending on the volume of data available, deep learning methods can also be used, mainly to price existing products for which the history of customer usage behavior is available.

Figure 1. Price engine framework.

2.3 The Need for Knowledge-Based Pricing

Pricing of products and services is more complicated in the telecommunication industry than in most other sectors. One of the primary reasons is that the majority of cost components are unknown, while the list of cost items is numerous [32]. For example, many mobile operators find it challenging to ascertain the cost that they incur to provide a megabyte (MB) of data for their customers. Complicated costs such as spectrum cost, regulatory cost, base station associated cost, fiber cost, cost related to the core side of the network, and acquisition cost are cost line items. If mobile network providers find it challenging to cost their data services, how can they price accurately?”

Unlike other industries, pricing services and products in the mobile telecommunication industry is determined mainly by competition and regulation. Firstly, regulatory bodies set the minimum pricing threshold along with data, voice, and inter-connect rates in many markets, which establishes the minimum or sometimes maximum pricing level of products and services. Competition, on the other hand, determines how far each operator can go beyond the regulatory benchmark. This regulatory approach has saved many markets from eroding their entire value as a result of price wars. With these two substantial factors, any analysis that would be acceptable for pricing in this space needs to consider the demand, the offering, and the overall company strategic objectives for pricing or pricing adjustment.

The main pricing strategic objective is precisely driven by what the company wants to achieve. This can be the type of brand the company is trying to build, the segment of the market targeted by the offer, or the size of the company’s market share,

among other factors. In an emerging mobile market, where competition is very fierce due to the customers’ low acquisition cost, the pricing moves and decisions on price adjustment depend mostly on what the market leader or new entrant is doing. For example, consequences can be enormous if a market leader makes a pricing move, and others do not follow or delay in following the leader in a creative way.

However, as data revenue is compensating in part for the declining voice revenues of the mobile industry, firms within the industry must begin to consider all associated pricing problems as portfolio optimization. In doing so, all products of a mobile operator are priced as part of the entire portfolio, such that profits are maximized along with the achieved strategic objectives [35].

3. Fuzzy Expert Pricing System

3.1 Expert Systems

Expert systems find their origins in the branch of computing that is now referred to as artificial intelligence [36]. Expert systems are a part of computer science utilizing symbolic and non-algorithmic methods to solve tasks that seemingly are too difficult to be executed by a human. They are computer programs that use problem-solving knowledge and simulations at a level comparable to human experts [19, 37]. The main components of an expert system are knowledge base, inference engine, fuzzifier, defuzzifier, and user interface [14, 38], as shown in Figure 2. The inference engine is responsible for bringing decisions based on its understanding and interpretation

Figure 2. Expert system tools and associated components.

of the expert's knowledge. The major participants in the expert system are the domain experts, responsible for making decisions. These are engineers and users with vast experience and knowledge about strategies of problem-solving by leveraging the similarities between past solved problems and current problems. When the expert system is being developed, knowledge engineers rely on domain experts to carefully explain every step of the decision-making process.

3.1.1 Components of expert systems

The fuzzification process takes the input variables and compares them with the membership functions of the antecedent part of the fuzzy rule, assigning membership values to each linguistic label.

On the other hand, defuzzification is the entire process that combines the output of fuzzy sets generated by the inference mechanism. The overall objective of this process is to obtain a clear meaning of the fuzzy set, transforming it from a set of aggregation into one of numerical values that can be utilized by the user. In a fuzzy logic system, defuzzification is the last process, and it generates crisp output from a combined aggregation of the output of a fuzzy set. It translates the entire fuzzy output into a single crisp value along the degree of membership values, and the system then consumes the applied crisp values. When comparing it with fuzzification, it is an inverse transformation process representing a fuzzy set with a crisp number because, within the fuzzy system, the internal representation of data is in fuzzy sets. This process is critical: the output from the fuzzy system needs to be in the crisp form that can be consumed as commands performing specific functions [39–43].

The following are the architectural components of the system:

- The knowledge base is the part that houses the fuzzy production rules. These are in the form “If A then B,” such that A and B are fuzzy sets, which are respectively defined on input and output domains along with the defined membership functions of their possible values.
- The database is the part that stores the problem's parameter along with other facts.
- The inference engine is responsible for evaluating the fuzzy rules contained in the knowledge base.
- The fuzzification and defuzzification modules convert a crisp input into a fuzzy set and a fuzzy set into a crisp output, respectively.

3.2 Expert Pricing Tools

An expert system is a tool that is created with different components. In the pricing of digital services, Figure 1 described the architecture and the various elements forming the expert pricing tool, which resembles a shell containing all components of a typical expert system within a software environment [36]. In the application development environment, the shell describes the end-to-end development, configuration, and initiation of all relevant components. These processes align with our model for expert system price adjustment, as shown in Figure 3. In this case, the knowledge base comprises factual and heuristic knowledge using the IF-THEN rules. In the reasoning engine, the inference mechanism is at work; it conducts a manipulation of the information within the knowledge base to generate a line of reasoning for solving issues and problems.

The explanation subsystem explains all the actions in the system, whereas the user interface stands as the means for

Figure 3. Expert system tools and associated components for price adjustment.

communicating with the user. Unlike other areas of application of an expert system, the user interface is critical in the mobile telecommunication industry; in fact, the implementation of final decisions can be catastrophic if not managed well across all network elements [36, 44].

In practice, the most applied and popular method which is acceptable across applications is expert knowledge [11]. However, when expert knowledge is not available, a fuzzy classifier system and meta-rule methods that leverage the artificial neural network or genetic algorithm are considered. Rules determination and various approaches are detailed in [45].

In simple terms, the fuzzy rule contains an expression If-Then rule such that the premise and the conclusion are both fuzzy sets. The “If” part, which is the antecedent, and the “Then” part, which is the consequence, are the two primary components. Single or combined set conditions that are joined by operators “OR” and “AND” can be composed of the antecedent. The step following the determination of rules is to perform the inference process along the degree of inputs according to the fuzzy rules. To suppress the membership functions of the rule’s consequent, two methods commonly used are “clipping” and “scaling” [16].

3.2.1 Fuzzy modeling and aggregation

Fuzzy rules are the underlying technique behind complex and ill-defined systems applying the fuzzy set theory. Some of these applications are fuzzy expert systems, fuzzy logic control, and fuzzy system modeling [46–48]. According to [49], these situations are set of n rules that take the form:

$\mathcal{R}_1$: If x is A_1 then y is C_1 ,

$\mathcal{R}_2$: If x is A_2 then y is C_2 ,

.....

$\mathcal{R}_n$: If x is A_n then y is C_n .

In the fuzzy inference process, the following four-step algorithms are involved [47]:

- Each rule is determined and matched according to its relevance to the current input values.
- The output of each rule is also determined as a fuzzy subset of the output space. This individual rule output is denoted as $\mathcal{R}_j$.
- The collation or aggregation of each of the rules in order to obtain the overall fuzzy system output as the fuzzy subset of the output space. This overall output is represented as $\mathcal{R}$.
- Some actions are selected based on the output set.

4. Price Adjustment – A Case

4.1 Problem Statement

The objective was to solve the problem faced by a mobile service provider in an emerging market, which was predominantly a prepaid market with an upward price adjustment of the firm’s data services portfolio and characterized by a severe price war of data services. The situation worsened for all the players when the market leader jumped on the bandwagon and reduced data price significantly, leading to tremendous value erosion. As a result, the mobile service provider in question became the most expensive operator in the market. At the start of the price war, the firm retained its pricing by leveraging its network quality and customers’ perception of the firm’s better network quality as compared to the competition. Shortly after the market leader reduced the prices of data-related services, the firm needed to protect its customer base as it was clear that value and volume share would shift to the market leader in no time; this was due to the predominantly prepaid nature of the market, which had customers carrying multiple SIM cards. Therefore, the firm responded by also reducing its prices of the data services portfolio. As a result of this response, the following happened:

- The firm’s network capacity became congested, especially in vital geographical locations that were critical to the business revenue. The traffic grew significantly within a very short time.
- Customer experience was impacted due to degraded network quality.
- Gross margin was negatively impacted.

Due to the above changes in the business metrics, the firm was left with only two options, namely (i) to invest in the network expansion to improve the quality of service, or (ii) to adjust the price upward to allow traffic growth to align with business revenue. The latter was the preferred option for the firm as the former would require considerable capital expenditure, which the firm was not ready to invest in the network at that time.

4.2 Price adjustment objectives

The objectives are to set the price of all data service offerings within the portfolio with the aim to:

- 1) Protect the revenue of the existing data customers within the customer base.
- 2) Reduce data traffic to address customer experience due to the data network congestion experience.
- 3) Increase the overall revenue of the data portfolio.

4.3 Fuzzy Pricing Model Development

This paper proposes and implements a new fuzzy knowledge-based pricing expert system for mobile telecommunication services named FDPS. It provides a solution to the four major problems that are associated with strategic pricing in the mobile market: demand estimation, cost estimation, competitive analysis, and final price point recommendation [50, 51]. The available data across the enterprise of a mobile service provider, coupled with the data from market research and the years of experience with different functions in the mobile operators' commercial roles, would serve as input to the system. The FDPS organizes all this information accordingly to create and form a "knowledge base".

In a competitive environment, the price point that maximizes profitability and aligns with strategic objectives is generated from the knowledge base through the underlying mathematical tools. This system uses fuzzy logic and fuzzy reasoning in the computation of appropriate combinations of the price points for telecommunication digital services and products. The pricing output is expected to align with the overall business strategy and the marketing strategy of the firm while considering all the associated strategic constraints. While the system is somewhat restricted to short or midterm pricing as a result of pricing volatility in the telecommunication industry, the inference leverages the price changes in the market with a projected competition reaction to an adjustment in price [36].

4.3.1 FDPS constructs

The FDPS utilizes a model that depends on three phases of construction, as shown in Figures 1-3 [51, 52]. In the first phase, the pricing and commercial experts showcase their knowledge of the market, competitions, and their historical expertise about outcomes of price changes through a combination of *what-if scenarios* and rich customer data about customer behavior that are readily available within the service provider enterprise, along with market research data to improve its knowledge base.

A rigorous interrogation of the knowledge base by the inference mechanism takes place in the second phase to discuss

profit margin maximization around different sensitivity parameters. This stage provides projected sales and profit margin on the products as outputs. In the last and the third phase, the extracts—new data resulting from system profit maximization decisions—are used as back-check, and the model trains itself to learn about the environment to enrich its knowledge base and improve future decision-making.

4.3.2 What-if scenarios

A key feature of the FDPS is that all its workings follow what-if scenarios, which are the "brain" of the entire inference procedure of the FDPS. Different scenarios also compute price adjustment by competition, adoption, and revenue from various products and services. The fuzzy what-if scenarios are used in the FDPS system alongside the fuzzy rules [53].

The FDPS considers the mobile operator in this case (Firm A) with two competitions offering the same digital products. The product offerings, in this case, are data services provided to customers as data bundles of different volumes in megabytes and gigabytes (MB/GB) with divergent validity or expiry date at various price points, as shown in Table 1.

Firm A is this study's case firm, and Firms B and C are the competition within the market. Suppose a price adjustment is conducted by Firms B and C on their data portfolio. A fuzzy what-if scenario for the problem that is also a fuzzy rule may be represented as follows:

IF $dPriceA$ is $PNegativeHigh$,
 AND $dPriceB$ is $PNegativeLow$,
 AND $dAPrice$ is $PZero$,
 THEN $dASales$ is $SNegativeMedium$.

Here, $dPriceA$ and $dPriceB$ are fuzzy linguistic variables representing adjustment in the prices of the data services of competitor A and competitor B, respectively, and $dAPrice$ and $dASales$ are fuzzy linguistic variables representing the adjustment in price and products sales of the firm A. $PNegativeHigh$, $PNegativeLow$, $PZero$, and $SNegativeMedium$ are fuzzy sets representing a high decrease in price point, a low decrease in price point, and almost no change in price, and high decrease in sales, respectively [51].

Human experts formulate the what-if scenarios, and appropriate fuzzy sets are defined for the antecedents and the descendent rule following the business managers' expert intuition. The systems take several similar scenarios. In the case of data services that are bundled products for telecommunication operators, the

Table 1. Competitive landscape of data services in the market

Validity	Data price (NGN)	Volume (MB)			Comments
		FIRM A	FIRM B ^{a)}	FIRM C	
24 hours	100	50	30	30	-
7 days	200	200 ^{b)}	200	200 ^{c)}	-
30 days	500	500	750	750	-
	1,000	1,000	1,500	1,500	-
	1,200	1,500	-	-	Only Firm A has this price point
	2,000	2,000	3,500	3,500	-
	2,500	3,500	-	5,000	Firm B does not compete at this price point
	3,500	5,000	-	7,000	Firm B does not compete at this price point
	5,000	-	10,000	10,000	Firm A does not have this price point
	8,000	11,500	-	16,000	Firm B does not compete at this price point
	10,000	15,000	22,000	22,000	-

NGN, Nigerian Naira.

^{a)} Introduces a 500% deal on selected price plans.

^{b)} At this price point, Firm A has a night plan of 1 GB (11 pm–5 am) with a 7-day validity.

^{c)} Firm C has an acquisition offer at this price point, and a one-off offer for the weekend.

intra-portfolio side effects are easy to manage. When a typical network provider makes a price move in the data services portfolio, the move cuts across all products within the data services portfolio, and the daily, weekly, and monthly bundles will be adjusted accordingly. This is because of the nature of the products. For some, the intra-portfolio side effects may need to be accommodated and accounted for. This effect is the impact that adjusting the price of some offerings within the company portfolio has on the sales of other offerings and products within it [36].

However, due to the complexity and sensitivity of price adjustment, human decision-making as a role will remain essential. Experienced commercial managers still need to make the final decision among several alternatives. In this FDPS, this point is taken into consideration as several price points are obtained with final decisions in the hands of human experts.

4.3.3 FDPS architecture

Illustration of the FDPS architecture is given in Figure 4. The FDPS is a combination of several fuzzy experts working in parallel with simple blocks and underlying computations [17]. Price adjustment by the competition serves as input into the system along with every product of the firms. The impact of price adjustment is predicted by all the products (N) in the portfolio and by a layer of fuzzy expert systems that are

independent. Along the what-if scenarios that have been built, the effect of price adjustment on the revenue of the individual product is captured, and market characteristics are obtained by the rules contained in each expert system. Reactions are fed into the fuzzy expert system following any price move by the competition. At this stage, several outputs are considered based on acceptance or rejection following their alignment with the organization's overall strategic objective. In the case of the telecommunication industry, network capacity, regulatory, and other factors would be considered at this stage.

A final selection is made from the final table following the possible level of price adjustments with a view to align with the company's overall strategic aims, such as profit, sales, and other network metrics (e.g., capacity).

4.4 Experiments, Procedures, and Result

4.4.1 System and structure

The system inputs are the various changes in data pricing across all players in the market at each product level. These contain all product price points, validity, and data volume at every level. The expected output that is desired from the system is a set of values for all data offerings that will address the three objectives above.

Similar problems were treated by [51, 54, 55] in their systems, which they referred to as PRICESTRAT, FUZZYPRICE, and

Figure 4. System architecture.

exPrice, respectively. While the industries they considered were different from the mobile telecommunication industry, the modeling processes were similar. In addition, the strategic aim of price adjustment altered the approach and could not enable a side by side comparison. Moreover, the market portfolio was segmented by the validity of data offers into daily, weekly, and monthly bundles under each product segment, and every competition had a list of offerings (Table 1).

That of price increase is a highly sensitive exercise—especially in a fiercely competitive market that is predominantly prepaid, where the cost of switching is meager. No assumption was made regarding the sales of the competition, and strategic constraints were the objectives of price adjustment, as mentioned in the above section.

Three fuzzy expert systems were developed and designed with 70 rules each and with price changes in the competition products as their inputs; the outputs were represented by the changes in product uptake and revenue of *firm A*. A fourth expert system was designed. Since price adjustment would shift the uptake of daily, weekly, and monthly takers, a fourth fuzzy expert system was used to compensate for this intra-portfolio effects of price adjustment for different models. The fourth fuzzy expert system contained 92 rules from the subject experts' experience and reasoning.

Several scenarios were created following the competition

price changes along with the data product segments (daily, weekly, and monthly.) A research was conducted to understand customer preference for the price adjustment direction. Considering the situation of the *firm A* at that time, three were the clear approaches to adopt to increase the price of data services, all of which had to address the strategic constraints of revenue increase and protection, network congestion management, and customer experience:

- 1) Reduction of volume in MB and reverting to the old price.
- 2) Retaining the data volume but increasing the price per MB.
- 3) Retaining the data price and volume but off-loading portion of the data volume to the off-peak period when the network is relatively underutilized.

These three scenarios were loaded into the three fuzzy expert systems that highlighted revenue projection for each product, along with the fourth system, which compensated for the cannibalization of the products within the three other segments—the intra-portfolio effects. The system was insensitive to the absolute figure as a result of inputs and outputs that were percentages of change, and a single array was mapped out with the input-output pairs of the results. Strategic constraints were considered, and restrictions were also applied, excluding the combination. The linear programming procedure was used for the evaluation

of the final combinations, and those with maximum fitness were selected following the desired criterion.

4.4.2 Results

In managing constraints and management objectives, the customer base is segmented into existing data bundle customers: those currently buying data services, or existing customers (EC); those with a prospective data bundle, or new customers (NC), who are not buying data services or are newly acquired customers. From these two broad segments, we have others such as price-sensitive customers (PS) and non-price-sensitive customers (NPS). Price and non-price-sensitive customers are known for their past responses to promotional campaigns on the network. The off-loading of the recent incremental data flux on all certain data products to off-peak is one of the outputs of the simulation, positioned to reduce over-utilization during the off-peak period and potentially increase data revenue. However, this is managed well to ensure that customer experience is not affected. All these segments are fed into different models. Business managers select the price adjustment approach that fits different segments and implement it, along with the various marketing mix strategies, as shown in Figure 5.

For the customers that are new to data services or for non-data customers (NC), appropriate price adjustment and price points for each product segment are suggested. In addition,

price adjustment approach and price points at the product level are presented to decision-makers for existing data customers.

With a well-thought-through approach using the proposed FDPS, different price points and strategies are then suggested for all products and services. The business managers' selection achieved the desired business objectives of firm A; data services revenue increased instantly by 5% month on month with a 1.3% increase in gross margin. The network witnessed a 14% reduction in data traffic, resulting in better throughput and network quality and, consequently, in a better customer experience, which impacted the net promoter score of the firm in the following quarter.

Other marketing mix, such as channels of engagement, was managed well during the implementation period. Existing codes for purchases were maintained for existing customers, and new codes with different price points were created for new customers. No above the line (ATL) campaigns were conducted on TV, radio, or social media for the data price adjustment as to manage customer perception of its expensiveness. All communication was conducted below the line in a one-to-one marketing approach, and all online, retail, and billboards were updated accordingly with commercially available revamped data plans. The firm used an aggressive below-the-line marketing campaign to drive uptake and performance.

Figure 5. The architectural representation of product portfolio: current and FDPS output. PAYG, Pay as You Go pricing (non-bundle pricing). a) Potential revenue increase, b) existing price plans, c) new billing opportunity, d) innovation, e) proposed strategy.

5. Conclusion

This study developed a knowledge-based pricing system through fuzzy logic for the pricing of mobile telecommunication data-related products and service. Our FDPS was developed and implemented for making pricing decisions on a large cellular network with clear objectives and constraints. The expert pricing system addresses cost estimation, demand estimation, competitive issue (price war), and price point recommendation, which are the critical pricing strategic issues facing mobile service providers in a competitive and vast market environment.

A knowledge base was formed through the outcomes of the marketing research conducted. Moreover, the years of experience of marketing staff and other staff from network and product development as well as rich customer data across all network elements within the enterprise contributed to it. While data traffic of mobile service providers will continue to grow as a result of demand from customers and an increasing number of connected devices and terminals with data-intensive applications [56], mobile service providers must be equipped with robust pricing tools and techniques not only to avoid price wars amongst competitors but also to be profitable and manage CAPEX investment.

In this paper, the proposed pricing tool, the FDPS, is used for recommending price points across all segments for data-related services during the time of price war period and network investment constraints due to the lack of CAPEX investment. Through a careful pilot implementation of the FDPS price points recommendations, which was later scaled up to a larger customer base, revenue increased along the gross margin with a massive reduction in network data traffic. However, although we achieved outstanding results across the critical pricing strategic objectives, we believe that further improvement in the system can still be achieved, leading to the accuracy of the recommended price points with a better impact on customer experience. This will be an exciting area for future work.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

Acknowledgments

The authors wish to thank the University of Pecs under the Higher Education Institution Excellence Program of the Ministry of Innovation and Technology in Hungary within the frame-

work of the 4th Thematic Program, “Enhancing the Role of Domestic Companies in the Re-industrialization of Hungary”.

References

- [1] W. Riaz and A. Tanveer, “Marketing mix, not branding,” *Asian Journal of Business and Management Sciences*, vol. 1, no. 11, pp. 43-52, 2012.
- [2] G. Nan, S. Wang, Z. Li, and R. Dou, “A novel pricing strategy for mobile broadband carriers using two-stage Stackelberg model,” *Knowledge-Based Systems*, vol. 142, pp. 45-57, 2018. <https://doi.org/10.1016/j.knosys.2017.11.024>
- [3] G. Rekettye and J. Liu, *Pricing: The New Frontier*. London, UK: Transnational Press London, 2018.
- [4] D. Jobber and D. Shipley, “Marketing-orientated pricing,” *European Journal of Marketing*, vol. 46, no. 11/12, pp. 1647-1670, 2012. <https://doi.org/10.1108/03090561211260022>
- [5] G. Nan, C. Zang, R. Dou, and M. Li, “Pricing and resource allocation for multimedia social network in cloud environments,” *Knowledge-Based Systems*, vol. 88, pp. 1-11, 2015. <https://doi.org/10.1016/j.knosys.2015.08.017>
- [6] P. Kotler, K. L. Keller, S. H. Ang, S. M. Leong, and C. T. Tan, *Marketing Management: An Asian Perspective*, 6th ed. Singapore: Pearson, 2013.
- [7] K. S. Yogi, “An empirical and fuzzy logic approach to product quality and purchase intention of customers in two wheelers,” *Pacific Science Review B: Humanities and Social Sciences*, vol. 1, no. 1, pp. 57-69, 2015. <https://doi.org/10.1016/j.psrb.2016.02.001>
- [8] D. Austin, S. Seljan, J. Monello, and S. Tzeng, “Reserve price optimization at scale,” in *Proceedings of 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, 2016, pp. 528-536. <https://doi.org/10.1109/DSAA.2016.32>
- [9] E. Cox, *The Fuzzy Systems Handbook: A Practitioner's Guide to Building, Using, and Maintaining Fuzzy Systems*, 2nd ed. San Diego, CA: Academic Press, 1998.
- [10] G. Bojadziev and M. Bojadziev, *Fuzzy Logic for Business, Finance, and Management*. Singapore: World Scientific Publishing, 1997.

- [11] A. Haji and M. Assadi, "Fuzzy expert systems and challenge of new product pricing," *Computers & Industrial Engineering*, vol. 56, no. 2, pp. 616-630, 2009. <https://doi.org/10.1016/j.cie.2007.03.005>
- [12] D. R. Lehmann and R. S. Winer, *Product Management*, 3rd ed. Boston, MA: McGraw-Hill, 2002.
- [13] C. T. Lin and C. T. Chen, "New product go/no-go evaluation at the front end: a fuzzy linguistic approach," *IEEE Transactions on Engineering Management*, vol. 51, no. 2, pp. 197-207, 2004. <https://doi.org/10.1109/TEM.2003.822458>
- [14] S. Thaker and V. Nagori, "Analysis of fuzzification process in fuzzy expert system," *Procedia Computer Science*, vol. 132, pp. 1308-1316, 2018. <https://doi.org/10.1016/j.procs.2018.05.047>
- [15] Y. Jiang, J. Shang, Y. Liu, and J. May, "Redesigning promotion strategy for e-commerce competitiveness through pricing and recommendation," *International Journal of Production Economics*, vol. 167, pp. 257-270, 2015. <https://doi.org/10.1016/j.ijpe.2015.02.028>
- [16] H. J. Zimmermann, *Fuzzy Set Theory and Its Applications*, 3rd ed. Boston, MA: Kluwer Academic Publishers, 1996.
- [17] M. Li, L. Liu, and C. B. Li, "An approach to expert recommendation based on fuzzy linguistic method and fuzzy text classification in knowledge management systems," *Expert Systems with Applications*, vol. 38, no. 7, pp. 8586-8596, 2011. <https://doi.org/10.1016/j.eswa.2011.01.062>
- [18] X. Y. Djam, G. M. Wajiga, Y. H. Kimbi, and N. V. Blamah, "A fuzzy expert system for the management of malaria," *International Journal of Pure and Applied Sciences and Technology*, vol. 5, no. 2, pp. 84-108, 2011.
- [19] V. K. Gupta and S. Celtek, "A fuzzy expert system for small business loan processing," *Journal of International Information Management*, vol. 10, no. 1, article no. 2, 2001.
- [20] M. H. Goodarzi and V. Rafe, "Educational advisor system implemented by web-based fuzzy expert systems," *Journal of Software Engineering and Applications*, vol. 5, no. 7, article no. 19735, 2012. <https://doi.org/10.4236/jsea.2012.57058>
- [21] S. S. Sikchi, S. Sikchi, and M. S. Ali, "Generic medical fuzzy expert system for diagnosis of cardiac diseases," *International Journal of Computer Applications*, vol. 66, no. 13, pp. 35-44, 2013.
- [22] J. R. Nolan, "A prototype application of fuzzy logic and expert systems in education assessment," in *Proceedings of the 10th Innovative Applications of Artificial Intelligence Conference (IAAI)*, Madison, WI, 1998, pp. 1134-1139.
- [23] H. Y. Lin, P. Y. Hsu, and G. J. Sheen, "A fuzzy-based decision-making procedure for data warehouse system selection," *Expert Systems with Applications*, vol. 32, no. 3, pp. 939-953, 2007. <https://doi.org/10.1016/j.eswa.2006.01.031>
- [24] T. R. Razak, M. A. Hashim, N. M. Noor, I. H. Abd Halim, and N. F. F. Shamsul, "Career path recommendation system for UiTM Perlis students using fuzzy logic," in *Proceedings of 2014 5th International Conference on Intelligent and Advanced Systems (ICIAS)*, Kuala Lumpur, Malaysia, 2014, pp. 1-5. <https://doi.org/10.1109/ICIAS.2014.6869553>
- [25] G. Jyothi, C. Parvathi, P. Srinivas, and S. Althaf, "Fuzzy expert model for evaluation of faculty performance in Technical educational Institutions," *International Journal of Engineering Research and Applications*, vol. 4, no. 5, pp. 41-50, 2014.
- [26] J. Rhuggenaath, A. Akcay, Y. Zhang, and U. Kaymak, "Fuzzy logic based pricing combined with adaptive search for reserve price optimization in online ad auctions," in *Proceedings of 2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, New Orleans, LA, 2019, pp. 1-8. <https://doi.org/10.1109/FUZZ-IEEE.2019.8858975>
- [27] P. C. Verhoef and K. N. Lemon, "Successful customer value management: key lessons and emerging trends," *European Management Journal*, vol. 31, no. 1, pp. 1-15, 2013. <https://doi.org/10.1016/j.emj.2012.08.001>
- [28] J. Bernstein and D. Macias, "Engineering new-product success: the new-product pricing process at Emerson," *Industrial Marketing Management*, vol. 31, no. 1, pp. 51-64, 2002. [https://doi.org/10.1016/S0019-8501\(00\)00116-4](https://doi.org/10.1016/S0019-8501(00)00116-4)
- [29] K. B. Kim and D. H. Song, "Automatic intelligent asymmetry detection using digital infrared imaging with k-means clustering," *International Journal of Fuzzy Logic*

- and Intelligent Systems*, vol. 15, no. 3, pp. 180-185, 2015. <https://doi.org/10.5391/IJFIS.2015.15.3.180>
- [30] W. Ahmad, T. Ahmed, and B. Ahmad, "Pricing of mobile phone attributes at the retail level in a developing country: hedonic analysis," *Telecommunications Policy*, vol. 43, no. 4, pp. 299-309, 2019. <https://doi.org/10.1016/j.telpol.2018.10.002>
- [31] A. Chen, N. Feamster, and E. Calandro, "Exploring the walled garden theory: an empirical framework to assess pricing effects on mobile data usage," *Telecommunications Policy*, vol. 41, no. 7-8, pp. 587-599, 2017. <https://doi.org/10.1016/j.telpol.2017.07.002>
- [32] A. Futter and A. Gillwald, "Zero-rated internet services: what is to be done," 2015, Available <https://www.researchictafrica.net/docs/Facebook%20zerorating%20Blogpost%20Final.Web.pdf>
- [33] W. Dettling and A. Hitz, "Mobile communication price parity and index: making money off the poor," *Telematics and Informatics*, vol. 33, no. 1, pp. 187-204, 2016. <https://doi.org/10.1016/j.tele.2015.07.003>
- [34] X. Ma, T. Deng, M. Xue, Z. J. M. Shen, and B. Lan, "Optimal dynamic pricing of mobile data plans in wireless communications," *Omega*, vol. 66, pp. 91-105, 2017. <https://doi.org/10.1016/j.omega.2016.02.001>
- [35] T. J. Gerpott and P. Meinert, "Choosing a wrong mobile communication price plan: an empirical analysis of predictors of the degree of tariff misfit among flat rate subscribers in Germany," *Telematics and Informatics*, vol. 34, no. 4, pp. 303-313, 2017. <https://doi.org/10.1016/j.tele.2016.08.003>
- [36] M. Hesami, H. E. Nosratabadi, and H. Fazlollahtabar, "Design of a fuzzy expert system for determining adjusted price of products and services," *International Journal of Industrial and Systems Engineering*, vol. 13, no. 1, pp. 1-26, 2013. <https://doi.org/10.1504/IJISE.2013.050543>
- [37] S. J. Cho and H. M. Chung, "Intelligent mobile agents in personalized u-learning," *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 10, no. 1, pp. 49-53, 2010.
- [38] C. Muriana, T. Piazza, and G. Vizzini, "An expert system for financial performance assessment of health care structures based on fuzzy sets and KPIs," *Knowledge-Based Systems*, vol. 97, pp. 1-10, 2016. <https://doi.org/10.1016/j.knosys.2016.01.026>
- [39] Y. Bae, "Chaotic phenomena in addiction model for digital leisure," *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 13, no. 4, pp. 291-297, 2013. <https://doi.org/10.5391/IJFIS.2013.13.4.291>
- [40] C. Wong, Z. X. Guo, and S. Y. S. Leung, *Optimizing Decision Making in the Apparel Supply Chain using Artificial Intelligence (AI): From Production to Retail*. Cambridge, UK: Woodhead Publishing Ltd., 2013.
- [41] S. Ketsarapong, V. Punyangarm, K. Phusavat, and B. Lin, "An experience-based system supporting inventory planning: a fuzzy approach," *Expert Systems with Applications*, vol. 39, no. 8, pp. 6994-7003, 2012. <https://doi.org/10.1016/j.eswa.2012.01.048>
- [42] I. Burhan Turksen, *An Ontological and Epistemological Perspective of Fuzzy Set Theory*. San Diego, CA: Elsevier, 2006.
- [43] E. Kayacan and M. A. Khanesar, *Fuzzy Neural Networks for Real Time Control Applications*. Amsterdam, The Netherlands: Elsevier Butterworth Heinemann, 2016.
- [44] M. Omid, M. Lashgari, H. Mobli, R. Alimardani, S. Mohtasebi, and R. Hesamifard, "Design of fuzzy logic control system incorporating human expert knowledge for combine harvester," *Expert Systems with Applications*, vol. 37, no. 10, pp. 7080-7085, 2010. <https://doi.org/10.1016/j.eswa.2010.03.010>
- [45] A. Bastian, "Identifying fuzzy models utilizing genetic programming," *Fuzzy Sets and Systems*, vol. 113, no. 3, pp. 333-350, 2000. [https://doi.org/10.1016/S0165-0114\(98\)00086-4](https://doi.org/10.1016/S0165-0114(98)00086-4)
- [46] L. A. Zadeh, "A theory of approximate reasoning," in *Machine Intelligence 9: Machine Expertise and the Human Interface*. Chichester, UK: Ellis Horwood Ltd., 1979. p. 149-194.
- [47] R. R. Yager, "Aggregation operators and fuzzy systems modeling," *Fuzzy Sets and Systems*, vol. 67, no. 2, pp. 129-145, 1994. [https://doi.org/10.1016/0165-0114\(94\)90082-5](https://doi.org/10.1016/0165-0114(94)90082-5)
- [48] R. R. Yager, and D. P. Filev, "Essentials of fuzzy modeling and control," *SIGART Bulletin*, vol. 6, no. 4, pp. 22-23, 1995.

- [49] J. Diamond, R. McLeod, and W. Pedrycz, "A fuzzy cognitive system: examination of a referential neural architecture," in *Proceedings of 1990 International Joint Conference on Neural Networks (IJCNN)*, San Diego, CA, 1990, pp. 617-622.
- [50] S. G. Tzafestas, "Fuzzy systems and fuzzy expert control: an overview," *The Knowledge Engineering Review*, vol. 9, no. 3, pp. 229-268, 1994. <https://doi.org/10.1017/S0269888900006949>
- [51] S. G. Tzafestas, S. Raptis, and N. Moschos, "A hybrid pricing expert system based on fuzzy reasoning," *Foundations of Computing and Decision Sciences*, vol. 24, no. 4, pp. 171-188, 1999.
- [52] B. Ruiz-Mezcua, A. Garcia-Crespo, J. L. Lopez-Cuadrado, and I. Gonzalez-Carrasco, "An expert system development tool for non AI experts," *Expert Systems with Applications*, vol. 38, no. 1, pp. 597-609, 2011. <https://doi.org/10.1016/j.eswa.2010.07.009>
- [53] W. C. Flores, E. E. Mombello, J. A. Jardini, G. Ratta, and A. M. Corvo, "Expert system for the assessment of power transformer insulation condition based on type-2 fuzzy logic systems," *Expert Systems with Applications*, vol. 38, no. 7, pp. 8119-8127, 2011. <https://doi.org/10.1016/j.eswa.2010.12.153>
- [54] M. G. Singh and J. C. Bennavil, "Price-Strat: a knowledge support system for profitable decision-making during price wars," *Information and Decision Technologies*, vol. 19, pp. 277-296, 1994.
- [55] S. Bijaksic, B. Markic, and A. Bevanda, "Expert pricing system as part of marketing mix," *Informatologia*, vol. 50, no. 3-4, pp. 141-150, 2017.
- [56] E. J. Oughton, Z. Frias, S. van der Gaast, and R. van der Berg, "Assessing the capacity, coverage and cost of 5G infrastructure strategies: analysis of the Netherlands," *Telematics and Informatics*, vol. 37, pp. 50-69, 2019. <https://doi.org/10.1016/j.tele.2019.01.003>

Adeolu Olukorede Dairo received his M.Sc. Financial and Industrial Mathematics from Dublin City University in 2004. He is pursuing Ph.D. degree in the Faculty of Business and Economics, University of Pecs, Hungary. He is also a senior consumer marketing executive in mobile telecommunication industry with research interest in consumer marketing analytics in firms with large customer base.
E-mail: dairo.adeolu@pte.hu

Krisztián Szűcs is an Associate Professor of Faculty of Business and Economics of University of Pecs, Hungary. His main research areas are the changing methodology of the applied marketing research in the digital era and the segmentation models of consumer markets.
E-mail: szucsk@ktk.pte.hu