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An integrated decision approach for energy procurement and tariff definition for prosumers aggregations

Massimiliano Ferrara [a], Antonio Violi [b,*], Patrizia Beraldi [c], Gianluca Carrozzino [c], Tiziana Ciano [a]

[a] Department of Law, Economics and Human Sciences, Mediterranean University of Reggio Calabria, via dell'Universitá, 25, 89100 Reggio Calabria (RC), Italy
[b] Department of Law, Economics, Management and Quantitative Methods, University of Sannio, Piazza Arechi II, 82100 Benevento (BN), Italy
[c] Department of Mechanical, Energy and Management Engineering, University of Calabria, via P. Bucci 41C, 87036 Rende (CS), Italy

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ABSTRACT

The paper deals with the energy procurement and economic management problem for an aggregation of prosumers at a strategic/tactical level. This decision process, usually in charge of the "aggregator", the entity which coordinates market operations and resource management for the entire coalition, consists into the definition of the optimal mix of energy to procure from the available sources (bilateral contracts, self-production, day-ahead market) and the tariff scheme to offer to the members of the coalition for buying and selling energy. This problem is made more complex by the presence of several sources of uncertainty, like market prices, overall demand of the coalition and production from renewable systems. To the best of our knowledge, even if several contributions have been proposed to deal with the energy procurement and tariff definition problems separately, none of them has addressed the decision process as a whole. In this paper, we propose a multiperiod 2-stage stochastic programming approach, which models the strict relations between the decisions to be made and controls risk exposure by a mean-risk objective function with the Conditional Value at Risk as risk measure. Moreover, the proposed approach aims at defining 2-components tariffs, with a variable part that is related to the random evolution of market prices, in order to enhance prosumers' responsiveness. Preliminary computational results show the effectiveness of the proposed approach as a decision support tool to guarantee the economic sustainability of the coalition and the convenience of single prosumers.

1. Introduction

In recent liberalized electric energy markets, the role of end-users is rapidly changing, also because of the availability of production and storage resources at an affordable cost, and they are becoming "prosumers", that is consumers and producers at the same time. In order to allow prosumers to have a more active role and to benefit from market opportunities, many coalitions are emerging in several countries. These users groupings, also called microgrids (Werner and Remberg (2008)) or Virtual Power Plants (VPP) (Martin-Martínez et al. (2008)) according to the availability of resources, aim at creating a sort of cooperative system, aggregating a number of prosumers to act as a single user w.r.t. power market and to fully exploit the available resources (Beraldi et al. (2018)), usually coordinated by a single entity, the "aggregator" in the following. According to this setting, single users can buy and sell energy by interacting just with the aggregator, which is responsible of offering these users more convenient tariffs w.r.t. those they could find otherwise and to make sustainable from an economic point of view the aggregation as a whole. The effective energy management for the entire coalition imposes the definition of several decisions both at a strategic/tactical and operational level. As regards the former, the main decision processes refer to the energy procurement planning considering the different available sources (bilateral contracts, self-production and day-ahead electricity market or DAEM) and the definition of tariff structures for buying and selling energy by prosumers within the coalition. However, the context in which these decisions are set is characterized by a high level of uncertainty. The overall energy demand is typically difficult to predict exactly since it refers to future needs. Market prices are known only after all producers and consumers submit their selling and bidding curves (Beraldi et al. (2004)), and, thus, they are unknown in advance. Furthermore, the power generation from renewable resources can not be accurately predicted because it can depend, for example, on the weather conditions.

To the best of our knowledge, the decision problem briefly described above has not been investigated as a whole, but recent contributions have been proposed to handle separately the energy procurement and the tariff definition, with different methodological approaches. As far as the medium-long term energy procurement, many contributions, like for example Conejo et al. (2008) and Hatami et al. (2009), propose

* Corresponding author.
E-mail addresses: massimiliano.ferrara@unisannio.it (M. Ferrara), antonio.violi@unisannio.it (A. Violi), patrizia.beraldi@unical.it (P. Beraldi), gianluca.carrozzino@unical.it (G. Carrozzino), tiziana.ciano@unirc.it (T. Ciano).

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deterministic approaches. Among these, in Carrión et al. (2005) authors solve a deterministic procurement problem over a medium-term time horizon. The model considers a set of bilateral contracts, hourly changing spot prices and the possibility of self-producing energy. More recently, in many contributions the uncertainty is explicitly modelled. For example, in Conejo and Carrión (2006) the authors extend the previous contribution by addressing a similar problem for a shorter time horizon and accounting for cost volatility by an estimation of the covariance of the spot price. In Carrión et al. (2007b) the authors consider the perspective of a large consumer that owns a limited self-production facility and propose a stochastic programming model for the energy procurement plan. They include a risk measure in the objective function in order to find a trade-off between risk and expected cost but without considering the uncertainty which affects energy demand. A similar trade-off is also investigated in Zare et al. (2010) by the use of the information gap theory with the aim of evaluating the robustness of the solutions against high spot prices or high procurement costs. In Beraldi et al. (2011) the authors propose a recourse two-stage formulation for the procurement problem over a short-term planning horizon. The problem is solved in a rolling-horizon fashion using each time the more updated information. More recently, Beraldi et al. (2017c) analyse the procurement problem from the perspective of an aggregator and propose a multi-period two-stage stochastic programming formulation. In Beraldi et al. (2017b) and Beraldi et al. (2017a) authors deal with the procurement problem under uncertainty by adopting the paradigm of joint chance constraints to define reliable plans that are feasible with a high probability level. Risk exposure has been also controlled by means of a mean-risk objective function, with the Conditional Value at Risk (CVaR) as risk measure. In Leo and Engell (2009) authors address the optimal operation of power-intensive plants by proposing a stochastic multi-stage mixed-integer linear programming model that considers uncertain product demands and equipment breakdowns to determine a solution to the integrated electricity procurement and production scheduling problem.

The optimal tariff structure definition problem has been addressed mainly by the point of view of retailers, which usually act as intermediary between the market and the end-users. Also this problem, however, is highly affected by uncertain factors, like market prices and energy demand. For example, Carrión et al., 2007 provide a stochastic programming model that allows an electricity retailer to engage in medium-term forward contracts and to optimally set selling prices to customers, with the final aim of maximizing the expected profit given a pre-specified risk level on profit volatility. In Triki and Violi (2009) authors propose a dynamic and flexible tariff structure for a distribution company that protects customers against the excessive fluctuations of the wholesale market prices, by means of a two-stage pricing scheme with a static and a dynamic component. In Fotouhi Ghazvini et al. (2017), the selling price problem for a retail energy provider (REP) is addressed by the robust optimization approach.

Since the definition of tariff for users' coalition is a quite recent problem, the number of scientific contribution is still limited. In Nojavan et al. (2014) a scenario based approach for a smart grid where the selling tariff is determined on the basis of a real-time pricing is proposed. In Fridgen et al. (2018) the authors have carried out a comparison among 12 different tariffs schemes to propose to different residential microgrids, analysing the impact of some relevant tariff features. More recently, In Kovacs (2019) a bilevel programming approach to electricity tariff optimization for demand response management (DRM) in smart grids, using a generic game-theoretic model, is proposed. In particular, the author presents a primal-dual reformulation for convert the bilevel optimization problem into a single-level quadratically constrained quadratic program (QCQP), with a linear programming algorithm as solution method. In Violi et al. (2018) authors propose a stochastic programming model based on the paradigm of integrated chance constraints for the tariff definition problem for a coalition of prosumers, but considering already set the procurement plan.

In this work, we propose a decision approach for the energy procurement and the tariff definition in an integrated fashion. We have adopted the stochastic programming framework in order to effectively manage the uncertainty, which characterizes the overall decision process. Starting from the results proposed in Beraldi et al. (2017c) and Violi et al. (2018), a first contribution consists in the modelling of the decision process as a whole, exploiting the inherent relations between the decisions that the aggregator has to deal with, that is how much energy to procure from each available source and the tariff scheme to offer to prosumers within the coalition, and considering the same uncertainty representation. Another innovative issue is related to the definition of "quasi-dynamic" tariff structures, which present some components related to the observation of uncertain parameters (overall demand and production from renewable systems, market prices). This feature can be a very useful stimulus for an efficient behaviour of prosumers, as a sort of demand responsiveness strategy. The economic convenience for prosumers to stay within the coalition is also explicitly imposed, so to guarantee the definition of tariffs which can be attractive w.r.t. other opportunities. A modern risk measure is considered in the mathematical model as well, in order to control the overall sustainability of the coalition from a financial standpoint.

The rest of the paper is organized as follows: the following Section 2 introduces the decision problem characteristics and the mathematical formulation. Section 3 presents and discusses the numerical experience that has been carried out in order to evaluate the effectiveness of the proposed model. Concluding remarks and future research developments are discussed in Section 4.

2. An integrated decision model

As already stated, we consider the problem faced by the aggregator of a medium size prosumers' aggregation and a time lapse from several months to one year that can be considered a "usual" planning horizon when the procurement and management plan for a coalition at a strategic level is defined. The energy procurement regards the choice of the optimal mix to procure from the available sources, that is from bilateral contracts, production from both conventional and renewable systems, and the day-ahead market (DAEM). The tariff definition is related to the design of price schemes to apply to different prosumers' groups for both selling and buying energy within the coalition. For each month of the planning horizon, the hours of the different days are articulated into a set F of time-of-use (TOU) blocks (e.g. peak, intermediate and off-peak). Under this assumption the elementary time period is the [month-TOU block] pair, indexed with $[t,f]$. This choice is coherent with a medium-long term planning, since many of the decisions related to [month-TOU block] pairs will be an input for the operative energy management, which is performed with a day-by-day frequency. However, other choices can be set without any impact on the model consistency.

We assume that the coalition energy needs can be covered by bilateral contracts, self-production from renewable and/or non renewable systems and by the day-ahead market, and that the coalition can have prosumers with different characteristics (for example, residential or industrial users), which can be clustered in a certain set of groups H. As already stated, decisions refer to both the procurement plan and the tariff structures to offer to the prosumers. More in detail, as regards the former, the amount of energy to procure from each selected bilateral contract, the energy to produce from traditional systems and the quantity to buy and sell on the day-ahead market. For the tariff structure, the unit price of energy bought and sold for each group of prosumers within the coalition.

Let N be the set of bilateral contracts to be evaluated, assuming that at most N^{max} can be accepted. For each contract $i \in N$, we denote by LB_{itf} and UB_{itf} the lower and upper bound for energy assumed for the TOU block f of month t, if i is selected, and by PB_{itf} the unit price for purchasing energy for the TOU block f of month t. We also consider a fixed component FB_i that accounts for administrative costs for contract acceptance. The aggregator is assumed to have a set of traditional production systems, which he can use for producing energy for each TOU block f of each month t, at a production cost G and with an upper bound Q_f^{max} for each TOU block.

In order to explicitly address the inherent stochastic nature of the decision problem, related to demand, production from renewable sources and market prices, we have adopted the 2-stage multiperiod stochastic programming framework. Here, the uncertain parameters are modelled as random variables defined on a given probability space $(\Omega, \mathscr{F}, \mathcal{P})$. Under the assumption of discrete distributions, the future uncertain evolution of DAEM prices, electricity demands and renewable production levels is represented by a set S of scenarios, each occurring with probability π_s. The potential correlation between these random variables is not explicitly modelled within the mathematical model we present, but it can be eventually represented in the scenario generation phase. We denote by D_{tfh}^s the uncertain overall demand of customers of group h and by P_{tf}^s the unitary price from purchasing energy from the market at month t and TOU block f under scenario s. Moreover, we indicate with R_{tf}^s the overall production from renewable systems. Since our model also considers the possibility to sell energy in excess to the demand, let B_{tf}^s be the selling price for the market zone in which the coalition is located. We observe that demand and supply prices could be different, according to the specific rules of several national markets like the Italian one (Beraldi et al. (2004)).

As regards tariff structures, our idea is to define a fixed and a variable component for both the buying and the selling side, with the second one related to the specific real-life evolution of market prices. This approach is motivated by two issues. On the one hand, the need to keep the coalition sustainable from a financial standpoint imposes to link as much as possible tariffs with the specific evolution of unpredictable demand, production and market dynamics. On the other hand, this articulation can stimulate prosumers to better schedule energy consumption in order to have economic benefits: if a great part of the overall demand can be satisfied by internal production, preferably by renewable systems, and/or by bilateral contracts market operations can be reduced and also tariffs can be more convenient for prosumers. An evidence of this effect will be shown in Section 3.

According with the two-stage framework, in this case first-stage variables are related to the procurement plan and to the fixed tariff components, whereas second-stage decisions stand for the variable tariff components and corrective actions that guarantee the fulfilment of the energy needs by drawing energy from the balance market. More in detail, as regards first-stage variables, let k_i be the binary decision variable associated to the acceptance of bilateral contract i and x_{itf} the amount of electricity to purchase through contract i in TOU block f of month t. As regards market operations, we indicate with y_{tf} and w_{tf} the amount to buy and to sell on the DAEM for month t and TOU block f, respectively. Q_{tf} is the amount to produce at time t and TOU block f from controllable production units. For the tariff structure we denote with $TC1_{tfh}$, the unit base price for prosumers in group h for the amount of consumed energy for month t and TOU block f with α_h, that is the percentage of the deviation of the market price from the average value adopted for consumers group h. Similarly, let $TP1_{tf}$ be the unit base price for energy sold by a prosumer and μ the percentage of deviation of market price for the selling side. As regards second-stage variables, let Δ_{tf}^{s-} and Δ_{tf}^{s+} represent the amounts of energy required to balance (excess/shortage) the aggregated needs under scenario s, traded on the secondary market. Moreover, as regards tariff components, $TC2_{tfh}^s$ unit variable price for energy bought by prosumers in group h and $TP2_{tf}^s$ the unit variable price on the selling side, for month t and TOU block f.

2.1. Constraints

The operative conditions that limit the decision process have been modelled by means of the constraints reported below.

$$\sum_{i \in N} x_{itf} + y_{tf} + Q_{tf} + R_{tf}^s + \Delta_{tf}^{s+} = D_{tfh}^s + w_{tf} + \Delta_{tf}^{s-} \qquad \forall t, \forall f, \forall s \tag{1}$$

$$w_{tf} \le Q_{tf} + R_{tf}^s \qquad \forall t, \forall f, \forall s \tag{2}$$

$$Q_{tf} \le Q_f^{max} \qquad \forall t, \forall f \tag{3}$$

$$LB_{itf} k_i \le x_{itf} \le UB_{itf} k_i \quad \forall t, \forall f, \forall i \tag{4}$$

$$\sum_{i \in N} k_i \le N^{max} \tag{5}$$

$$\sum_{t \in T} \sum_{f \in F} \left(TC1_{tfh} + TC2_{tfh}^s \right) D_{tfh}^s \le \left(1 + \Theta^B \right) \sum_{t \in T} \sum_{f \in F} P_{tf}^s D_{tfh}^s \qquad \forall h, \forall s \tag{6}$$

$$\sum_{t \in T} \sum_{f \in F} \left(TP1_{tf} + TP2_{tf}^s \right) R_{tf}^s \ge \left(1 - \Theta^S \right) \sum_{t \in T} \sum_{f \in F} B_{tf}^s R_{tf}^s \quad \forall s \tag{7}$$

$$\gamma_h^{LB} \sum_{s \in S} \pi_s P_{tf}^s \le TC1_{tfh} + \sum_{s \in S} \pi_s TC2_{tfh}^s \le \gamma_h^{UB} \sum_{s \in S} \pi_s P_{tf}^s \qquad \forall t, \forall f, \forall h \tag{8}$$

$$\eta^{LB} \sum_{s \in S} \pi_s B_{tf}^s \le TP1_{tf} + \sum_{s \in S} \pi_s TP2_{tf}^s \le \eta^{UB} \sum_{s \in S} \pi_s B_{tf}^s \qquad \forall t, \forall f \tag{9}$$

$$TC2_{tfh}^s = \alpha_h \left(P_{tf}^s - \sum_{r \in S} \left(\pi_r P_{tf}^r \right) \right) \qquad \forall t, \forall f, \forall h, \forall s \tag{10}$$

$$\alpha_h \le \tau_h \qquad \forall h \tag{11}$$

$$TP2_{tf}^s = \mu \left(B_{tf}^s - \sum_{r \in S} \left(\pi_r B_{tf}^r \right) \right) \qquad \forall t, \forall f, \forall s \tag{12}$$

$$\mu \le \varphi \tag{13}$$

$$x_{itf} \ge 0 \qquad \forall t, \forall f, \forall i \tag{14}$$

$$k_i \in \{0, 1\} \qquad \forall i \tag{15}$$

$$y_{tf} \ge 0 \qquad \forall t, \forall f \tag{16}$$

$$w_{tf} \ge 0 \qquad \forall t, \forall f \tag{17}$$

$$Q_{tf} \ge 0 \qquad \forall t, \forall f, \tag{18}$$

$$TC1_{tfh} \ge 0 \qquad \forall t, \forall f, \forall h \tag{19}$$

$$TC2_{tfh}^s \ge 0 \qquad \forall t, \forall f, \forall h, \forall s \tag{20}$$

$$\alpha_h \ge 0 \qquad \forall h \tag{21}$$

$$TP1_{tf} \ge 0 \qquad \forall t, \forall f \tag{22}$$

$$TP2_{tf}^s \ge 0 \qquad \forall t, \forall f, \forall s \tag{23}$$

$$\mu \ge 0 \tag{24}$$

$$\Delta_{tf}^{s-}, \Delta_{tf}^{s+} \ge 0 \qquad \forall t, \forall f, \forall s \tag{25}$$

Eq. (1) represents the energy balance for each period and under each scenario between overall demand and procurement sources, considering also the possibility to sell on the market the energy in excess. Condition (2) limits to the production level the amount that can be sold on the market, so to avoid a too speculative attitude. Constraint (3) represents a technological upper bound on the amount that can be produced by controllable systems in each period, while condition (4) limits the amount that can be absorbed by each active bilateral contract. In order to avoid a too big administrative effort, we limit the number of active bilateral contracts by means of (5).

Conditions (6, 7) impose the economic convenience for buying and selling energy within the coalition. In many energy systems individual prosumers cannot operate directly on the market, so they interface with other operators, like distribution companies on the buying side. For this reason the convenience of prosumers to stay within the coalition has been represented considering the mark-up for these operators. According to this assumption, on the buying side, (6) states that the overall cost for prosumers of group h has to be lower than the cost that they should pay to a distribution company, considering as unit price the market price plus a certain percentage mark-up Θ^B. Similarly, the convenience on the selling side modelled by (7) states that the overall revenue for energy sold should be greater than the revenue obtained outside, considering as unit price the market price minus a certain percentage mark-up Θ^S.

With (8) we define the range for the buying side overall tariff, with bounds that are proportional to the expected value of the market price by means of a percentage lower (γ_h^{LB}) and upper bound (γ_h^{UB}). Similar restrictions are imposed to the overall selling side tariff by means of (9), with η^{UB} and η^{UB} representing the percentage lower and upper bound for selling side overall tariff.

Eq. (10) defines the variable unit price for the buying side for each prosumer group as a percentage of the deviation from the expected value of the observed market price for each time-block of each month. The percentage α_h is constrained to be lower than a threshold τ_h (11), that can be defined according to the nature of the prosumer group. For example, residential users can be subject to a lower variability w.r.t. commercial ones. Similar conditions are defined also for the selling-side variable component by means of (12,13), with μ limited by a certain percentage threshold φ. Finally, constraints (14–25) define the nature of decision variables.

2.2. Objective function

The final aim of the aggregator is to define a procurement plan and a tariff scheme that guarantee the economic sustainability of the coalition as a whole and the convenience of each prosumer at the same time, also considering the uncertainty which characterizes the decision process. We assume that he can act like an investor which aims at both maximizing profits, which in this case represents the economic sustainability, and reducing risk exposure. Since these two objectives can be potentially conflicting in a scenario based formulation, we have adopted a mean-risk structure for the objective function:

$$\max\left[(1-\lambda)E[\Upsilon]+\lambda CVaR_\beta\right], \tag{26}$$

where the first term is the expected value of the overall profit of the aggregator (i.e. of the coalition) and the second one is the Conditional Value at Risk (CVaR), a modern risk measure widely adopted in several domains (Rockafellar and Uryasev (2000)). The parameter λ, ranging in $[0,1]$, represents the risk-aversion attitude of the decision-maker. A high value of λ stands for a "conservative" planning, while if $\lambda=0$ a risk-neutral position is modelled. The overall profit under each scenario s is given by the sum of different components:

$$\Upsilon^s=V^s_{TC}+V^s_{MKT}-C^s_{TP}-C_{BC}-C_{Prod}-C^s_{MKT}-C^s_{Err} \qquad \forall s \tag{27}$$

$$V^s_{TC}=\sum_{t\in T}\sum_{f\in F}\sum_{h\in H}\left(TC1_{tfh}+TC2^s_{tfh}\right)D^s_{tfh} \qquad \forall s \tag{28}$$

$$V^s_{MKT}=\sum_{t\in T}\sum_{f\in F}B^s_{tf}w_{tf} \qquad \forall s \tag{29}$$

$$C^s_{TP}=\sum_{t\in T}\sum_{f\in F}\left(TP1_{tf}+TP2^s_{tf}\right)R^s_{tf} \qquad \forall s \tag{30}$$

$$C_{BC}=\sum_{i\in N}\left[FB_ik_i+\sum_{t\in T}\sum_{f\in F}PB_{itf}x_{itf}\right] \tag{31}$$

$$C_{Prod}=\sum_{t\in T}\sum_{f\in F}\left(GQ_{tf}\right) \tag{32}$$

$$C^s_{MKT}=\sum_{t\in T}\sum_{f\in F}P^s_{tf}y_{tf} \qquad \forall s \tag{33}$$

$$C^s_{Err}=\sum_{t\in T}\sum_{f\in F}\left(Z^{s+}_{tf}\Delta^{s+}_{tf}-Z^{s-}_{tf}\Delta^{s-}_{tf}\right) \qquad \forall s. \tag{34}$$

Here, C_{BC} is the cost related to procurement form bilateral contracts, and is made of both a variable and a fixed amount, as already stated, while C_{Prod} represents the cost of the energy produced by conventional production systems. These cost components are deterministic, since they do not depend on the outcomes of uncertain parameters. On the contrary, all the other terms are scenario dependent. V^s_{TC} and C^s_{TP} represent the revenue and the cost due to the energy sale and purchase by prosumers within the coalition, while V^s_{MKT} and C^s_{MKT} are the revenue and the cost for market operations under scenario s, that is for a specific evolution of market prices. Finally, in (34 C^s_{Err} is the cost for the energy balance on the secondary market, with Z^{s+}_{tf} and Z^{s-}_{tf} representing the unit price on this market for the buying and selling side respectively.

As already stated, we have adopted a risk measure the CVaR, which allows to control the "tail" risk, that is the expected value of the losses exceeding the Value at Risk. Moreover, CVaR has a lot of useful properties, mainly its coherency and consistency with the second order stochastic dominance (Pichler (2014)), and is easily tractable from a computational standpoint. In the following, rather than considering the distribution of the losses, we deal with the distribution of the overall profit. In this case, for a given confidence level $\beta\in(0,1)$, the VaR is the $(1-\beta)$-quantile of the profit distribution, whereas the CVaR measures the expected worst-case profits less than VaR:

$$CVaR_\beta=E\left[\Upsilon|\Upsilon\leq VaR_\beta\right], \tag{35}$$

where Υ denotes the average profit for the entire planning horizon. Under the assumption of discrete distribution function, the risk measure can be reformulated as follows:

$$CVaR=VaR-\frac{1}{1-\beta}\sum_{s\in S}\pi^s[VaR-\Upsilon^s]_+ \tag{36}$$

where Υ^s is the profit under scenario s and the operator $[.]_+$ is used to denote the maximum between 0 and $(VaR-\Upsilon^s)$. This last term can be easily linearised by the introduction of support non negative variables σ^s satisfying the following constraints:

$$\sigma^s\geq VaR-\Upsilon^s \qquad \forall s \tag{37}$$

where the VaR represents a free decision variable.

As already stated, the resulting model belongs to the class of mixed-integer multiperiod two-stage stochastic programming problems. It is worthwhile noting that the binary variables are just related to the selection of bilateral contracts, thus their number is limited for real-life decision problems and do not impact too much on the solution process. A complete list of symbols used to represent parameters and variables is reported in Appendix A.

3. Computational experience

In this section we report on the computational experience carried out in order to validate the effectiveness of the proposed decision

Fig. 1. Optimal procurement plan.

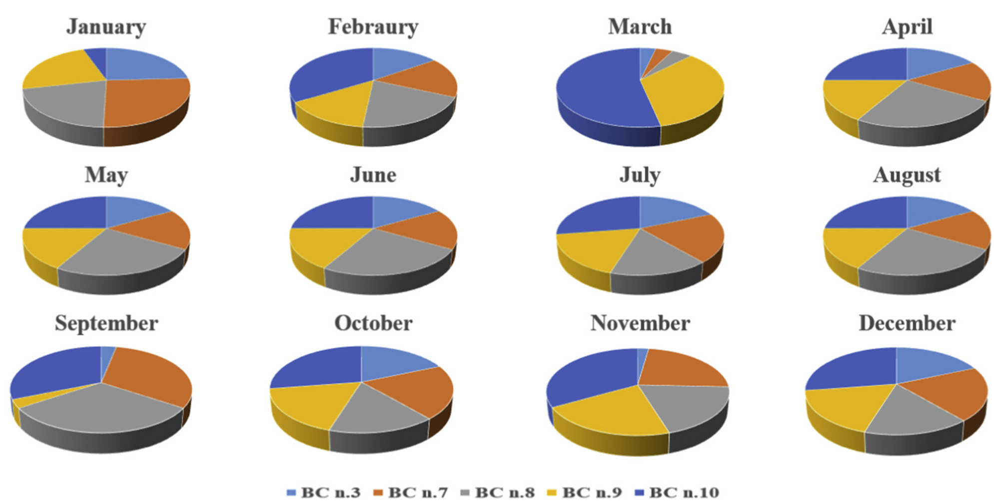

Fig. 2. Energy procured from bilateral contracts for $\lambda = 0.5$.

approach. The model has been implemented by using GAMS 24.7.1[1] as algebraic modelling system, with CPLEX 12.6.1[2] as solver for mixed integer linear problems, and MATLAB R2015a[3] for the scenario generation and parameters set-up phases. As testbed we have considered a "virtual" coalition, made up by 3 prosumers groups (residential, commercial, public utility), with a set of small photovoltaic plants with an overall capacity of 2 MWp and a set of conventional production systems with the same nominal capacity. Starting from the available data, which refer to a limited number of prosumers of each group, the expected values of the aggregated demand and production from renewable systems for each TOU block and each month have been calculated by scaling up the values calculated on the basis of historical series. In 6 the expected values of demand and production for the coalition as a whole are reported. We are considering a planning horizon of 12 months and 3 TOU blocks, F1 (peak), F2 (intermediate) and F3 (off-peak), according to the Italian electricity market. As already stated, a different choice for the planning horizon can be suitable as well. We have also considered a set of 10 bilateral contracts with different characteristics, the same adopted in Beraldi et al. (2017c). In Appendix C we have reported the price components for each bilateral contract considered. We have fixed to 5 the maximum number of contracts that can be activated.

As regards the uncertainty representation, the scenario set for each test case has been generated by using a mean-reverting process for the market prices (see Menniti et al. (2010)) and by adopting random increment or decrement to the expected values for overall demand and production from renewable systems. We have considered overall demand of the coalition, renewable production and market prices as independent random variables, that is the aggregation acts like a price-taker operator. According to this assumption, the whole scenario set has been generated by merging the scenario sets obtained for each random variable independently through Cartesian product and then by adopting a scenario reduction technique like the one proposed in Beraldi et al. (2010). For most test instances we have considered 500 scenarios along the time horizon.

Several computational experiments have been carried out in order to assess the effectiveness of the proposed approach and to evaluate the impact of different issues on the decision process.

[1] www.gams.com
[2] https://www.ibm.com/it-it/analytics/cplex-optimizer
[3] www.mathworks.com

Table 1
Buying side average tariffs in F1 (€/MWh).

Month	Residential	Commercial	Public Util.	Market
Jan	70.15	72.95	75.16	75.55
Feb	64.89	67.48	70.08	70.59
Mar	57.56	59.86	62.16	62.01
Apr	52.68	54.79	56.89	57.25
May	54.40	56.58	58.06	58.82
Jun	58.01	60.33	60.65	62.67
Jul	65.36	67.97	68.59	70.47
Aug	59.77	62.16	64.56	64.67
Sep	64.54	67.12	67.70	70.23
Oct	68.13	70.86	73.58	74.20
Nov	78.02	81.14	81.26	84.04
Dec	78.99	82.15	82.31	85.06

Table 2
Selling-side average tariff in F1 (€/MWh).

Month	Coalition	Market
Jan	59.19	38.36
Feb	55.42	35.84
Mar	47.79	30.99
Apr	44.67	29.23
May	47.77	31.29
Jun	50.84	33.11
Jul	57.95	37.75
Aug	53.04	34.32
Sep	57.15	36.81
Oct	53.20	34.48
Nov	65.76	42.30
Dec	62.16	40.95

3.1. Solution analysis

First of all, the solution of a single instance of the problem provides managerial insights about the optimal procurement mix and the tariff structure for the entire coalition. In Fig. 1 we report the amount of energy to procure from the different available sources for each TOU block of each month, obtained by solving the problem with an intermediate risk-aversion attitude parameter value ($\lambda = 0.5$).

As evident, the optimal procurement mix is quite variable over the time horizon, with for example the percentage of energy bought from bilateral contracts that for some months is higher than the quantity purchased from the market. Also the amount procured from each bilateral contract is quite variable, as reported in Fig. 2, and this is mainly due to the different unit cost proposed by each contract for each [month-TOU block] pair.

The average values of overall unit tariffs related to TOU block F1 for both the buying and the selling side are described in Table 1 and Table 2, where we report also the market alternative, that is the cost (for the buying side) and the revenue (for the selling side) that a single prosumer would have outside the coalition. These values have been calculated by considering the mark-up of the retailer equal to 35% both for the buying and the selling side.

Even if these values have been obtained with an in-sample solution, the economic benefit for both the buying and selling side is clear, thus confirming the convenience for each prosumer to stay within the aggregation. We outline also that on the buying side the cost components for the considered prosumers' groups are quite different. We have imposed different variability range for the 3 groups, in particular preserving residential users by a high tariff volatility.

3.2. Efficient frontier

We have also analysed the impact of the risk-aversion attitude of the aggregator on the energy management plan for the entire coalition. Fig. 3 reports the efficient frontier, that is the set of optimal planning obtained for different values of the risk-aversion parameter.

The lower the value of λ the more profitable, but also the more risky (in terms of worst-case profit), the planning. This result shows how the proposed model can be a useful tool to implement different policies or to find the best trade-off between risk and economic convenience. The risk-aversion attitude has also an effect on the optimal procurement mix, as confirmed by Table 3.

Again, a more conservative attitude of the aggregator, that is high levels of λ, reduces the energy amount to buy from the market, preferring to procure energy from sources with a price known in advance.

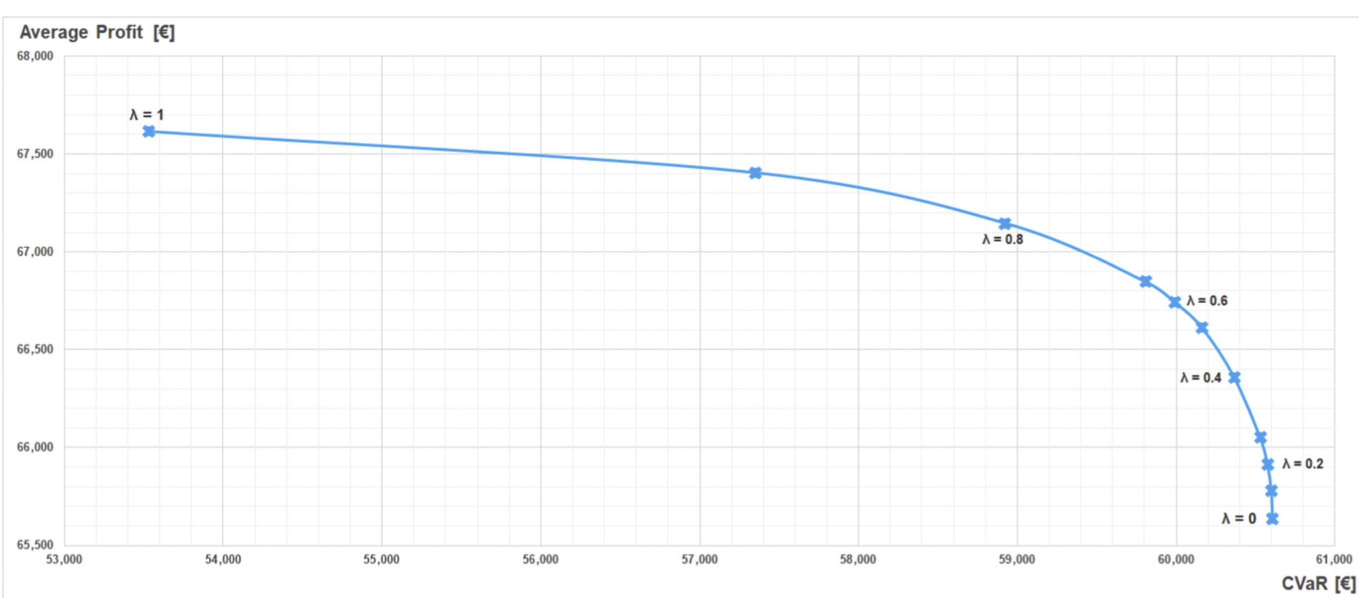

Fig. 3. Efficient frontier.

Table 3
Energy procurement mix (MWh) for different values of λ.

λ	Bilateral contracts	DAEM	Self-production	Total
0.01	2217.5	2058.9	262	4538.40
0.5	2542	1712	284.40	4538.40
0.99	2754	1458.40	326	4538.40

3.3. Value of stochastic solution

Another set of computational experiments has been carried out in order to evaluate the benefit obtained by explicitly modelling uncertainty in the decision process. We have compared the stochastic solution provided by the proposed model with its deterministic counterpart, by means of the value of stochastic solution (VSS) (see Ruszczyński and Shapiro (2003)). Since we have adopted a mean-risk objective function, the VSS can be be formulated as the weighted sum of the difference of the values of the two objectives:

$$VSS = \lambda\left(\overline{H}^{Sto} - \overline{H}^{Det}\right) + (1-\lambda)\left(CVaR^{Sto} - CVaR^{Det}\right) \tag{38}$$

Table 4
Value of stochastic solution.

λ	VSS %	λ	VSS %
0.01	33.9	0.6	26.25
0.1	32.64	0.7	25.27
0.2	30.77	0.8	24.66
0.3	28.92	0.9	22.75
0.4	28.25	0.99	21.70
0.5	27.34		

Here, $CVaR^{Sto}$ and $\overline{H}^{Sto}$ are the values obtained by solving the stochastic programming model, whereas $CVaR^{Det}$ and $\overline{H}^{Det}$ are determined by solving the same stochastic problem with the first-stage variables fixed to the values of the optimal solution of the deterministic (with the expected values) problem (also known as EEV). The following Table 4 reports the relative VSS expressed in percentage (with the respected to EEV) for different values of risk aversion parameter λ.

The results show that the VSS values are higher when a risk neutral position is considered (low values of λ). In this case, accounting for uncertainty can lead to more effective solutions.

3.4. Solution stability

In order to evaluate the stability of the solutions different experiments have been carried out by varying the size of the scenarios set. Preliminary tests have shown that the adopted scenario generation technique exhibits good in-sample stability properties. These results are summarized in Fig. 4 where we report the expected terminal profit and CVaR values obtained by solving different problem instances by varying the size of the scenario set.

More specifically, for each scenario set ($S = 250, 500, 750, 1000$), several stochastic programming problems have been iteratively generated and solved from randomly generated scenario samples to test the solution stability with respect to each set of problems. As evident from Fig. 4, the radius of the circle measured by the standard deviation is sufficiently small so to guarantee robust solutions for sets also with 500 scenarios. The advantage of adopting larger scenario sets is not so relevant, considering also the computational drawback due to the increment of the problem size.

3.5. Out-of-sample analysis

A last set of computational experiments have been devoted to assess the effectiveness of the approach with an out-of-sample analysis. We

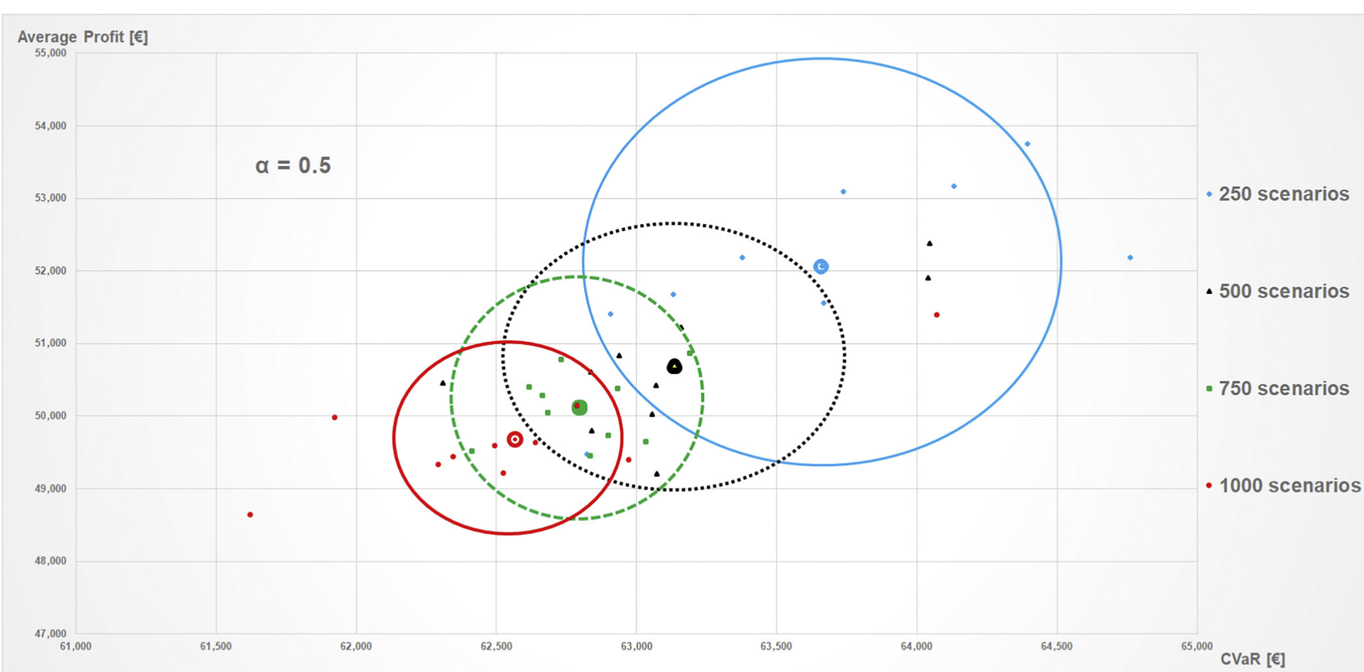

Fig. 4. Solution stability.

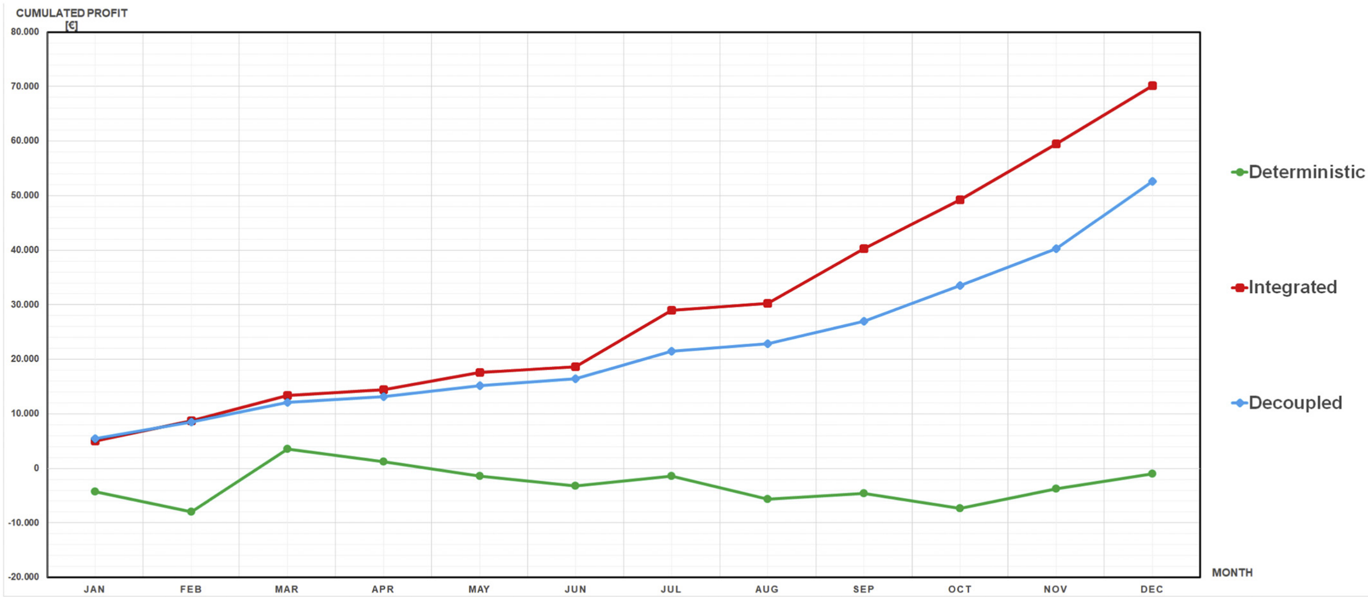

Fig. 5. Out-of-sample solutions comparison.

have evaluated the economic performance of the overall aggregation energy planning by considering the really observed values of the uncertain parameters each TOU block of 12 months starting from January 2019. Moreover, we have compared the solution provided by the proposed approach with other possible decision policies. The first one is the deterministic counterpart, that is with the solution of the model with the value of each uncertain parameters set to the corresponding expected value calculated on the historical series. The second benchmark we have considered is a sort of "decoupled" approach, in which the aggregator solves a first procurement planning problem and then, on the basis of the solution obtained, defines the tariff structure which can fit with the procurement plan and guarantee the economic convenience for prosumers. Fig. 5 depicts the profit/loss evolution of the solutions obtained with the proposed "integrated" model and the two considered benchmarks for a test case with $\lambda = 0.5$ and $\beta = 0.95$.

As we can see, the planning obtained with our model provides more benefits, making the overall coalition much more globally sustainable, in particular w.r.t. the deterministic counterpart where no uncertainty management is implemented. The benefit of about 33% of the integrated approach w.r.t. the decoupled one is due to the more flexibility guaranteed by the possibility to define in an integrated fashion decisions that are closely related.

In order to assess in an out-of-sample fashion also the economic convenience for the prosumers, in the following we report the actual tariff components, obtained after the observation of the real values of market prices. Table 5 contains the buying and selling side final tariffs for residential prosumers in F1 and the corresponding market alternative prices with a 35% mark-up.

As we can see, the advantage for the prosumers is evident for both the buying and selling side, so to ensure the attractiveness of the coalition. Similar results have been obtained for the other prosumers group (on the buying side) and for all the TOU blocks.

Table 5
Buying and Selling-side real tariff for residential prosumers in F1 (€/MWh).

	Buy		Sell	
Month	Coalition	Market	Coalition	Market
Jan	73.38	79.33	58.60	37.98
Feb	63.59	69.18	60.96	41.22
Mar	64.47	71.31	43.97	34.71
Apr	46.88	50.95	46.01	30.69
May	52.22	56.47	48.73	32.23
Jun	63.81	68.94	54.91	35.76
Jul	60.13	64.83	56.21	36.62
Aug	63.95	69.20	55.16	35.69
Sep	56.79	61.80	45.72	29.45
Oct	71.54	77.91	50.54	32.76
Nov	93.62	100.85	59.18	38.07
Dec	81.36	87.61	68.89	43.4

4. Conclusions

In this paper we have addressed the complex decision problems related to the energy procurement and the tariff definition for a coalition of prosumers in an integrated fashion. The different nature of the decisions to be made and the inherent uncertain nature of many parameters make the problem very complex to deal with. To the best of our knowledge, the problems have always be faced separately, also because prosumers aggregations are raising just in the last few years. Our contribution aims at dealing with decisions that can appear to be independent at a first sight, but are strictly related for an effective planning and management of a coalition. We have proposed a mathematical model based on the multiperiod 2-stage stochastic programming framework, with a mean-risk objective function with the CVaR as risk measure. As regards the tariff definition we have designed price schemes with a fixed component and a variable one, in order to give the prosumers an active role for their economic savings. Moreover, we have included the possibility to have different tariffs on the basis of the nature of the prosumers, thus allowing the aggregator to implement various policies. The computational experience, carried out on a coalition built starting from real-life data, has shown that the proposed approach can be a useful and articulated decision support tool for the economic sustainability of a prosumers aggregation. The comparison with two decision benchmark in an out-of-sample fashion has further demonstrated the effectiveness of our integrated approach to the problem. As future research we aim at including more complex tariff schemes, oriented towards individual plans, in order to enhance the responsiveness of single prosumers. Another possible enhancement is related to the inclusion in the medium-long term energy procurement of “seasonal” storage systems, which can implemented also by means of clusters of commercial batteries, in order to improve the flexibility in the management. Finally, our goal is to integrate the model with support tools for other decision problems, like for example the selection and scheduling of storage systems and the day-by-day energy management for the coalition as a whole.

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Appendix A. Model Notation

The following Tables A.6 and A.7 report all the parameters and variables introduced in the mathematical model.

Table A.6
Model Notation part 1.

Sets	
T	Time horizon articulated in elementary time periods (e.g. months)
F	Set of time-of-use blocks, in which hours are classified
H	Set of prosumers groups (e.g. residential, commercial, public)
N	Set of bilateral contracts available for the coalition
S	Scenario set
Parameters	
N^{max}	Maximum number of bilateral contracts tah can be accepted
LB_{itf}, UB_{itf} [kWh]	Lower and upper bound for energy bought from bilateral contract i (if selected) in TOU block f of time period t
FB_i [€]	Fixed cost for the acceptance of bilateral contract i
PB_{itf} [€/kWh]	Unit price for energy from bilateral contract i in TOU block f of time period t
G [€/kWh]	Unit production cost from traditional production systems
Q_f^{max} [kWh]	Upper bound on the energy from traditional production systems in TOU block f of each time period
τ_h	Upper bound on variable α_h
φ	Upper bound on variable μ
Θ^B	Mark-up percentage on the purchasing unit price out of the coalition
Θ^S	Reduction percentage on the selling unit price out of the coalition
γ_h^{LB}, γ_h^{UB}	Percentage lower and upper bound on the overall unit purchasing tariff for group h w.r.t. the average value of the unit purchasing price on the DAEM
η^{LB}, η^{UB}	Percentage lower and upper bound on the overall unit selling tariff w.r.t. the average value of the unit selling price on the DAEM
λ	Risk aversion parameter
β	Confidence level for CVaR
π_s	Probability of occurrence of scenario s
D_{tfh}^s [kWh]	Overall demand of prosumers of group h in TOU block f of time period t under scenario s
P_{tf}^s [€/kWh]	Unit purchasing price from the DAEM under scenario s in TOU block f of time period t
R_{tf}^s [kWh]	Overall production from renewable systems of the coalition in TOU block f of time period t under scenario s
B_{tf}^s [€/kWh]	Unit selling price on the DAEM under scenario s in TOU block f of time period t
Z_{tf}^{s+} [€/kWh]	Unit purchasing price on the balance market
Z_{tf}^{s-} [€/kWh]	Unit selling price on the balance market

Table A.7
Model Notation part 2.

First-stage Decision Variables	
k_i	Acceptance of bilateral contract i (binary)
x_{itf} [kWh]	Energy to buy by bilateral contract i in TOU block f of time period t
Q_{tf} [kWh]	Energy to produce with traditional production systems in TOU block f of time period t
y_{tf} [kWh]	Energy to buy from the DAEM in TOU block f of time period t
w_{tf} [kWh]	Energy to sell on the DAEM in TOU block f of time period t
$TC1_{tfh}$ [€/kWh]	Unit base purchasing tariff for prosumers in group h for TOU block f of time period t
α_h	percentage of deviation of the real market purchasing price from the historical average value to adopt for the variable purchasing tariff for prosumers in group h
$TP1_{tf}$ [€/kWh]	Unit base selling tariff for all the prosumers for TOU block f of time period t
μ	percentage of deviation of the real market selling price from the historical average value to adopt for the variable selling tariff for all the prosumers
Second-stage Decision Variables	
Δ_{tf}^{s+} [kWh]	Energy to buy on the Balance Market in TOU block f of time period t under scenario s
Δ_{tf}^{s-} [kWh]	Energy to sell on the Balance Market in TOU block f of time period t under scenario s
$TC2_{tfh}^s$ [€/kWh]	Unit variable purchasing tariff for prosumers in group h for TOU block f of time period t under scenario s
$TP2_{tfh}^s$ [€/kWh]	Unit variable selling tariff for all the prosumers for TOU block f of time period t under scenario s
Auxiliary Variables	
σ^s [€]	Auxiliary variables for CVaR linearization
Derived Quantities	
Υ^s [€]	Overall profit for the coalition under scenario s
V_{TC}^s [€]	Revenue from energy sold by the aggregator to the prosumers under scenario s

(continued on next page)

V^s_{MKT} [€]	Revenue from energy sold on the DAEM under scenario s
C^s_{TP} [€]	Cost for the energy bought by the aggregator from the prosumers under scenario s
C_{BC} [€]	Cost for energy procurement from bilateral contracts
C_{Prod} [€]	Cost for energy production from traditional systems
C^s_{MKT} [€]	Cost for energy bought on the DAEM
C^s_{Err} [€]	Cost (revenue) for energy bought and sold on the balance market
VaR_β [€]	Value at Risk at a confidence level β for profit distribution
$CVaR_\beta$ [€]	Conditional Value at Risk at a confidence level β for profit distribution

Appendix B. Coalition data

The following Table B.8 reports the expected values of the overall demand for each group, while Table B.9 contains the expected values of renewable production.

Table B.8
Expected value of energy demand for each prosumer group (MWh).

		TOU block		
Prosumer group	Month	F1	F2	F3
Residential	Jan	26.28	28.96	28.83
	Feb	28.34	30.14	22.96
	Mar	29.94	25.87	19.03
	Apr	16.31	17.47	20.52
	May	12.43	22.68	24.02
	Jun	16.77	22.81	26.05
	Jul	30.49	36.32	25.12
	Aug	14.70	15.11	20.82
	Sep	12.03	19.33	22.06
	Oct	16.37	26.28	22.54
	Nov	14.48	25.70	21.88
	Dec	20.46	25.14	27.44
Commercial	Jan	78.84	86.87	86.48
	Feb	85.03	90.41	68.89
	Mar	89.81	77.61	57.08
	Apr	48.92	52.41	61.55
	May	37.30	68.03	72.05
	Jun	50.31	68.44	78.15
	Jul	91.47	78.97	75.35
	Aug	44.11	45.32	62.45
	Sep	36.08	58.00	66.18
	Oct	49.11	78.84	67.63
	Nov	43.44	77.11	65.63
	Dec	61.38	75.43	82.32
Public utility	Jan	52.56	57.91	57.65
	Feb	56.68	60.27	45.92
	Mar	59.88	51.74	38.05
	Apr	32.61	34.94	41.03
	May	24.87	45.35	48.04
	Jun	33.54	45.62	52.10
	Jul	60.98	52.65	50.24
	Aug	29.40	30.21	41.63
	Sep	24.05	38.66	44.12
	Oct	32.74	52.56	45.08
	Nov	28.96	51.41	43.75
	Dec	40.92	50.28	54.88

Table B.9
Expected value of energy production from renewable systems (MWh).

	TOU block				TOU block		
Month	F1	F2	F3	Month	F1	F2	F3
Jan	78.13	16.36	21.22	Jul	171.99	40.44	29.11
Feb	77.22	22.21	21.55	Aug	184.24	37.77	24.12
Mar	139.02	16.34	14.53	Sep	77.40	23.84	22.13
Apr	167.28	13.44	19.22	Oct	87.47	20.10	11.88
May	121.74	45.93	17.27	Nov	64.43	5.51	5.09
Jun	116.65	37.52	40.64	Dec	68.55	11.33	5.38

Appendix C. Bilateral contracts

Since the price components for each contract can differ for each month, in Table C.10 we report just the average unit price for each time-of-use block and the fixed cost. A more detailed description of the considered bilateral contracts is reported in Appendix B of Beraldi et al. (2017c).

Table C.10
Bilateral contracts price components.

		BC1	BC2	BC3	BC4	BC5	BC6	BC7	BC8	BC9	BC10
Aver. price	F1	42.3	42.3	42.3	41.6	41.4	42.0	40.9	40.8	40.9	40.8
[€/MWh]	F2	43.3	43.3	43.3	43.7	42.4	41.3	41.3	40.9	40.9	41.4
	F3	35.8	35.7	35.6	35.6	35.1	34.6	34.5	34.5	34.4	34.7
Fixed cost [€]		650	675	575	375	725	650	625	500	550	850

References

Beraldi, P., Conforti, D., Triki, C., Violi, A., 2004. Constrained auction clearing in the italian electricity market. 4OR 2, 35-51.

Beraldi, P., De Simone, F., Violi, A., 2010. Generating scenario trees: a parallel integrated simulation optimization approach. J. Comput. Appl. Math. 233, 2322–2331.

Beraldi, P., Violi, A., Scordino, N., Sorrentino, N., 2011. Short-term electricity procurement: a rolling horizon stochastic programming approach. Appl. Math. Model. 35, 3980–3990.

Beraldi, P., Violi, A., Bruni, M., Carrozzino, G., 2017a. A probabilistically constrained approach for the energy procurement problem. Energies 10, 2179.

Beraldi, P., Violi, A., Carrozzino, G., Bruni, M., 2017b. The optimal electric energy procurement problem under reliability constraints. Energy Procedia 136, 283–289.

Beraldi, P., Violi, A., Carrozzino, G., Bruni, M., 2017c. The optimal energy procurement problem: a stochastic programming approach. In: Sforza, A., Sterle, C. (Eds.), Optimization and Decision Science: Methodologies and Applications, Springer International Publishing https://doi.org/10.1007/978-3-319-67308-0.

Beraldi, P., Violi, A., Carrozzino, G., Bruni, M., 2018. A stochastic programming approach for the optimal management of aggregated distributed energy resources. Comput. Oper. Res. 62, 200–212.

Carrión, M., Conejo, A., Arroyo, J., 2005. Energy procurement for large consumers in electricity markets. IEE Proc.-Gener., Transm. and Distrib. 152 357–364.

Carrión, M., Conejo, A., Arroyo, J., 2007. Forward contracting and selling price determination for a retailer. IEEE Trans. on Power Syst. 22, 2105–2114.

Carrión, M., Philpott, A., Conejo, A., Arroyo, J., 2007b. A stochastic programming approach to electric energy procurement for large consumers. IEEE Trans. on Power Syst. 22, 744–754.

Conejo, A., Carrión, M., 2006. Risk-constrained electricity procurement for a large consumer. IEE Proc.-Gener., Transm. and Distrib. 153, 407–413.

Conejo, A., Garcia-Bertrand, R., Carrión, M., Caballero, A., de Andres, A., 2008. Optimal involvement in futures markets of a power producer. IEEE Trans. on Power Syst. 23, 703–711.

Fotouhi Ghazvini, M., Soares, J., Morais, H., Castro, R., Vale, Z., 2017. Dynamic pricing for demand response considering market price uncertainty. Energies 10, 1245.

Fridgen, G., Kahlen, M., Ketter, W., Rieger, A., Thimmel, M., 2018. One rate does not fit all: an empirical analysis of electricity tariffs for residential microgrids. Appl. Energy 210, 800–814.

Hatami, A., Seifi, H., Sheikh-El-Eslami, M., 2009. Optimal selling price and energy procurement strategies for a retailer in an electricity market. Electr. Power Syst. Res. 79, 246–254.

Kovacs, A., 2019. Bilevel programming approach to demand response management with day-ahead tariff. Journal of Modern Power Systems and Clean Energy 7, 1632–1643.

Leo, E., Engell, S., 2009. Multi-stage integrated electricity procurement and production scheduling. Computer Aided Chemical Engineering 44, 1291–1296.

Martin-Martínez, F., Sanchez-Miralles, A., Rivier, M., 2008. A literature review of microgrids: a functional layer based classification. Renew. Sust. Energ. Rev. 62, 1133–1153.

Menniti, D., Scordino, N., Sorrentino, N., Violi, A., 2010. Short-term forecasting of day-ahead electricity market price. 2010 7th international conference on the European energy market, EEM 2010.

Nojavan, S., Qesmati, H., Zare, K., Seyyedi, H., 2014. Large consumer electricity acquisition considering time-of-use rates demand response programs. Arab. J. Sci. Eng. 39, 8913–8923.

Pichler, A., 2014. Evaluations of risk measures for different probability measures. SIAM J. Optim. 23, 530–551.

Rockafellar, R., Uryasev, S., 2000. Optimization of conditional value-at-risk. Journal of Risk 2, 21–41.

Ruszczyński, A., Shapiro, A., 2003. Stochastic Programming, Handbook in Operations Research and Management Science. Elsevier Science, Amsterdam.

Triki, C., Violi, A., 2009. Dynamic pricing of electricity in retail markets. 4OR 7, 21–36.

Violi, A., Beraldi, P., Ferrara, M., Carrozzino, G., Bruni, M., 2018. The optimal tariff definition problem for a prosumers' aggregation, in: Daniele, P., Scrimali, L. (Eds.), New Trends in Emerging Complex Real Life Problems, Springer International Publishing. pp. 483–492.

Werner, T., Remberg, R., 2008. Technical, economical and regulatory aspects of virtual power plant. Third international conference on electric utility deregulation and restructuring and power technologies, 2427–2433.

Zare, K., Moghaddam, M.P., Sheikh El Eslami, M.K., 2010. Electricity procurement for large consumers based on information gap decision theory. Energy Policy 38, 234–242.