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Virtual Power Plant as a Tool for Cost-Reflective Network Charging Tariff

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***Abstract*—This paper presents a novel approach to applying the Virtual Power Plant (VPP) concept and for the Cost-Reflective Network Charging Tariff. The paper proposes an innovative energy trade concept based on current research and literature analysis. The technical novelty of the paper is motivated by reviewing the current developments in the Lithuanian renewable energy sector and related research on VPPs and cost-reflective pricing. The components of the VPP, including balancing of generation and consumption profiles, load forecasting, and solar generation predicted, are thoroughly described, along with a method for determining the network and VPP costs. An optimisation algorithm for cost optimisation is also presented. The paper concludes by demonstrating the implementation and operation of the EA-SAS Cloud Virtual Power Plant platform, which represents a significant contribution to the field of smart energy management.**

***Index Terms*—Energy management; Demand side management; Distributed power generation; Virtual power plants.**

I. Introduction

In light of the rapid growth of Distributed Energy Resources (DER) part in the energy mix, new challenges arise for the development and charging of power networks. Installing new capacity results in additional network costs. However, in most cases, the network is not developed in a sustainable way. Usually, equipment is selected on the basis of nominal or reserved power ratings as recommended by authorities and operators. This often leads to surplus investments or requires additional investments for the reconstruction of transformer substations when installing residential solar power plants.

Another challenge arises with respect to investments in the network and network charging. The increasing proportion of DERs in the energy mix indicates that more and more consumers in the network are becoming prosumers and that the energy demand from the network operator will decrease. For the network operator, recovering network costs is becoming increasingly challenging.

Another aspect of sustainable network development is the practise of installing DER power plants geographically close to consumption areas. This allows for electricity generation and consumption in relatively the same area, avoiding high energy transmission costs. Successful implementation of such a measure requires smart energy management. Smart energy management aims to solve the aforementioned techno-economic challenges related to the growing proportion of the DERs in the energy mix and to optimise network costs. The Virtual Power Plant (VPP) concept is commonly seen as one of the main pillars of smart energy management. To successfully implement a VPP, the creation of an advanced information system is required.

II. Current Developments in the Lithuanian Renewable Energy Sector

Lithuania, like many other countries, has been increasingly exploring the potential of prosumers, who generate their own electricity using solar panels or wind turbines and can sell the excess back to the grid. The Government of Lithuania has been promoting the development of renewable energy, including remote prosumers, as part of its efforts to transition to a low-carbon economy.

In terms of initiatives, there have been some recent developments in Lithuania. Following the Strategy of Ministry of Energy of the Republic of Lithuania, in 2018 a company called "Ignitis Renewables" opened a solar park rental platform [1], which allows individuals and businesses to rent out solar panels in exchange for a portion of the electricity generated. As stated by D. Maikštėnas, CEO of Ignitis Group, it is the first open energy platform in the world that allows any household in the country to purchase a power plant online [2].

At the end of 2022, the company rebranded a platform and introduced a proposal for prosumers to rent part of the wind turbine developed in Lithuania. Wind turbine tenants will benefit not from the net metering system (storing energy in the grid to be consumed during demand peaks) but rather from the net billing system (selling energy at the given NordPool market price) [3].

In 2022, the number of prosumers in the Lithuania electricity distribution network increased more than twice: from 18 833 to 42 438 prosumers. In March 2023, in Lithuania, there is a total of 50 825 prosumers with an installed capacity of 553,6 MW. 11 573 or 23 % of those

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prosumers are remote.

Looking for the future, the Lithuanian Distribution Network Operator (ESO) conducted a study "Evaluation of the suitability of the distribution network and the legal regulation environment suitability and the level of preparation for the transformation of the energy sector" [4]. According to the analysis, the effective and rational development of renewable energy resources and the connection of solar power plants to the Operator network can reach from 170 thousand to 190 thousand prosumers with a total installed capacity of 1.2–1.3 gigawatts (GW) by 2030. This amount would cover around 7 % of the total electricity demand of Lithuania at that time [5]. ESO views remote prosumers as a priority that would allow to achieve a higher number of connected prosumers, higher installed capacity, effectively utilise solar power parks whose development is currently in the planning stage, and to reach cost efficiency for prosumers, economy of scale for solar power parks development, and also sustainable development of the network.

In conclusion, Lithuania's renewable energy sector has experienced significant growth in recent years, with the number of prosumers increasing rapidly. This growth, coupled with the potential for further expansion, highlights the need for advanced energy management systems such as Virtual Power Plants (VPPs). Initiatives such as the "Ignitis Renewables" solar park rental platform and the proposal for prosumers to rent part of a wind turbine demonstrate the country's commitment to transitioning to a low-carbon economy. With the ESO prioritising the development of remote prosumers, the future looks promising for the continued growth and sustainability of the country's renewable energy sector.

III. Challenges of a Traditional Cost-Reflective Network Charging

The number of prosumers is increasing exponentially and it is changing the standard practise of cost recovery for Distribution Network Operators (DNOs). As self-sufficient prosumers decrease the amount of electricity purchased from the Operator, it results in lower revenue collected while prosumers generate additional costs. The Operator may need to increase the tariffs to cover these costs, resulting in cross-subsidisation, where residential consumers without solar installation pay higher network fees and cover additional costs which prosumers avoid paying [6].

Network tariffs usually consist of several components, including the electricity spot price (electricity generation or purchase from the international power market), transmission and distribution network costs, system services costs (reserves, congestion management, voltage control and reactive power support, black start capability, and system balancing), and non-network-related policy costs, such as taxes, levies, and costs of support schemes for renewable energy sources (RES) and stranded power generation [7]. There are various methodologies for determining Operator costs, one of which is Long-Run Average Incremental Cost (LRIC or LRAIC). Tariffs are determined for a certain future period based on forecasted costs and benefits created by prosumers, including the energy they supplied to the Operator for technological processes.

In traditional electricity and network charging, there is a common practise of setting a price tariff for residential prosumers consisting of all the constant components described above. Tariffs for separate components are revised each year, half a year, or more often if necessary. However, this approach does not accurately reflect the real costs created in the network.

Figure 1 shows an example of a fragment of a distribution network. One branch is connected to the Virtual Power Plant (VPP) via a blue dashed line, whereas another branch is depicted as a perspective connection to the VPP through a red dashed line. This demonstrates that the operation of a VPP is not geographically or technologically limited, and it can expand through the different regions and voltage levels. Finally, for comparison, there is a branch that is not connected to the VPP, representing a traditional network and network charging concept (Consumer S_3 and Prosumer P_2). Surplus energy generated by Prosumer P_2 is supplied to the network, where it is consumed by residential Consumer S_3, a neighbouring geographically nearby.

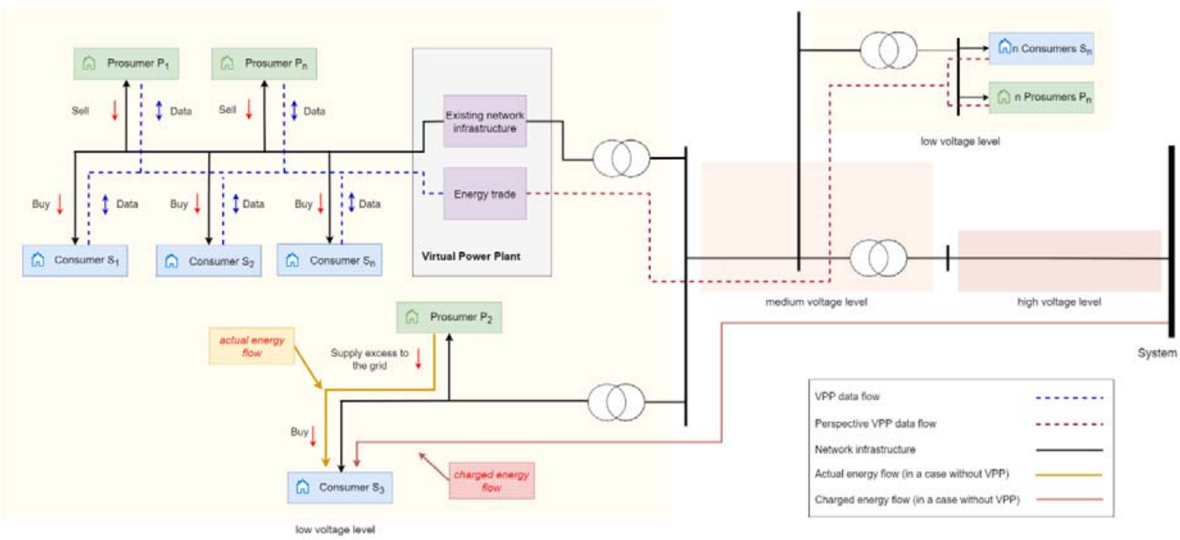

Fig. 1. Virtual power plant energy trade in comparison to actual and charged energy flows in traditional network charging.

The network operation in question is a manifestation of the fundamental principle of electrical energy, where the power flows towards the closest point of load resistance, as shown by the yellow line. Even though energy is consumed locally, the Consumer for this energy is charged the full price with network usage tariff, including costs of a high voltage transmission network and medium voltage distribution network part. However, in fact, this energy flow does not generate any costs in the medium and high voltage levels parts of the network and is consumed locally.

This charging policy does not encourage sustainable development and effective usage of the network. VPP solves this problem by allowing for optimal network costs and efficient use of the network through the optimisation of energy flows from both technical (reducing loading on transformers and lines) and socio-economic aspects (charging, impact on smart energy usage, which can lead to a reduced energy price).

IV. Related Works

Examples of Virtual Power Plant (VPP) utilisation for cost-reflective pricing have appeared in scientific research, although it may not be considered a thoroughly analysed topic. In recent years, it has gained increasing attention as a tool for managing challenges that appear with the integration of distributed energy resources into electricity grids. While there is a growing body of literature on VPPs and cost-reflective pricing, much of the research and development is still in its early stages, and there are many challenges to be addressed. An analysis of related works and implemented methods was performed to gain an understanding of the requirements and risks to consider in the development of an IT infrastructure for VPPs.

The VPP evaluates a wide range of network characteristics and equipment parameters. One of the parameters that must be considered in the objective function of cost optimisation is the generator degradation cost, as stated in [8]. In a study, the authors applied the Differential Evolution (DE) algorithm to minimise the operation cost of the generators, which allowed them to minimise the total costs by 7.06 % per day.

The methods for Optimal Planning of VPPs can be divided into the following categories [9].

– *Classical optimisation methods*, e.g., Linear Programming (LP). The linear programming method is the simplest classical mathematical optimisation method that is applied when all objectives and constraints are linear or are assumed to be linear because the real relationships may be very complex [10].

– *Heuristic and meta-heuristic methods*, e.g., Point Estimate Method (PEM) [11], Particle Swarm Optimisation (PSO) algorithm[12], Genetic Algorithm (GA), and Monte Carlo simulation for optimal planning to increase profit by considering Demand Response (DR) [13], [14]. Heuristic methods aim to achieve a particular outcome for a given problem while balancing accuracy of the solution and computational cost. Meta-heuristicapproaches are high-level procedures designed to solve various optimisation problems without requiring specific knowledge about the problems and combine multiple heuristics to achieve an optimal or near-optimal solution [9].

– *Methods based on learning*, e.g., supervised, unsupervised and reinforcement learning, deep learning techniques, including Convolutional Neural Network (CNN), and Recurrent Neural Networks (RNNs). Unlike conventional optimisation methods, these approaches do not require significant expertise for utilisation [15].

A distributional robust optimisation model is utilised in some cases of VPPs models for day-ahead [16] and real-time market price modelling [17]. It utilises moment information (e.g., mean and covariance) of the unknown parameter [16].

The multi-objective black widow optimisation algorithm (MOBWO) was also utilised for the multi-objective optimal scheduling together with a peak valley power pricing strategy. The optimal scheduling of VPP is achieved by performing a multi-objective scheduling strategy, which is day-ahead (on an hourly basis) and 15 min-based (for a one-day profile) to observe the behaviour of the anticipated system with a better constraint handling method [18]. The authors in [19] suggest a communication-efficient decentralised optimisation algorithm (DOA) based on the extended Alternating Direction Method of Multipliers (ADMM) for the multi-period optimal power flow problem and power management. ADMM ensures that the connected communication nodes exchange only the information that they are interested in.

A network-constrained stochastic model in auction-based local market clearing is another approach to energy management in a VPP [20]. The model analysed the bills of consumers at different nodes of the network. The bill costs of consumers in the context of VPP have been reduced on average by about 4.58 %.

Another pricing mechanism utilised for VPPs operation is the Frequency Control Ancillary Service-Critical Peak Rebate (FCAS-CPR). This method focusses on customising pricing strategies to the rebates in coupled distributed resources and frequency control ancillary service markets, thus reflecting the potential abilities of VPPs to reduce peak load and support system frequency [21]. The FCAS-CPR method is complex and uses various methodologies, including feature extraction-based clustering [22], Clustering by Fast Search and Find of Density Peaks (CFSFDP) [23], Prospect Theory (PT) [24], Cumulative Prospect Theory (CPT) [25], and the Salp Swarm Algorithm (SSA) for solving Stackelberg game [21], [26], [27].

Although there has been progress in developing methods for optimal planning and pricing of VPPs, more research is needed to address the challenges and risks involved and to improve the accuracy and efficiency of these methods and to fully realise the potential of VPPs for managing distributed energy resources in electricity grids.

V. Understanding the Fundamentals of Virtual Power Plants

A. An Overview of Distributed Energy Resources Aggregation and Coordination

Data aggregation at the Virtual Power Plant (VPP) is described as one of the main pillars of smart energy supply [28]. It enables advanced control of generation, energy storage, and controllable loads, providing balance and the ability to participate in the markets of energy supply, reserve, balance, and CO_2 certificates.

The VPP is a virtual infrastructure that aggregates the Distributed Energy Resource (DER) generation data and coordinates and optimises their control based on energy consumption in the network. The logic of the VPP trade is illustrated in Fig. 1: Prosumers can sell surplus generated electricity and Consumers can purchase it directly from Virtual Power Plant instead of Operator. The main components of the VPP are often described as energy generators, energy storage units, and controllable loads [4]. In the case of smart, data-driven control, the VPP is only able to operate by controlling DERs and conducting energy trade in the market when self-generation is not sufficient to cover the demand.

VPPs typically perform several main tasks [28], including:

– Forecasting, balancing, and coordination of all aggregated assets such as generators, energy storages, and controllable loads, including highly volatile wind and photovoltaic generation [28];

– Day-ahead energy trade scheduling for aggregated assets and scheduled energy sale in the electricity market;

– Online monitoring of generation and consumption data and estimation of deviations;

– Decision making in the optimising process whether to use its own resources to compensate fluctuations or to use the external reserve provided by the Operator.

VPPs are different from micro networks in the way that they are a virtual infrastructure with no geographically defined borders, while micro networks have defined borders and can disconnect from the main grid in island operation. VPPs can expand or shrink in response to real-time market conditions [29] and can extend over a much wider geographical region. In cases when demand is lower than the power supply due to energy conservation, VPPs can manage this excess and sell the electricity to other companies on a “Negawatt market” exchange, rather than wasting the energy [29]. The Negawatt market model is defined as the energy customers’ right to buy energy that is produced due to a change in their energy consumption behaviour, offering prosumers the opportunity to participate in the energy market by trading the right to buy energy instead of energy demand [30].

Another important aspect in the implementation of VPP is determining the boundaries of responsibility between the Network Operator and the VPP Customer. VPPs must ensure supplying demanded energy to connected Consumers. It can be achieved by advanced control of local DERs without extracting additional energy from the Operator. This allows for decreased reserved capacity from the grid, creating benefits for both consumers and Operator. Consumers benefit from reduced energy bills, and Operators are able to effectively expand the network by connecting more consumers because of available capacity without additional investments to the infrastructure.

As VPPs aggregate and distribute power flows locally, they also allow for determining the actual costs of network usage and reducing load on separate transmission lines [29]. Nowadays, most energy consumers have smart meters and all prosumers are required to have smart meters that allow knowing power flows in the system real-time. When developing VPPs, these data are collected to the VPP virtual infrastructure. Data are collected in the Cloud by collecting it directly from the meters or from a separate database.

The main purpose of VPPs is advanced control of a power system by controlling power generators and consumers in a way that minimises energy losses. In addition, using VPPs as a tool to determine cost-reflective variable network tariffs requires determining actual network costs.

B. Balancing of Generation and Consumption Profiles

The implementation of VPPs relies on the increasing level of digitalisation in the network, where each prosumer has a net metering system with smart meters and most residential consumers also have smart metering. Smart grid deployment is one of the three priority thematic areas that aims to help integrate renewable energy, complete the European energy market, and allow consumers to better regulate their energy consumption [31]. Creating possibilities for collecting and gathering data from various sources in one platform enables implementation of VPPs.

VPPs collect consumption data of connected consumers and analyse Consumption Profiles. For this purpose, in European countries, Meter-Bus (M-Bus) communication is usually used because it is an European standard (EN 13757) for remote reading of gas, electricity, and other consumption meters. Data reading can be implemented through either wired or wireless connection, with wireless connections being the most widely used method nowadays. To interfere with the network and perform advanced control, a two-way connection must be ensured. In this way, consumption can be managed by controlling controllable loads such as Heating, Ventilation and Air Conditioning (HVAC) units, charging electric vehicles, or energy storage units.

The EA-SAS Cloud Virtual Power Plant is a component of the pre-existing EA-SAS Platform infrastructure, which can collect data from smart meters or databases, such as those created by energy system operators. The examples of such platforms are Data Hub and Data Bridge. Data Hub is Lithuania’s distribution network operator (“Energijos skirstymo operatorius” (ESO)) created platform [32]. The purpose of the Data Hub is to easily exchange data between operators, energy suppliers, and clients. Another smart grid project is Data Bridge [31], an international project powered by the European Union, aiming to build a common European Data Bridge Platform to enable integration of different data types (smart metering data, network operational data, market data) [31]. This collection of various data can be used in VPP for advanced control and network taxation.

Furthermore, after data collection, forecasting energy demand is a crucial feature of VPPs. To perform forecasting, the EA-SAS Cloud VPP Virtual Power Plant model was created. Based on forecasted energy consumption and generation, the VPP evaluates the optimal balancing measure that creates the lowest cost. This could include determining whether to utilise the external energy source or the internal energy source in case of an energy shortage based on the lowest energy generation cost and price in the market. Additionally, the VPP can schedule the usage of energy storage systems or determine the need for investments in network infrastructure.

C. *Determining the Network Costs for Variable Cost-Reflective Charging*

The main purpose of network charging and taxation is to reflect the costs of the network. To determine network costs, a typical segment of the distribution network can be analysed, as shown in Fig. 2. Here, P_i represents the installed power of a DER power plant (active), S_{i_low} is apparent power of a low voltage segment, while S_{i_middle} and S_{i_high} are the apparent power of middle and high voltage network segments.

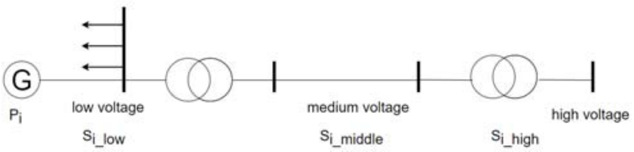

Fig. 2. Simplified segment of a power distribution network.

Figure 2 shows a simplified segment of a power distribution network, and the whole power network consists of such segments, which all reflect the costs of the network operator.

Network costs reflect the deterioration of the network elements, which is the result of power flows in the network caused by loads and generators. If S is an apparent power and P is the active power, then the network costs C caused by the DER plant P_i can be expressed as in (1)

$$C = price\ tariff \times \left(\frac{P_i}{S_{i\_low}} + \frac{P_i}{S_{i\_middle}} + \frac{P_i}{S_{i\_high}} \right). \qquad (1)$$

The power system can be divided into branches (network zones, regions). Branches, depending on their structure and configuration, can have a determined capacity S. In the case when the capacity is high S_i >>, expression (2) shows that if the DER power decreases, costs increase

$$If\ \ S_i\ and\ P_i \downarrow \Rightarrow C \uparrow . \qquad (2)$$

The other borderline case is that if the network capacity is low and the DER power increases, costs decrease

$$If\ \ S_i \ll and\ P_i \uparrow \Rightarrow C \downarrow . \qquad (3)$$

The capacities of regions in a power network are unevenly distributed and depend on geographical and demographic conditions. While traditional cost-reflective charging only takes into account the costs of the whole network and distributes it evenly, VPP creates a possibility to utilise real-time data and algorithms for determining the real costs at a given moment and propose tariffs reflecting those costs

$$C = price\ tariff \times \frac{P_i}{S_{i_{used}}}. \qquad (4)$$

Equations (1)–(4) describe the main approach to defining network costs. Network costs can be determined by combining EA-SAS Cloud VPP infrastructure and EA-PSM Power System Modelling software [33]. The EA-PSM software is used to create a technical model of an electrical network. An example of modelled part of the network at the EA-PSM GIS interface is depicted in Fig. 3.

Figure 3 shows the power losses calculation results of a typical distribution segment line using EA-PSM software. The software allows the technical data of each network element (e.g., cables' parameters such as length, cross-section, material, insulation types, etc., transformers' parameters, and modelling different types of loads in the system) to be described. Combining technical network data with real metering data allows calculations to be performed, such as the results of line power losses shown in Fig. 3, which help to determine network costs and control the network. This allows for the calculation and proportional assignment of actual network costs and the optimisation of these costs by deciding the most optimal way to manage both energy and economic (costs and tariffs paid by Customers) flows. The VPP cost optimisation control logic is described in more detail in Section VII-A.

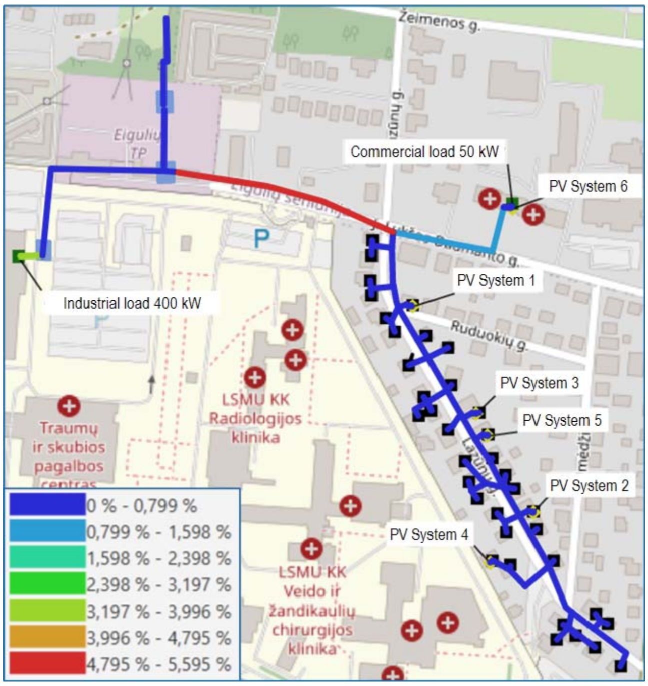

Fig. 3. Results of a typical distribution segment line power losses calculation using EA-PSM software, voltage drop in percents.

VI. Cost Optimisation Algorithm

This section describes the cost optimisation algorithm used in the EA-SAS Virtual Power Plant (VPP). The method used for non-linear programming is the Objective Penalty Function Method, [34] which has good convergence and differs from other penalty function algorithms. The objective of the cost optimisation algorithm is to minimise the total cost of the network while satisfying all operational constraints. The algorithm considers various factors such as energy prices, network constraints, and generator constraints to find the optimal dispatch of available resources. The algorithm uses a penalty function approach to handle operational constraints and ensure that the solution is feasible.

The objective penalty function can be expressed as

$$F(x,M)=\left(f_0(x)-M\right)^2+\sum_{i\in I} f_i^+(x)^p, \tag{5}$$

where $M\in R$ is called an "objective penalty parameter" and

$$f_i^+(x)=max\{0,f_i(x)\}, i\in I. \tag{6}$$

The algorithm that generates an optimal solution is described below [34] (see Algorithm 1).

Algorithm 1. Objective Penalty Function for cost minimisation.

1. Choose $p>1, c>0, x^0\in X$, and $a_1<f_0(x^0)$. Let $k=1, b_1=f(x^0)$, and $M_1=(a_1+b_1)/2$;
2. Solve $\min_{x\in Y} F(x,M_k)$. Let x^k be the obtained optimal solution;
3. If x^k is not a feasible solution to (*P*), let $b_{k+1}=b_k$, $a_{k+1}=M_k$, $M_{k+1}=(a_{k+1}+b_{k+1})/2$, and go to Step 5. Otherwise, $x^k\in X$ and go to Step 4.
4. If $F(x^k,M_k)=0$, let $a_{k+1}=a_k$, $b_{k+1}=M_k$, and $M_{k+1}=(a_{k+1}+b_{k+1})/2$, and go to Step 5. Otherwise, $F(x^k,M_k)>0$, x^k is an optimal solution to (*P*), and the algorithm is terminated.
5. If $|b_{k+1}-a_{k+1}|<\in$, then the algorithm terminates and x^k is an approximately optimal solution. Otherwise, let $k=k+1$, and go to Step 2 [34].

The cost optimisation algorithm evaluates technical and cash flows by feasible alternatives and allows optimal control of the network. The optimal control logic is more thoroughly described in Section VII-A.

VII. Virtual Power Plant IT Infrastructure

A. VPP Operation and Control Logic for Cost Optimisation

The cost optimisation algorithm employed in EA-SAS Cloud Virtual Power Plant (VPP) is presented in Fig. 4. The EA-SAS Cloud VPP forecasts the load, solar, and wind generation, and the energy prices in the market using smart metering consumption data to create consumption profiles, meteorological data to create solar and wind generation profiles, market data for market price forecasting, and technological data of the network equipment. These data sources are used directly in the calculations or combined with the EA-PSM calculation results [33], as described in the Section V-C ("Determining the Network Costs for Variable Cost-Reflective ").

On the basis of forecasting data, the optimal network control decision is made using Energy Balance and Finance Balance calculations. The optimal scenario (optimisation problem target) for the electrical network is when generation equals consumption, and electrical energy is supplied to the Consumer at minimal cost. If forecast generation is higher than consumption, VPP has two options: charge batteries or sell surplus energy to market. When forecasted generation is lower than consumption, the VPP has several options: discharge energy from batteries, buy energy from market (network operator) or generate more energy from own resources, such as turning on diesel generators. The financial balance calculation is performed to determine the optimal mode of operation. The costs and potential profits of each option are calculated, and the VPP sends a control task to the control system based on the results. Variable cost-reflective charging is enabled by evaluating the energy tariff from various sources and determining the network usage tariff based on the network costs, as described in Section V-C ("Determining the Network Costs for Variable Cost-Reflective "). Tariffs for connected Prosumers and Consumers are calculated for smart energy trade. Calculations can be performed in 5 minutes, 15 minutes, or 1 hour time steps.

B. Data Collection and Calculations

The VPP solution was implemented on the EA-SAS Cloud system [35]. The EA-SAS Cloud dashboards are fully flexible for configuration. The example of hourly energy consumption display at EA-SAS VPP platform is depicted in Fig. 6. EA-SAS Web interface allows multiple tabs, language support, dashboard by user group, and presents real-time data (data real-time update). It supports Apache Airflow [36] task scheduling or allows calculation to be scheduled within the EA-SAS platform. Parallel, cascade, and dependent calculations are available. Calculations within EA-SAS are performed in Phyton.

EA-SAS Cloud is capable of collecting the necessary data directly from meters, Production Control Units (PCU), SCADA systems, databases (SQL servers) or other software (i.e., market data). The EA-SAS Cloud Data collection process is depicted in Fig. 5.

Data Collector is an application responsible for collecting measurement data from configured data readers and exchanging data with the main EA-SAS Cloud server. Usually, it is installed on the premises of the customer IT infrastructure, since most of the data are collected via the local network. If data can be accessed from the external network, Data Collector can be installed and configured in the Cloud.

The Data Collector configuration allows IT admin to change the frequency of data collection from configured Data Readers. Data Collector serves as a data pusher via the REST API. In this configuration, Data Collector periodically pushes data to the main EA-SAS Cloud server. The authentication is ensured by the security token.

Data Reader is a service that is part of Data Collector. It is responsible for collecting data from the source. The frequency of data update is configurable in the Data Collector.

EA-SAS allows SCADA data reading through S7, H1, Modbus, Profinet, Profibus, OPC, Rest API, and other protocols.

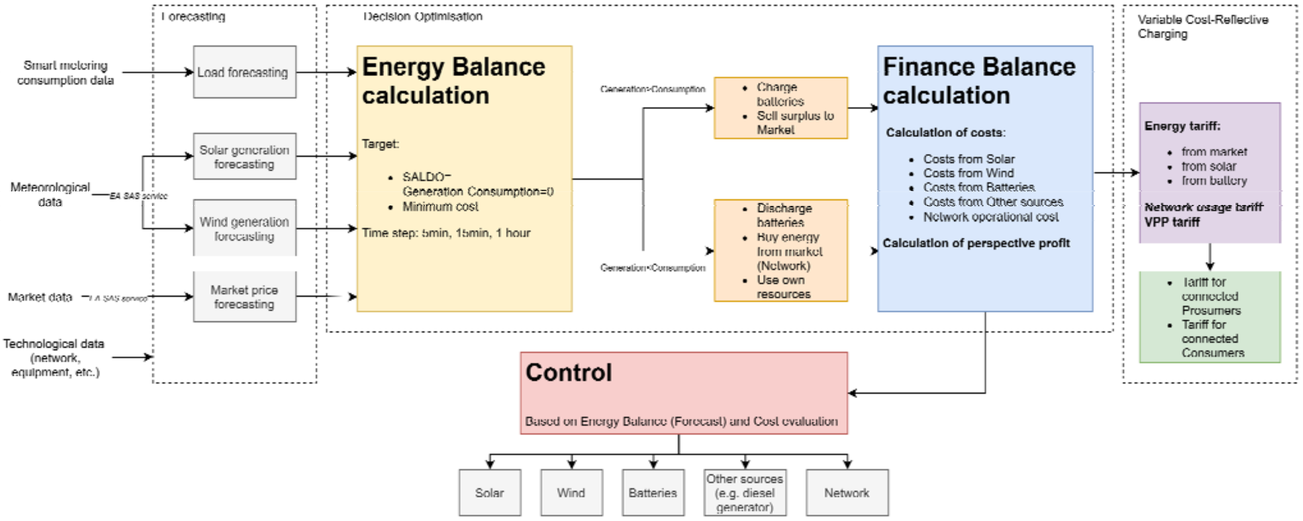

Fig. 4. Schematic view of the VPP cost optimisation control algorithm.

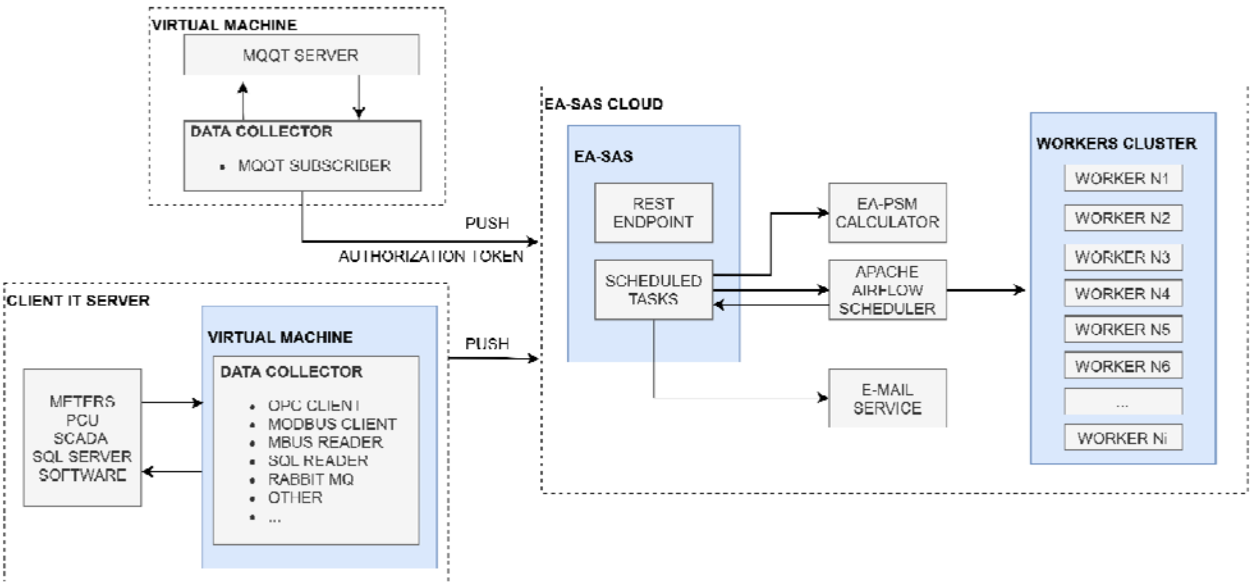

Fig. 5. The principal scheme of the EA-SAS Cloud infrastructure.

VIII. Results. Proposed Methodology for Cost-Reflective Charging with VPP

In the case of traditional cost-reflective pricing, the price for residential consumers consists of tariffs as described in (5)

$$C = T_{acq} + T_{transm} + T_{distrib\ medium} + T_{distrib\ low} + T_{sys} + T_{taxes}, \quad (7)$$

where T_{acq} is the electricity spot price (price for power acquisition), T_{transm} is the transmission network tariff, $T_{distrib\ medium}$ is the distribution network tariff, medium voltage network, $T_{distrib\ low}$ is the distribution network tariff, low voltage network, T_{sys} is the system services tariff, and T_{taxes} is the non-network-related policy tariff (taxes, levies, support schemes).

These tariffs, as discussed in Section III (), are usually determined for a certain future period, typically a year, and do not accurately reflect actual costs in the network.

If network costs are determined based on the presented methodology, consumers can purchase electrical energy from the Virtual Power Plant (VPP) for the tariff as described in (8)

$$C_{VPP} = T_{acq} + T_{variable\ transm}(v_1, v_2) + T_{variable\ distrib\ med}(w_1, w_2) + \\ + T_{variable\ distrib\ low}(x_1, x_2) + T_{taxes} + T_{VPP}, \quad (8)$$

where T_{VPP} is the VPP services tariff, and $T_{variable\ transm}$, $T_{variable\ distrib\ med}$, and $T_{variable\ distrib\ low}$ are variable functions that depend on the corresponding parameters. Let $T_{variable\ transm}$ be a function that maps two parameters v_1 and v_2 to a real number

$$T_{variable\ transm} : R \times R \to R. \quad (9)$$

Then, we can express the ranges of these parameters for any given v_1 and v_2 as follows

$$v_1 \le T_{variable\ transm}\left(v_1, v_2\right) \le v_2. \tag{10}$$

Analogically for $T_{variable\ distrib\ med}$ and $T_{variable\ distrib\ low}$:

$$w_1 \le T_{variable\ distrib\ med}\left(w_1, w_2\right) \le w_2, \tag{11}$$

$$x_1 \le T_{variable\ distrib\ low}\left(x_1, x_2\right) \le x_2. \tag{12}$$

Then the bounds of these ranges can be determined based on (1)–(4) and can be expressed as:

$$v_1 = \min\left(price\ tariff \times \frac{P_i}{S_{i_{high}}}\right), \tag{13}$$

$$v_2 = \max\left(price\ tariff \times \frac{P_i}{S_{i_{high}}}\right), \tag{14}$$

$$w_1 = \min\left(price\ tariff \times \frac{P_i}{S_{i_{middle}}}\right), \tag{15}$$

$$w_2 = \max\left(price\ tariff \times \frac{P_i}{S_{i_{middle}}}\right), \tag{16}$$

$$x_1 = \min\left(price\ tariff \times \frac{P_i}{S_{i_{low}}}\right), \tag{17}$$

$$x_2 = \max\left(price\ tariff \times \frac{P_i}{S_{i_{low}}}\right). \tag{18}$$

Equations (13)–(18) allow to propose price tariffs that accurately describe actual costs in the network at a given moment. Analogically, variable cost-reflective prices can be determined for the Prosumers for both selling and buying energy from the VPP actions.

A case was analysed where such cost-reflective charging was applied and the variable value for the low voltage distribution network tariff was evaluated. In this case, it is assumed that the household consumer purchases electrical energy from a nearby source in the low voltage grid, and there is no energy transmission through high voltage and medium voltage networks. When energy is consumed locally and middle and high voltage networks are not utilised for energy transmission, then:

$$T_{variable\ transm} = 0, \tag{19}$$

$$T_{variable\ distrib\ medium} = 0, \tag{20}$$

$$x_1 = 0, \tag{21}$$

$$x_2 = 3.5. \tag{22}$$

The values of the price tariff components are shown in Table I. To understand the benefit gained from the point of view of the household consumer, the expenses for electricity were compared in a case where it was purchased from the public supply (Network Operator) and the VPP.

Purchasing electrical energy from the Virtual Power Plant instead of public electricity supply can result in lower energy expenses for household consumers of 21 % to 47 % depending on the situation in the network. Cost-reflective charging through VPPs evaluates the actual costs that occur in the network, and VPP control can ensure that the VPP is operating in condition where network costs are optimal. However, these results do not evaluate the impact of smart energy management on the price of energy acquisition on the market (electricity spot price). Under feasible legal regulations, smart energy management must be able to impact the price of energy in the market.

TABLE I. VALUES OF ELECTRICITY PRICE COMPONENTS AS OF 2022.

Tariff	Value	Explanation
***C*, €/kWh**	0.167	Electricity price when purchasing electricity from the Network Operator (Public supply)
T_{acq}, €/kWh	0.06214	Electricity spot price
T_{sys}, €r/kWh	0.00613	System services tariff-
T_{taxes}, €r/kWh	0.00091	Non-network related policy tariff
$T_{variable\ transm}$, €/kWh	0	In the analysed case, VPP ensures that this price component is non-existent (high voltage transmission network is not used, therefore no transmission costs)
$T_{variable\ distrib\ medium}$, €/kWh	0	In the analysed case, VPP ensures that this price component is non-existent (medium voltage distribution network is not used, therefore no such costs)
$T_{variable\ distrib\ low}$, €/kWh	Variable from 0 to 0.035	VPP allows variable cost-reflective charging and control to operate in the scenario with minimal costs
T_{VPP}, €/kWh	0.00346	Tariff for the VPP infrastructure
$C_{VPP\ Consumer}$, €/kWh	0.073	Electricity price when purchasing electricity from the VPP

IX. Conclusions

In conclusion, the research presented in this paper highlights the potential benefits of implementing a Virtual Power Plant (VPP) for smart energy management, in the context of the growing proportion of Distributed Energy Resources (DERs). By using a cost-reflective charging tariff through VPPs, actual network costs can be evaluated, and optimal VPP operation can be ensured. Purchasing electrical energy from VPPs can result in significant cost savings for households. However, the impact of smart energy management on the electricity spot price in the energy market was not evaluated in this study, requiring further research. VPPs have the potential to optimise network costs and promote sustainable energy development. Promoting VPPs through a government supported scheme would enable the engagement of private capital, increase the number of distributed power plants, and reduce the price of electricity in the market. This approach can address the shortcomings of the current system and reduce the tax burden on both Prosumers and Consumers.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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