Efficiency and Fairness Optimization in Energy Management

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Abstract — The paper proposes a solution to the problem of distributing electricity originating from various sources. In the proposed model, each source has a different cost of acquisition and is characterized by varying energy efficiency factors. Additionally, in the case of renewable sources, the costs of storing energy are taken into consideration as well. This work presents a fair and cost-efficient approach to distributing the demands of energy providers. A model has been developed and verified for the purpose of corroborating the process.

Keywords — fair distribution of limited resources, linear programming, microgrids, renewable energy sources

1. Introduction

One of the most important areas of research currently undertaken in the field of energy is the smart use of renewable energy sources, such as wind, water, and the sun. The first factor that needs to be taken into account is to ensure the highest degree of environmental protection. The use of renewable energy sources is an alternative to fossil fuels which are the primary source of carbon dioxide and thus adversely impact the earth's climate. Furthermore, the extraction of fossil fuels causes environmental degradation, which is another factor to consider.

Recently, new concepts for the production and use of hydrogen have emerged that expand the range of alternatives to fossil fuels. Taking into account the constantly growing demand for energy, new energy generation plants (referred to as agents) will be established. A smaller plant may operate as a standalone unit or may work in cooperation with other suppliers, with the latter solution being more cost-effective in various scenarios.

In such a complicated landscape, the paper presents a method for organizing such cooperation between agents, so that everyone benefits from the relationships established between them. The financial profit generated in the cooperative approach is a finite resource that must be shared fairly too. The paper describes and presents a linear optimization approach allowing for fair distribution of resources to all agents participating in the process, and introduces a relevant energy management system (EMS).

2. Energy Management Approach

The development of a system capable of optimally pricing energy poses a great challenge. Among the different types of management approaches, demand side management (DSM), also known as demand response management, is often considered. In the DSM approach, control is exercise by ensuring an even distribution of energy demand throughout the day.

This involves the use of solutions that are capable of managing temporary energy loads in separate energy sub-networks, usually with their own energy-generating facilities, especially those relying on renewable sources. In modern distribution networks, costs of energy vary over time and are a function of market demand that changes depending on the time of day, day of the week and is different on non-working days as well.

Furthermore, in the case under consideration, rapid changes in demand resulting from incidents, such as natural disasters, may occur. Smart grid (SG) energy management systems are designed to provide energy to consumers in the cheapest possible way. This concept is based on dynamic electricity tariffs and household consumption estimates.

Consequently, energy suppliers are capable of reducing costs by better matching energy supply with current demand levels. Unclaimed energy must be stored, or its surplus must be eliminated in power plants that produce energy, which increases the cost of their operation.

The control mechanism that allows for the handling of energy surpluses, as well as minimizing energy shortages in selected periods, is the key feature that drives consumer demand. Controlling the price over a given period of time is one of the main factors that boost demand. This creates new challenges in decision-making processes that are related to energy distribution and reduces costs for users actively participating in generating energy (prosumers), as well as for those who are only receiving energy, but pay non-flat rates.

The problem of choosing an energy supplier by individual users in a given period of time is researched in [1]. The situation described in the article deals with finding an optimal schedule for assigning the k-th user to the energy supplier in the t-th hour, in a way that minimizes costs.

Nowadays, the development of a market of solutions enabling households to generate their own electricity allows to adopt

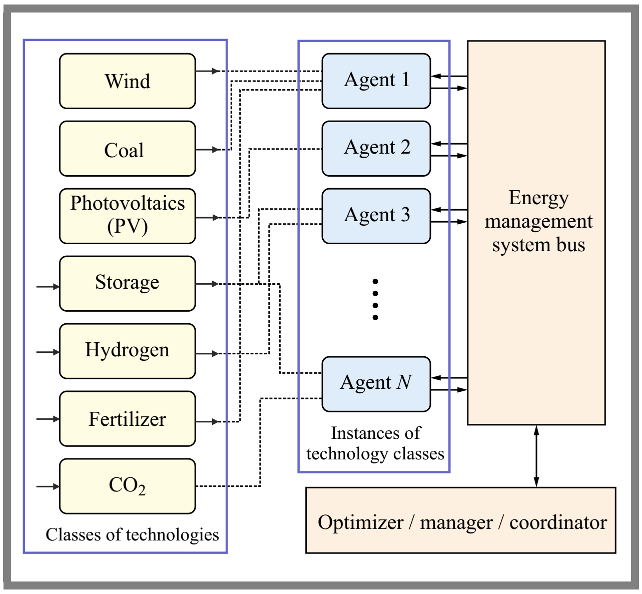

Fig. 1. Concept of the proposed energy management system.

a slightly different approach to decision making. In such a case, the goal is to develop an energy flow management system by defining a time-dependent list of prices at which energy is imported and exported by system agents [2].

Therefore, intermediate solutions have appeared on the market, with their task being to deliver energy to the end user and provide a load for suppliers, such as power plants.

Currently, a large number of power plants operate on fossil fuels and coal, with global demand for energy increasing continuously. Another significant trend is associated with the development of new, renewable energy sources. Many government policies focus on the promotion of privately-operated energy generation installations, usually based on solar energy. Scientific work is closely related to decision-making processes, with this approach often being referred to as micro networks or "power to x".

Various studies verifying the environmental impact of different energy generation technologies have been performed. It is undoubtedly worth considering the main trends on the energy market, placing an ever great emphasis on the negative environmental impact, such as CO_2 emissions, water consumption, acoustic noise level, environmental degradation caused by combustion products or the quantities of toxic residues (e.g. chemical compounds) generated in these processes [3].

The concept of smart grids is often considered to be an effective way of managing the relations between multiple energy suppliers and consumers.

The main goal is to minimize the total cost of energy while maintaining a balance between demand and supply. Prices may depend on the time of day, day of the week, month, and year. The cost is also related to the amount of energy supplied at a given moment in time. For example, when the demand for electricity is low at night, the price of energy is lower. Most energy suppliers have variable tariffs to encourage users to increase their energy consumption when the supply exceeds the demand.

The concept of smart grid addresses this problem by introducing dynamic unit energy costs. As part of this approach, various hardware solutions are proposed to support dynamic demand and supply control processes. To improve the efficiency of energy distribution systems, current technologies allow for the purchase of energy from consumers and producers. Therefore, the energy management system should take into account the equal treatment of each of these agents (consumers, prosumers, energy producers) in order to prevent their discrimination or uneven treatment.

An optimization process that is based solely on a simple criterion of minimizing cost may lead to such a situation. Therefore, the optimization model should be defined in such a manner as to protect against the undesirable case of "starving" some consumers or "ignoring" the supply of energy generated by selected producers.

3. Problem Analysis

A decision management system is based on the exchange of information between agents operating within the energy distribution chain and having the capacity to control the flow of resources. Agents present in the system may either distribute, consume or store energy, simultaneously generating other resources, such as waste.

The proposed approach is presented in Fig. 1, with the general concept intended to create a universal model capable of solving a wide array of problems. Each agent in the model may be described using a vector of incomes (demand) and outcomes (supply). In the example considered, relations between agents are taken into consideration, as an intelligent energy management system should rely on a process of optimizing the energy flow.

To make this possible, it is important to adopt one of two assumptions. The first of them is related to a scenario in which there is no exchange of information between agents, meaning none of the agents has any knowledge about prices, costs, or supply volumes. The second assumption is based on the cooperative approach, in which agents exchange information and jointly implement the process of optimizing the distribution of energy and determining the trade terms. To ensure such a functionality, an energy management system bus has been introduced in the proposed model to enable information to be exchanged between agents.

The main idea behind an energy management system (EMS) is to establish connections between each agent and use such an internal bus to exchange relevant data. Thanks to EMS, agents receive recommendations about the unit costs and expected quantities of energy (or other products) to be generated and resources to be provided to the agent or transferred further. EMS also helps better organize material flows using a cooperation-based approach.

An alternative to this is an individual approach, where each agent works as a standalone operation. The input and output flows influence the profits of the agents.

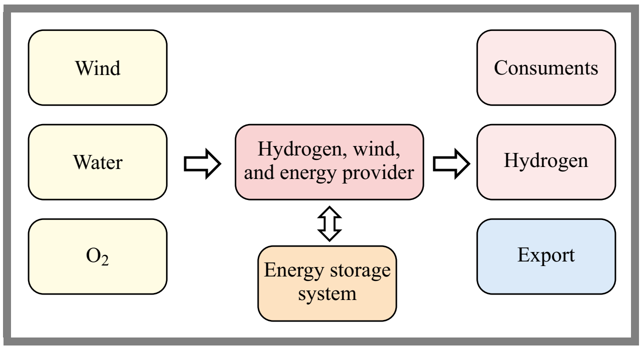

Fig. 2. Relationships between main energy resources, facilities and processes involved in energy transformation processes.

In this work, we focus on comparing these approaches and propose a model that allows for effective and fair distribution of incomes.

4. Flow of Information

Let us consider a scenario aiming to help several agents make decisions based on their mutual cooperation.

Here, the resource that is to be distributed by the system is the amount of energy transferred from sources (i.e., energy generators) to consumers with a specific demand level. We assume that given input and output flow vectors are constant and reflect situations where each operator acts separately, in a manner that is optimal considering their own needs.

In this approach, we treat the EMS bus as a control system that exchanges information between agents and, during the dynamic optimization process, as an output that provides recommendations (Fig. 2).

According to the game theory, a solution in which players cooperate will always be more profitable for the general public than competition. Therefore, additional savings and incomes are expected for each agent. These profits should be distributed so that partners feel treated unfairly. Such an approach is shown in Fig. 3.

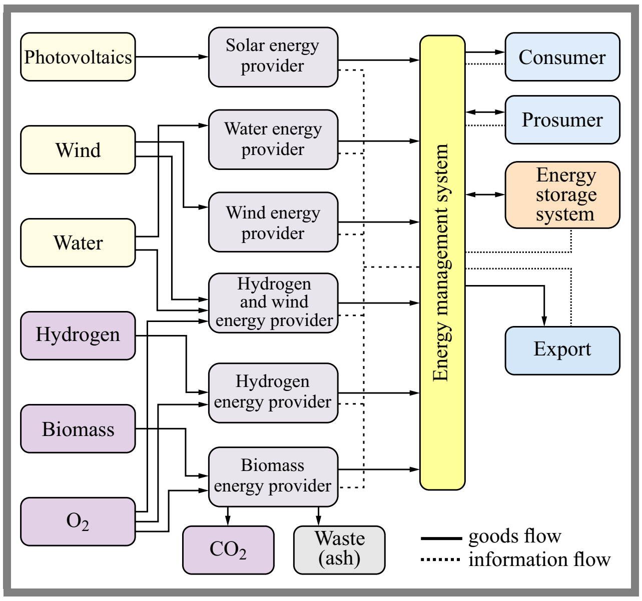

Fig. 3. Processes, information flow, and resource exchange in EMS.

Here, we are dealing with networks where agents often play the role of prosumers and, hence, the relationship between agents within the network is bidirectional.

This leads to the creation of areas where energy exchange between agents, supervised by EMS, occurs and where energy is temporarily stored. The proposed solution is similar to the one presented in [4], where an approach was introduced with a system of cooperating agents. The principle of operation comes down to the fact that when one of them reports a need for increased power consumption, it passes such a request to the system, and each of the remaining participants report their offers. In this way, a decision is made that minimizes energy costs.

5. Case Study

5.1. Individual Agent Approach

The approach of an individual agent does not rely on mutual information exchange and no energy management system bus is present within the solution. The energy prices are obtained directly from the market and each agent covers all decision-making processes (Fig. 4). An agent buys a unit of energy at price c and sells it at price p, where $p > c$ and it is assumed that all material flows have optimal values that satisfy the agent's efficiency requirements. The input and output flow vectors are considered to be optimal and stable values. This means that the revenues, costs, and profits are calculated for each agent.

In such a scheme, the income constraint of i-th agent may be formulated as:

$$I_i = \sum_{n \in i, suppliers} x_{n,i}\, p_n, \quad \forall\, i \in agents \ , \tag{1}$$

where x is the variable that refers to units of goods traded. Total cost constraint of the i-th agent is defined in the following way:

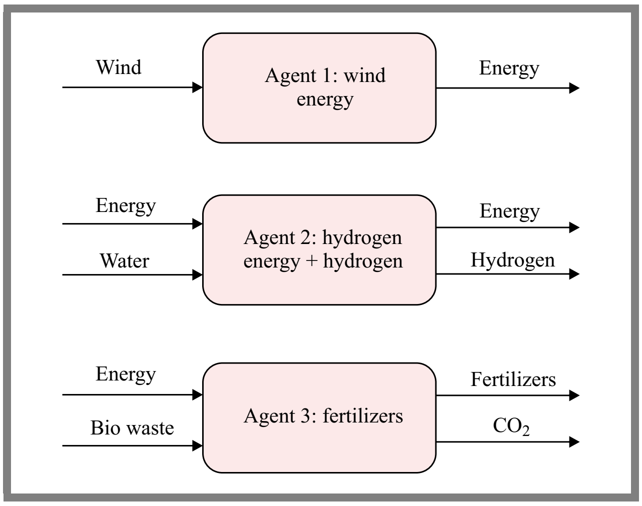

Fig. 4. The concept of an individual approach to energy prosumers.

$$C_i = \sum_{n \in i, demands} y_{n,i}\, c_n, \;\; \forall\, i \in agents \;\; , \tag{2}$$

where y is the variable referring to units whose costs are calculated.
The revenue constraint of i-th agent is:

$$R_i = I_i - C_i, \;\; \forall\, i \in agents \;\; , \tag{3}$$

The system individual total revenue may be defined as:

$$TR_{ind} = \sum_{i \in A} R_i \;\; . \tag{4}$$

5.2. Cooperative Approach

In the cooperative approach, an energy management system bus is used for the optimization process to achieve the highest possible performance – see Fig. 5. Here, each agent declares his capacity demands for materials and supplies. These values are added to a shared pool of requirements, i.e., cooperation demands (CD) and resources, i.e., cooperation supplies (CS).

In the next step, the requirements vector is considered for each agent. If the agent demands a resource located in the CS pool, it gets its requested value without payment.

Then, the values of the agent's supply vector are considered in the same way. Here, the agent is initially obliged to meet the demand for cooperation concerning a given resource and cannot sell at the market price.

The income for the agent at this stage is based solely on the sale of the surplus of goods, i.e., the supply minus the demand of CD. Similarly, the demand for a resource for the agent is not a cost if its resources are in the cooperation pool. In the next phase, the vector is calculated to determine the differences between the cooperative and individual solutions to find maximum values. The weights are computed as percentage losses of agents between the cooperation and individual models.

In this approach, the EMS system is responsible for controlling the energy network load between the seller and the buyer. However, it should be noted that several energy sources can be used to meet the agent's demand. The fairness criterion provided in this case guarantees that no sources are discriminated against or ignored due to price.

In a simple approach based on minimizing costs, while maintaining constraints, an outcome is possible in which the entire energy demand will be met by the cheapest supplier. This may lead to undesired elimination of competition, as energy obtained from fossil fuels is still cheaper than power generated from renewables.

The authors' proposal is based on a linear optimization model that can be tuned to promote those producers who are less competitive price-wise.

In the cooperative scenario, the following equations are used to design the model.
Cooperation demands pool (CD):

$$CD_n = \sum_{i \in agents} y_{n,i}\, , \;\; \forall n \in i.supplies \;\; . \tag{5}$$

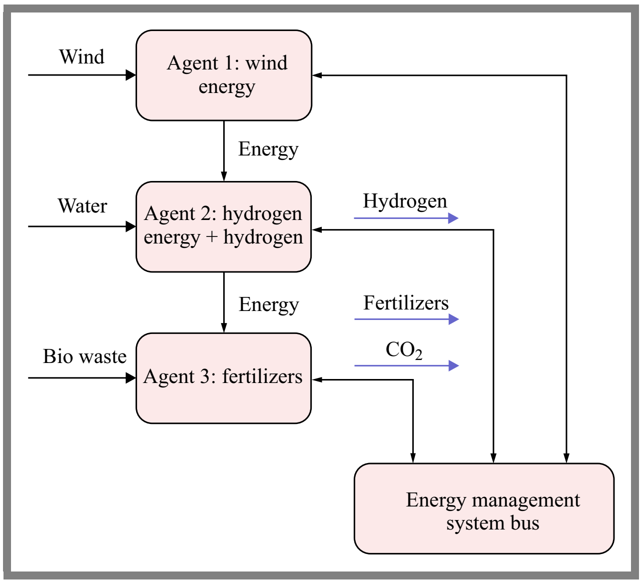

Fig. 5. Cooperative approach to energy prosumers.

Cooperation supplies pool (CS):

$$CS_n = \sum_{i \in agents} x_{n,i}\, , \;\; \forall\, n \in i.demands \;\; . \tag{6}$$

Income constraint of the i-th agent is determined from:

$$I_i = \begin{cases} \sum_{n \in i.sup} x_{n,i}\, p_n, & \text{if } CS_n = 0 \\ \sum_{n \in i.sup} (x_{n,i} - CS_n)\, p_n, & \text{if } 0 < CS_n < x_{n,i} \\ 0, & \text{otherwise} \end{cases} \;\; . \tag{7}$$

The total cost constraints of the i-th agent are:

$$C_i = \begin{cases} \sum_{n \in i.sup} y_{n,i}\, p_n, & \text{if } CD_n = 0 \\ \sum_{n \in i.sup} (x_{n,i} - CS_n)\, p_n, & \text{if } 0 < CS_n < x_{n,i} \\ 0, & \text{otherwise} \end{cases} \;\; . \tag{8}$$

Revenue constraint from the i-th agent is derived as:

$$R_i = I_i - C_i\, , \;\; \forall\, i \in agents \;\; . \tag{9}$$

Total revenues resulting from the system's cooperation may be formulated from:

$$TR_{coop} = \sum_{i \in A} R_i \;\; . \tag{10}$$

The system gain difference is:

$$\Delta coop - ind = TR_{coop} - TR_{ind} \;\; . \tag{11}$$

5.3. Fairness Linear Optimization Model

The multi-criteria optimization process is designed to distribute the profit resulting from the cooperation approach between the specific agents. The fairness criteria in the model are implemented by the appropriate treatment of agents, taking into account the profits gained from a simple individual approach, compared to those earned from the cooperation scheme. During the optimization process, the first assumption is to find a resource allocation scheme in which no one gains less than the in the individual scenario. This is the model that offers the most equal approach, based on the max-min concept [5].

Unfortunately, this scheme is usually not an efficient solution. Therefore, two multicriteria models have been proposed to increase the efficiency of the solution: the ratio model (RGM) and the ordered weighted averages (OWA). Furthermore, the fairness optimization ratio uses the Gini index as the inequality measure defined by the following set of equations:

$$\min \frac{z_0 + \varepsilon}{z - \tau} \ , \tag{12}$$

$$z_0 = \frac{\sum_{i \in A} \sum_{j \in A} q_{ij}}{2\, m^2}, \ \ q_{ij} \geqslant 0 \ , \tag{13}$$

$$z = \frac{1}{m} \sum_{i \in A} z_i \, W_i \, , \ \ z_i \geqslant 0 \ , \tag{14}$$

$$z \geqslant \tau + \varepsilon \ , \tag{15}$$

$$\sum_{i \in A} z_i \leqslant \Delta_{coop-ind} \ , \tag{16}$$

$$q_{ij} \geqslant z_i, w_i, \ \forall \, i, j \in A \ , \tag{17}$$

$$q_{ij} \geqslant z_j, w_j, \ \forall \, i, j \in A \ , \tag{18}$$

$$\tau = \frac{\Delta_{coop-ind}}{m} \ . \tag{19}$$

where m is the number of agents and ε is the model parameter (0.001 – 0.1).

To linearize the model, a substitution set of equations is used:

$$\begin{aligned} v = \frac{z}{z-\tau}, \ \ v_0 = \frac{1}{z-\tau}, \ \ \widetilde{z_i} = \frac{z_i}{z-\tau} \ , \\ \widetilde{q_i j} = \frac{q_i \, j}{z-\tau}, \ \ \widetilde{z_i \, j} = \frac{z_i \, j}{z-\tau} \ . \end{aligned} \tag{20}$$

Using Eq. (20), the model could be presented in linear form as:

$$\min \frac{\sum_{i \in D} \sum_{j \in D} \widetilde{q_{ij}}}{2\, m^2} + \varepsilon \, v_0 \ , \tag{21}$$

$$v = \frac{1}{m} \sum_{i \in A} \widetilde{z_i} \, W_i \ , \tag{22}$$

$$1 \geqslant v_0 \, \varepsilon \ , \tag{23}$$

$$1 = v - \tau \, v_0 \ , \tag{24}$$

$$\widetilde{q}_{ij} \geqslant \widetilde{z}_i \, w_i - \widetilde{z}_j \, w_j, \ \forall \, i, j \in A \ , \tag{25}$$

$$\widetilde{q}_{ij} \geqslant \widetilde{z}_j \, w_j - \widetilde{z}_i \, w_i, \ \forall \, i, j \in A \ , \tag{26}$$

where w_i stands for weight of i-th agent related to the cost difference between individual and cooperation models, and z_i is value of the amount of energy units transmitted to i-th agent.

The OWA model can be defined as follows:

$$\max \sum_{d=1,\ldots,m} \overline{\omega_d} \, \eta_d \ . \tag{27}$$

In Eq. (27) the following constraints are applied:

$$\eta_d = dt_d - \sum_{i=1}^{m} z_{di} \ , \tag{28}$$

$$t_d - z_{di} \leqslant h_i \, r_i \ , \tag{29}$$

$$z_{di} \geqslant 0 \ , \tag{30}$$

$$\omega_d \geqslant 0 \ . \tag{31}$$

These equations define the typical constraints affecting the process of optimizing an ordered vector of ratings. The OWA model takes into account the weights ω assigned to the next smallest values of the rating vector. The largest weight is the smallest value of the allocation of the resource under consideration, i.e., the energy obtained from the least competitive supplier. The last and smallest weight is assigned to the most attractive energy supplier. Such an approach allows the non-increasingly ordered vectors of weight to control the significance of the model fairness criterion.

The model also includes auxiliary variables t and η, required to enable dynamic determination of possible permutations of the allocation vector within the studied area of feasible solutions.

6. Experiments

The proposed model was developed assuming cooperation-based and individual sales approaches, and is divided into two parts. The first of them predicts the expected total revenue value obtained from the two types of sales mentioned above. The difference between the calculated revenues is treated as a limited resource that must be fairly assigned to agents. This is the second part of the problem solving process.

Fairness models were implemented and compared to perform the allocation between agents. Firstly, the simple max-min model was used to find the most discriminated demand and increase it as much as possible. In other words, the model solver will return the solution where all demands have possible maximum values, with special consideration given to the smallest values of the objective function vector.

The second part is the OWA model which can be controlled by weight parameters. In the proposed model, the number of weights and the number of demands must be equal. The weights have to be sorted in a non-increasing manner and are related to the following objective function vector values (starting from the smallest value).

For example, when there are three demands, the weight vector [5, 1, 1] will return a solution similar to max-min. On the other hand, weights such as [5, 5, 5] will return a solution similar to the simple maximization problem (effmax) which assigns all resources to the demand offering the highest revenue. Revenue is related to the value of the income difference of a given agent between the individual and the cooperation sales models.

Tab. 1. Results achieved with the use of specific optimization methods.

Method	Agent 1	Agent 2	Agent 3	Agent 4	Agent 5	Agent 6	Agent 7	Agent 8	Agent 9
Maxmin	8050	8050	8050	8050	8050	8050	8050	8050	8050
Effmax	0	0	0	0	0	0	0	40250	40250
OWA	14999.77	8107.99	8107.99	7594.82	8450.58	8571.3	0	6451.52	6451.52
RGM 1	0	9964.74	9964.74	9334.06	10385.79	10534.16	0	7928.93	7928.93
RGM 4	0	12146.35	12146.35	11377.6	12659.58	12840.43	0	9664.84	9664.84

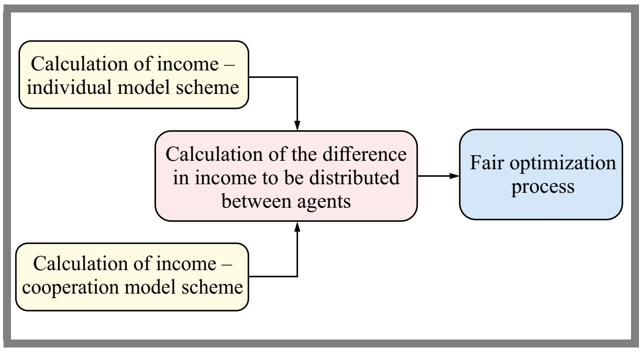

Fig. 6. Initial optimization process in which limits are set and tested.

The last business fairness model is a ration model which considers efficiency maximization and simultaneously uses the Gini index minimization scheme. This model takes only one input parameter and returns the variety of solutions from the fairest to the best (in terms of efficiency). The fairness optimization model may also be developed by relying on other inequality measures used in statistics [6].

7. Results

In the simulation, several instances of the problem were taken into consideration and the number of agents and flows of given materials and goods were varied. The models were optimized in the Python 3.8 environment, with Python Pyomo libraries used for linear optimization.

Table 1 illustrates the results of simulations obtained using the profit vector shown in Tab. 2. The calculations were carried out for the case in which there is cooperation between the system agents and the solution is achieved by means of a central system controlling flows by returning recommendations on energy distribution.

Optimization models were developed to take into account the maximization of the total profit from the sale of energy but also to ensure equal distribution, i.e. taking into account the criterion of fairness. Linear optimization models are characterized by the short lead time required to achieve the result and can be used successfully in real-time decision support systems.

Tab. 2. Revenue vector.

Agent no.	1	2	3	4	5	6	7	8	9	10
Revenue	93	100	78	78	49	44	43	0	58	58

8. Discussion and Conclusions

Table 1 presents the results achieved with the use of the linear optimization methods, where the load vector was assessed for each agent and one unit of the resource allocated to the agent was associated with the unit of profit. For the final assessment, two opposing criteria were taken into account. The first is the total profit (effmax method). It is the simplest solution with no restrictions on the maximum value of resources allocated to the associated agents.

Maximization of the smallest value of the resulting vector (max-min method) is a more complicated approach, but us still simple to implement. Such solutions are the most effective, because they allow for allocating resources to each agent evenly. However, max-min optimization is often characterized by a significant drop in performance due to the even distribution of the result vector.

This work aims to present the results achieved by methods using the model's parameters to control the final solution, i.e. the ordered weighted averages (OWA) method. The parameters controlling the methods include the vector of weights assigned to each agent, making it possible to force the model to assign high priority to the next least efficient allocation (agent), i.e. the one bringing the most negligible revenue.

Another method allows to control the result to achieve a compromise between the uniformity of the solution (fairness) and its efficiency, considered as the allocation of resources to subsequent agents. RGM offers the possibility of returning several solutions which, via one parameter, allow for returning a spectrum of solutions by means of parametrization.

This is a useful feature for decision makers aiming to analyze a range of solutions, from the fairest to the most efficient one, and to choose the one that is good enough for their needs.

The RGM method shows the most desirable features in the optimization process, where two opposing evaluation criteria are considered. In the case under consideration, where the total cost is minimized and the fairness criterion is maximized (no discrimination of less competitive suppliers), the RGM method is much easier to control due to using only one parameter τ in Eq. (12).

In the optimization process, in order to obtain a set of solutions, from the fairest (least cost-effective) to the least fair (most cost-effective), the approach with recursive parameters tuned between the average allocation value from the max-min approach and those from the previous solution is worth considering. This allows to obtain many solutions between the max-min and the simple minimization of the single-criterion model focused on cost minimization.

Acknowledgments

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