ТЕХНИЧКО РЕШЕЊЕ

Назив	Систем за анализу ефеката управљања потрошњом електричне енергије на исплативост ОИЕ
Аутори	Марко Јелић, Марко Батић, Никола Томашевић (Институт Михајло Пупин, Универзитет у Београду)
Категорија	Битно побољшано техничко решење на националном нивоу (М84) Доказ: Објављен рад категорије М23 M. Jelić, M. Batić, and N. Tomašević, “Demand-Side Flexibility Impact on Prosumer Energy System Planning,” *Energies*, vol. 14, no. 21, p. 7076, Oct. 2021. https://www.mdpi.com/1996-1073/14/21/7076
Кључне речи	флексибилна потрошња, оптимизација, планирање пројеката, обновљиви извори енергије

За кога је решење рађено (правно лице или грана привреде):
Техничко решење је рађено за потребе научне заједнице
Година када је решење комплетирано:
2021.
Година када је почело да се примењује и од кога:
Примена техничког решења је почела у 2021. години након објављивања методологије у научном часопису Корисник: научна заједница
Област и научна дисциплина на коју се техничко решење односи:
Техничко-технолошке науке; информационо-комуникационе технологије

Технички елаборат:

- Проблем који се техничким решењем решава
- Стање решености тог проблема у свету
- Опис техничког решења са карактеристикама, укључујући пратеће илустрације и техничке цртеже
- Референце

ТЕХНИЧКИ ЕЛАБОРАТ

Проблем који се техничким решењем решава:

Introduction

As a part of the transition towards a greener energy supply and in line with contemporary directives, buildings are increasingly being equipped with local energy sources and granted with capability to conduct individual energy management strategies, yielding a new entity in energy systems referred to as prosumer. However, ensuring a widespread transition from consumers towards prosumers depends on the economic viability of renewable energy sources and accompanying equipment. Although renewable energy sources are already a relatively mature technology, prosumers are still facing significant issues regarding upfront investments, making it hard to level up with the cost-effectiveness of conventional energy supply from coal and gas. Aiming to overcome this issue and spark the necessary widespread adoption of renewable technologies, national governments implemented various incentive programs and mechanisms such as feed-in or generation tariffs, carbon credits, tax refunds, and procurement subsidies tailored for each type of renewable technology. All these measures share a common goal to alleviate the economic impact of associated capital and operational expenditures. In doing so, they intend to make the overall investment profitable on the long run and render the transition from conventional to renewable sources viable for consideration.

Problem definition

Innovative energy management technologies not only increase operational efficiency of renewables but also contribute to increased reliability and availability of energy supply in the context of multisource hybrid renewable energy systems (HRES). Given the intermittent nature of renewable energy sources, the latter becomes increasingly important as the transition to renewables in urban areas also needs to meet very high availability and quality of energy supply standards. Therefore, to establish a cost-effective and reliable prosumer, one would need to assess two fundamental aspects:

a) Planning/dimensioning problem, which represents an optimal rated power split of different renewable sources and storage capacities within prosumer systems, resulting from a multicriteria decision making process against complex objectives combining maximization of economic performance, environmental neutrality, and independence from the power grid.

b) The operation problem, which focuses on optimal energy management strategy for a given prosumer and its energy assets. Moreover, it considers optimization of prosumer's energy imports and exports as well as internal power flows between multiple renewable/conventional energy sources and storages against multiple technological, economic, and environmental criteria.

In order to properly analyze both problems simultaneously, an integral approach needs to be developed that takes into account both supply and demand-side flexibility as well as relevant indicators describing the performance of each designed system.

Стање решености тог проблема у свету:

State of the art solutions

There are two crucial aspects to the system that is being analyzed, the planning approach and the underlining optimization methodology. The considered planning problem was extensively investigated starting from standalone HRES in isolated rural areas, where there was a lack of conventional energy supply to those grid-connected, as the penetration of local energy sources in urban areas became more significant. An approach for both stand-alone and grid-connected modes using the energy filter was discussed in [1], while [2] proposes a multicriteria decision analysis for PV-WT grid connected systems. A research effort conducted on HRES in the form of a microgrid system in [3] incorporates the addition of a battery energy storage systems (BESS) and employs two procedures, a source sizing and battery sizing algorithms in sequence. Scalfati et al. in [4] proposes a mixed-integer linear programming (MILP) based solution for sizing that can, in its general form, be used for different microgrid architectures and storage technologies. Sizing with sensitivity of a microgrid structure specific for a university campus is discussed in [5], while optimal sizing with implemented DR strategies is discussed in [6] where a HRES configuration is considered. HRES optimizations with regards to energy, economic, and environmental indicators can also be found in [7] where a multiobjective optimization was employed to determine the best system configuration. The authors note that no single system configuration can simultaneously satisfy the selected three criteria and proposes the selection of a trade-off Pareto optimal solution. Economic parameters and capital investment benefit analyses can also be found in [8] where optimal sizing and power management of prosumers equipped with PV was considered using a two-step approach, with the first step analyzing the technical model (short-term assessment resulting in outputs such as component sizing and battery lifetime), and the second one tackling the long-term assessment through economic modeling. The authors report that an increase of profitability by up to 14% was achieved. Finally, a stochastic approach using MILP for determining optimal sizes of prosumer assets (PV generation capacities and batteries) is proposed in [9]. The authors describe a methodology that minimizes the joint combination of investment, maintenance, and operational costs in different scenarios that result in varying energy consumption levels from the grid.

On the other hand, regarding the optimization problem, various different techniques can be found in the related literature. As the proposed methodology includes a proactive approach based on utilization of demand-side management (DSM), and in line with findings from a systematic review from [10], the most prominent technique for this type of problem is linear programming (LP) with its mixed-integer variant being the one most commonly used. For example [11] proposes a multiobjective mixed integer linear programming (MOLIP) technique to facilitate residential DSM in a system where effects of storage systems are specifically analyzed. Also, [12] formulates a MILP model to be used for optimizing profit on the electricity market of a system with photovoltaic (PV) panels and BESS. These optimizations are performed for a horizon of 24 h with hourly varying prices. This model does not consider load to be appliance-based but rather views it as an aggregate value. Also, since the simulation is performed for a short amount of time, the monetary investments and maintenance costs of running such a system are not considered. Paper [13] continues with a MILP model also employed for a 24 h simulation horizon but with a shorter, 15 min-long sample period. The modeled system considers optimal appliance scheduling with a PV source present, with load scheduled on a per appliance basis. The results were obtained and discussed for both single and multiuser scenarios. However, the investment and maintenance costs related to running a renewable energy source are also not considered. The framework laid out in [14] also implements a MILP model for optimal appliance scheduling during a 24 h horizon with a 15 min sampling period. The chain rule, defining that a given appliance can only be started after another one finishes its operation, is introduced. The model output is discussed for three scenarios in a specific use case: a fixed price tariff, a variable price tariff with ripple control (devices that switch on or off appliances based on the current tariff), and a variable price tariff with optimal scheduling. Concluding that, because of the insignificant difference in the applied price tariffs, it would not be viable for an average domestic consumer to look for a solution more sophisticated than ripple control. The authors also state integrating distributed generation and storage into the model as a future research point. Finally, [15] focuses on optimizing energy management of a residential microgrid with the goal of analyzing the relation between the level of demand flexibility and cost savings. This paper also models investment, maintenance and replacement costs of BESS as well as distributed PV and wind turbine (WT) generators, and it introduces a discreetly operated appliance whose operation can be split into multiple nonconsecutive time periods.

Опис техничког решења са карактеристикама, укључујући пратеће илустрације и техничке цртеже:

Proposed Algorithm

Building on top of the optimization process depicted in [16] and extending it with a multi-criteria decision-making algorithm (MCDMA), the proposed methodology implements a two-step approach as depicted in Figure 1. Firstly, in the evaluation stage, the values like demand profiles, financial information and RET parameters are collected and fed into the model. A set of predefined HRES configurations deemed fit for the selected use case is defined, and when it comes to the definition of the search space for the optimal HRES configuration, a set of context-defined and user-defined constraints is established. The following list summarizes the most influential design constraints into several categories, which are simultaneously assessed by the proposed methodology to deliver optimal HRES topology and sizing:

- Renewable energy sources (RES) harvesting potential (solar irradiation data, wind data, ambient temperature, ground temperatures);
- Building characteristics and space availability constraints (indoor area (basement), outdoor area, roof, wall facades, surrounding area);
- Energy demand requirements and flexibility (electricity demand, heating/cooling demand, hot water demand);
- Dynamic energy pricing (dynamic import/export energy prices, feed-in tariffs);
- Financing conditions (budget/loan, cost of capital, governmental incentives, inflation, increase of energy prices);
- RET equipment characteristics (photovoltaic panel, wind turbine, solar collector, geothermal heat pump, auxiliaries (DC/DC, DC/AC), battery storage, boiler);
- RET installation parameters (wind turbine installation height, azimuth and elevation of photovoltaic panels, etc.)

The listed constraints, in fact, define a set of boundaries for the space in which the optimal design solution is searched for. The operation optimization stage is initiated by equipping the model iteratively with one of the predefined alternatives.

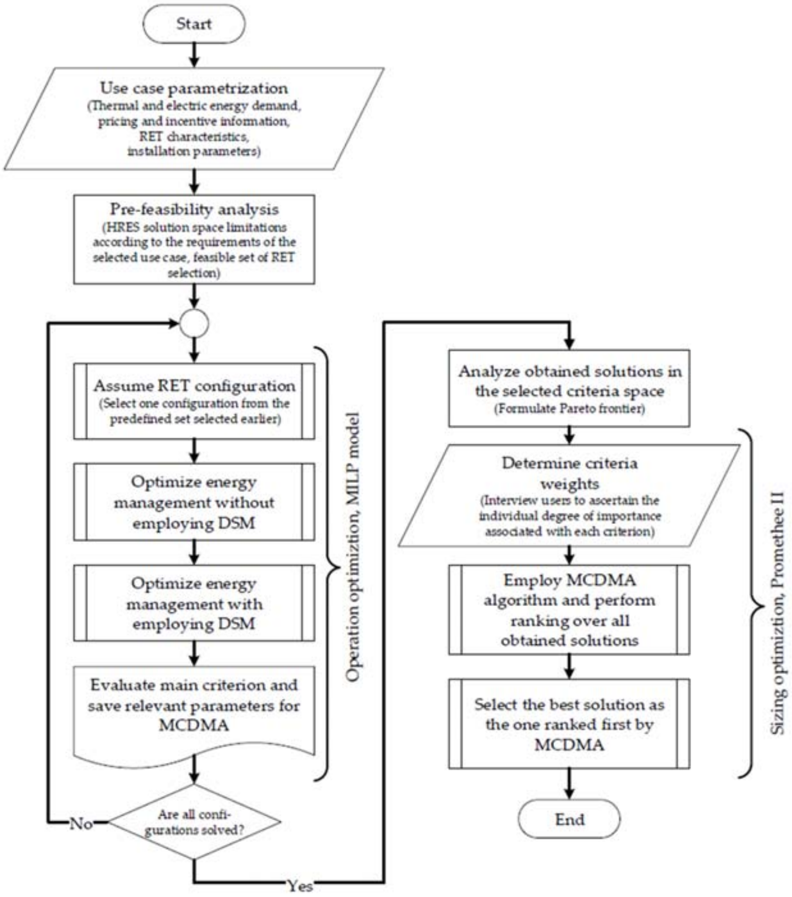


Figure 1 - Optimization process flowchart

When the iterative simulation procedure of the inner (optimization) loop is concluded following the methodology in [16], and the list of evaluation criteria is derived for each configuration, it is necessary to establish appropriate ranking among the configurations, considering multicriteria (multidimensional) evaluation space. To do so, an existing MCDMA algorithm was employed for this segment, previously called the outer loop.

At the initial stage, the MCDMA is fed a list of alternatives A, which ought to be simultaneously ranked across multiple criteria C. Each alternative A, represented by an individual HRES configuration, is first individually evaluated across the whole range of criteria C, referred to as evaluation criteria in the dynamic performance assessment elaboration. Following is the assignment of the weighting factors w to each criterion C. These weight factors allow for non-uniform distribution of the level of importance assigned to each criterion, allowing end user to practically steer the selection process according to desired needs and preferences. Following the findings from [17] noting its common applications for technology evaluation}, the acknowledged performance ranking organization method for enrichment evaluation (Promethee) II algorithm [18] was utilized for the purpose of development of MCDMA functionality, as described below.

Firstly, a comprehensive pair-wise comparison is calculated as

$$d_k(a_i, a_j) = c_k(a_i) - c_k(a_j).$$

Afterwards, those differences are passed through a preference degree function $\pi_k(a_i, a_j)$ where P_k can be defined in a variety of ways, with the most common being a linear variant

$$P_k(x) = \min\left\{\max\left\{0, \frac{x - q_k}{p_k - q_k}\right\}, 1\right\}$$

bounded by q_k and p_k. Every pair of actions is compared using a multicriteria preference degree

$$\pi(a_i, a_j) = \sum\nolimits_{k=1}^{q} w_k P_k(a_i, a_j)$$

where a constant to weights is applied

$$(\forall k)(w_k \geq 0) \quad \text{and} \quad \sum\nolimits_{k=1}^{q} w_k = 1.$$

After calculating

$$\phi^+(a) = \frac{1}{n-1} \sum_{\alpha \in A} \pi(a, \alpha) \quad and \quad \phi^-(a) = \frac{1}{n-1} \sum_{\alpha \in A} \pi(\alpha, a)$$

a net value is calculated $\phi(a) = \phi^+(a) - \phi^-(a)$. Finally, ranking all alternatives according to $\phi(a)$ gives a complete ranking considered as the output of the Promethee II algorithm.

The proposed methodology can easily consider different design criteria, which can be summarized into four general categories. In the following list, these categories are out-lined with detailed elaboration of each category that was implemented and its items following later in the text:

- Technical criteria: Loss of Power Supply Probability (LPSP), Wasted energy
- Financial criteria: Capital Expenditure (CAPEX), Operational Expenditure (OPEX), Net Present Value (NPV), Internal Rate of Return (IRR), Payback Period (PP)
- Environmental criteria: greenhouse gas emissions (CO2, NOx, SOx)
- Social/Economic/Political criteria: Fuel Reserve Years, Job creation, Inter-country energy dependence etc.

The objective of individual configuration optimizations is defined as the minimization of operational costs while each configuration is represented with three criteria in the MCDMA:

1. Total costs (including equated monthly installment (EMI) and maintenance for assets) as

$$C_C = J_c + \sum\nolimits_{i\in E}\left(X_I^{EMI} + X_i^{maint}\right)$$

where the EMIs are computed as

$$X_i^{EMI} = B_i\delta\frac{(1+\delta)^{12\gamma_i}}{(1+\delta)^{12\gamma_i}+1}$$

where B_i is the total cost of a piece of equipment i, $\delta = 0.42\%$ the discount rate and γ_i is the estimated lifetime in years and the estimated maintenance cost X_i^{maint} is evaluated at 2% of the appropriate EMI.

2. Net-Zero Energy Building (nZEB) rating as

$$C_{NZEB} = \sum\nolimits_{k=1}^{N}(P_{out}(k) - P_{in}(1,k) - P_{in}(1,k))T_s$$

   where N is the total number of time steps in the simulation horizon, P_{in} and P_{out} the imported and exported power and T_s is the sample rate.

3. CO2 Emissions as

$$C_{CO2} = \sum\nolimits_{k}\left(f_{WT}^{C}P_{in}(1,k) + f_{PV}^{C}P_{in}(2,k) + f_{grid}^{C}P_{in}(3,k)\right)T_s$$

   where f_{WT}^{C}, f_{PV}^{C} and f_{grid}^{C} are the effective carbon footprint coefficients of different considered energy sources (based on life-cycle emission estimates for RES power $P_{in}(\{1,2\},k)$ in kgCO2/kWh and energy mix for the grid imports $P_{in}(3,k)$).

Use case demonstration

To display the capabilities of the proposed methodology, a concrete use case is assumed in form of a simulated residential household property located on the Ravenscliff Road in Motherwell, Scotland, United Kingdom (GPS coordinates 55.80, -3.96). The Energy Hub model for the operational optimization is defined with the following set of matrices that instantiate the model from [16]

$$S_{in} = \begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix}, S_{qin} = \begin{bmatrix}0 & 0 & 0\\0 & 0 & 0\\0 & 0 & 0\end{bmatrix}, F_{in} = \begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix}, C = \begin{bmatrix}\eta_{WT} & 0 & 0\\0 & \eta_{PV} & 0\\0 & 0 & \eta_{grid}\end{bmatrix}$$

and

$$D_{exp} = \begin{bmatrix}0 & 0 & 0\\0 & 0 & 0\\0 & 0 & 1\end{bmatrix}, R_{exp} = \begin{bmatrix}0\\0\\0\end{bmatrix}, F_{out} = [1 \quad 1 \quad 1], S_{out} = 1, S_{qout} = 1,$$

resulting in the diagram from Figure 2.

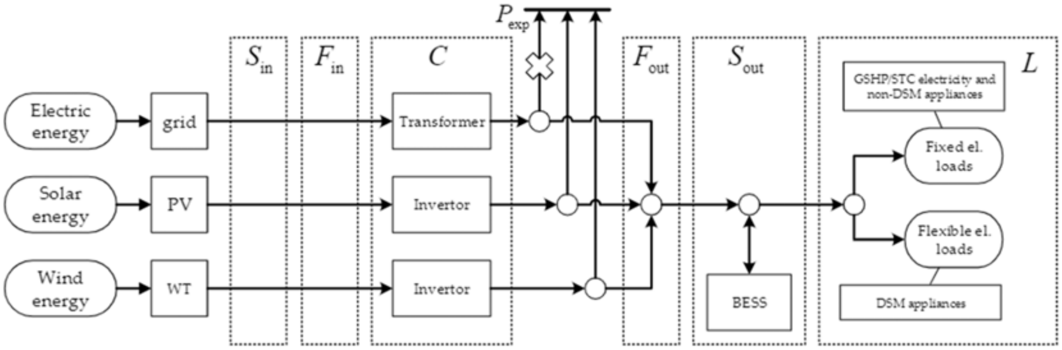
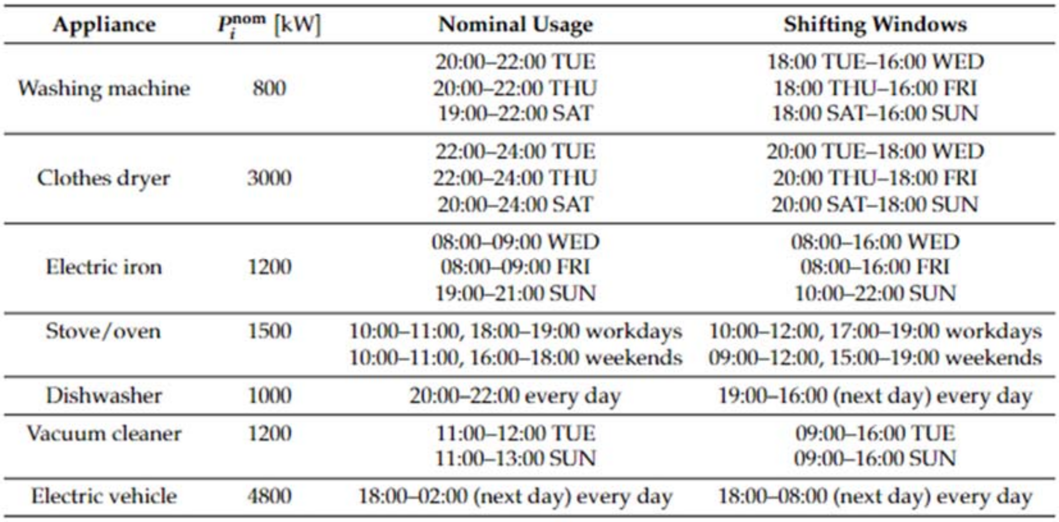


Figure 2 - Implemented structure of Energy Hub

The use case is instantiated with locally applicable tariffs described in [19], a base fixed load inferred from a portion of the estimated electric energy consumption as well as the demand coming from the heat pump system, as well as a flexible appliance schedule depicted in Table 1 that provides options for the optimization algorithm.

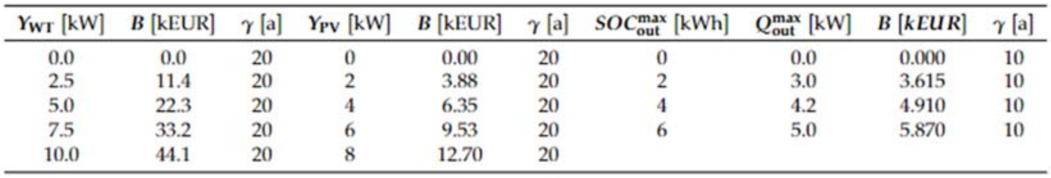
Table 1 - Flexible load weekly usage plan



Appliance	P_i^{nom} [kW]	Nominal Usage	Shifting Windows
Washing machine	800	20:00–22:00 TUE 20:00–22:00 THU 19:00–22:00 SAT	18:00 TUE–16:00 WED 18:00 THU–16:00 FRI 18:00 SAT–16:00 SUN
Clothes dryer	3000	22:00–24:00 TUE 22:00–24:00 THU 20:00–24:00 SAT	20:00 TUE–18:00 WED 20:00 THU–18:00 FRI 20:00 SAT–18:00 SUN
Electric iron	1200	08:00–09:00 WED 08:00–09:00 FRI 19:00–21:00 SUN	08:00–16:00 WED 08:00–16:00 FRI 10:00–22:00 SUN
Stove/oven	1500	10:00–11:00, 18:00–19:00 workdays 10:00–11:00, 16:00–18:00 weekends	10:00–12:00, 17:00–19:00 workdays 09:00–12:00, 15:00–19:00 weekends
Dishwasher	1000	20:00–22:00 every day	19:00–16:00 (next day) every day
Vacuum cleaner	1200	11:00–12:00 TUE 11:00–13:00 SUN	09:00–16:00 TUE 09:00–16:00 SUN
Electric vehicle	4800	18:00–02:00 (next day) every day	18:00–08:00 (next day) every day

With regards to the design problem, a set of renewable technologies that are selected to be paired with the determined energy consumption profiles include photovoltaic arrays of different capacities, small-scale residential wind turbines and a set of batteries with different characteristics depicted in Table 2.

Table 2 - WT, PV and BESS options



Y_{WT} [kW]	B [kEUR]	γ [a]	Y_{PV} [kW]	B [kEUR]	γ [a]	SOC_{out}^{max} [kWh]	Q_{out}^{max} [kW]	B [$kEUR$]	γ [a]
0.0	0.0	20	0	0.00	20	0	0.0	0.000	10
2.5	11.4	20	2	3.88	20	2	3.0	3.615	10
5.0	22.3	20	4	6.35	20	4	4.2	4.910	10
7.5	33.2	20	6	9.53	20	6	5.0	5.870	10
10.0	44.1	20	8	12.70	20				

Results

The results in the (C_C, C_{NZEB}, C_{CO2}) space of the proposed criteria for all considered configurations are presented in Figure 3. The Pareto frontier formed by the set of nondominated solutions depicting the best compromise-free solution set is accented over the rest of the obtained results. However, given that the end result of the optimization process is considered to be only one, best solution, in the context of MCDMA ranking, the final outcome is highly dependent on the selected weights of each of the criteria that are imposed. Since each user will have different preferences, the decision space is practically infinite, however a couple of concrete examples are discussed to showcase the capabilities of the proposed planning strategy. Several different use cases will be presented to provide illustrative examples of how the optimum configuration changes in line with the criteria weight selection process.

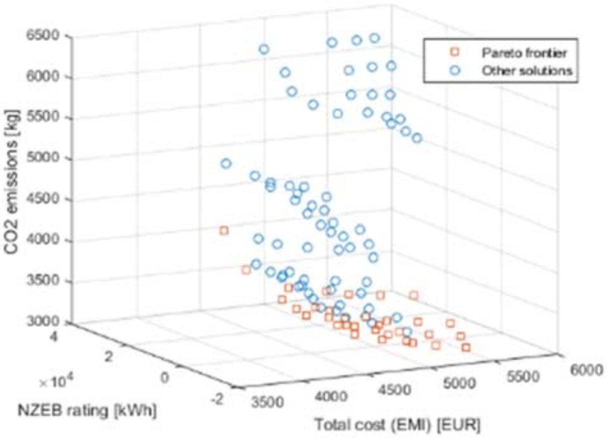


Figure 3 - Considered HRES configurations in criteria space

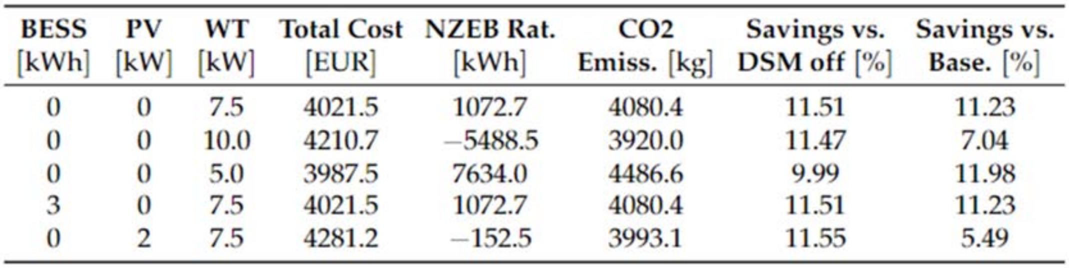
i. Total Cost as the Primary Criterion

Choosing different weights allows for the user to specify what criteria he deems relevant, and thus, the software adjusts the optimal configuration rankings. One such mixed case where cost is still the primary focus, but the other two environmental criteria are also taken into consideration can be defined by selecting appropriate weights to equal

$$w_C = 60\%, \quad w_{NZEB} = 20\% \quad \text{and} \quad w_{CO2} = 20\%.$$

After ranking the optimally preforming configurations in accordance with the above-mentioned weights, the best combination and a list of best alternatives is obtained and presented inTable 3. The results show that although monetary savings are still the prevalent considered parameter, this type of selection slightly favors large renewable sources due to the associated decrease in discrepancy between the spent and produced amount of energy and the equivalent amount of CO2 emitted.

Table 3 - List of five best configurations when primarily focusing on cost with DSM turned on



BESS [kWh]	PV [kW]	WT [kW]	Total Cost [EUR]	NZEB Rat. [kWh]	CO2 Emiss. [kg]	Savings vs. DSM off [%]	Savings vs. Base. [%]
0	0	7.5	4021.5	1072.7	4080.4	11.51	11.23
0	0	10.0	4210.7	−5488.5	3920.0	11.47	7.04
0	0	5.0	3987.5	7634.0	4486.6	9.99	11.98
3	0	7.5	4021.5	1072.7	4080.4	11.51	11.23
0	2	7.5	4281.2	−152.5	3993.1	11.55	5.49

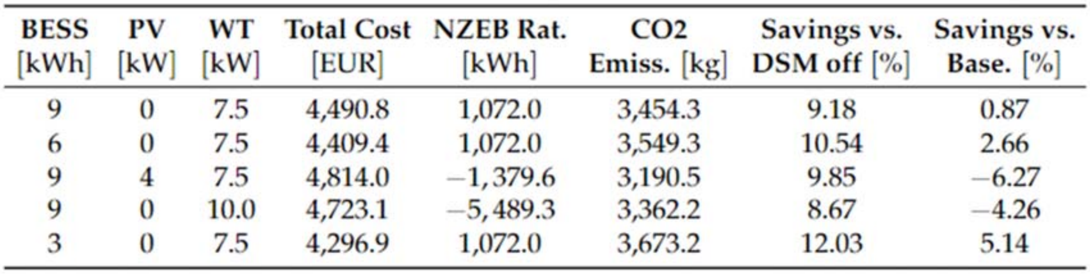
ii. CO2 Emissions as the Primary Criterion

Finally, amongst environmentally friendly use cases, the main stressed criterion could be emissions, as is accomplished by

$$w_C = 30\%, \quad w_{NZEB} = 10\% \quad \text{and} \quad w_{CO2} = 60\%.$$

The resulting ranking in this case is presented in Table 4. As was expected, the best solutions are, just like in the aforementioned case, not the most profitable, but offer significant environmental features. Nonzero BESS units now appear in all of the selected configurations because of the need to minimize the emissions trough using locally produced electricity as opposed to grid imports.

Table 4 - List of five best configurations when primarily focusing on emissions with DSM turned on



BESS [kWh]	PV [kW]	WT [kW]	Total Cost [EUR]	NZEB Rat. [kWh]	CO2 Emiss. [kg]	Savings vs. DSM off [%]	Savings vs. Base. [%]
9	0	7.5	4,490.8	1,072.0	3,454.3	9.18	0.87
6	0	7.5	4,409.4	1,072.0	3,549.3	10.54	2.66
9	4	7.5	4,814.0	−1,379.6	3,190.5	9.85	−6.27
9	0	10.0	4,723.1	−5,489.3	3,362.2	8.67	−4.26
3	0	7.5	4,296.9	1,072.0	3,673.2	12.03	5.14

Референце:

References

[1] L. Xu, X. Ruan, C. Mao, B. Zhang, and Y. Luo, “An improved optimal sizing method for wind-solar-battery hybrid power system,” *IEEE Transactions on Sustainable Energy*, vol. 4, no. 3, pp. 774–785, 2013, doi: 10.1109/TSTE.2012.2228509.

[2] M. Alsayed, M. Cacciato, G. Scarcella, and G. Scelba, “Multicriteria optimal sizing of photovoltaic-wind turbine grid connected systems,” *IEEE Transactions on Energy Conversion*, vol. 28, no. 2, pp. 370–379, 2013, doi: 10.1109/TEC.2013.2245669.

[3] U. Akram, M. Khalid, and S. Shafiq, “Optimal sizing of a wind/solar/battery hybrid grid-connected microgrid system,” *IET Renewable Power Generation*, vol. 12, no. 1, pp. 72–80, Jan. 2018, doi: 10.1049/IET-RPG.2017.0010.

[4] A. Scalfati, D. Iannuzzi, M. Fantauzzi, and M. Roscia, “Optimal sizing of distributed energy resources in smart microgrids: A mixed integer linear programming formulation,” pp. 568–573, Dec. 2017, doi: 10.1109/ICRERA.2017.8191125.

[5] M. Husein and I. Y. Chung, “Optimal design and financial feasibility of a university campus microgrid considering renewable energy incentives,” *Applied Energy*, vol. 225, pp. 273–289, Sep. 2018, doi: 10.1016/J.APENERGY.2018.05.036.

[6] X. Wang, A. Palazoglu, and N. H. El-Farra, “Operational optimization and demand response of hybrid renewable energy systems,” *Applied Energy*, vol. 143, pp. 324–335, Apr. 2015, doi: 10.1016/J.APENERGY.2015.01.004.

[7] D. Mazzeo, C. Baglivo, N. Matera, P. M. Congedo, and G. Oliveti, “A novel energy-economic-environmental multi-criteria decision-making in the optimization of a hybrid renewable system,” *Sustainable Cities and Society*, vol. 52, p. 101780, Jan. 2020, doi: 10.1016/J.SCS.2019.101780.

[8] J. C. Hernández, F. Sanchez-Sutil, F. J. Muñoz-Rodríguez, and C. R. Baier, “Optimal sizing and management strategy for PV household-prosumers with self-consumption/sufficiency enhancement and provision of frequency containment reserve,” *Applied Energy*, vol. 277, p. 115529, Nov. 2020, doi: 10.1016/J.APENERGY.2020.115529.

[9] E. Achiluzzi, K. Kobikrishna, A. Sivabalan, C. Sabillon, and B. Venkatesh, “Optimal Asset Planning for Prosumers Considering Energy Storage and Photovoltaic (PV) Units: A Stochastic Approach,” *Energies 2020, Vol. 13, Page 1813*, vol. 13, no. 7, p. 1813, Apr. 2020, doi: 10.3390/EN13071813.

[10] A. Barbato and A. Capone, “Optimization Models and Methods for Demand-Side Management of Residential Users: A Survey,” *Energies 2014, Vol. 7, Pages 5787-5824*, vol. 7, no. 9, pp. 5787–5824, Sep. 2014, doi: 10.3390/EN7095787.

[11] B. Lokeshgupta and S. Sivasubramani, “Multi-objective home energy management with battery energy storage systems,” *Sustainable Cities and Society*, vol. 47, p. 101458, May 2019, doi: 10.1016/J.SCS.2019.101458.

[12] C. Clastres, T. T. Ha Pham, F. Wurtz, and S. Bacha, “Ancillary services and optimal household energy management with photovoltaic production,” *Energy*, vol. 35, no. 1, pp. 55–64, Jan. 2010, doi: 10.1016/J.ENERGY.2009.08.025.

[13] A. Barbato, A. Capone, G. Carello, M. Delfanti, M. Merlo, and A. Zaminga, “House energy demand optimization in single and multi-user scenarios,” *2011 IEEE International Conference on Smart Grid Communications, SmartGridComm 2011*, pp. 345–350, 2011, doi: 10.1109/SMARTGRIDCOMM.2011.6102345.

[14] Z. Bradac, V. Kaczmarczyk, and P. Fiedler, “Optimal Scheduling of Domestic Appliances via MILP,” *Energies 2015, Vol. 8, Pages 217-232*, vol. 8, no. 1, pp. 217–232, Dec. 2014, doi: 10.3390/EN8010217.

[15] R. Atia and N. Yamada, “Sizing and Analysis of Renewable Energy and Battery Systems in Residential Microgrids,” *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1204–1213, May 2016, doi: 10.1109/TSG.2016.2519541.

[16] M. Jelić *et al.*, “Towards Self-Sustainable Island Grids through Optimal Utilization of Renewable Energy Potential and Community Engagement,” *Energies 2020, Vol. 13, Page 3386*, vol. 13, no. 13, p. 3386, Jul. 2020, doi: 10.3390/EN13133386.

[17] I. Siksnelyte, E. K. Zavadskas, D. Streimikiene, and D. Sharma, “An Overview of Multi-Criteria Decision-Making Methods in Dealing with Sustainable Energy Development Issues,” *Energies 2018, Vol. 11, Page 2754*, vol. 11, no. 10, p. 2754, Oct. 2018, doi: 10.3390/EN11102754.

[18] J. P. Brans and Ph. Vincke, “Note—A Preference Ranking Organisation Method,” *http://dx.doi.org/10.1287/mnsc.31.6.647*, vol. 31, no. 6, pp. 647–656, Jun. 1985, doi: 10.1287/MNSC.31.6.647.

[19] M. Jelić, M. Batić, and N. Tomašević, “Demand-Side Flexibility Impact on Prosumer Energy System Planning,” *Energies 2021, Vol. 14, Page 7076*, vol. 14, no. 21, p. 7076, Oct. 2021, doi: 10.3390/EN14217076.

ПРИЛОЗИ

- Доказ: Објављен рад категорије М23
- Код и пример података
- Листа раније прихваћених техничких решења (појединачно по аутору и за све ауторе)