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Article

Evaluating the Balancing Properties of Wind and Solar PV Production

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Abstract: This research evaluates how wind and solar PV balance together. Increasing the share of stochastic renewable energy production in electricity and hot turning reserve deficit are welcome compensation issues. This research used weather station data from an open seashore for the last 10 years, 2014-2023, on the Estonian island Saaremaa's west coast to evaluate yearly fluctuations. We use the indicator demand cover factor to estimate the coincidence of wind generation and PV solar electricity. For clarity, the initial data was prepared by assuming equality of production and consumption annual data by scaling the obtained data. The study demonstrates that the best compensating possibilities are the share of wind generation and solar PV electricity mix, respectively, equal to 0.7/ 0,3 and 0.8/0.2, reaching the demand cover factor of 0.62. The article evaluates the demand cover factor's dependence on increased production compared to consumption. The article uses different batteries to research the influence of these demand cover factors. Furthermore, this research makes a significant contribution by showcasing - how to turn weather station data into real wind generator and PV panel production data.

Keywords: PV solar; self-consumption; battery; energy storage; weather data; wind speed; solar total irradiation; data scaling; simulation of microgrids; demand cover factor

1. Introduction

The increasing share of renewable energy sources in electricity generation is essential for achieving a sustainable and low-carbon energy system [1]. Among the most widely used renewable energy technologies, wind power (wind) and solar photovoltaic (solar PV) systems stand out due to their availability, scalability, and decreasing costs. However, both sources exhibit stochastic production patterns, leading to challenges in balancing supply and demand within the power grid. Understanding the relationship between these two sources is essential for optimizing energy generation, minimizing curtailment, and ensuring a stable electricity supply [2,3] .

The balance between wind and solar PV production has become a key concern in energy system planning, particularly in regions with high penetration of variable renewable energy. While wind and solar PV are complementary to some extent, their combined production characteristics must be thoroughly analyzed to determine the optimal mix that maximizes electricity generation while minimizing reserve deficits. The main challenge arises from the intermittent nature of these energy sources, requiring effective strategies to enhance grid stability and self-sufficiency [4].

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There has been a slight setback in the development of green technologies recently. For example, the USA plans to withdraw from green agreements. Europe has begun to realize the negative economic impact of overly rapid clean energy development plans. Despite everything, the development of renewable energy—specifically wind and solar—continues regardless of the wishes of top executives. The driving force behind this is humanity's pursuit of a cleaner environment for future generations. There have not been many studies in recent years specifically on the compensatory properties between wind and solar PV generation equipment and their practical applicability.

Wind and solar PV are combined, with biomass also included, proposed in [5]. However, it does not analyze the interaction between wind and solar PV. Moreover, batteries are listed alongside energy sources such as wind and solar PV, which is incorrect. The seasonal variations of solar and wind energy are analysed in the Commonwealth of Kentucky, USA. When considering daily patterns, the wind was found to follow solar generation with an offset [6]. The results indicate the potential of solar and wind energy across most African regions and emphasize the importance of considering solar, wind, or their combined energy mix for local energy planning and storage solutions [7]. The use of flexible solar and wind fleets as a secondary reserve, combined with an implicit storage technique, has been proposed [8]. Integrating multiple energy sources into a single hybrid renewable energy system effectively addresses challenges like intermittency and geographical limitations associated with individual renewable systems. Therefore, the continuous development and implementation of an energy management system are crucial for achieving key objectives such as energy efficiency, resilience, stability, and sustainability [9]. Several studies related to this field have been reviewed and are summarized as follows:

Benato et al. [10] examined the integration of energy storage systems with photovoltaic power plants, showing that the Virtual Power Plant (VPP) model effectively smooths PV power peaks and enhances supply stability. Niu and Luo [11] explored economic efficiencies of distributed PV systems and storage solutions, revealing that optimized storage frameworks enhance grid adaptability and stability. Ho-Tran and Fiedler [12] studied seasonal extreme events in Germany's renewable production, highlighting increased risk of low power production in summer due to stationary cyclonic weather patterns. Fasihi et al. [13] investigated the potential of green ammonia production using hybrid PV-wind plants, identifying cost-competitive scenarios by 2040. Dietrich [14] analysed zero-energy buildings in different climates, emphasizing land-use trade-offs and optimized renewable integration strategies. Salkuti [15] proposed optimal railway electrification using renewable sources, demonstrating cost benefits and enhanced grid integration.

Chen et al. [16] examined land-use conflicts in renewable energy deployment in Northern Europe, concluding that offshore wind expansion could reduce land demands. Silva et al. [17] proposed a stochastic approach for optimizing renewable energy market participation, showing significant profit gains and imbalance reductions. Nnodim et al. [18] analyzed wind and solar integration into electricity grids, recommending curtailment and storage for effective intermittency management. Al-Dahidi et al. [19] developed machine learning models for PV power predictions, improving forecasting accuracy for better grid management. Santos-Alamillos et al. [20] studied wind-solar spatiotemporal balancing in the Iberian Peninsula, concluding that co-location reduces generation variability. Veluchamy [21] introduced an optimization algorithm for microgrid energy management, achieving cost reductions in distributed networks. Velosa et al. [22] developed an open-source simulator for energy community power demand and generation scenarios, facilitating testing of optimization strategies. Lippert [23] discussed lithium-ion energy storage in wind farms, demonstrating effective output control and ancillary service provision. Tafarte et al. [24] investigated bioenergy's role in mitigating fluctuations from wind and solarPV, concluding that flexible bioenergy operation enhances grid stability. Schmidt et al. [25] analyzed Brazil's hydro-thermal system, highlighting the benefits of wind-PV expansion in reducing thermal backup needs. Carbajales-Dale et al. [26] assessed storage energy costs for wind and solar PV, revealing that wind energy can support

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large-scale storage while PV is limited in storage affordability. Haegel and Kurtz [27] tracked global PV adoption trends, showing rapid expansion and increasing storage integration.

Hadi et al. [28] proposed a demand response algorithm to optimize renewable penetration in microgrids, reducing peak demand and enhancing system balance. Stamatakis et al. [29] examined energy management in super-tankers, demonstrating CO_2 reductions through PV-wind-hydrogen integration. Shepherd et al. [30] developed feasibility tools for green ammonia production, assessing storage needs and balancing strategies. Hou et al. [31] analyzed climate change impacts on solar power generation, identifying changes in seasonal production variability. Madiba et al. [32] optimized under-frequency load shedding in microgrids, improving reliability through renewable integration. Coles et al. [33] studied tidal stream power's impact on energy system security, demonstrating its role in supply-demand balancing. Jiang et al. [34] applied machine learning for energy management in grid-connected microgrids, achieving cost reductions and efficiency improvements. Following Table 1. summarizes methodologies, objectives, and results from relevant studies.

Table 1. Comparison of some high-related studies.

Study	Methodology	Objectives	Results
Benato et al. [10]	Integration of energy storage with PV systems	Optimize power output stabilization	Virtual Power Plant model improved power stability
Niu & Luo [11]	Economic analysis of distributed PV & storage	Evaluate grid adaptability & storage efficiency	Optimized framework enhanced stability & reliability
Frank et al. [35]	Analysis of seasonal renewable production in Germany	Study extreme low power events	Identified increased risk of summer production deficits
Fasihi et al. [13]	Green ammonia production with hybrid PV-wind	Assess cost competitiveness	Found feasible cost levels for green ammonia by 2040

Unlike previous studies that focus on large-scale datasets, our research provides a site-specific analysis by examining real-world data from Saaremaa, Estonia, offering localized insights into wind and PV integration. The use of a decade-long dataset (2014-2023) ensures robustness in assessing renewable energy balancing, making our findings more reliable. Furthermore, this study applies the demand cover factor indicator to quantitatively evaluate the effectiveness of wind-PV synergy in covering local electricity consumption, a methodology that is rarely explored in existing literature. While previous studies primarily analyze wind and PV separately, our research uniquely assesses the role of different battery storage solutions in influencing the demand cover factor. Additionally, our findings provide practical recommendations for policymakers and grid operators in Estonia and similar regions, contributing to renewable energy policy advancements.

The core objective of this research is to identify the most effective combination of wind and solar PV generation that enhances energy balance and minimizes reliance on external energy sources. The research presents a comprehensive analysis of the balancing issues between wind and solar PV production, emphasizing the significance of data-driven approaches in optimizing renewable energy generation. The study highlights the importance of selecting an appropriate energy mix, utilizing advanced forecasting techniques, and incorporating battery storage solutions to achieve a more reliable and sustainable energy supply. The insights derived from this research will be valuable for informing future renewable energy policies and strategies, particularly in regions with similar climatic and geographical conditions.

2. Data and Methods

In the article, the settlement of Roomaassaare on the west coast of Saaremaa was chosen as the location for the wind generator and PV panels described in the article. This choice was primarily due to good wind conditions and the simultaneous availability of PV and wind speed data at the measuring station. Another factor in favor of this choice was that the location is on an island and at the same time in a remote area with a foreseeable weak electricity grid. The article interpreted the wind and solar PV production data using hourly wind speed and total solar radiation data from the Roomassare weather station (N58°13´05"; E22°30`3") [36]. The article uses 10 years of hourly data from 2014-2023. Wind speed data are measured at the weather station at a height of 10 m. Figure 1 shows that the wind generator and PV solar production data are sometimes summarized and sometimes exist alone. It is the best time in spring to follow the coincidence of wind and PV solar production data.

Scaling wind generator production and solar PV data means that the sums of both annual data sets equal the sum of yearly consumption.

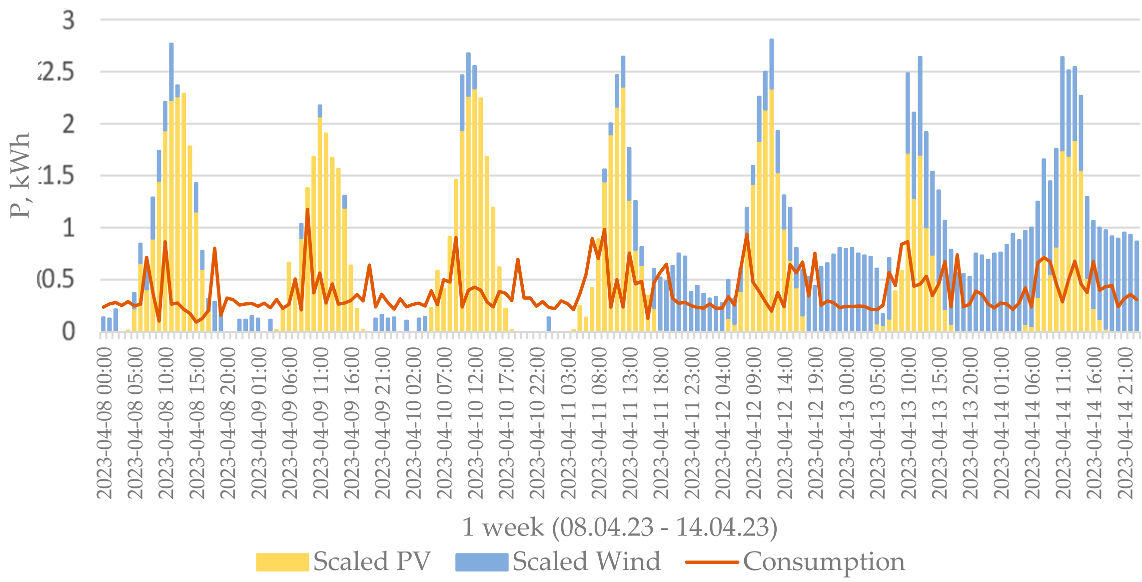

Figure 1. Production and consumption scaled profiles in one week (08.04.2023-14.04.2023).

Wind speed from a height of 10 m was extrapolated to 18 m as the initial data of wind generator TUGE 20 [37] using a logarithmic equation [38]:

$$V_2 = V_1 \cdot \frac{ln \cdot \left(\frac{h_2}{z_0}\right)}{ln \cdot \left(\frac{h_1}{z_0}\right)} \tag{1}$$

where V_2 – extrapolated wind speed at the height of 18 m, m/s;

V_1 – measured wind speed at the height of 10 m, m/s;

h_2 – wind generator hub height, 18 m;

h_1 – the height of measured wind speed in the weather station, 10 m ;

z_0 – roughness coefficient, for flat landscape, z_0= 0.03.

TUGE 20 power curve data [37] turn to interpolation by the formula 2, R_2 = 0,9994:

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$$P = 7 \cdot 10^{-6} \cdot V_0^6 - 0.0006 \cdot V_0^5 + 0.022 \cdot V_0^4 + 0.3904 \cdot V_0^3 + 3.3587 \cdot V_0^2 - 10.894 \cdot V_0 + 12.753, \quad (2)$$

where P – wind generator output capacity, kW;

V_0 – scaled wind speed at a height of 18 m;

The power curve described by Formula 2 is present in Figure 1.

Figure 2 shows that the sixth-order polynomial is described quite well for the power curve, R_2 = 0.9994. As the cut in wind speed for TUGE 20 is 3.5 m/s, power values below 3.5 m/s were removed. It is a typical small wind generator power curve.

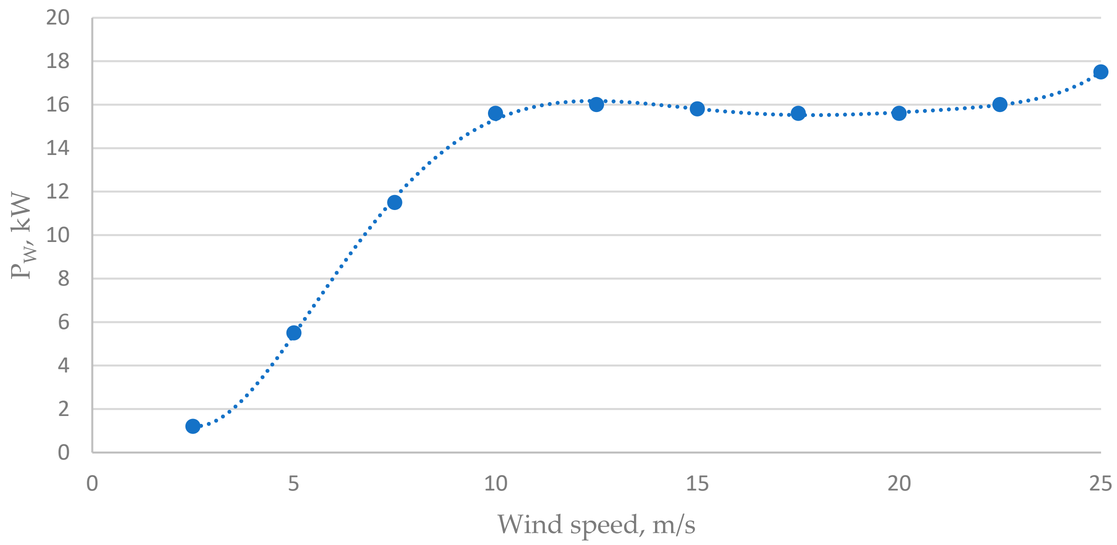

Figure 2. The power curve of the wind generator is TUGE 20 [37].

The approximation of the solar irradiation data from the weather station horizontal plane measurements for real PV panels output data (angle to the ground 35°, azimuth 180°, efficiency 0.213; panel size a´= 2297 x 1134 mm, quantity 10, Ja Solar JAM72S30 550W, monocrystal) starting from the angle of incidence calculations by Formula 3 [39]:

$$A_f = \cos(\theta_z) \cdot \cos(\beta) + \sin(\theta_z) \cdot \mathrm{si}(\beta) \cdot \cos(\gamma_s - \gamma), \quad (3)$$

where A_f – angle of incidence, °;

Θ_z – zenith angle, °;

β – slope, the angle between the plane of the surface in question and horizontal, °;

Υ_s – solar azimuth angle, °;

Υ – surface azimuth angle, °.

Clear sky index [40]:

$$K_t = \frac{GHI}{G_0 \cdot \cos(Z_s)}, \quad (4)$$

where K_t – clearness index;

GHI – total sun solar irradiation on a horizontal surface in Roomassaare weather station, W/m²;

G_0 – solar constant, 1367 W/m²;

Z_s – zenith angle, °.

Diffuse horizontal irradiance - *DHI* [40]:

$$DHI = GHI \cdot (1 - F), \quad (5)$$

where *F*

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$$F = \begin{cases} 1 - 0.249 \cdot K_t, & when\ K_t < 0.35 \\ 1.577 - 1.84 \cdot K_t, & when\ 0.35 \le K_t < 0.75, \\ 0.1, & when\ K_t \ge 0.75 \end{cases} \quad (6)$$

Direct normal irradiance – *DNI*:

$$DNI = \frac{GHI - DHI}{\cos{(Z_s)}}, \quad (7)$$

Direct solar irradiance – G_{dir}:

$$G_{dir} = DNI \cdot A_f, \quad (8)$$

Solar diffused irradiation - G_{dif}:

$$G_{dif} = DHI \cdot \frac{(1 + \cos(\beta))}{2}, \quad (9)$$

Solar irradiation reflection G_{ref}:

$$G_{ref} = GHI \cdot \frac{(1 - \cos(\beta))}{2}, \quad (10)$$

Total irradiation – G_{total}:

$$G_{total} = G_{otse} + G_{dif} + G_{ref},, \quad (11)$$

PV panel production – *P*:

$$P = G_{total} \cdot S \cdot \eta, \quad (12)$$

where *P* – PV panel produced capacity, W;

S - total panel area, m²;

η - PV panel efficiency.

The modelled family size in a private house is two people and an area of 90 m². The consumption schedule is measured in 2023. The yearly 2023 consumption is 3276 kWh. The household has wood log stoves, electrical floor heating in the WC, two refrigerators, and an electric stove. There are no heat pumps. The yearly consumption graph is supposed to be close for all years from 2014 to 2023. New devices were not obtained during these ten years in this private house.

Calculations in the article scaled the wind generator and PV panel's annual productions to equal the yearly consumption. PV panel production scaling by the consumption:

$$P_{PV}'(h) = K_{PV} \cdot P_{PVh} \quad (13)$$

where $P_{PV}'(h)$ scaled annual production graph equal to the sum of consumption, kWh;

P_{PVh} – hourly production of PV panels, kW;

K_{VP} – scaling coefficient for PV panels:

$$K_{PV} = {W_{cy}}/{W_{PVy}}, \quad (14)$$

where W_{cy} – the yearly sum of consumption graph, kWh;

W_{PVy} – the sum of yearly PV panel consumption, kWh.

Wind generator production by consumption:

$$P_W'(h) = K_W \cdot P_{Wh}, \quad (15)$$

where $P_W'(h)$ scaled wind generator annual production equal to the sum of consumption, kWh;

P_{Wh} – hourly production of wind generator, kW;

K_W – scaling coefficient for wind generator:

$$K_W = {W_{cy}}/{W_{Wy}}, \quad (16)$$

where W_{wy} – is the sum of yearly wind generator production, kWh.

Total power graph, what is equal to the consumption:

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$$P_{total}(h) = a \cdot P_{PV}^{`}(h) + b \cdot P_{W}^{`} \;, \tag{17}$$

where a – percentage 0…1, b = (1-a)

The indicator being modelled is the self-consumption rate or in other words, the demand cover factor Y_D [41–44]:

$$Y_D = \frac{\int_{t_0}^{t_1} P_D dt + \int_{t_1}^{t_2} P_S dt}{\int_{t_0}^{t_2} P_D dt}, \tag{18}$$

where P_S is the local power supply, and P_D is the local power demand. The time when $P_D(t) \leq P_S(t)$ is denoted as $t_0 \ldots t_1$ and $t_1 \ldots t_2$ is the time when $P_D(t) \geq P_S(t)$ [41]. The demand cover factor is defined as `the ratio in which the local supply covers the energy demand and indicates the „self-generation" [41].

This article investigates whether there may be differences in the best wind and PV electricity in different years when self-consumption is highest. It finds the margins of the fluctuation and evaluates the optimal battery size.

The article is used for the comparison of production capabilities among years in the capacity factor (CF) [45]

$$CF = \frac{\int_0^{8760} P dt}{P_{rated} \cdot t}, \tag{19}$$

where P – annual production graph hourly capacities, kW;

P_{rated} – rated capacity of production device, kW;

t – hours per year, t = 8760 h.

The capacity factor is the quotient between annual actual production, conceivable production, and the yearly permanent rated production.

The multiplication coefficient F_D is calculated as follows [46]:

$$F_D = \frac{W_{prod}}{\int_{t_0}^{t_2} P_D dt}, \tag{20}$$

where W_{prod} – actual wind generator and PV panel production mix, kWh;

$\int_{t_0}^{t_2} P_D dt$ – yearly consumed electricity, kWh.

3. Results

This section presents results for calculating wind and PV solar balancing properties together. Table 2 presents capacity factors CF_{wind} and CF_{PV} as annual capacity factors for wind generators and PV panels, V_{avg} is the average wind speed by year, P_{wind} and P_{PV} are the average yearly scaled wind generator and PV panel capacities. CF_{wind} is desired high for this site. CF_{PV} is similar in all places in Estonia. In the seashores and lakeshores, it is a little higher as here presents and inland, it keeps near 0.11. The fluctuations are higher with CF_{wind} due to the nature of the wind conditions. In conclusion, the analysis of CF_{wind} and CF_{PV} representatives separated the average year 2019, minimum 2018, and maximum 2020, when both capacities were similarly average, minimum or maximum.

Table 2. Yearly properties of production devices.

Year	Capacity	Factor	V_{avg}	P_{wind}	P_{PV}
	CF_{wind}	CF_{PV}	m/s	kW	kW
2023	0.363	0.120	5.13	7.26	0.66
2022	0.367	0.117	5.21	7.35	0.65
2021	0.382	0.116	5.37	7.65	0.64
2020	0.488	0.118	6.48	9.77	0.65

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2019	0.398	0.116	5.53	7.96	0.64
2018	0.346	0.121	4.91	6.91	0.66
2017	0.397	0.111	5.54	7.95	0.61
2016	0.372	0.114	5.24	7.44	0.63
2015	0.443	0.117	5.96	8.87	0.64
2014	0.394	0.115	5.48	7.88	0.64
Average	0.395	0.116	5.49	7.90	0.64

This means that by high yearly solar irradiation, the potential output of wind generators is high, too. More energy from the sun induces more energy in the wind. P_{wind} and P_{PV} denote the average annual capacity by 100 % of production separately.

Figure 3 presents the demand cover factor Y_D by different energy mixes. Energy mixes are annual electricity productions.

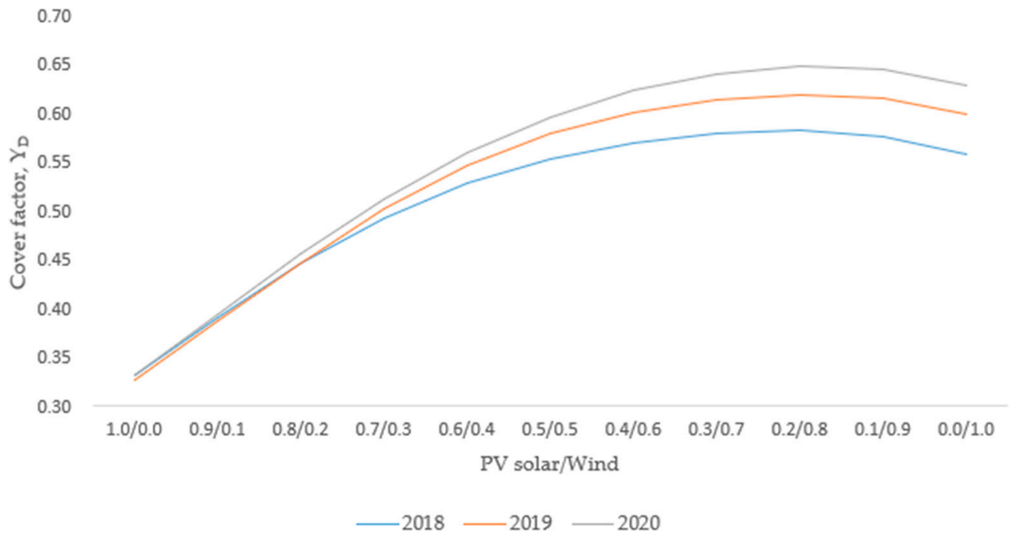

Figure 3. Dependence on a share of wind and solar PV for CF in 1018, 2019 and 2020.

Figure 3 depicts Y_D dependence from different wind and solar PV energy mixes. The highest value of 2019 $Y_D = 0.62$ was achieved in the energy mix values 0.2/0.8 and 0.3/0.7 simultaneously, as well as solar PV and wind. In this area, the curve is very smooth; it lowers rapidly on the side of 100 % PV solar $Y_D = 0.33$ and the opposite side of the figure when wind share is 100 % $Y_D = 0.6$. This means that wind generation has more influence on the Y_D than solar PV.

Figure 4 depicts the influence of the multiplicity F_D of production on consumption in 2019 by energy mix 0.2/0.8.

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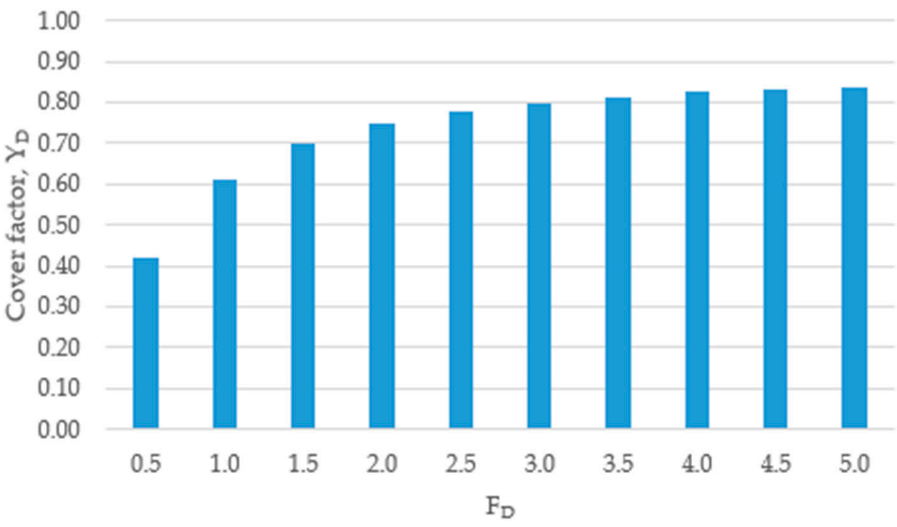

Figure 4. Dependence from a multiplicity of production to Y_D in the year 2019.

According to analyses supported by Figure 4, some consequences can be made. The Y_D is significantly reduced by reducing production to half of consumption according to expectation. The Y_D growth slackens by increasing F_D over one, reaching the value $F_D = 2.5$ when Y_D has reached 0.78. This means that Y_D no longer grows proportionally when F_D increases beyond 2.5. More precisely, the limit could be considered as $F_D = 2$.

Figure 5 depicts the influence of adding batteries to the solution by $F_D = 1$ in 2019, using an energy mix of 0.2/0.8.

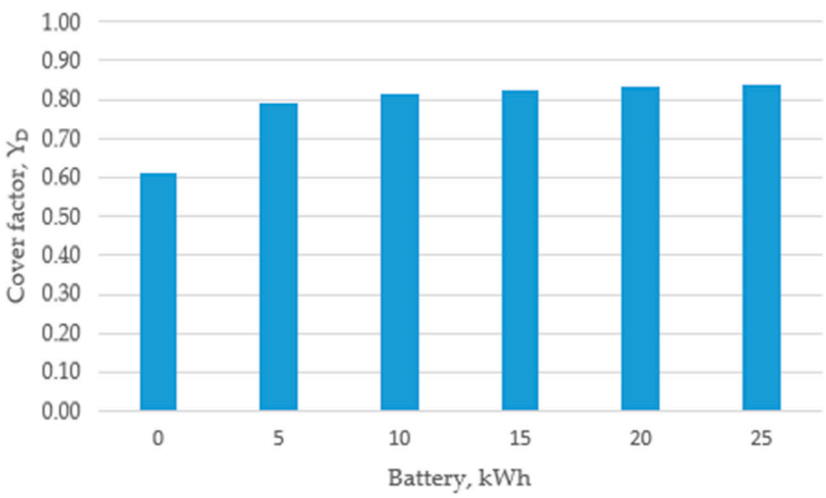

Figure 5. Dependence on the capacity volumes in 2019.

Figure 5 depicts logic similar to that of the previous figure. Increasing the battery volume by over 10 kWh is no longer effective. It is identical to the asymptotic function, like the previous Figure 4. By switching a battery of 10 kWh to the system, the Y_D reaches 0.82.

4. Discussion

This calculation does not take battery efficiency and ageing parameters into account. The authors assume that modern lithium batteries have high efficiency and that ageing parameters remain within the range uncertainty. The calculated Y_D appears relatively high compared to previous results [46]. Earlier calculations used a wind generator with CF_{wind} = (0.05…0.08); now, it is around 0.4. Solar PV

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CF was a little bit less, too. Previous used different consumer data [41] were used at night with zero consumption. The current consumption data is an unbroken chart. There are fewer consumption at night and more in the daytime. However, consumption was still small at night.

As depicted in Figures 4 and 5, the Y_D is calculated using the average value in 2019. If using minimum and maximum year values, the Y_D is changed between margins 0.59 and 0.65. The uncertainty is less than ± 5 %.

Wind speed and total solar irradiation are often measured at weather stations, but how can these measurements be interpolated into technical production data? This article addresses that question. Although it appears to be a case study, it provides insights that can be scaled up or down to another solution.

5. Conclusions

This study provided significant insight into balancing wind and PV solar production research in small-scale regions like Estonia. We used self-consumption, measured as a demand cover factor Y_D, as an indicator for evaluating wind and solar PV balancing potential together. A smooth peak appears on the demand cover factor curve, wind and solar PV production, particularly in shares of 30/70 and 20/80 for PV solar and wind, respectively. The maximum Y_D in the peak is 0.62 and maintaining a high level of Y_D favors wind generation, where 100% wind production yields a Y_D of 0.6, compared to only 0.33 for 100% solar PV energy. Production capacity needed to be increased relative to consumption to achieve optimal results, with the best outcomes occurring at F_D = 2.5 and Y_D = 0.78. F_D increases over 2.5 slowly, rapidly. Adding battery storage further improved capacity utilization, with a 10-kWh battery achieving a Y_D of 0.82. It is important to note that wind conditions with a high CF, as presented in this study, provide only a small balancing effect between wind and solar PV production, whereas lower *CF* values for wind enhance the impact of balancing. Finally, this article presents a method for calculating the actual output of production devices based on measured weather, wind and total solar irradiation data.

Author Contributions: Conceptualization, A.A. and W.Y.; methodology, A.A., Ri.M; software, Ri.M.; validation, K.H., W.Y.; formal analysis, K.H., Re.M., M.G.; investigation, A.A.; resources, A.A., K.H.; data curation, Ri.M, Re.M.; writing—original draft preparation, Re.M., M.G.; A.A. writing—review and editing, A.A., Re.M., M.G.; visualisation, Ri.M., M.G.; supervision, A.A.; project administration, A.A. All authors have read and agreed to the published version of the manuscript.

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