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Design optimization and power forecasting of photovoltaic power plants

Thesis booklet by

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1 Objectives and outline

Solar energy became one of the most important renewable energy sources due to the abundant solar resource and the technological advancements of the previous decades. Photovoltaics (PV) is the most dynamically expanding renewable electricity production technology with an average annual growth rate of 39% in the last decade. The cost of electricity produced by utility-scale PV plants decreased by 82% from 2010 to 2019, and now PV is not only the cheapest option for new electricity generation capacity but also undercuts the marginal operating costs of many existing coal-fired power plants around the world even without financial incentives. Based on these tendencies, the expansion of PV capacity is expected to continue with an increasing pace in the next decade, which puts the design and grid integration of PV systems among the most important research topics in the field of renewables.

Photovoltaic plants are weather-dependent, non-dispatchable power generators, i.e., their maximum power output is determined by the solar irradiance and other meteorological parameters, and it can not be adjusted freely to meet the power demand. The solar resource has an intermittent tendency due to clouds and atmospheric conditions, which pose difficulties for the accurate prediction of PV output and the scheduling of other power plants. The inaccuracies of the PV power forecasts threaten the stability of the grid and increase of cost of power reserves [1]. PV power forecasts are mostly based on irradiance forecasts created by numerical weather prediction (NWP) models or satellite imagery [2]. Forecasting solar irradiance is strongly linked to the field of meteorology, while irradiance to power conversion is more connected to the field of solar and photovoltaic engineering. The expected power output is calculated by modeling the PV plant using a physical, statistical, or hybrid approach [3]. This thesis focuses on the physical power forecasting method as it does not require historical production data, which is a huge benefit in the case of new PV installations.

The cost and performance of a PV plant depend on several technical design parameters that should be optimized to ensure the best profitability of the plant. Several commercial PV simulation software tools are available to facilitate the plant design process, but none of them offers a comprehensive optimization functionality. An effective PV optimization method could facilitate the decision-making process, reduce the design and installation costs, and improve the technical standard of the installed PV plants. Moreover, the current design practice only accounts for the installation costs and the expected energy production and revenues of the plants to maximize the financial return on the investment. Integrating other factors, like environmental impacts and the expected predictability, into the design process would ensure that not only the private but the total social benefits are maximized [4]. This thesis presents a general ground-mounted PV plant optimization framework and reveals the most important factors that influence the uncertainties and reliability of design optimization.

Physical power forecasting and design optimization of ground-mounted PV plants are two different topics from the application point of view; however, their methodology is similar as they both rely on the modeling of the performance of PV plants based on either a forecasted or a representative historical weather dataset. The power output of the plant is calculated as a function of the main meteorological variables as the irradiance, ambient temperature, and wind speed by a *model chain* illustrated in Fig. 1. The seven main calculation steps are the 1) separation of the global irradiance into the beam and diffuse components, the 2) transposition of the horizontal irradiance to the tilted plane of the PV array, the 3) reflection from the module surface, the 4) calculation of the cell temperature, the 5) calculation of the PV module efficiency, the 6) estimation of the shading losses, and 7) calculation of the inverter losses. As there are no universally accurate modeling methods in neither of these calculation steps, many different component models are collected from the literature and presented with a uniform nomenclature, making this thesis the most comprehensive overview of the modeling of PV plants.

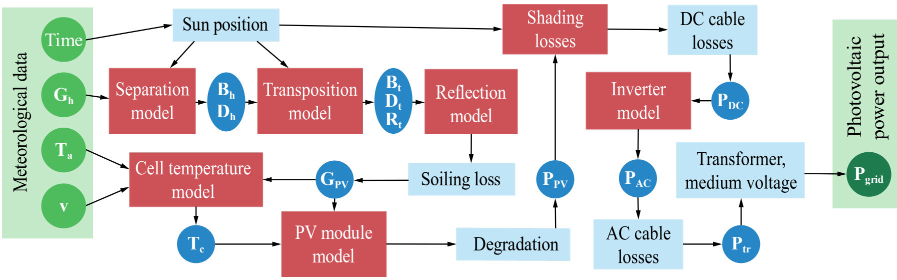

Fig. 1 Concept of the physical PV performance modeling based on weather data. Red boxes indicate the seven main modeling steps where multiple model variants are compared

Physical modeling is a widely used approach for irradiance to power conversion in solar forecasting papers. However, the selection of the implemented model chain is mostly arbitrary, as only three papers are known that presented a comparison of different model chains, and these studies are also limited to several steps of the whole modeling process [5,6]. No study has yet been prepared to evaluate and quantify the effect and significance of the model selection in all calculation steps. Therefore, no answers can be found in the literature to such relevant questions as 1) how the selection of the physical models influences the power forecast accuracy, 2) what are the most critical modeling steps, and 3) which model chain should be chosen for an operational PV forecasting? Answering these questions not only contributes to a deeper understanding of the physical modeling process but also crucial in many applications. Identifying the most accurate model chain can directly decrease the forecast error and enhance the grid integration of the PV plants while quantifying the uncertainty due to the model chain selection increases the reliability of all physical power forecasting studies.

Most PV design optimization studies published in the literature focus on only one or several aspects of the PV plant design, like inverter sizing, module layout, tilt angle, row spacing, cable losses. Moreover, the PV simulation is mostly based on overly simplified model chains, while even the studies with detailed technical modeling used only five calculation steps. This thesis presents the most comprehensive design optimization method for ground-mounted PV plants with ten decision variables based on the detailed model chains. Economic and environmental models are also to calculate the profitability and economic impacts of the plants as design objectives. They are both based on the number of components, the amount of materials, and the area of land required to install the PV plant, which are estimated using basic assumptions derived from the literature and real projects. The installation costs are then calculated using basic cost functions, and the different financial metrics are derived by an economic model. The environmental impacts are estimated using the life-cycle assessment (LCA) method, developed in a collaboration with Artúr Szilágyi [7]. The general schematic of the design optimization framework, along with the ten decision variables, is shown in Fig. 2.

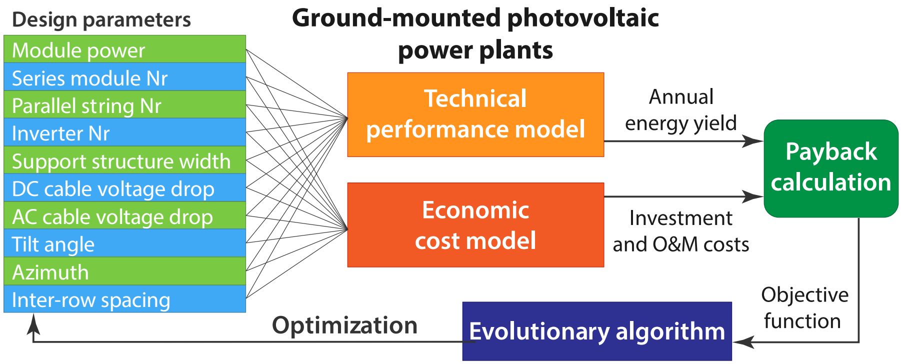

Fig. 2 Concept of the design optimization of ground-mounted PV plants for the financial payback

The objective functions of the proposed PV design optimization problem are multimodal functions of the decision variables with many local extrema; therefore, advanced metaheuristic optimization methods are required to find the global optimum consistently. Population-based metaheuristic algorithms are among the most commonly used global optimization methods for such complex problems in the literature. Selecting the best algorithm and parametrization is essential for the effective and reliable solution of the PV optimization problem. The reliability of the optimization results generally depends on the input meteorological dataset, the simulation model, and the cost functions. The uncertainties of the optimal design resulting from these factors are quantified by a sensitivity analysis. The PV design simulations are most commonly based on hourly satellite-derived irradiance datasets.

However, low-resolution datasets have a known effect of underestimating the inverter clipping losses in PV systems, but the consequence of this error on the design optimization results has not been analyzed before [8]. Minute-resolution ground-measured datasets are the most reliable source of radiation data. Quantifying the difference between the different data sources, resolutions, and model chains improves the reliability of the design optimization and the bankability of PV projects.

2 Methods

The research of physical PV power forecasting is based on the verification results of 151200 different model chains, constructed as all possible combinations of ten separation, fourteen transposition, four reflection, five cell temperature, six PV power, three shading, and three inverter models. The power forecasts are created for 16 ground-mounted PV plants of the MVM Green Generation Ltd. at 14 geographical locations well distributed among the different parts of Hungary. The numerical weather prediction (NWP) data used as the inputs of the power forecasting are provided by the Hungarian Meteorological Service from their operational AROME model. The PV production and NWP data are available in 15-minute temporal resolution for the whole year of 2019. The forecast time horizon is 48 hours, and it is separated into intraday (0-24 h) and day-ahead (24-48 h) parts. The number of valid daytime data points remaining after the data quality control is around 17000 for each PV plants and horizons.

The verification is based on the latest recommendations of the scientific literature to ensure the comparability with other studies and the long-term value of the analysis [9]. Six metrics are calculated for each 4838400 individual forecast verifications covering all model chains, plants, and time horizons. The metrics are the mean absolute error (MAE), mean bias error (MBE), root mean square error (RMSE), skill scores over the persistence and optimal climatology-persistence forecast [10], and the variance ratio. The evaluation is based on the average performance of each component model, the range and distribution of the error metrics for each location, and the identification of the best performing model chains. The methods and benefits of the optimal model selection and the effect of wind speed data are also assessed.

The most effective optimization method and parametrization for PV design optimization are found by the meta-optimization and comparison of different population-based metaheuristic algorithms. Three single-objective algorithms, the genetic algorithm, differential evolution, and particle swarm optimization, and one multi-objective method, the widely used non-dominated sorting genetic algorithm (NSGA-II) are included in the study. All algorithms are implemented using the *Distributed Evolutionary Algorithms in Python* (DEAP) Python package, which enables the modular and flexible construction and customization of different evolutionary algorithms. The meta-optimization is performed for several discrete values of the main parameters by a grid search algorithm, which tests all possible combinations of the pre-selected parameter values. Due to the stochastic nature of the algorithms, each test is composed of five optimization runs with the same parameter combination to provide a more reliable picture of the accuracy, consistency, and runtime of the method with the given parameter set.

The sensitivity analyses of the optimal design are performed using the differential evolution with its best parametrization. Four locations are selected for the analysis from four different climate zones, as listed in Table 1. The minute-resolution radiation data is retrieved from the ground measurement stations of the Baseline Surface Radiation Network (BSRN). The satellite-based data are downloaded from the SARAH (Surface Solar Radiation Data Set – Heliosat) database for European, and NSRDB (National Solar Radiation Database) for the American sites through the Photovoltaic Geographical Information System (PVGIS). The effect of the meteorological data resolution is assessed by performing the optimization for 5-min, 10-min, 15-min, 30-min, and 1-h datasets aggregated from the 1-min BSRN data. The aggregation of the data is performed using two methods; one is the generally used simple averaging, while the other is the sampling of the value from the middle of each interval.

Table 1 Name, location, and climate of the four selected BSRN stations

Location	Country	Climate
Lindenberg	Germany	Warm-summer humid continental
Rock Springs	Pennsylvania, US	Hot-summer humid continental
Carpentras	France	Hot-summer Mediterranean
Desert Rock	Nevada, US	Cold desert

3 Results and theses

The new scientific results are summarized in the nine theses, where Thesis 1-4 are connected to power forecasting, while Thesis 5-9 to the design optimization topics. The analysis of the PV power forecast verification results reveals the effect of the model selection on the overall power forecast accuracy and the most critical steps of the calculation process.

Thesis 1

The selection of the physical model chain for photovoltaic power forecasting has a significant effect on the forecast accuracy. On average, the most accurate model chains lead to a 17% lower mean absolute error, 13% less root mean square error, and 26-38% higher skill scores compared to the worst-performing ones. The model selection has a different impact on the overall forecast accuracy in each calculation step. The impact of the steps in decreasing order: 1)

transposition, 2) separation, 3) temperature, 4) PV power, 5) shading, 6) reflection, and 7) inverter modeling. [P1-2]

The accuracy of the physical PV power forecasts depends on both the forecast time horizon and the location of the PV plant. The effect of these factors in Hungary is quantified based on the comparison of the verification results for the intraday and day-ahead time horizons and the PV plants in different geographical regions. The identification of the regional differences is important to determine the reasonable expectations of the forecast accuracy at different locations.

Thesis 2

The physical photovoltaic power forecasting accuracy depends on both the time horizon and the location of the plant, according to the following statements.

a) Physical photovoltaic power forecasts have a 3.8-9.5% (on average 6.8%) lower mean absolute error and a 3.9-8.7% (on average 6.3%) lower root mean square error on intraday (0-24 h) than on day-ahead (24-48 h) time horizon in Hungary.

b) The photovoltaic power plants on the Great Hungarian Plain have an 8.0% lower mean absolute error and a 7.6% lower root mean square error on average for physical power forecasting compared to the other parts of the country. The more accurate forecast is due to the lower variability of the weather in the flatland compared to the hilly areas. [P1]

The MAE and RMSE are both widely used error metrics for forecast accuracy evaluations with many known advantages and disadvantages. However, it has not been analyzed before how the choice of the error metric influences the power forecasts created by optimized model chains, even though this knowledge is essential for the proper selection of the most suitable error metric for a given application.

Thesis 3

Mean absolute error (MAE) and root mean squared error (RMSE) are two conflicting error metrics of physical photovoltaic power forecasts, as there is no such model chain that has the lowest error in both terms. The RMSE-optimized model chains consist of more simple models, and they capture only 78-85% of the total variance of power production. In contrast, the MAE-optimized model chains feature more complex models, and they capture 92-101% of the real power variance. Due to the high underdispersion of the RMSE-optimized forecasts, the MAE-optimized forecasts are recommended when the prediction of the extremely low and high power outputs is also important. [P1]

The wind speed has a well-known effect on the temperature and power output on the PV modules, and it is required for the accurate performance modeling of PV systems. However, the importance of wind speed data is not clear if the power calculations are created from highly uncertain weather forecasts. The benefits of forecasted wind speed data are quantified based on the comparison of PV power forecasts calculated using forecasted and constant wind speeds.

Thesis 4

The wind speed forecasts have only a marginal effect on the physical photovoltaic power forecast accuracy. The power forecasts created with a constant, long-term average wind speed have a similar or even better average accuracy compared to the forecasts based on the predicted wind speed; however, the difference is less than 0.1% in mean absolute error, mean bias error, and root mean square error. [P1]

The main design variables of ground-mounted PV plants can be effectively optimized for a wide range of objectives based on detailed technical, economic, and environmental modeling of the system. The most suitable method for finding the global optimum of such a complex optimization problem is found by the comparison and meta-optimization of three commonly used population-based metaheuristic optimum search algorithms.

Thesis 5

Three population-based metaheuristic global optimization algorithms, the genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) were fine-tuned and compared to optimize the ten main design parameters of PV plants for the lowest levelized electricity cost. Based on the meta-optimization results, the following parametrizations make these algorithms most effective in solving the PV optimization problem:

- **GA: population size of 100 individuals, 80% crossover probability, 10% elite ratio, and termination after less than 10^{-5} relative change in the best objective value over 50 generations.**
- **DE: population size of 50 individuals, 80% crossover rate, 0.5 *F* weighting factor, and termination after less than 10^{-6} relative change in the best objective value over 50 generations.**
- **PSO: population size of 25 particles, inertia weight of 1, a cognitive learning rate of 0.5, a social learning rate of 2, and termination after less than 10^{-5} relative change in the best objective value over 100 generations.**

Comparing the three algorithms with their optimal parametrization, DE provides the most accurate and consistent approximation for the global optimum, followed by the PSO on the second, and GA on the third place. In general, DE is the most suitable algorithm to solve the proposed PV plant optimization problem. [P3-4]

The multi-objective optimization of PV plants is an effective tool to discover the tradeoff between different objectives, e.g., identifying the difference between optimal design parameters required for the best economic payback and lowest environmental impacts is essential for the deeper understating of the significance of the ecodesign of PV plants. The best practice for using the NSGA-II algorithm for the multi-objective PV optimization problem is determined by a meta-optimization and the comparison of different population sizes.

Thesis 6

The non-dominated sorting genetic algorithm (NSGA-II) is an effective tool for the multi-objective optimization of ground-mounted PV plants with the following parametrization: 80% crossover probability, a distribution index of 10 for the simulated binary crossover and polynomial mutation operators, and termination after less than 10^{-4} relative increase in the hypervolume dominated by population and bounded by the nadir point over 50 generations. The resolution of the resulting Pareto-front and the runtime of the algorithm are both linearly proportional to the population size; therefore, this parameter should be chosen based on the accuracy requirements and the available time. In the case only the extreme points are required, it is faster and more accurate to determine them by multiple single-objective optimizations instead of a multi-objective one. [P4-5]

A high-resolution meteorological input dataset is essential for the accurate simulation of PV plants. However, high-resolution datasets are not suitable for PV optimization due to the long calculation times. The comparison of the optimization results based on datasets created by different data aggregation times and techniques revealed both the errors induced by the low data resolution and the best method for accurate design optimization.

Thesis 7

The reliability of the optimization results for a ground-mounted PV plant is largely affected by the resolution of the meteorological input data. The optimization based on averaged datasets with resolutions between 5-min and 1-hour underestimates the optimal AC/DC power ratio, overestimates the expected annual energy production, and underestimates the levelized cost of electricity compared to the reference minute-resolution dataset. Aggregating the minute-resolution dataset by sampling the middle values of each interval instead of averaging is better for maintaining the diversity of the irradiance data. The optimization based on the sampled dataset provides similar results to the 1-min data even up to hourly aggregation times.

The runtime of the PV optimization is proportional to the number of meteorological data entries; therefore, the minute-resolution datasets are not suitable for PV optimization due to the long calculation time. The optimization

based on sampled lower resolution datasets provides reliable results after a much shorter runtime.

The most critical step of the physical PV model chains is transposition modeling, which has a significant effect on the optimization results of PV plants. The comparison of the fourteen transposition model for four locations revealed that identifying the most accurate model for the given climate and region is essential for reliable design optimizations.

Thesis 8

The simulated tilt and azimuth of the plane of maximum irradiation depend on the transposition model selection. In the optimization of ground-mounted PV plants, the transposition models affect not only the optimal tilt and azimuth but also the AC/DC power ratio and row spacing. The difference between the results calculated by different models is higher for locations with a high diffuse fraction. The simulations based on a less accurate transposition model result in suboptimal plant design and an erroneous estimation of the expected energy production and profitability. The most accurate transposition model for a given region can be identified based on the measurement data of a station with pyranometers of several different orientations. [P3,P6]

The costs of the PV modules have been continuously decreasing over the last decade. The proposed PV plant optimization framework is an effective tool to analyze the expected effect of this cost reduction tendency on optimal design variables and the levelized cost reduction potential for the PV-produced electricity.

Thesis 9

The presented ground-mounted PV plant optimization framework is suitable to discover the sensitivity of the optimal design to different technical and economic parameters. The reduction of the PV module costs decreases the optimal AC/DC ratio, tilt angle, and row spacing, while slightly increase the optimal design voltage drops; therefore, the PV design guides should be regularly refreshed to accommodate these changes. Even a 50% decrease in the wholesale modules prices could only decrease the levelized electricity cost of PV production by 15%, which highlights the importance of the optimization of the other system components. [P3]

4 Application of the results

The developed physical PV power forecasting method serves as the basis of the PV forecasting service developed by the MVM Hungarian Electricity Ltd. in the frame of the FIEK (Center for University-Industry Cooperation) program. This algorithm is suitable for the power forecasting of new PV installations with a default model chain, while the accuracy can be further improved by tailoring the model chain for the local conditions as historical production data become available. The revealed regional difference in the forecast accuracy is useful extra information for the PV investors in finding the most suitable site for a new PV installation. The main traits of the MAE and RMSE-optimized forecasts are useful knowledge for policymakers to design such a surcharge system for the forecast error that is the best representation of the real forecast value. The finding related to the marginal effect of the find speed helps to avoid the extra costs of purchasing the rather unnecessary wind forecast.

The PV design optimization framework can be used as a decision-making tool to support the design procedure of ground-mounted PV plants, e.g., by commercially releasing it as a new or including it in an existing PV design simulation software tool. The results related to the meteorological data resolution and transposition models are important to ensure the reliability of the optimization results, not only by the presented methodology but also in any practical, iterative design optimization applications. The description of the effects of the decreasing PV costs is important to foresee the expected tendencies and changes in the design parameters of PV plants in the following years.

The presented results can serve as a basis for many further research directions. Regarding the power forecasting, the verification of the model chains for other climatic regions could reveal the dependence of the best model chains on the local conditions and identify the worldwide best model chains. Another important step to further analyze the universality of the best model chains is to compare the power predictions created from different irradiance forecasts, e.g., further NWP providers of even satellite-derived forecasts. The accuracy of the power forecasts could be further improved using machine learning hybridized with the presented physical modeling methodology. Finding the most suitable learning algorithm and the best way of hybridization is a wide field for further research. Additional studies are also required to identify whether the MAE, the RMSE, or their weighted sum is the best representation of the value of the forecast for the different market participants. The variance of the MAE-optimized forecasts can be reduced by a smoothing post-processing technique (e.g., moving average), but it still has to be discovered how this smoothing affects the RMSE of the forecast.

The PV design optimization framework can be used for a wide range of further research, e.g., a detailed analysis of the effect of different financial subsidies or the changes in the electricity market prices. The framework can be further broadened by other objectives, like minimizing the balancing energy costs resulting from forecast inaccuracies. The extension of the model to describe the effects of a battery storage system can result in an effective tool for evaluating the benefits of the batteries with different storage strategies. Incorporating the design optimization and the expected cost-changing tendencies to a long-term energy system modeling framework can improve the projections for the energy mix and electricity prices of the future.

References

[1] Antonanzas J, Perpinan-Lamigueiro O, Urraca R, Antonanzas-Torres F. Influence of electricity market structures on deterministic solar forecasting verification. Sol Energy 2020:1–3. doi:10.1016/j.solener.2020.04.017.

[2] Wolff B, Kühnert J, Lorenz E, Kramer O, Heinemann D. Comparing support vector regression for PV power forecasting to a physical modeling approach using measurement, numerical weather prediction, and cloud motion data. Sol Energy 2016;135:197–208. doi:10.1016/j.solener.2016.05.051.

[3] Antonanzas J, Osorio N, Escobar R, Urraca R, Martinez-de-Pison FJ, Antonanzas-Torres F. Review of photovoltaic power forecasting. Sol Energy 2016;136:78–111. doi:10.1016/j.solener.2016.06.069.

[4] Perez-Gallardo JR, Azzaro-Pantel C, Astier S, Domenech S, Aguilar-Lasserre A. Ecodesign of photovoltaic grid-connected systems. Renew Energy 2014;64:82–97. doi:10.1016/j.renene.2013.10.027.

[5] Pelland S, Galanis G, Kallos G. Solar and photovoltaic forecasting through post-processing of the Global Environmental Multiscale numerical weather prediction model. Prog Photovoltaics Res Appl 2013;21:284–96. doi:10.1002/pip.1180.

[6] Dolara A, Leva S, Manzolini G. Comparison of different physical models for PV power output prediction. Sol Energy 2015;119:83–99. doi:10.1016/j.solener.2015.06.017.

[7] Szilágyi A, Gróf G. Estimating the environmental footprint of a grid-connected 20 MWp photovoltaic system. Sol Energy 2020;197:491–7. doi:10.1016/j.solener.2020.01.028.

[8] Hofmann M, Seckmeyer G. Influence of Various Irradiance Models and Their Combination on Simulation Results of Photovoltaic Systems. Energies 2017;10:1495. doi:10.3390/en10101495.

[9] Yang D, Alessandrini S, Antonanzas J, Antonanzas-Torres F, Badescu V, Beyer HG, et al. Verification of deterministic solar forecasts. Sol Energy 2020:1–18. doi:10.1016/j.solener.2020.04.019.

[10] Yang D. Making reference solar forecasts with climatology, persistence, and their optimal convex combination. Sol Energy 2019;193:981–5. doi:10.1016/j.solener.2019.10.006.

Publications connected to the theses

[P1] Mayer MJ, Gróf G. Extensive comparison of physical models for photovoltaic power forecasting (In Press). Applied Energy 2020.

[P2] Mayer MJ, Dán A. Complex method for performance prediction of photovoltaic systems. Renewable Energy and Power Quality Journal 2014;1:948–53. doi:10.24084/repqj12.542.
[P3] Mayer MJ, Gróf G. Techno-economic optimization of grid-connected, ground-mounted photovoltaic power plants by genetic algorithm based on a comprehensive mathematical model. Solar Energy 2020;202:210–26. doi:10.1016/j.solener.2020.03.109.
[P4] Mayer MJ, Szilágyi A, Gróf G. Ecodesign of ground-mounted photovoltaic power plants: economic and environmental multi-objective optimization. Journal of Cleaner Production 2020;278:123934. doi:10.1016/j.jclepro.2020.123934.
[P5] Mayer MJ, Szilágyi A, Gróf G. Environmental and economic multi-objective optimization of a household level hybrid renewable energy system by genetic algorithm. Applied Energy 2020;269:115058. doi:10.1016/j.apenergy.2020.115058.
[P6] Mayer MJ. Napelemparkok optimális méretezése. Energiagazdálkodás 2017;6:26–31.

Other publications

[P7] Mayer MJ, Dán A. Napelemes rendszerek modellezése. Elektrotechnika 2013;108:5–9.
[P8] Mayer MJ. Naphőerőművek szerves Rankine-körfolyamat alkalmazásával. Energiagazdálkodás 2015;56:38–42.
[P9] Mayer MJ, Nyerges V, Schroth A. Geotermikus erőmű illesztése kimerült szénhidrogén kutakhoz. Magyar Energetika 2015;1:8-13.
[P10] Mayer MJ. Comparison of different solar energy utilization methods: Photovoltaic systems and solar thermal power plants. 2015 5th International Youth Conference on Energy; 2015, p. 1–7. doi:10.1109/IYCE.2015.7180791.
[P11] Mayer MJ, Nyerges V, Schroth A. Investigation of geothermal power generation on abandoned hydrocarbon wells. 2015 5th International Youth Conference on Energy; 2015, p. 1–7. doi:10.1109/IYCE.2015.7180820.
[P12] Mayer MJ. Naphőerőművek magyarországi lehetőségeinek modellalapú vizsgálata. Magyar Energetika 2016;23:42–7.
[P13] Mayer MJ. Model-based analysis of the viability of concentrating solar power plants. Renewable Energy and Power Quality Journal 2016;1:885–9. doi:10.24084/repqj14.506.
[P14] Mayer MJ, Gács I. Naphőerőművek. Magyar Tudomány 2017;5:574-82.
[P15] Mayer MJ. Naphőerőművek típusai, helyzete és jövőképe. Épületgépész 2018;11:35-9.
[P16] Mayer MJ. Absorption cooling in concentratng solar power plants. 13th

International Conference on Heat Engines and Environmental Protection Proceedings; 2019, pp. 99-107.
[P17] Lénárt F, Mayer MJ. Háztartás energiaellátásának optimalizálása megújuló energiaforrások segítségével. Energiagazdálkodás 2019;60:40-5.
[P18] Varga Á, Mayer MJ. Naperőművek invertereinek optimális megválasztása és komplex elemzése. Energiagazdálkodás 2019;60:46-50.
[P19] Varga N, Mayer MJ. Model-based analysis of shading losses in ground-mounted photovoltaic power plants (submitted manuscript). Solar Energy 2020.