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Operational Dispatch Optimization of an Agrivoltaic System

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Abstract. Agrivoltaic systems, which integrate solar photovoltaic (PV) arrays with agricultural land, present a promising solution to enhance both energy and food security by facilitating the simultaneous production of energy and food. However, there is a lack of comprehensive research on the operational strategies required for the efficient and profitable operation of grid-connected agrivoltaic systems. To address this gap, this paper introduces a new method for optimizing the dispatch strategy of agrivoltaic systems. This includes strategies for temporal energy arbitrage with the grid and maximizing self-consumption of excess solar PV generation. The effectiveness of the proposed method is demonstrated through numerical simulations using real-world data from an agrivoltaic system in Aotearoa New Zealand, equipped with stationary battery storage. A conceptual model of a battery-supported agrivoltaic system is used as a test case, focusing on optimizing hourly dispatch to enhance energy efficiency, demand management, and economic viability. The study employs linear programming to optimize the storage system's performance, utilizing 24-hour forecasts for electricity prices, local energy production, and demand. The goal is to charge the storage system when electricity prices are low and discharge it as needed to minimize costs. The results from the application of the method to the case study in Aotearoa New Zealand demonstrate its effectiveness, contributing to the broader goals of energy and food security by enhancing the profitability and reliability of grid-connected agrivoltaic systems.

Keywords: Agrivoltaic, Microgrid, Optimisation

1. Introduction

The imperative for improving both energy and food security has gained prominence in recent years. The escalating global population and the adverse effects of climate change underscore the urgent need for reliable, cost-effective, and sustainable energy sources. Additionally, securing arable land to sustain food supply chains is becoming increasingly challenging [1]. Accordingly, agrivoltaic systems have emerged as a promising solution. These systems leverage the integration of solar photovoltaic (PV) arrays into agricultural land, facilitating a symbiotic relationship between energy and food production [2]. However, the existing body of literature has overlooked the systematic operational considerations required to ensure the reliable and profit-maximizing performance of grid-connected agrivoltaic system [3].

This research gap necessitates the formulation of a comprehensive, system-level strategy that optimizes the dispatch of grid-connected agrivoltaic systems, considering their localized energy dynamics and individual components. To this end, this paper introduces a novel method for the optimization of the dispatch strategy of agrivoltaic systems, including temporal energy arbitrage with the grid and improved self-consumption of excess solar PV generation. The effectiveness of the proposed method in improving the economic feasibility of grid-connected agrivoltaic systems has been demonstrated through numerical simulations. These simulations are based on real-world data from an agrivoltaic system supported by stationary battery storage systems, numerically tested for implementation in Aotearoa New Zealand.

This study highlights the dual role of agrivoltaic systems: as a means to generate renewable energy and as an enabler for addressing the distinct energy requirements of agricultural operations. These operations often involve dynamic and seasonally varying energy demands, such as irrigation, refrigeration, and machinery usage. By tailoring energy dispatch strategies to these specific needs, the proposed approach aims to maximize self-consumption, reduce energy costs, and enhance operational resilience. Furthermore, this paper emphasizes the relevance of grid-connected agrivoltaic systems in optimizing energy flows to align with both economic and agricultural objectives, thereby bridging a critical research gap.

Although optimization strategies can benefit various microgrid types, this study specifically addresses the unique challenges and opportunities of agrivoltaic systems, which integrate energy production with agricultural activities requiring customized operational strategies.

2. Test-case system

Focused on optimizing operational dispatch for grid-connected agrivoltaic microgrids, a conceptual battery-supported agrivoltaic system, shown in Figure 1, serves as a test case. This case study explores optimal hourly dispatch strategies, emphasizing energy efficiency, demand management, and economic viability. The elevated solar PV panels, and the multi-mode inverter were modelled as in [4].

The solar PV panels used in this analysis had a rated capacity of 0.33 kW each and were installed facing north with a tilt angle of 40 degrees. The battery energy storage system (BESS) was a generic lithium-ion model with a rated capacity of 1 kWh, following the specifications outlined in [5]. The load profile included a water pump for irrigation and electricity consumption in home sheds. A complete list of the technical and economic specifications for all product models can be found in [5].

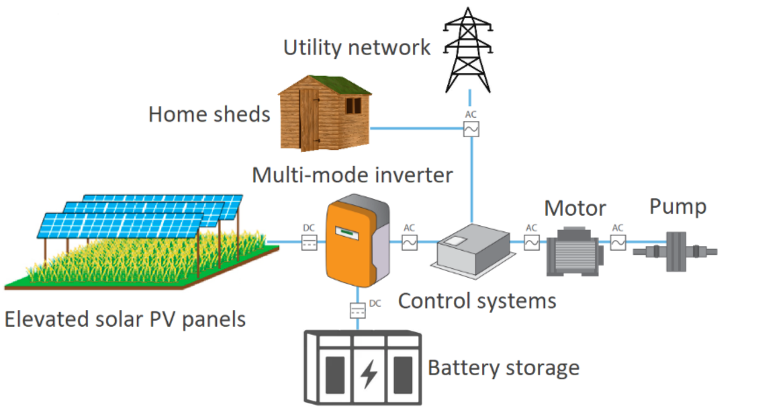

Figure 1. *Schematic diagram of a notional agrivoltaic microgrid as a test-case system.*

3. Methodology

The primary goal of optimizing operational dispatch in grid-connected agrivoltaic microgrids is to maximize profit subject to a set of constraints to capture operational constraints, battery dynamics, and load requirements. The methodology employs linear programming to optimize the performance of the energy storage system, strategically managing charging and discharging cycles based on 24-hour forecasts for wholesale electricity prices, local energy generation, and forecasted demand.

The storage system follows an arbitrage-based charge-and-discharge strategy, prioritizing charging during periods of low electricity prices and discharging discreetly when needed to meet demand or take advantage of high prices. The optimization is conducted on a day-ahead basis with hourly intervals, enabling accurate alignment of storage operations with forecasted hourly variations in prices, generation, and demand.

The objective function and associated constraints are defined as follows, where bold-face characters represent 24-hour column vectors (refer to Figure 2 for the overall model structure) [6]:

$$\max\ \boldsymbol{Pr} = \boldsymbol{P_{ex}}\boldsymbol{FiT}^T\Delta t - \boldsymbol{P_{im}}\boldsymbol{\pi}^T\Delta t - 10^{-6}\|\boldsymbol{u}\|_1, \tag{1}$$

subject to:

$$\boldsymbol{P_{im}} - \boldsymbol{P_{ex}} = \boldsymbol{P_L} - \boldsymbol{P_{PV}} + \boldsymbol{P_{ch}} - \boldsymbol{P_{dch}}, \tag{2}$$

$$E_B(t) = E_B(t-1).(1 - \sigma_B.\Delta t) + \eta_{ch}.P_{ch}(t).\Delta t - \frac{P_{dch}(t).\Delta t}{\eta_{dch}} \quad \forall t, \tag{3}$$

$$E_B^{min} \leq E_B(t) \leq E_B^{max} \quad \forall t, \tag{4}$$

$$0 \leq P_{ch}(t) \leq u_{ch}(t).P_{ch}^{max} \quad \forall t, \tag{5}$$

$$0 \leq P_{dch}(t) \leq u_{dch}(t).P_{dch}^{max} \quad \forall t, \tag{6}$$

$$u_{ch}(t) + u_{dch}(t) = 0 \quad \forall t, \tag{7}$$

$$0 \leq P_{im}(t) \leq u_{im}(t).P_{im}^{max} \quad \forall t, \tag{8}$$

$$0 \leq P_{ex}(t) \leq u_{ex}(t).P_{ex}^{max} \quad \forall t, \tag{9}$$

$$u_{im}(t) + u_{ex}(t) \leq 1 \quad \forall t, \tag{10}$$

where $\boldsymbol{Pr}$ is the profit of the system over the 24-hour period, $\boldsymbol{P_{ex}}$ is the exported power, $\boldsymbol{P_{im}}$ is the imported power, $\boldsymbol{P_L}$ is the load power, $\boldsymbol{P_{PV}}$ is the solar PV power, $\boldsymbol{P_{ch}}$ and $\boldsymbol{P_{dch}}$ respectively denote the charging power and discharging power of the battery bank, $\boldsymbol{FiT}$ is the feed-in-tariff, $\boldsymbol{\pi}$ is the wholesale prices, $\|\boldsymbol{u}\|_{\boldsymbol{1}}$ is the the L-1 norm of the storage schedules, $\Delta\boldsymbol{t}$ is the time-step length, $\boldsymbol{E_B}$ is the energy content of the battery bank, $\boldsymbol{\sigma_B}$ is the self-discharge rate of the battery bank, $\eta_{\boldsymbol{ch}}$ and $\eta_{\boldsymbol{dch}}$ are the charge and discharge efficiencies of the battery bank, respectively, $\boldsymbol{P_{ch}}$ and $\boldsymbol{P_{dch}}$ respectively denote the charging power and discharging power, binary variables $\boldsymbol{u_{ch}}$ and $\boldsymbol{u_{dch}}$ ensure non-simultaneous charging and discharging, binary variables $\boldsymbol{u_{im}}$ and $\boldsymbol{u_{ex}}$ ensure non-simultaneous importing and exporting, while the superscripts max and min respectively denote the maximum and minimum values for the corresponding variables.

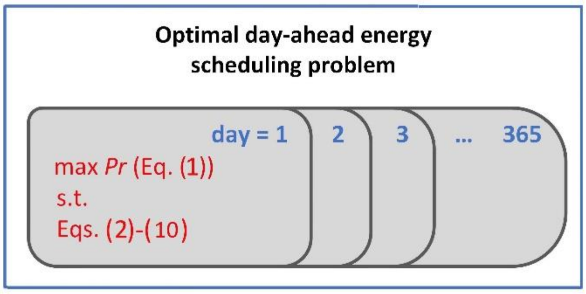

Figure 2. *Overall structure of look-ahead optimal scheduling over a 24-hour time window.*

The optimization problem is solved using the moth-flame optimization algorithm [7], a nature-inspired technique that has been shown to be effective in microgrid optimization scenarios in prior research [8], [9].

4. Case study

4.1. Input data

A case study of a dairy farm located in Canterbury, Aotearoa New Zealand (coordinates: -43°45'19", 172°12'58"), was conducted to evaluate the effectiveness of the proposed modelling framework in optimizing the sizing of components within an agrivoltaic microgrid. Figure 3 illustrates both the broader location of the site on a map of Aotearoa New Zealand, as well as a detailed map view highlighting its specific position.

Figure 3. *Location and detailed map view of the site of interest.*

Solar irradiance and ambient temperature data were sourced from the CliFlo database maintained by the Aotearoa New Zealand National Institute of Weather and Atmospheric Research (NIWA) [10]. A decade-long (2013-2022) dataset encompassing hourly measurements of solar irradiance and temperature was collected and averaged to establish a representative, year-round profile comprising 8,760 data points. Figure 4 illustrates the derived meteorological profiles on a monthly mean basis, considering that Aotearoa New Zealand is located in the Southern Hemisphere.

Monthly average global horizontal irradiance (GHI) and temperature were derived from hourly irradiance data by averaging all hourly values for each month. This calculation ensures consistency with the hourly temporal resolution used throughout the optimization model and aligns with the operational focus of the study.

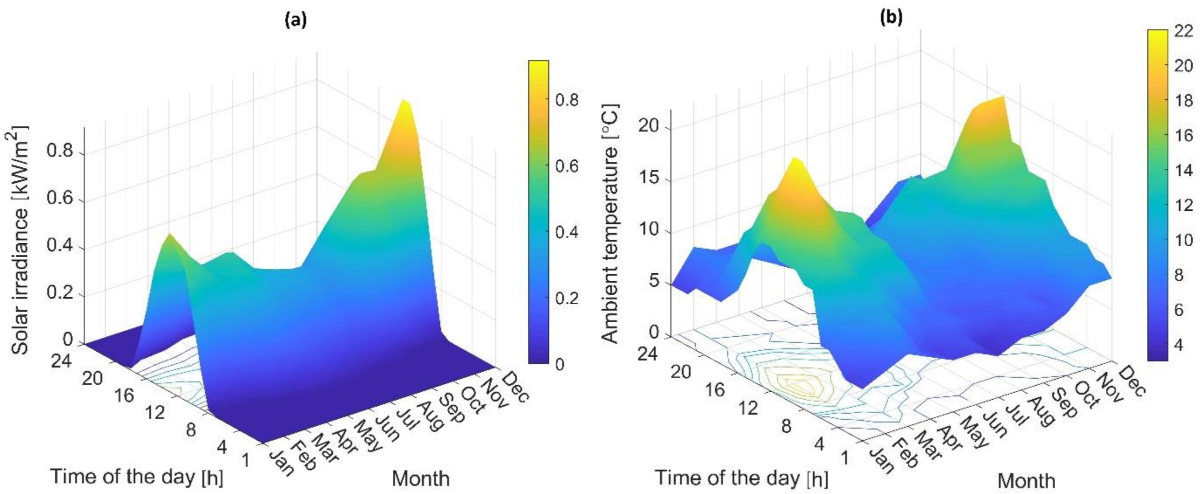

Figure 4. *Monthly mean daily profile for **(a)** global horizontal irradiance and **(b)** temperature for the site of interest.*

Additionally, wholesale electricity prices for the specified location were sourced from the Aotearoa New Zealand Electricity Authority's wholesale database [11] for the period spanning January 2013 to December 2022. This data was then processed using a weighted rolling average method to derive a representative year-long profile. Figure 5 presents the resulting total load profile of the agrivoltaic microgrid alongside the monthly mean wholesale prices. The differences in energy consumption among the months are primarily driven by variations in agricultural irrigation demand, which depend on factors such as crop growth stages and climatic conditions (particularly, temperature). During warmer and drier months, the irrigation system operates more intensively to meet increased water demand, leading to higher energy consumption. Conversely, during cooler or wetter months, water demand decreases, resulting in lower energy consumption.

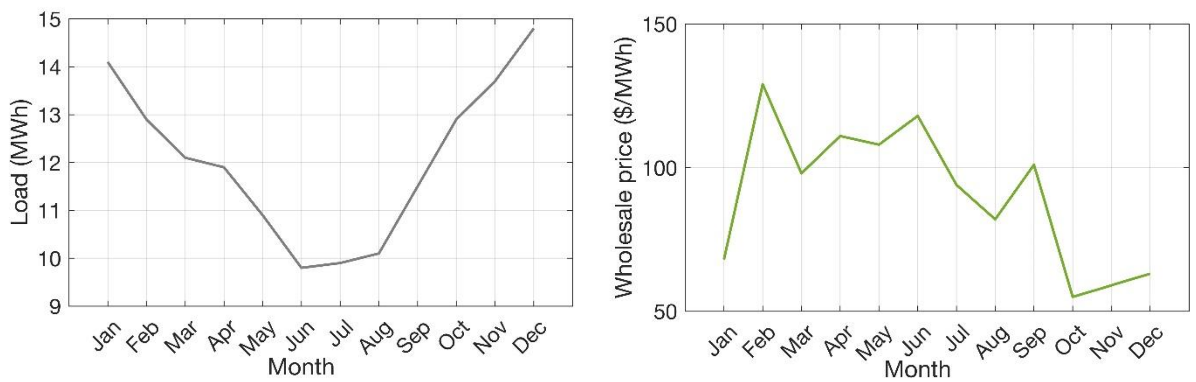

Figure 5. *Monthly mean power load and wholesale prices.*

4.2. Simulation results

The proposed optimization model was applied to the Canterbury dairy farm case study, using the collected meteorological, load, and electricity price data. To assess the effectiveness of the model, simulations were conducted over a one-year period, comparing the optimized operation of the agrivoltaic microgrid with a baseline scenario where the battery storage system was not actively managed.

The key distinction between the optimized and baseline scenarios lies in the management of battery storage. The baseline scenario assumes a simpler dispatch strategy where energy is either consumed directly or exported to the grid without consideration of dynamic factors such as maximizing self-consumption of excess solar energy. In contrast, the optimized scenario incorporates a battery storage management strategy, which allows for the storage of surplus solar energy during low-demand periods and its discharge during higher-demand periods or times of peak electricity prices. This process, known as temporal energy arbitrage, reduces the need for grid electricity during expensive periods and enhances the self-consumption of solar energy, thereby improving the overall economic performance of the agrivoltaic system. The optimization of battery usage is therefore a critical factor in reducing energy costs and maximizing profits, as it allows the system to make more efficient use of available solar power while minimizing reliance on external energy sources.

4.2.1. Optimal dispatch and energy flows

The optimization model generated hourly dispatch schedules for the microgrid, dictating the charging and discharging of the battery storage system and the energy exchange with the grid. Figure 2 illustrates a representative 24-hour dispatch schedule, showcasing the model's ability to leverage price differentials and solar generation patterns for optimal energy management.

The energy flows within the microgrid were analyzed to quantify the impact of the optimization model. Table 1 presents a summary of the annual energy flows for both the optimized and baseline scenarios over a year-long operation. The baseline scenario represents a case where a basic cycle charging strategy is implemented.

Table 1. *Summary optimal dispatch results with and without the proposed framework.*

Energy flow	Optimized (MWh/annum)	Baseline (MWh/annum)
Solar generation	485.2	485.2
Load consumption	384.7	384.7
Grid import	82.3	129.6
Grid export	36.8	126.1
Battery charge	129.5	14.8
Battery discharge	121.3	11.6
Self-consumption ration	74.2%	60.1%

The optimized operation significantly increased the self-consumption ratio of solar energy from 60.1% to 74.2%, highlighting the model's effectiveness in utilizing locally generated energy. This resulted in a substantial reduction in grid imports, from 129.6 MWh to 82.3 MWh annually. Furthermore, the optimized operation enabled the microgrid to export significantly more excess energy to the grid (from 36.8 MWh to 126.1 MWh), generating additional revenue.

4.2.2. Economic performance

The economic impact of the optimization model was assessed by comparing the annual energy costs and revenue for the optimized and baseline scenarios. Table 2 presents a summary of these metrics for the two cases of with and without the proposed optimization-based scheduling framework on a year-round operation.

Table 2. *Comparison of the economic metrics between the optimized and baseline cases.*

Economic Metric	Optimized (NZ$)	Baseline (NZ$)
Energy cost	11,801	15,625
Revenue	1,998	0
Net profit	-9,803	-15,625

The optimization model resulted in a significant 24.5% reduction in annual energy costs, amounting to savings of NZ$3,824[1]. Additionally, the ability to export excess energy to the grid generated NZ$1,998 in revenue. This translated to a substantial improvement in the net profit of the microgrid, increasing from a loss of NZ$15,625 in the baseline scenario to a loss of NZ$9,803 in the optimized scenario.

4.2.3. Discussion

The simulation results demonstrate the efficacy of the proposed optimization model in maximizing profit (or better put, reducing the net cost) and enhancing the economic viability of grid-connected agrivoltaic microgrids. The model's ability to optimally schedule the charging and discharging of the battery storage system based on forecasts is instrumental in achieving these results. The increased self-consumption of solar energy, reduced reliance on the grid, and additional revenue from energy exports all contribute to the improved economic performance of the microgrid.

The proposed methodology acknowledges similarities with microgrid optimization but differentiates itself by addressing the specific needs of agrivoltaic systems, such as agricultural energy demands and their temporal variability.

However, it is important to acknowledge that the model's performance is contingent upon the accuracy of the input data and the underlying assumptions. Future research could focus on refining the model by incorporating more sophisticated forecasting techniques and exploring the impact of uncertainties in the input data. Nonetheless, the current results provide a compelling case for the widespread adoption of optimization models in the design and operation of agrivoltaic systems.

5. Conclusions and future work

This study has successfully demonstrated the efficacy of a novel optimization method for dispatch strategies in grid-connected agrivoltaic systems. By applying this method to a real-world case study in Aotearoa New Zealand in a numerical way, the paper has shown its potential to enhance energy efficiency, demand management, and economic viability. The integration of energy storage, guided by 24-hour forecasting and linear programming, proves instrumental in optimizing system performance and increasing profitability for agrivoltaic operators. These findings highlight the importance of strategic energy management in agrivoltaic systems and their significant contribution to sustainable energy production and food security.

Future research should expand the model to incorporate additional variables like weather forecasts and crop growth models. Investigating diverse energy storage technologies and assessing the environmental impact of agrivoltaic systems will further advance this field. Finally, evaluating the scalability of the proposed optimization method for larger systems could pave the way for widespread adoption, accelerating the global transition towards sustainable practices.

Data availability statement

Data will be made available on request from the Chair in Sustainable Energy Systems: https://www.wgtn.ac.nz/sustainable-energy-systems.

[1] 1 NZD = 0.61 USD in 2023 on average [12].

Underlying and related material

The related modelling that underpins the research is available on request from the Chair in Sustainable Energy Systems: https://www.wgtn.ac.nz/sustainable-energy-systems.

Author contributions

Soheil Mohseni: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Resources, Software, Validation, Visualization, Writing – original draft. Alan C. Brent: Supervision, Project administration, Formal analysis, Investigation, Resources, Validation, Writing – review editing editing.

Competing interests

The authors declare no competing interests.

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