Applied Energy 278 (2020) 115534

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Photovoltaic systems on dairy farms: Financial and renewable multi-objective optimization (FARMOO) analysis

M. Breen[a,b], J. Upton[b], M.D. Murphy[a,*]

[a] Department of Process, Energy and Transport Engineering, Cork Institute of Technology, Cork, Ireland
[b] Teagasc, Animal & Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland

HIGHLIGHTS

- A method to perform multi-objective optimization for dairy farms was proposed.
- Multi-objective optimization was based on financial & renewable criteria.
- Photovoltaic (PV) model created and validated using experimental data.
- Model used as part of a test case for multi-objective optimization on dairy farms.
- Load shifting and PV may negate the need for battery storage on farms.

ARTICLE INFO

Keywords:
Dairy farm
Photovoltaic system
Multi-objective optimization
Trade-off analysis
Agriculture
Renewable energy

ABSTRACT

The aim of this study was to develop a financial and renewable multi-objective optimization (FARMOO) method for dairy farms. Due to increased global milk production and European Union policies concerning renewable energy contributions, the optimization of dairy farms from financial and renewable standpoints is crucial. The FARMOO method found the optimal combination of dairy farm equipment and management practices, based on a trade-off parameter which quantified the relative importance of maximizing farm net profit and maximizing farm renewable contribution. A PV system model was developed and validated to assess the financial performance and renewable contribution of this technology in a dairy farming context. Seven PV system sizes were investigated, ranging from 2 kWp to 11 kWp. Multi-objective optimization using a Genetic Algorithm was implemented to find the optimal combination of equipment and management practices based on the aforementioned trade-off parameter. For a test case of a 195 cow spring calving dairy farm in Ireland, it was found that when the relative importance of farm net profit was high, a PV system was not included in the optimal farm configuration. When net profit and renewable contribution were of equal importance, the optimal farm configuration included an 11 kWp PV system with a scheduled water heating load at 10:00. Multi-objective optimization was carried out for the same test case with the goals of maximizing farm net profit and minimizing farm CO_2 emissions. Under this scenario, the optimal farm configuration included an 11 kWp PV system when the relative importance of farm net profit was low. This study included a sensitivity analysis which investigated the use of a 40% grant aid on PV system capital costs. This sensitivity analysis did not significantly improve the financial feasibility of PV systems on dairy farms. Moreover, it was found that load shifting of a farm's water heating enabled the majority of the PV system's electricity output to be consumed. Hence the use of batteries with small PV systems on dairy farms may not be necessary. The method described in this study will be used to inform policy and provide decision support relating to PV systems on dairy farms.

1. Introduction

1.1. Background to research

Optimizing dairy farm equipment and management practices under financial and renewable criteria, including the potential use of solar photovoltaic (PV) systems, is important for three reasons: 1) European Union (EU) countries have agreed that at least 32% of final energy consumption in the EU as a whole will be provided by renewable energy by the year 2030 [16]. Hence, if policymakers wish to incentivize

---

* Corresponding author at: Department of Process, Energy and Transport Engineering, Cork Institute of Technology, Bishopstown, Co. Cork, Ireland.
E-mail address: michaeld.murphy@cit.ie (M.D. Murphy).

https://doi.org/10.1016/j.apenergy.2020.115534
Received 19 January 2020; Received in revised form 23 June 2020; Accepted 15 July 2020
Available online 12 August 2020

the adoption of PV systems in order to ensure that this target is met, information is needed regarding the financial performance and renewable contribution of these systems.

2) As part of the 2030 climate & energy framework, the European Commission (EC) has targeted a 40% reduction in greenhouse gas (GHG) emissions for the EU by 2030, compared to 1990 levels [15]. In Ireland, the EC has set a 30% reduction target for GHG emissions by 2030 compared to 2005 levels [15]. Reaching this target is unlikely to happen under current conditions [28], meaning that further GHG mitigation measures are required. One possible GHG mitigation strategy recommended by Lanigan et al. [28] was the use of primary energy saving measures such as the implementation of PV systems on farms. A previous analysis conducted by Breen et al. [7] demonstrated the potential of PV systems for CO_2 mitigation on dairy farms. It was found that the annual percentage CO_2 reduction upon the addition of a PV system varied from 10% to 34%, depending on farm size, PV system size and farm technology configuration.

3) Since the abolition of EU milk quotas in 2015, milk production in Ireland has increased by 34.2% [8]. This increase in milk output may make the purchase of new on-farm equipment necessary, thereby increasing electricity costs per litre of milk produced [46]. Hence, it is important to provide information concerning the long term financial feasibility of potential cost saving measures, such as the installation of PV systems. With this in mind, clarity is required around the performance of PV systems to ascertain whether they are optimal under financial and renewable criteria, when different farm equipment and management practices are considered.

Previous research by Nacer et al. [35] assessed the feasibility of PV systems on seven dairy farms and found the optimal PV system size to meet each farm's electricity demand. A similar analysis was performed by Nacer et al. [36] whereby wind turbines were considered along with PV systems for meeting demand on the same seven farms. Nadjemi et al. [37] implemented an optimal sizing procedure for PV systems, wind turbines and batteries on dairy farms. However, all three of these studies utilized static load profiles to represent farm electricity consumption, and therefore did not take into account changes in milk cooling, water heating and milking technologies on the farm and how they influence PV system performance. They also did not take into account the altering of the farm's milking times or the shifting of the farm's milk cooling and water heating loads to take advantage of the PV system output. The use of PV systems with battery storage has been explored for many applications such as residential buildings [19,24] and electric vehicle charging [23], but has not been extensively researched in the context of dairy farms.

Bey et al. [2] found the optimal PV system size for one farm to reduce its reliance on purchasing electricity from the grid. The optimal water pumping and lighting systems on the farm were also found. However, no analysis was carried out to find the optimal milk cooling system, water heating system or milking machine, with these being the three largest energy consumers on dairy farms [44]. Furthermore, the PV output simulations were based on an assumption regarding module efficiency rather than a validated model. Zhang et al. [50] investigated the use of PV systems on eleven dairy farms, however the PV systems were exclusively used for water pumping and no other on-farm processes. De Blas et al. [12] analysed the performance of a PV system providing electricity to a dairy farm milk cooling system, with the analysis focusing solely on the experimental setup used and therefore not being generalizable. In an Irish context, Wrixon [49] evaluated the performance of a PV system on a dairy farm on Fota Island, Cork, Ireland. Again this analysis was not generalizable, since the work focused on one specific farm.

1.2. Gaps in knowledge and contribution

Gaps in knowledge have been identified based on the literature review described above and are outlined below, along with the contributions of this study:

- This study is novel as it explored how best to configure a dairy farm to effectively utilize the output of a PV system. Previous research (discussed above) has used static farm load profiles, which lack the scope to assess how different technologies relating to milk cooling, water heating and milking affect the farm's electricity consumption. Since these technologies contribute approximately 75% of a typical dairy farm's electricity consumption [44], assessing which configuration of these best utilizes PV system output is of great importance.
- Since PV systems produce electricity during daytime hours the farm's electricity consumption may be altered to ensure that PV systems provide as much of the farm's electricity as possible. Hence, the use of load shifting to alter the times at which milk cooling, water heating and milking take place throughout the day is extremely important and should be assessed. This was not possible when using the static farm load profiles seen in previous research. This study considered various potential on-farm technologies and load shifting measures and used optimization techniques to find the combination of these which best utilized PV systems on-farm, both from a financial and renewable perspective. To our knowledge this has not previously been carried out in the literature.
- Another contribution of this study concerns the implementation of multi-objective optimization to obtain optimal trade-offs between the aforementioned financial and renewable criteria. The application of multi-objective optimization in the context of dairy farming has been carried out in a previous study [4], which utilized a Genetic Algorithm (GA) and the weighted sum method (WSM). GA and the WSM have been used for multi-objective optimization in a number of cognate studies [4,14,17,27].
- Unlike previous studies relating to PV utilization on dairy farms this study employed experimental data to construct and validate a scalable, generalizable model of a PV system.

The objective of this study was to carry out multi-objective optimization, while considering various combinations of dairy farm equipment and management practices, optimizing based on a scalable financial and renewable trade-off parameter. A PV model was developed and validated, and used to demonstrate the multi-objective optimization on a simulated test case farm.

2. Materials and methods

2.1. Overview of methodology

Sections 2.2 and 2.3 describe the methods by which multi-objective optimization of financial and renewable criteria on dairy farms was carried out. Fig. 1 illustrates the operation of a typical dairy farm with an installed PV system - a PV system provides electricity to the farm, as well as exporting excess electricity to the grid if necessary. The farm also purchases electricity from the grid, but the amount of electricity required varies depending on the size of the PV system used as well as the farm's equipment and management practices. For example load shifting may be employed by altering the times when milking, water heating and milk cooling take place, in order to increase the PV output consumed on-farm. The multi-objective optimization carried out in this study found the optimal combination of equipment and management practices to maximize farm net profit (Section 2.3.2) while also maximizing farm renewable contribution (Section 2.3.3), based on a joint objective function employing a financial and renewable trade-off parameter.

2.2. Modelling of PV system output

2.2.1. Equipment for PV data collection

In order to simulate the output of a PV system and assess its effect on dairy farm electricity consumption, a model was created using data obtained from a PV system in the USA. The equipment used to gather

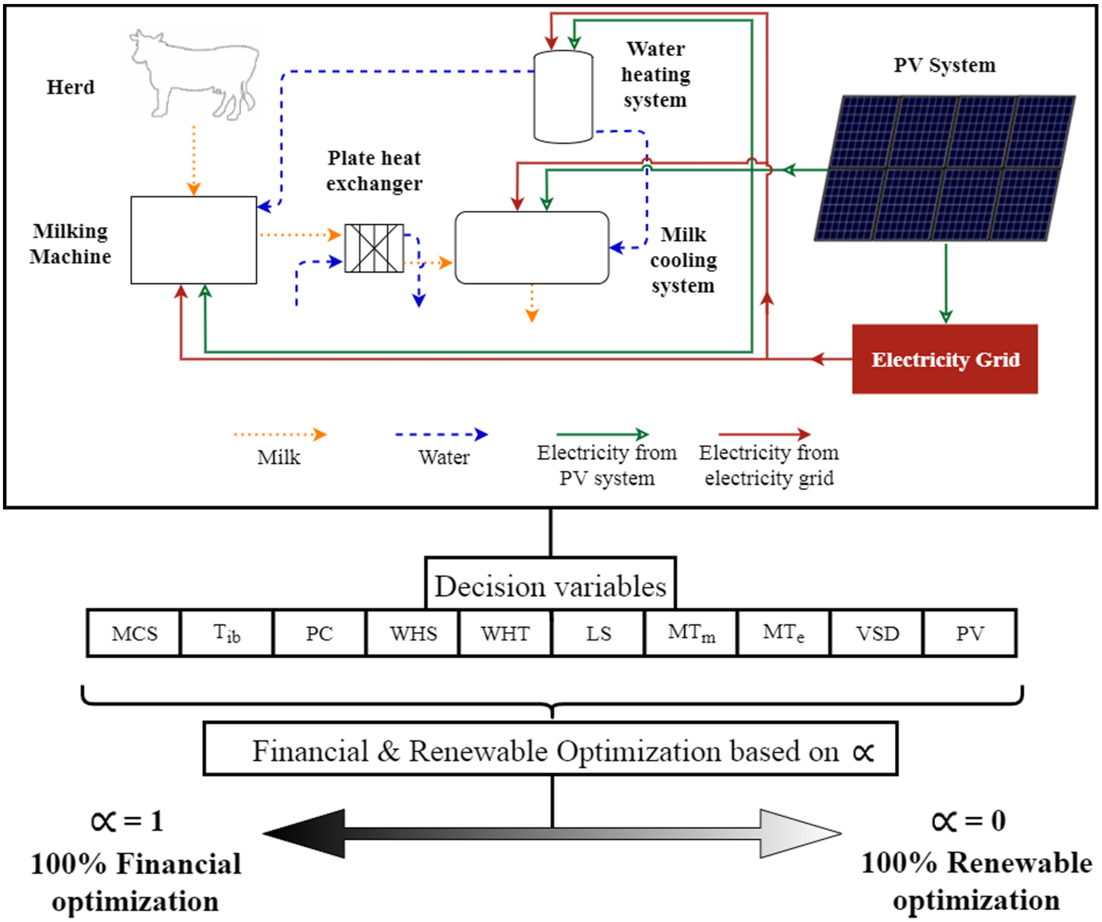

Fig. 1. Overview of methodology deployed. Multi-objective optimization is utilized to find the optimal farm configuration to maximize farm net profit and renewable contribution based on a trade-off parameter α. Acronyms used: "MCS" = Milk cooling system; "T_{ib}" = Ice bank start time; "PC" = Precooling; "WHS" = Water heating system; "WHT" = Water heating timer; "LS" = Load shifting; "MT_m" = Morning milking time; "MT_e" = Evening milking time; "VSD" = Variable speed drives; "PV" = Photovoltaic system.

this data was located at the Net-Zero Energy Residential Test Facility (NZERTF) on the National Institute of Standards and Technology campus in Gaithersburg, Maryland. Details pertaining to the system can be found in Davis et al. [11], and the data is open source [21,22].

2.2.2. Data for PV model development and validation

Data in the form of irradiance (W/m^2), wind speed (m/s), ambient temperature (°C) and power output (W) were recorded at one minute intervals for two years - from July 1, 2013 to June 30, 2014 and from February 1, 2015 to January 31, 2016. This study used an hourly time step, and hence hourly values of irradiance, wind speed, ambient temperature and power output were calculated based on the aforementioned data. The resulting hourly values could then be used for model validation. The irradiance, wind speed and ambient temperature data used for PV model development and validation is summarized in Table A.1 in Appendix A.

2.2.3. PV model development

The PV model described by Villalva et al. [48] was used in this work. The equation employed by the model which describes the current–voltage characteristic of a PV cell is as follows:

$$I = I_{pv} - I_o\left[exp\left(\frac{V + R_s I}{V_t a}\right) - 1\right] - \frac{V + R_s I}{R_p} \tag{1}$$

where I and V are the array current and voltage, respectively, I_{pv} and I_o are the PV and saturation currents, respectively, of the array and V_t is the thermal voltage of the array, a is the diode ideality constant, R_s is the series resistance and R_p is the parallel resistance.

The parameters I_{pv}, I_o, a, R_s and R_p were unknown. A value of 1.3 was chosen for a [48] and thus the four unknown parameters I_{pv}, I_o, R_s and R_p could be determined using Equations (2) – (5):

$$I_o = I_{o,n}\left(\frac{T_n}{T}\right)^3 exp\lfloor\frac{qE_g}{ak}\left(\frac{1}{T_n} - \frac{1}{T}\right)\rfloor \tag{2}$$

$$I_{o,n} = \frac{I_{sc,n}}{exp(V_{oc,n}/aV_{t,n}) - 1} \tag{3}$$

$$P_{max,e} = V_{mp}\left\{I_{pv} - I_o\left[exp\left(\frac{q}{kT}\frac{V_{mp} + R_s I_{mp}}{aN_s}\right) - 1\right] - \frac{V_{mp} + R_s I_{mp}}{R_p}\right\} \tag{4}$$

$$R_p = V_{mp}\left(\frac{V_{mp} + I_{mp}R_s}{\left\{V_{mp}I_{pv} - V_{mp}I_o exp\left[\frac{V_{mp} + I_{mp}R_s}{N_s a}\frac{q}{kT}\right] + V_{mp}I_o - P_{max,e}\right\}}\right) \tag{5}$$

where $I_{o,n}$ is the nominal saturation current, T_n is the nominal cell temperature (K), T is the cell temperature (K), E_g is the bandgap energy of the semiconductor (eV), q is the electron charge (1.60217646 × 10^{-19}C), k is the Boltzmann constant (1.3806503 × 10^{-23} J/K), $I_{sc,n}$ is the nominal short circuit current (A), $V_{oc,n}$ is the nominal open circuit voltage (V), $V_{t,n}$ is the nominal thermal voltage (V), $P_{max,e}$ is the maximum experimental power from the datasheet (W), I_{mp} and V_{mp} are the array current (A) and voltage (V) at maximum power point, respectively, N_s is the number of cells in series.

PV cell manufacturers generally provide datasheet values measured at standard test conditions. Model parameters I_{pv}, I_o, R_s and R_p were determined using Equations (2) – (5) above, however these may vary greatly in a real life scenario since cells from different manufacturers vary in terms of performance. Hence, the values for I_{pv}, I_o, R_s and R_p found using Equations (2) – (5) and the chosen value of parameter a (1.3) may not be a true reflection of their values under real conditions. Therefore the five parameters were tuned to minimize errors between measured and predicted power output. In this study a method similar to that described by Ismail et al. [26] was utilized for parameter tuning. The five parameters were used as decision variables in a Genetic Algorithm (GA), whereby the error between measured and predicted power output represented the GA objective function. The GA then altered the decision variables (i.e. the five parameters) in order to minimize this objective function.

The five parameters were constrained to the ranges below for the GA [25,34]:

$I_{pv} \in [1, 8]$
$I_o \in [1 \times 10^{-12}, 1 \times 10^{-5}]$
$a \in [1, 2]$
$R_s \in [0.1, 2]$
$R_p \in [100, 5000]$

The mean absolute percentage error (MAPE) between hourly measured and predicted PV power output (W) was used as the objective function value to be minimized. The GA configuration (population size etc.) was determined based on the method described by Breen et al. [6].

Using the method described, the parameters I_{pv}, I_o, a, R_s and R_p had final values of 7.65 A, 6×10^{-7} A, 1.69, 1.67 Ω and 940 Ω, respectively.

2.2.4. PV model validation

The accuracy of the developed PV model was assessed by comparing the measured output power values to those predicted using the model described in Section 2.2.3. Accuracy was determined using stratified k-fold cross validation with a k value of 10 [41]. Model accuracy was measured using the root mean square error (RMSE), relative prediction error (RPE) [38], and concordance correlation coefficient (CCC) [29]. Model bias was assessed using the MAPE and the mean square prediction error (MSPE), consisting of mean bias (MB), line bias (LB) and random variation (RV) [3]. These indicators have been used in previous agriculture related studies [1,20,39,41,47]. Validation results can be found in Appendix B.

2.2.5. Integration of PV model with model for electricity consumption on dairy farms

To assess the effect of PV systems on dairy farm electricity consumption, it was necessary to use the developed PV model in conjunction with the model for electricity consumption on dairy farms (MECD), which was developed by Upton et al. [47]. The MECD predicts dairy farm electricity consumption, monetary costs and electricity related CO_2 emissions by applying mechanistic modelling techniques. The MECD was validated using data from three farms. All of the model inputs and outputs consisted of a month × daily hour (12 × 24) matrix structure. Therefore the PV model outputs used the same 12 × 24 structure.

2.3. Optimization

This section describes the multi-objective optimization procedure used in this study. A similar method was used in the authors' previous work – please see Breen et al. [4] for a more detailed explanation.

2.3.1. Optimization procedure

The weighted sum method (WSM) transforms numerous objectives into a singular objective problem and was used for multi-objective optimization in this study. The WSM assigns weights to each objective function in a multi-objective problem through the use of a trade-off parameter. Varying the trade-off parameter allows multiple optimal points in the search space to be found. These points are known as pareto optimal solutions. A solution is pareto optimal if there is no other feasible solution that improves one objective without deteriorating another [31]. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) [13] was also considered for multi-objective optimization in this study and obtained the same solutions as the WSM. Since the NSGA-II generally provides a diverse range of solutions on the true pareto front this validated the results obtained by the WSM. However, the NSGA-II method did not allow for a trade-off parameter to be specified prior to multi-objective optimization being carried out and hence the WSM was employed in this study. To find the optimal combination of dairy farm equipment and management practices under a financial and renewable trade-off parameter, the financial criterion considered was the farm's annual after tax net profit (ATNP) over a specified time horizon in years. The renewable criterion considered was the farm's annual renewable contribution (RC).

2.3.2. Financial criterion – After tax net profit (ATNP)

The procedure for financially assessing specific configurations of farm equipment and management practices is shown in Fig. 2. A dairy farm scenario of interest, i.e. a dairy farm with a particular equipment and management combination, was entered into the MECD described in Section 2.2.5. The scenario of interest was defined using 45 variables relating to herd management, milk cooling, water heating, milk precooling, milking machine, miscellaneous equipment and electricity/oil/gas/milk pricing. More information on this procedure can be found in Breen et al. [6]. An additional variable included in this study pertained to the use of PV systems on the farm. This is described in further detail in Section 2.3.4. Of the 45 variables, 35 were fixed variables while 10 were decision variables. Upon the input of these variables, the total annual electricity consumption and related costs for the farm were calculated using the MECD. These electricity costs as well as equipment investment costs were used, along with farm financial performance data from the Teagasc eProfit monitor [43] to calculate the farm's annual ATNP over a specified time horizon in years. The ATNP was calculated using the method described in Upton et al. [45].

2.3.3. Renewable criterion – Renewable contribution (RC)

When a dairy farm scenario of interest was entered into the MECD, the farm renewable contribution was also computed. The total farm electricity consumption was calculated in a 12 × 24 matrix structure as described in Section 2.2.5. The RC was defined as the amount of the farm's annual gross electricity consumption which was provided by a PV system. The RC was examined in order to ascertain how well the farm's electricity consumption profile coincided with the PV system output. If the RC was high and the amount of electricity exported to the grid by the PV system was low it indicated that the majority of the PV system's output was used on-farm (i.e. self-consumption). However if the RC was low and the amount of electricity exported to the grid was high it indicated that little PV system output was used on-farm, which could greatly affect the financial potential of PV systems in the absence of a feed-in tariff. It was assumed that any electricity produced by the PV system which wasn't consumed on-farm was exported to the national electricity grid. Therefore the annual renewable contribution for a given farm was calculated as follows:

$$RC(x, y) = \frac{Q_{pv}(y)}{Q_{f,mecd}(x)} \tag{6}$$

where $RC(x, y)$= Annual renewable contribution for farm x and PV system y (%), $Q_{pv}(y)$= Annual electricity production of PV system y consumed on-farm (kWh), $Q_{f,mecd}(x)$ = Annual gross electricity consumption of farm x calculated from MECD (kWh).

2.3.4. Decision variables

The 10 decision variables used in this study are described below. More details on these decision variables can be found in the authors'

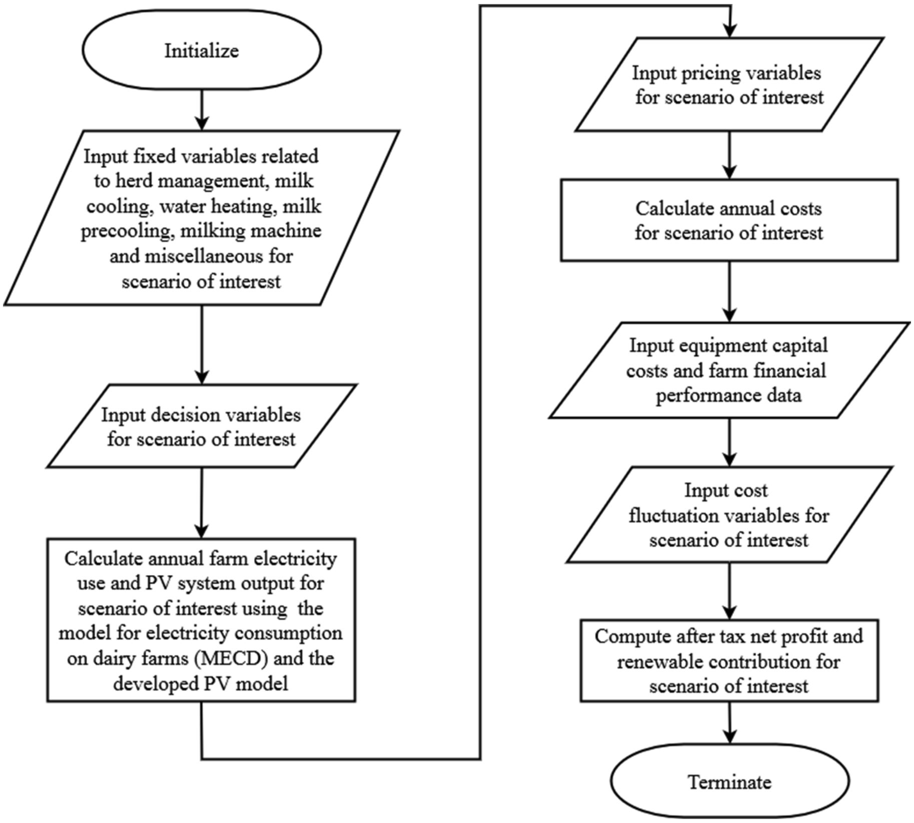

Fig. 2. Procedure for calculating after tax net profit and renewable contribution.

previous studies [4,6]:

- Milk cooling system (MCS) – Two options considered: Direct expansion (DX) and Ice bank (IB).
- Ice Bank start time (T_{ib}) – 24 options considered - Times from 00:00 to 23:00 in hourly increments.
- Precooling (PC) – Two options considered – “Yes” or “No”.
- Water heating system (WHS) – Three options considered – electric, oil and gas.
- Water heating timer (WHT) – Two options considered – “Yes” or “No”.
- Load shifting (LS) – Times to which the water heating load could be shifted– 24 options considered - Times from 00:00 to 23:00 in hourly increments.
- Morning milking time (MT_m) – Two options considered – 07:00 or 08:00.
- Evening milking time (MT_e) – Two options considered – 17:00 or 18:00.
- Variable speed drives (VSD) – Two options considered – “Yes” or “No” option.
- PV systems – Seven options considered – Six sizes of PV systems, five of which ranged from 2 kWp to 10 kWp in increments of 2 kWp, one of size 11 kWp (the largest PV system size for which the user is considered a microgenerator in Ireland) and one option whereby no PV system was used.

2.3.5. Objective function

The financial and renewable criteria described previously were used as objective functions for multi-objective optimization. These objective functions were as follows:

$$\text{Objective function A: Maximise } ATNP(x) \tag{7}$$

$$\text{Objective function B: Maximise } RC(x) \tag{8}$$

Where x = vector of the 10 decision variables, $ATNP(x)$ = average after tax net profit over the specified time horizon using x decision variables, $RC(x)$ = annual renewable contribution over the specified time horizon using x decision variables. The methods for obtaining $ATNP(x)$ and $RC(x)$ are described in Section 2.3.2 and 2.3.3.

The overall objective function $J(x)$ was defined as a trade-off between objective functions A and B, with both objective functions normalized within the range [0,1] to facilitate the use of trade-off parameter α, as follows:

$$\text{Maximise } J(x) = (\propto)(ATNP(x)') + (1 - \propto)(RC(x)') \tag{9}$$

$\propto$ = trade-off parameter in the range [0,1] which assigned relative importance to the financial and renewable criteria within the overall objective function $J(x)$, $ATNP(x)'$ = ATNP using x decision variables normalized to a value in the interval [0,1], $RC(x)'$ = RC using x decision variables normalized to a value in the interval [0,1]. $ATNP(x)'$ and $RC(x)'$ were computed using Equations 10 and 11.

$$ATNP(x)' = \frac{ATNP(x) - ATNP_{min}}{ATNP_{max} - ATNP_{min}} \tag{10}$$

Where $ATNP_{max}$ = Maximum ATNP value, $ATNP_{min}$ = Minimum ATNP value.

$$RC(x)' = \frac{RC(x) - RC_{min}}{RC_{max} - RC_{min}} \tag{11}$$

Where RC_{max} = Maximum RC value, RC_{min} = Minimum RC value.

For the analysis presented, the 10 decision variables were represented using a vector of integer values: [MCS, T_{ib}, PC, WHS, WHT, LS, MT_m, MT_e, VSD, PV]. J(x) was maximized for eleven different values of α, ranging from 0 to 1 in increments of 0.1.

The following constraints were used in the optimization process (Equations 12–15):

$$T_{ib} \le MT_m - CD \tag{12}$$

where T_{ib} = Ice bank start time, MT_m = morning milking time,

CD = Maximum daily milk cooling duration (hours).

$$T_{wh} \leq MT_e + EMD - WHD \tag{13}$$

where T_{wh} = Water heating timer start time, MT_e = evening milking time, EMD = Maximum daily evening milking duration (hours), WHD = Maximum daily water heating duration (hours).

$$07:00 \leq MT_m \leq 08:00 \tag{14}$$

where MT_m = morning milking time.

$$17:00 \leq MT_e \leq 18:00 \tag{15}$$

where MT_e = evening milking time.

Once optimization was carried out, the annual CO_2 emissions (kg) were calculated for each farm configuration obtained for the 11 α values. This provided an additional performance measure to assess the optimization results, but did not affect the optimization itself. To obtain the annual CO_2 emissions for a particular farm configuration firstly the total farm electricity consumption was calculated using MECD (Section 2.2.5). To compute the CO_2 emissions associated with this electricity consumption, the method described by Breen et al. [4] was used. If electricity was exported to the grid by a PV system, this electricity could be considered "green" and therefore would offset CO_2 emissions when purchased from the grid by other customers. Hence, it was assumed that every kWh of exported electricity reduced the farm's CO_2 emissions by the average CO_2 intensity per kWh at the time when exporting took place.

A further analysis was carried out whereby objective function B was to minimize annual farm CO_2 emissions, while objective function A (maximize ATNP) remained the same. The multi-objective optimization procedure to carry out this analysis was the same as that explained above and that performed by Breen et al. [4].

2.3.6. GA implementation for multi-objective optimization

The method by which GA was used for multi-objective optimization in this study is illustrated in Fig. 3. The overall objective function (Equation 9) was utilized to evaluate the performance of a population of decision variable combinations. These combinations were then reordered based on their performance using genetic operators comprising selection, crossover and mutation. A stopping criterion in the form of a maximum number of iterations was employed. The parameters for the GA were selected based on the method described by Breen et al. [6]. The parameters selected were as follows: Population size = 120, Type of selection = Rank selection, Type of crossover = Two point crossover, Crossover probability = 0.85, Mutation probability = 0.05.

2.4. Test case for application of methods

The test case used in this study was the same as that used by Upton et al. [45] and Breen et al. [4,6] i.e. a farm with annual milk yield of 774,089L and a 195 cow spring calving herd. Simulations were carried out over a ten year time horizon. The multi-objective optimization using ATNP and RC (Section 2.3.5) shall be referred to as Scenario 1 while that using ATNP and CO_2 emissions shall be referred to as Scenario 2. A sensitivity analysis was also carried out whereby grant aid of 40% was applied to the cost of PV systems. Equipment costs including cost of installation are shown in Table 1. These were based on information taken from DAFM [10] as well as relevant suppliers.

Electricity, gas, oil and milk prices did not fluctuate year-on-year over the ten year time horizon. The prices of these commodities for the test case were as follows: Oil and gas prices were €0.08/kWh and €0.06/kWh respectively [40], while milk price was €0.33/L and electricity price was €0.09/kWh from 00:00 to 09:00 and €0.17/kWh from 09:00 to 00:00 [6].

To simulate the test case in this study weather data consisting of irradiance, wind speed and ambient temperature measurements were required. The data obtained for this purpose consisted of six years (2013 to 2018 inclusive) of hourly measurements obtained from six weather stations throughout Ireland. Data was averaged over the six year period and over the six locations to obtain a typical year of Irish weather conditions. The data, provided by Met Éireann [33], is summarized in Appendix A, Table A.2.

3. Results

All simulations were carried out in MATLAB 2014a using a computer with the following properties: Windows 7 64-bit, 3.50 GHz Core i3-4150 CPU, and 8 GB RAM. On average each run of the multi-objective optimization algorithm took 45 min and 29 s.

The multi-objective optimization results for Scenario 1 (optimizing ATNP and RC) are shown in Table 2. The optimal combination of decision variables for each of the 11 α values are listed, along with their corresponding average ATNP and RC over the ten year time horizon. The annual CO_2 emissions are also listed for each value of α, as well as the electricity exported annually by the PV system (kWh) and the exported electricity as a percentage of annual PV production. When an α value of 1 was used, the optimal milk cooling system, water heating system, morning milking time and evening milking time were DX, Electric, 07:00, and 18:00, respectively while the farm used milk precooling, a water heating timer with a start time of 00:00, no VSDs and no PV system. This optimal scenario had an ATNP of €61,876, an RC of 0%, no electricity exported and CO_2 emissions of 14,217 kg. Upon decreasing α, the optimal scenario remained the same as that for α = 1 until an α value of 0.6 was reached at which point load shifting of water heating to 10:00 was implemented and an 11 kWp PV system was introduced. The farm had an ATNP of €59,859, an RC of 39%, 879 kWh electricity exported (6.7% of annual PV production), and CO_2 emissions of 8,322 kg. The optimal scenario remained the same until an α value of 0.4 was reached at which point VSDs were introduced and the farm had an ATNP of €59,535, an RC of 43%, 982 kWh electricity exported (7.5% of annual PV production), and CO_2 emissions of 6,998 kg. The optimal scenario remained the same for all values of α from 0.3 to 0.

The multi-objective optimization results for Scenario 2 (optimizing ATNP and CO_2 emissions) are shown in Table 3. When an α value of 1 or 0.9 was used, the optimal farm configuration, ATNP, CO_2 emissions, RC, and electricity exported were the same as those for an α value of 1 in Table 2. When an α value of 0.8 was reached the water heating system changed to gas and the farm had an ATNP of €61,720, CO_2 emissions of 11,055 kg, an RC of 0% and no electricity exported. When an α value of 0.5 was reached VSDs were introduced to the optimal scenario, and the farm had an ATNP of €61,405, CO_2 emissions of 9,731 kg, an RC of 0% and no electricity exported. When an α value of 0.3 was reached an 11 kWp PV system was introduced, the evening milking time changed to 17:00 and the farm had an ATNP of €59,174, CO_2 emissions of 4,008 kg, an RC of 8%, and 10,478 kWh electricity exported (80.3% of annual PV production). When an α value of 0.2 was reached the evening milking time changed to 18:00 and the farm had an ATNP of €59,137, CO_2 emissions of 3,944 kg, an RC of 7%, and 11,099 kWh electricity exported (84.4% of annual PV production). The optimal scenario remained the same for α values of 0.1 to 0.

For Scenarios 1 and 2 a sensitivity analysis was carried out whereby grant aid of 40% was applied to the cost of PV systems. The results of this analysis are shown in Appendix C, Tables C.1 and C.2 for Scenarios 1 and 2 respectively. Results for all α values were similar to the corresponding results in Tables 3 and 4 but with higher ATNP values due to the implementation of grant aid.

4. Discussion

The results for Scenario 1, whereby multi-objective optimization of ATNP and RC was carried out, are shown in Table 2. For an α value of 1, the optimal farm configuration was similar to that found by Breen et al. [6]. This was despite the potential inclusion of a PV system in the optimization space. A PV system was not included in the optimal farm configuration until

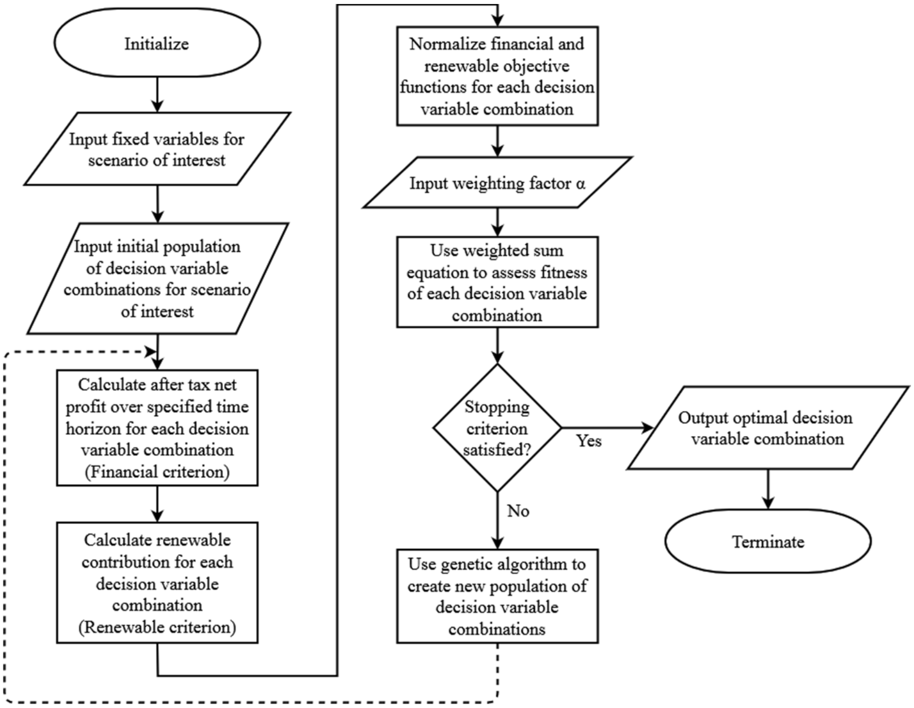

Fig. 3. Genetic Algorithm procedure for multi-objective optimization.

Table 1
Investment costs for equipment used in the test case, including installation costs.

Equipment	Investment cost (€)
DX milk cooling system	25,779
IB milk cooling system	27,469
Electric water heating system	1,200
Oil water heating system	2,400
Gas water heating system	3,000
Plate heat exchanger	2,390
Variable speed drives	3,350
PV system (per kWp)	1,400

an α value of 0.6 was reached (i.e. the relative importance of ATNP and RC were similar). The use of a PV system became optimal at this point, with an RC of 39% and a reduction in CO_2 emissions of 5,895 kg compared to the scenario where α = 1. As α values decreased incrementally from a value of 1, it could be seen that there were no changes to the optimal farm configuration before an α value of 0.6 was reached. At this point load shifting of water heating at 10:00 was implemented, in order to utilize the PV system output during daytime hours. Since the RC of the farm was one of the optimization objectives and load shifting of water heating was possible, the largest possible PV size was selected in order to consume as much of the water heating load as possible.

A sensitivity analysis was performed to assess how grant aiding of PV systems would affect the multi-objective optimization results. A grant aid of 40% on the capital costs of PV systems was introduced, similar to the PV grant amount on pig and poultry farms in Ireland [9]. These results can be seen in Appendix C, Table C.1. However, this sensitivity analysis yielded similar results to those displayed in Table 2, with PV systems also being introduced at an α value of 0.6. Again the largest possible PV system size was selected due to the possibility of load shifting.

The results for Scenario 2, whereby multi-objective optimization of ATNP and CO_2 emissions was carried out, are shown in Table 3. For an α value of 1 the optimal farm configuration was the same as that in Table 2. When an α value of 0.8 was used a gas water heating system was included in the optimal farm configuration. The reason for this was the use of CO_2 emissions as an objective instead of RC for Scenario 2, as seen previously in Breen et al. [4]. PV systems were optimal when α ≤ 0.3, however they were used with gas water heating rather than with electric water heating. Since load shifting to match PV system output was not possible due to the selection of gas water heating, this resulted in large amounts of PV electricity being exported to the grid (up to 84.4% of annual production). These configurations were optimal due to the fact that exported electricity reduced farm CO_2 emissions as described in Section 2.3.5. Hence a large PV system was selected to export as much electricity as possible when the relative importance of minimizing CO_2 emissions was high.

A sensitivity analysis with a PV grant aid of 40% was also carried out for Scenario 2. These results can be seen in Appendix C, Table C.2. This sensitivity analysis yielded similar results to those displayed in Table 3 where no grant aid was in place.

Under Scenarios 1 and 2, for PV systems to be included in the optimal farm configuration at a higher α value i.e. high relative importance of ATNP, their capital costs would have to reduce. The fact that PV systems did not become optimal until an α value of 0.6 was used in Scenario 1 and 0.3 was used in Scenario 2 indicates that their payback periods are relatively long. Furthermore, the addition of a 40% grant aid made little difference to the financial performance of PV systems for both scenarios. Comparing results to those of other studies is difficult due to the lack of literature concerning the financial performance of PV systems on dairy farms. However, the financial infeasibility of PV systems found in this study agrees with previous results reported by Nacer et al. [36] on dairy farms in Algeria. On the other hand Lukuyu et al. [30] demonstrated that PV systems were profitable for farms in Tanzania with high milk cooling requirements. However the study carried out by Lukuyu et al. assumed that lead acid batteries were used with PV systems.

Fig. 4 shows the average daily electricity consumption profile of the farm under Scenario 1 when α = 1, as well as the average daily electricity consumption profile of the farm when α = 0. The consumption profile for α = 0 does not take into account the use of the 11 kWp PV system selected as part of the optimal farm configuration for α = 0 in Table 2. The average daily electricity production of the 11 kWp PV system is also shown in Fig. 4, as well as the production for the day of the year with maximum PV output. It should be noted that the electricity

Table 2

Multi-objective optimization results for Scenario 1*. The optimal combination of decision variables for each of the 11 α values are listed, along with their corresponding average annual after tax net profit (ATNP) (€) and renewable contribution to annual farm gross electricity consumption (RC) values over the ten year time horizon. The total electricity exported annually by the PV system (kWh) and the exported electricity as a percentage of annual gross PV production are also listed, as well as the farm's total annual CO_2 emissions (kg).

	100% renewable optimization										100% financial optimization
α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Morning milking time	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00
Evening milking time	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00
Milk cooling system	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX
Ice bank start time	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Precooling	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Water heating system[ϕ]	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC
Water heating timer	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Timer start time (load shifting)	10:00	10:00	10:00	10:00	10:00	10:00	10:00	00:00	00:00	00:00	00:00
VSDs	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
PV	11 kWp	11 kWp	11 kWp	11 kWp	11 kWp	11 kWp	11 kWp	NONE	NONE	NONE	NONE
Annual ATNP (€)	59,535	59,535	59,535	59,535	59,535	59,859	59,859	61,876	61,876	61,876	61,876
Renewable contribution (%)[Ψ]	43	43	43	43	43	39	39	0	0	0	0
Annual electricity exported (kWh)	982	982	982	982	982	879	879	0	0	0	0
(% of PV production)	(7.5)	(7.5)	(7.5)	(7.5)	(7.5)	(6.7)	(6.7)	(0.0)	(0.0)	(0.0)	(0.0)
Annual CO_2 Emissions (kg)	6,998	6,998	6,998	6,998	6,998	8,322	8,322	14,217	14,217	14,217	14,217

* Scenario 1 = Multi-objective optimization of farm net profit and renewable contribution; Scenario 2 = Multi-objective optimization of farm net profit and CO_2 emissions. Under both scenarios the farm had a yearly milk output of 774,089L and herd size of 195 cows.

[Ψ] Renewable contribution = the amount of the farm's annual gross electricity consumption which was provided by a PV system; Annual electricity exported (% of PV production) = annual electricity exported by the PV system as a percentage of gross PV production.

[ϕ] ELEC = Electric water heating system.

Table 3

Multi-objective optimization results for Scenario 2*. The optimal combination of decision variables for each of the 11 α values are listed, along with their corresponding average annual after tax net profit (ATNP) (€) and the farm's total annual CO_2 emissions (kg) over the ten year time horizon. The renewable contribution to annual farm gross electricity consumption (RC), total electricity exported annually by the PV system (kWh) and the exported electricity as a percentage of annual gross PV production are also listed.

α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Morning milking time	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00
Evening milking time	18:00	18:00	18:00	17:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00
Milk cooling system	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX
Ice bank start time	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Precooling	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Water heating system[ϕ]	GAS	GAS	GAS	GAS	GAS	GAS	GAS	GAS	GAS	ELEC	ELEC
Water heating timer	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	YES	YES
Timer start time (load shifting)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	00:00	00:00
VSDs	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO
PV	11 kWp	11 kWp	11 kWp	11 kWp	NONE	NONE	NONE	NONE	NONE	NONE	NONE
Annual ATNP (€)	59,137	59,137	59,137	59,174	61,405	61,405	61,720	61,720	61,720	61,876	61,876
Annual CO_2 Emissions (kg)	3,944	3,944	3,944	4,008	9,731	9,731	11,055	11,055	11,055	14,217	14,217
Renewable contribution (%)[Ψ]	7	7	7	8	0	0	0	0	0	0	0
Annual electricity exported (kWh) (% of PV production)	11,009 (84.4)	11,009 (84.4)	11,009 (84.4)	10,478 (80.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)

* Scenario 1 = Multi-objective optimization of farm net profit and renewable contribution; Scenario 2 = Multi-objective optimization of farm net profit and CO_2 emissions. Under both scenarios the farm had a yearly milk output of 774,089L and herd size of 195 cows.

[Ψ] Renewable contribution = the amount of the farm's annual gross electricity consumption which was provided by a PV system; Annual electricity exported (% of PV production) = annual electricity exported by the PV system as a percentage of gross PV production.

[ϕ] ELEC = Electric water heating system.

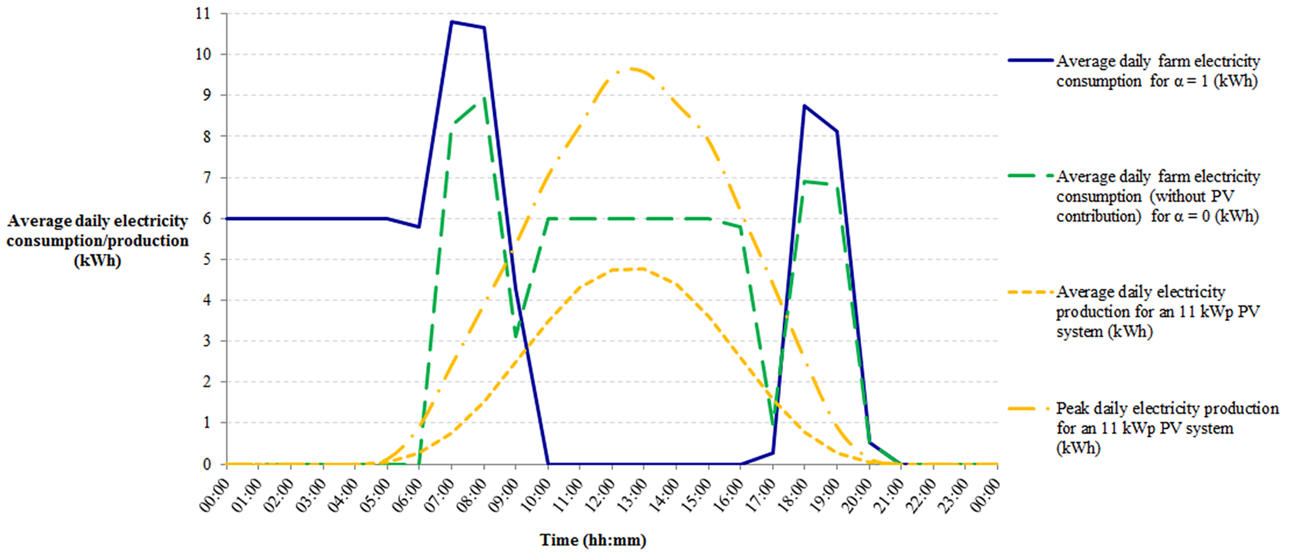

Fig. 4. Average daily farm electricity consumption for α = 1 (kWh), average daily farm electricity consumption (without PV contribution) for α = 0 (kWh), average daily electricity production for an 11 kWp PV system (kWh) and the peak daily electricity production for an 11 kWp PV system, all under Scenario 1 (Table 2).

production of the PV system varied greatly depending on weather conditions. Hence the amount of excess electricity exported to the grid from the PV system also varied day-to-day and month-to-month. Fig. 4 illustrates the differences between the electricity consumption profiles of the farm for α values of 0 and 1. It can be seen that when α = 0 load shifting is implemented, with water heating taking place at 10:00. When α = 1 load shifting is not implemented, with water heating taking place at 00:00. It can also be seen that when α = 0 the electricity consumption peaks corresponding to the farm's milking times are lower, due to the reduction in milking machine electricity use resulting from the adoption of VSDs. Fig. 4 also illustrates why an 11 kWp PV system was selected as part of the optimal farm configuration when α = 0 and why it was not selected when α = 1. It can be seen that the implementing of load shifting when α = 0 results in a small portion (approximately 8%) of the annual PV system output being exported to the grid. Hence it is possible for load shifting to consume the majority of the PV system's output, indicating that the requirement for batteries with PV systems on dairy farms could be alleviated. While this has been deduced from the test case examined, load shifting of milk cooling, water heating, and milking machine electricity use could be carried out on farms at any location. A study by Upton et al. [44] showed that over 90% of dairy farms used electric water heating, meaning all of these farms could implement load shifting. While PV system output may vary at different locations, the farm's load profile can be adjusted to coincide with the electricity production of a PV system.

On the other hand, not implementing load shifting (as shown in the electricity consumption profile for α = 1) would result in a large portion (approximately 83%) of the annual PV system output being exported to the grid. Simola et al. [42] previously investigated the use of PV systems on a Finnish dairy farm without a feed-in tariff, with results indicating that the most profitable PV system was that which exported 2% of its output. Hence if there is no feed-in tariff in place, the use of a PV system with no load shifting in place may yield low monetary savings. It has however been shown that having feed-in tariffs can lead to improved financial performance for PV systems on dairy farms in Algeria and Ireland [5,35,37]. However as there is currently no feed-in tariff structure in place in Ireland such an analysis was not considered in this study.

5. Conclusions

- A method for financial and renewable multi-objective optimization (FARMOO) of dairy farms was developed.
- The FARMOO method found the combination of dairy farm equipment and management practices which maximized farm net profit and farm renewable contribution based on a trade-off parameter.
- The FARMOO method also allowed the use of load shifting for milk cooling, water heating and milking to be investigated. This provided insight regarding which combination of farm equipment best utilized PV systems on-farm.
- It was found that for a 195 cow test case farm, an 11 kWp PV system was added to the optimal farm configuration when the relative importance of farm net profit and renewable contribution were similar.
- A 40% grant aid on PV systems made little difference to their financial feasibility.
- Load shifting of electric water heating consumed the majority of the PV system's output on the test case farm.
- It was determined that the requirement for batteries with small PV systems on dairy farms could be alleviated through thermal storage.

6. Future work

The FARMOO method will provide a useful means for farmers, farm managers and policymakers to garner advice relating to the use of PV systems on dairy farms. Further studies may include analyses relating to the use of batteries on dairy farms, which could be compared to results from this analysis. A financial analysis could also be carried out to find optimum levels of grant aid for PV systems and batteries in a dairy farm context, taking into account future electricity pricing scenarios.

CRediT authorship contribution statement

M. Breen: Writing - original draft, Conceptualization, Methodology, Software, Investigation, Visualization, Validation. **J. Upton:** Supervision, Writing - review & editing, Conceptualization. **M.D. Murphy:** Writing - review & editing, Conceptualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to acknowledge the support of the Teagasc Walsh Fellowship programme and the Sustainable Energy Authority of Ireland (SEAI) Research Development and Demonstration fund.

Appendix A. Data for PV model development, validation and simulation

(See Table A.1 and A.2)

Table A1
Summary of meteorological data (July 2013 to June 2014 and February 2015 to January 2016) used for model development and validation. The minimum, mean, median, maximum, standard deviation (SD) and inter-quartile range (IQR) for irradiance, ambient temperature and wind speed were aggregated across the two years for each month (January to December).

	Irradiance (W/m^2)						Wind Speed (m/s)						Ambient Temperature (°C)					
Month	Min	Mean	Median	Max	SD	IQR	Min	Mean	Median	Max	SD	IQR	Min	Mean	Median	Max	SD	IQR
Jan	0	244	220	694	178	254	0.5	2.5	2.4	5.6	1.1	1.5	−10.5	−0.7	−0.2	9.8	4.7	7.7
Feb	0	280	239	800	223	349	0.6	2.8	2.7	6.3	1.3	2.0	−11.2	−1.2	−1.3	11.9	4.1	5.2
Mar	0	289	265	863	216	343	0.6	2.8	2.8	7.0	1.2	1.7	−9.2	4.5	4.6	17.3	5.2	6.6
Apr	0	335	281	897	260	438	0.2	2.7	2.6	6.6	1.1	1.6	3.1	12.9	12.4	26.8	4.3	6.2
May	0	369	340	894	258	467	0.2	1.7	1.6	4.9	0.9	1.2	8.9	19.7	19.7	29.9	4.3	6.5
Jun	0	339	312	866	243	419	0.2	1.9	1.8	4.9	0.9	1.3	15.0	23.3	23.0	32.0	3.6	5.2
Jul	0	330	318	845	239	434	0.6	2.1	2.0	4.0	0.7	1.0	18.1	25.3	25.0	34.4	3.1	4.8
Aug	0	348	325	863	251	459	0.3	2.1	2.1	4.8	0.7	0.9	15.5	24.0	23.8	32.1	3.3	5.1
Sep	0	363	357	853	250	468	0.6	2.1	2.1	4.5	0.7	1.0	10.7	20.8	20.7	32.7	4.6	6.5
Oct	0	267	266	781	196	335	0.5	2.4	2.3	5.2	0.8	1.1	3.9	14.1	14.2	26.1	4.1	5.7
Nov	0	261	254	708	186	285	0.5	2.4	2.3	5.1	0.9	1.3	−2.2	9.2	9.1	22.6	5.0	7.3
Dec	0	179	140	599	151	249	0.7	2.3	2.2	5.4	0.9	1.2	−1.8	7.4	7.1	17.0	3.8	4.7

Table A2
Summary of data obtained from six weather stations throughout Ireland over a six year period (2013–2018). Data was averaged over the six year period and over the six locations in order to represent a typical year of Irish weather conditions. The minimum, mean, median, maximum, standard deviation (SD) and inter-quartile range (IQR) for irradiance, wind speed and ambient temperature for each month of the year are shown.

	Irradiance (W/m^2)						Wind Speed (m/s)						Ambient Temperature (°C)					
Month	Min	Mean	Median	Max	SD	IQR	Min	Mean	Median	Max	SD	IQR	Min	Mean	Median	Max	SD	IQR
Jan	0	76	81	181	44	70	3.7	6.4	6.4	9.4	1.4	2.1	3.2	6.2	6.3	9.1	1.3	1.6
Feb	0	132	134	305	79	134	4.1	6.2	6.1	10.3	1.0	1.4	2.6	5.5	5.4	9.5	1.4	1.8
Mar	0	198	204	444	117	196	3.5	5.8	5.7	8.0	0.9	1.3	2.8	6.3	6.1	10.0	1.6	2.5
Apr	0	281	287	623	171	285	2.8	5.2	5.1	7.8	1.1	1.7	4.3	8.4	8.3	13.7	2.0	3.1
May	0	305	323	722	192	334	2.9	5.1	5.1	8.1	1.1	1.5	6.5	11.2	11.1	15.9	2.0	3.1
Jun	0	328	339	698	195	355	2.3	4.5	4.5	6.7	0.9	1.4	8.9	13.9	14.0	17.9	2.0	3.4
Jul	0	297	306	638	184	342	2.2	4.3	4.3	6.5	0.9	1.4	11.4	15.4	15.4	20.0	1.9	3.1
Aug	0	262	278	551	157	278	2.8	4.8	4.8	7.2	0.9	1.4	11.5	14.7	14.6	17.8	1.6	2.9
Sep	0	221	232	481	131	225	3.2	4.7	4.6	7.7	0.9	1.1	10.2	13.3	13.0	17.1	1.6	2.7
Oct	0	151	154	342	89	155	3.1	5.2	5.2	7.5	0.8	1.1	8.3	11.4	11.2	14.6	1.4	2.1
Nov	0	95	95	248	57	84	3.3	5.4	5.4	8.1	0.9	1.4	4.1	8.1	8.1	12.3	1.6	2.3
Dec	0	57	61	132	35	50	3.0	6.4	6.6	9.5	1.2	1.7	5.1	7.6	7.8	10.2	1.0	1.4

Appendix B. PV model validation results

Using the model validation method described in Section 2.2.4, the PV model resulted in a RMSE of 225 W, a RPE of 4.9%, a CCC of 1.00 and a MAPE of 2.9% (Table B.1), indicating satisfactory model prediction, according to the rating system described by Fuentes-Pila et al. [18] and excellent strength of agreement between measured and predicted values, according to the rating system described by McBride [32].

Table B1
Model performance for PV model, using the relative prediction error (RPE), concordance correlation coefficient (CCC), root mean square error (RMSE), mean absolute percentage error (MAPE), mean square prediction error (MSPE), mean bias (MB), line bias (LB), random variation (RV) and number of data points at a resolution of one hour (n).

RPE	*CCC*	*RMSE*	*MAPE*	*MSPE*	*MB*	*LB*	*RV*	*n*
4.9%	1.00	225 W	2.9%	50,554 W^2	1.0%	0.1%	98.8%	5,768

Appendix C. Multi-objective optimization results – 40% grant aid for PV systems.

(See Table C.1 and C.2)

Table C1

Multi-objective optimization results for Scenario 1* with PV grant aid of 40%. The optimal combination of decision variables for each of the 11 α values are listed, along with their corresponding average annual after tax net profit (ATNP) (€) and renewable contribution to annual farm gross electricity consumption (RC) values over the ten year time horizon. The total electricity exported annually by the PV system (kWh) and the exported electricity as a percentage of annual gross PV production are also listed, as well as the farm's total annual CO_2 emissions (kg).

	100% renewable optimization ←									→ 100% financial optimization
α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Morning milking time	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00
Evening milking time	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00	18:00
Milk cooling system	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX
Ice bank start time	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Precooling	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Water heating system[ϕ]	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC	ELEC
Water heating timer	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Timer start time (load shifting)	10:00	10:00	10:00	10:00	10:00	10:00	10:00	00:00	00:00	00:00	00:00
VSDs	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
PV	11 kWp	11 kWp	11 kWp	11 kWp	11 kWp	11 kWp	11 kWp	NONE	NONE	NONE	NONE
Annual ATNP (€)	60,503	60,503	60,503	60,503	60,503	60,826	60,826	61,876	61,876	61,876	61,876
Renewable contribution (%)[ψ]	43	43	43	43	43	39	39	0	0	0	0
Annual electricity exported (kWh)	982	982	982	982	982	879	879	0	0	0	0
(% of PV production)	(7.5)	(7.5)	(7.5)	(7.5)	(7.5)	(6.7)	(6.7)	(0.0)	(0.0)	(0.0)	(0.0)
Annual CO_2 Emissions (kg)	6,998	6,998	6,998	6,998	6,998	8,322	8,322	14,217	14,217	14,217	14,217

* Scenario 1 = Multi-objective optimization of farm net profit and renewable contribution; Scenario 2 = Multi-objective optimization of farm net profit and CO_2 emissions. Under both scenarios the farm had a yearly milk output of 774,089L and herd size of 195 cows.

[ψ] Renewable contribution = the amount of the farm's annual gross electricity consumption which was provided by a PV system; Annual electricity exported (% of PV production) = annual electricity exported by the PV system as a percentage of gross PV production.

[ϕ] ELEC = Electric water heating system.

Table C2

Multi-objective optimization results for Scenario 2* with PV grant aid of 40%. The optimal combination of decision variables for each of the 11 α values are listed, along with their corresponding average annual after tax net profit (ATNP) (€) and the farm's total annual CO_2 emissions (kg) over the ten year time horizon. The renewable contribution to annual farm gross electricity consumption (RC), total electricity exported annually by the PV system (kWh) and the exported electricity as a percentage of annual gross PV production are also listed.

100% CO_2 optimization ⟷ 100% financial optimization

α	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Morning milking time	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00	07:00
Evening milking time	18:00	18:00	18:00	17:00	17:00	18:00	18:00	18:00	18:00	18:00	18:00
Milk cooling system	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX	DX
Ice bank start time	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Precooling	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Water heating system$^{\phi}$	GAS	GAS	GAS	GAS	GAS	GAS	GAS	GAS	GAS	ELEC	ELEC
Water heating timer	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	YES	YES
Timer start time (load shifting)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	00:00	00:00
VSDs	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO
PV	11 kWp	11 kWp	11 kWp	11 kWp	11 kWp	NONE	NONE	NONE	NONE	NONE	NONE
Annual ATNP (€)	60,105	60,105	60,105	60,141	60,141	61,405	61,720	61,720	61,720	61,876	61,876
Annual CO_2 Emissions (kg)	3,944	3,944	3,944	4,008	4,008	9,731	11,055	11,055	11,055	14,217	14,217
Renewable contribution (%)$^{\Psi}$	7	7	7	8	8	0	0	0	0	0	0
Annual electricity exported (kWh) (% of PV production)	11,009 (84.4)	11,009 (84.4)	11,009 (84.4)	10,478 (80.3)	10,478 (80.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)

[*] Scenario 1 = Multi-objective optimization of farm net profit and renewable contribution; Scenario 2 = Multi-objective optimization of farm net profit and CO_2 emissions. Under both scenarios the farm had a yearly milk output of 774,089L and herd size of 195 cows.

[Ψ] Renewable contribution = the amount of the farm's annual gross electricity consumption which was provided by a PV system; Annual electricity exported (% of PV production) = annual electricity exported by the PV system as a percentage of gross PV production.

[ϕ] ELEC = Electric water heating system.

References

[1] Baudracco J, Lopez-Villalobos N, Holmes CW, Comeron EA, Macdonald KA, Barry TN. e-Dairy: a dynamic and stochastic whole-farm model that predicts biophysical and economic performance of grazing dairy systems. Animal 2013;7:870–8. https://doi.org/10.1017/S1751731112002376.

[2] Bey M, Hamidat A, Benyoucef B, Nacer T. Viability study of the use of grid connected photovoltaic system in agriculture: Case of Algerian dairy farms. Renew. Sustain. Energy Rev. 2016;63:333–45. https://doi.org/10.1016/J.RSER.2016.05.066.

[3] Bibby J, Toutenburg H. Prediction and Improved Estimation in Linear Models. Wiley, New York, NY: A Wiley-Interscience publication; 1977.

[4] Breen M, Murphy MD, Upton J. Development of a dairy multi-objective optimization (DAIRYMOO) method for economic and environmental optimization of dairy farms. Appl. Energy 2019;242:1697–711. https://doi.org/10.1016/J.APENERGY.2019.03.059.

[5] Breen, M., Murphy, M.D., Upton, J., 2015. Development and validation of photovoltaic and wind turbine models to assess the impacts of renewable generation on dairy farm electricity consumption. 2015 ASABE Annu. Int. Meet., ASABE Paper No. 152189379. https://doi.org/https://doi.org/10.13031/aim.20152189379.

[6] Breen M, Upton J, Murphy MD. Development of a discrete infrastructure optimization model for economic assessment on dairy farms (DIOMOND). Comput. Electron. Agric. 2019;156:508–22. https://doi.org/10.1016/J.COMPAG.2018.11.018.

[7] Breen, M., Upton, J., Murphy, M.D., 2018. Photovoltaic systems on dairy farms: An economic analysis. 2018 ASABE Annu. Int. Meet., ASABE Paper No. 1800813. https://doi.org/https://doi.org/10.13031/aim.201800813.

[8] Central Statistics Office. Milk Production [WWW Document]. https://www.cso.ie/px/pxeirestat/Database/eirestat/Milk Production/Milk.Production_statbank.asp?SP = Milk Production&Planguage = 0 2019;(accessed:2.27.19).

[9] DAFM. Pig and Poultry Investment. Dublin: Scheme; 2018.

[10] DAFM, 2017. National Reference Costs.

[11] Davis M, Healy W, Boyd M, Ng L, Payne V, Skye H, et al. Monitoring Techniques for the Net-Zero Energy Residential Test Facility. 2014. https://doi.org/10.6028/NIST.TN.1854.

[12] De Blas M, Appelbaum J, Torres JL, García A, Prieto E, Illanes R. A refrigeration facility for milk cooling powered by photovoltaic solar energy. Prog. Photovoltaics Res. Appl. 2003;11:467–79. https://doi.org/10.1002/pip.507.

[13] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 2002;6:182–97. https://doi.org/10.1109/4235.996017.

[14] Di Somma M, Yan B, Bianco N, Graditi G, Luh PB, Mongibello L, et al. Multi-objective design optimization of distributed energy systems through cost and exergy assessments. Appl. Energy 2017;204:1299–316. https://doi.org/10.1016/J.APENERGY.2017.03.105.

[15] EC, 2016. Energy Union and Climate Action: Driving Europe's transition to a low-carbon economy. Brussels.

[16] EU, 2018. Directive of the European Parliament and of the council on the promotion of the use of energy from renewable sources (recast). Brussels.

[17] Fan Y, Xia X. A multi-objective optimization model for energy-efficiency building envelope retrofitting plan with rooftop PV system installation and maintenance. Appl. Energy 2017;189:327–35. https://doi.org/10.1016/J.APENERGY.2016.12.077.

[18] Fuentes-Pila J, DeLorenzo MA, Beede DK, Staples CR, Holter JB. Evaluation of Equations Based on Animal Factors to Predict Intake of Lactating Holstein Cows. J. Dairy Sci. 1996;79:1562–71. https://doi.org/10.3168/JDS.S0022-0302(96)76518-9.

[19] Gomez-Gonzalez M, Hernandez JC, Vera D, Jurado F. Optimal sizing and power schedule in PV household-prosumers for improving PV self-consumption and providing frequency containment reserve. Energy 2020;191. 116554 https://doi.org/https://doi.org/10.1016/j.energy.2019.116554.

[20] Hanrahan L, Geoghegan A, O'Donovan M, Griffith V, Ruelle E, Wallace M, et al. PastureBase Ireland: A grassland decision support system and national database. Comput. Electron. Agric. 2017;136:193–201. https://doi.org/10.1016/J.COMPAG.2017.01.029.

[21] Healy, W., Chen, T.H., Dougherty, B., Fanney, A.H., Ullah, T., Payne, W.V., Ng, L., Omar, F., 2018. Net Zero Energy Residential Test Facility Instrumented Data; Year 1. https://doi.org/https://doi.org/10.18434/T4/1503134.

[22] Healy, W., Fanney, A.H., Dougherty, B., Payne, W.V., Ullah, T., Ng, L., Omar, F., 2017. Net Zero Energy Residential Test Facility Instrumented Data; Year 2. https://doi.org/https://doi.org/10.18434/T46W2X.

[23] Hernández JC, Ruiz-Rodriguez FJ, Jurado F. Modelling and assessment of the combined technical impact of electric vehicles and photovoltaic generation in radial distribution systems. Energy 2017;141:316–32. https://doi.org/https://doi.org/10.1016/j.energy.2017.09.025.

[24] Hernández JC, Sanchez-Sutil F, Muñoz-Rodríguez FJ. Design criteria for the optimal sizing of a hybrid energy storage system in PV household-prosumers to maximize self-consumption and self-sufficiency. Energy 2019;186:115827. https://doi.org/https://doi.org/10.1016/j.energy.2019.07.157.

[25] Ishaque K, Salam Z, Mekhilef S, Shamsudin A. Parameter extraction of solar photovoltaic modules using penalty-based differential evolution. Appl. Energy 2012;99:297–308. https://doi.org/https://doi.org/10.1016/j.apenergy.2012.05.017.

[26] Ismail MS, Moghavvemi M, Mahlia TMI. Characterization of PV panel and global optimization of its model parameters using genetic algorithm. Energy Convers. Manag. 2013;73:10–25. https://doi.org/10.1016/J.ENCONMAN.2013.03.033.

[27] Jubril AM, Olaniyan OA, Komolafe OA, Ogunbona PO. Economic-emission dispatch problem: A semi-definite programming approach. Appl. Energy 2014;134:446–55. https://doi.org/10.1016/J.APENERGY.2014.08.024.

[28] Lanigan GJ, Donnellan T, Hanrahan K, Paul C, Shalloo L, Krol D, et al. An Analysis of Abatement Potential of Greenhouse Gas Emissions in Irish Agriculture 2021–2030. Ireland: Carlow; 2018.

[29] Lin LI-K. A Concordance Correlation Coefficient to Evaluate Reproducibility. Biometrics 1989;45:255–68. https://doi.org/10.2307/2532051.

[30] Lukuyu JM, Blanchard RE, Rowley PN. A risk-adjusted techno-economic analysis for renewable-based milk cooling in remote dairy farming communities in East Africa. Renew. Energy 2019;130:700–13. https://doi.org/10.1016/J.RENENE.2018.06.101.

[31] Machairas V, Tsangrassoulis A, Axarli K. Algorithms for optimization of building design: A review. Renew. Sustain. Energy Rev. 2014;31:101–12. https://doi.org/10.1016/J.RSER.2013.11.036.

[32] McBride, G.B., 2005. A proposal for strength-of-agreement criteria for Lin's concordance correlation coefficient, National Institute of Water & Atmospheric Research Ltd.

[33] Éireann Met. Open data [WWW Document] accessed 6.29.18 https://www.met.ie/about-us/specialised-services/opendata; 2018.

[34] Muhsen DH, Ghazali AB, Khatib T, Abed IA. Extraction of photovoltaic module model's parameters using an improved hybrid differential evolution/electromagnetism-like algorithm. Sol. Energy 2015;119:286–97. https://doi.org/https://doi.org/10.1016/j.solener.2015.07.008.

[35] Nacer T, Hamidat A, Nadjemi O. A comprehensive method to assess the feasibility of renewable energy on Algerian dairy farms. J. Clean. Prod. 2016;112:3631–42. https://doi.org/10.1016/J.JCLEPRO.2015.06.101.

[36] Nacer T, Hamidat A, Nadjemi O, Bey M. Feasibility study of grid connected photovoltaic system in family farms for electricity generation in rural areas. Renew. Energy 2016;96:305–18. https://doi.org/10.1016/J.RENENE.2016.04.093.

[37] Nadjemi O, Nacer T, Hamidat A, Salhi H. Optimal hybrid PV/wind energy system sizing: Application of cuckoo search algorithm for Algerian dairy farms. Renew. Sustain. Energy Rev. 2017;70:1352–65. https://doi.org/10.1016/J.RSER.2016.12.038.

[38] Rook AJ, Gill M. Prediction of the voluntary intake of grass silages by beef cattle. 1. Linear regression analyses. Anim. Sci. 1990;50:425–38. https://doi.org/10.1017/S0003356100004918.

[39] Ruelle E, Shalloo L, Wallace M, Delaby L. Development and evaluation of the pasture-based herd dynamic milk (PBHDM) model for dairy systems. Eur. J. Agron. 2015;71:106–14. https://doi.org/10.1016/J.EJA.2015.09.003.

[40] SEAI, 2018. Domestic Fuels: Comparison of Energy Costs [WWW Document]. URL https://www.seai.ie/resources/publications/Domestic-Fuel-Cost-Comparison.pdf (accessed 2.4.18).

[41] Shine P, Scully T, Upton J, Murphy MD. Multiple linear regression modelling of on-farm direct water and electricity consumption on pasture based dairy farms. Comput. Electron. Agric. 2018;148:337–46. https://doi.org/10.1016/J.COMPAG.2018.02.020.

[42] Simola A, Kosonen A, Ahonen T, Ahola J, Korhonen M, Hannula T. Optimal dimensioning of a solar PV plant with measured electrical load curves in Finland. Sol. Energy 2018;170:113–23. https://doi.org/10.1016/J.SOLENER.2018.05.058.

[43] Teagasc, 2017. The Teagasc eProfit Monitor (€PM) [WWW Document]. URL https://www-teagasc-ie.cit.idm.oclc.org/rural-economy/farm-management/financial-analysis/farm-profit-analysis/the-teagasc-eprofit-monitor-pm/ (accessed 8.8.17).

[44] Upton J, Humphreys J, Groot Koerkamp PWG, French P, Dillon P, De Boer IJM. Energy demand on dairy farms in Ireland. J. Dairy Sci. 2013;96:6489–98. https://doi.org/10.3168/JDS.2013-6874.

[45] Upton J, Murphy M, De Boer IJM, Groot Koerkamp PWG, Berentsen PBM, Shalloo L. Investment appraisal of technology innovations on dairy farm electricity consumption. J. Dairy Sci. 2015;98:898–909. https://doi.org/10.3168/JDS.2014-8383.

[46] Upton J, Murphy M, Shalloo L, Groot Koerkamp PWG, De Boer IJM. Assessing the impact of changes in the electricity price structure on dairy farm energy costs. Appl. Energy 2015;137:1–8. https://doi.org/10.1016/J.APENERGY.2014.09.067.

[47] Upton J, Murphy M, Shalloo L, Groot Koerkamp PWG, De Boer IJM. A mechanistic model for electricity consumption on dairy farms: Definition, validation, and demonstration. J. Dairy Sci. 2014;97:4973–84. https://doi.org/10.3168/JDS.2014-8015.

[48] Villalva MG, Gazoli JR, Filho ER. Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays. IEEE Trans. Power Electron. 2009;24:1198–208. https://doi.org/10.1109/TPEL.2009.2013862.

[49] Wrixon, G.T., 1984. The Fotavoltaic Project — A 50kW Photovoltaic System to Power a Dairy Farm on Fota Island, Cork, Ireland BT - Photovoltaic Power Generation, in: Palz, W. (Ed.), . Springer Netherlands, Dordrecht, pp. 153–169.

[50] Zhang C, Yang J, Zhang J. Can Solar Energy be an Alternative Choice of Milk Production in Dairy Farms? –-A Case study of Integrated PVWP System with Alfalfa and Milk Production in Dairy Farms in China. Energy Procedia 2017;105:3953–9. https://doi.org/10.1016/j.egypro.2017.03.822.