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Farm electricity system simulator (FESS): A platform for simulating electricity utilisation on dairy farms

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ABSTRACT

The objective of this paper was to define, validate and demonstrate a model capable of accurately simulating dairy farm electricity consumption across varying herd and parlour sizes, to facilitate research investigating renewable energy systems (RES) and demand side management (DSM). The Farm Electricity System Simulator (FESS) was developed using grey-box modelling techniques utilizing empirical data for parameter tuning. Empirical data were gathered from nine spring calving, pasture based dairy farms located in the Republic of Ireland. A k-means clustering analysis was conducted, separating the farms into three, near homogenous groups, from which representative farms were selected. FESS was trained using 12 months of data from three representative farms using the repeat hold out method for data partitioning with 75 % of data used for training and 25 % used for validation. An optimisation algorithm was used to minimize the error during model training. Through cross-validation, FESS achieved a root mean squared error (RMSE) of 7.65 kWh, mean absolute percentage error (MAPE) of 7.10 %, mean percentage error (MPE) of −0.86 % and a relative prediction error (RPE) of 7.56 % for total daily electricity consumption. Across the three farms, the simulated outputs of FESS achieved an average R^2 value of 0.72, demonstrating good agreement with observed data. FESS's utility was demonstrated by analysing the effects of different electricity pricing structures and on-site solar photovoltaic electricity generation on total farm energy costs. We concluded that FESS simulated on-farm electricity consumption with sufficient accuracy for the intended application. FESS accurately simulated dairy farm electricity consumption across three dairy farms of different herd and parlour sizes while evaluating the effects of demand side management and renewable generation on farm electricity consumption and costs.

1. Introduction

In the 2030 Climate Target Plan, the European Environment Agency has set a target of reducing emissions by 55 % by 2030 (EEA, 2023). The European Commission aims to achieve a minimum of 32 % of energy generation from renewables by 2030 with a clause for a possible upward revision to 40 % (EC, 2018).

In line with EU targets, the Irish government aims to reach net-zero emissions by no later than 2050 (CAP, 2024). The agriculture sector in Ireland was responsible for over 38.4 % of the total national greenhouse gas (GHG) emissions in 2022 (EPA, 2022). As an interim target, in the National Energy Climate Plan, Ireland aims to reduce agricultural emissions by 25 %, electricity generation emissions by 75 % and increase renewable generation capacity to 22 GW by 2030 (NECP, 2023). To assist this process, the Irish government have provided grants for energy efficient technologies and renewable energy systems (RES) for Irish farmers under the TAMS scheme (TAMS, 2024). It is forecasted that 25.5 MWh of renewable energy will be generated annually on agricultural premises by 2029 (EPA, 2022). The integration of such RES will be supported by upgrades to existing energy consuming systems to reduce the overall energy use of the agricultural sector. Improvements in dairy farm energy efficiency can be made through investments in plate coolers for milk pre-cooling (Murphy et al., 2013, Shine et al., 2019), variable speed drives (VSD) for vacuum pumps, hot water tank insulation, heat recovery from milk cooling (Rajaniemi et al., 2017, Rajaniemi et al., 2015), and energy efficient lighting (Shine et al., 2020). To minimise GHG emissions of the agricultural sector, a holistic approach assessing all available technologies, and how they interact with one another is required.

To ensure financial and environmental sustainability, it is vital for farmers to understand the impact that investing in new technologies will

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Nomenclature

Abbreviations:

FESS	Farm electricity system simulator
RES	renewable energy systems
DSM	demand side management
RMSE	root mean squared error
MAPE	mean absolute percentage error
MPE	mean percentage error
RPE	relative prediction error
COP	coefficient of performance
SFM	surface fitting model
VSD	variable speed drive
MLR	multiple linear regression
MECH	mechanistic
ANN	artificial neural networks
ANFIS	adaptive neuro-fuzzy interface system
PR	polynomial regression
SVM	support vector machine
SSE	sum of squared errors
TOU	time of use
PHE	plate heat exchanger
HR	heat recovery
DX	direct expansion
NC	number of milking cows
ER	effective reserve (litres/minute)
EC	estimated capacity (litres/minute)

Symbols:

Δ	change
η	efficiency
M	number of milking clusters
m	mass (kg)
Q	energy consumption (kWh)
T	temperature (K)
U	U-value of the bulk tank insulation (W/m^{2}K)
A	surface area of the bulk tank (m^2)
$\dot{Q}$	power (kW)
L	number of luminaires in the parlour
S	number of scrapers

Subscripts:

r	row
t	time
F	milking is finished
m	milk
k	one individual milking
b	bulk tank
g	gain
cooling	milk cooling system
comp	cooling compressor
pre	pre-cooled
sp	set point temperature
fan	cooling fan
ag	bulk tank agitator
mm	milking machine
mi	milking
p	pump
wa	wash
h	heating
l	heat loss
w	water
tank	hot water tank
u	hot water used
heating	water heating system
li	lighting system
mp	milk pump
sc	scrapers

have on farm energy use and associated costs. Energy metering has been used to investigate and describe energy consumption on dairy farms (Rajaniemi et al., 2017, Rajaniemi et al., 2015). Todic et al. (2022) used non-intrusive load monitoring to determine the electricity consumption of some of the main electricity consuming systems on three German dairy farms, such as the vacuum pump and compressors. While Todic et al. (2022) were able to successfully quantify the electricity demand of vacuum pumps, compressors, water pumps, and other electricity consuming systems with an accuracy above 95 %, their method was not always reliable with reported accuracy for a milking robot on one farm as low as 35 %, and transferability across farms was sighted as an issue. A review of dairy farm electricity use undertaken by Mohsenimanesh et al. (2021) highlighted that energy consumption on dairy farms varies widely depending on a number of factors including region, herd size, and management system, while identifying VSDs and pre-cooling heat exchangers as some of the most impactful technologies for reducing energy consumption. Useful insights can be gained from energy metering, however, predictive energy models are necessary for simulating future scenarios such as varying herd sizes, technologies and demand side management (DSM) practices. Therefore, accurate energy models compliment energy metering by providing farmers, researchers and policy makers with the tools required to make informed decisions regarding the future of farming.

Table 1 identifies 20 models for simulating energy use on dairy farms, across which, seven different types of models were used. Of these different model types, multiple linear regression (MLR) models were the most common, accounting for eight of the 20 models. Edens et al. (2003), presented MLR models for simulating energy use of milk harvesting, milk cooling, water heating and air compressors with monthly resolution. Sefeedpari et al. (2013), described the use of artificial neural networks (ANN) to model the annual output energy of milk. A mechanistic (MECH) model for simulating the total electricity use on dairy farms is described by Upton et al. (2014). Another study by Sefeedpari et al. (2014) describes the use of a linear regression model (Linear) and adaptive neuro-fuzzy inference systems (ANFIS) to simulate the annual output energy of milk. The use of multiple linear regression models (MLR) for simulating morning and evening milk cooling energy consumption are described by Mhundwa et al. (2017). Todde et al. (2017) presents two polynomial regression (PR) models for simulating annual total electricity and diesel use. Mhundwa and Simon (2020) described the use of surface fitting model (SFM) for predicting the electricity consumption of a milk cooling system. MLR and support vector machines (SVM) for simulating total monthly electricity consumption are described in two studies by Shine et al.,(2018b,2018a). Shine et al. (2022) described ANN models for simulating electricity consumption of milk cooling, milk harvesting, water heating systems as well as total dairy farm electricity consumption.

While these models have proven effective in simulating energy consumption on dairy farms, their scope is often limited to a single energy-consuming system (e.g., milk cooling or milk harvesting). Most of these models operate on a monthly time step, and none operate in time steps finer than daily steps. Models with such large time steps cannot capture the dynamic nature of electricity consumption on dairy farms, making them unable to accurately simulate DSM techniques. For example, the MECD model described by Upton et al. (2014) uses a 24*12 matrix as an output. The 24 columns represent the average energy

Table 1
Models for simulating energy consumption, and related carbon emissions, on dairy farms.

Study	Model Type	Application	Resolution	Accuracy		
				R^2	RMSE	RPE (%)
Edens et al. (2003)	MLR	Milk harvesting (kWh)	Daily/Monthly	0.44	n/a	n/a
Edens et al. (2003)	MLR	Milk Cooling (kWh)	Monthly	0.74	n/a	n/a
Edens et al. (2003)	MLR	Water Heating (kWh)	Monthly	0.34	n/a	n/a
Edens et al. (2003)	MLR	Air compressors (kWh)	Monthly	0.18	n/a	n/a
Edens et al. (2003)	MLR	Combined (kWh)	Monthly	0.62	n/a	n/a
Sefeedpari et al. (2013)	ANN	Output energy of milk (MJ/Cow)	Annual	0.88	0.015	n/a
Upton et al. (2014)	Mech	Total electricity (kWh)	Monthly	n/a	125	7.5
Sefeedpari et al. (2014)	Linear	Output energy of milk (MJ/Cow)	Annual	0.11	0.2	n/a
Sefeedpari et al. (2014)	ANFIS	Output energy of milk (MJ/Cow)	Annual	0.79	0.1	n/a
Mhundwa et al. (2017)	MLR	Morning milk cooling (kWh)	Daily	0.92	n/a	n/a
Mhundwa et al. (2017)	MLR	Evening milk cooling (kWh)	Daily	0.90	n/a	n/a
Todde et al. (2017)	PR	Total electricity (kWh)	Annual	n/a	n/a	11.4
Todde et al. (2017)	PR	Total diesel (kWh)	Annual	n/a	n/a	15
Mhundwa and Simon (2020)	SFM	Milk cooling (kWh)	Daily	0.80	4.16	18.54
Shine et al., (2018b)	MLR	Total electricity (kWh)	Monthly	0.72	543	16.1
Shine et al., (2018a)	SVM	Total electricity (kWh)	Monthly	0.94	241	12
Shine et al. (2022)	ANN	Total electricity (kWh)	Monthly	0.90	434.34	18
Shine et al. (2022)	ANN	Milk Cooling (kWh)	Monthly	0.90	167.67	23
Shine et al. (2022)	ANN	Milk Harvesting (kWh)	Monthly	0.81	93.14	22
Shine et al. (2022)	ANN	Water Heating (kWh)	Monthly	0.81	155.25	34

MLR = multiple linear regression; ANN = artificial neural network; Mech = mechanistic; Linear = linear regression model; ANFIS = adaptive neuro-fuzzy inference system; PR = polynomial regression; SVM = support vector machine; SFM = surface fitting model.

consumption for a given hour across a full month. This matrix method was used to conduct investment appraisals of various technologies, such as VSDs and plate coolers (Upton et al., 2015a) and to perform some basic DSM analysis (Breen et al., 2021). Though this matrix method was suitable for some investment appraisals and DSM analysis, the matrix cannot accurately reflect the individual daily load profile of a farm. This is because the matrix averages the energy consumption of all days in the month and does not account for day-to-day changes in load profile caused by events such as water heating to wash the bulk tank which only takes place on days where milk has been collected and the bulk tank is empty. Similarly, the NAIDEA model described by Shine et al. (2022), while found to accurately simulate electricity consumption on dairy farms, was developed with the intention of assessing monthly electricity use. NAIDEA does not generate a load profile and so cannot be used to investigate DSM or RES integration. Furthermore, these models do not account for variability within the milking process, such as row durations, the number of cows in each row or the mass flow rate of milk from the milking machine. In the context of the presented state of knowledge, no models exist which can accurately facilitate investigation into DSM or RES integration. The lack of such a model in the current climate of increased focus on RES integration and energy efficiency, requires the development of a new platform to provide this capability.

To successfully integrate DSM techniques, energy efficient technologies and RES at the individual farm level, an energy model which is transferable across farms and modular in design is required. Such a model should be able to account for farm specific practices, such as varying herd sizes, parlour sizes, and milking efficiency levels. Furthermore, the model should operate at an adequately fine time resolution (15-minute time step) to enable investigation of the viability of DSM techniques and RES on a farm-by-farm basis by providing accurate load profile dynamics (Goldwasser et al., 2018).

Therefore, the objectives of this paper were to:

- Define a model which simulates electricity consumption of a dairy farm in 15-minute time steps, providing a methodology facilitating further research into energy use and efficiency on dairy farms.
- Validate the model's accuracy across dairy farms of varying herd and parlour sizes.
- Demonstrate the model's ability to investigate DSM and RES integration on dairy farms, as intended to be used by researchers and farmers to investigate energy saving strategies and technologies and to provide decision support.

2. Materials & methods

Electricity consumption data (kWh) were acquired using autonomous electricity meters installed on nine Irish dairy farms Metering equipment from Carlo Gavazzi Automation SpA in Lainate, Italy, were used. Type EM24 DIN energy analysers, received electrical pulses from electricity meters distributed throughout the parlours. These meters were connected via a daisy chain network (RS485 Modbus) provided by Carlo Gavazzi Automation SpA. The network was further linked to an UR5i Libratum v2 modem also from Carlo Gavazzi Automation SpA. This modem transmitted cumulative consumption measurements at 15 min intervals through a 3G/GPRS network to a receiver stationed at the Teagasc research centre in Cork, Ireland. On-site, Powersoft data logging and recording software, again from Carlo Gavazzi Automation SpA, were utilized. This software, operating via a virtual VPN, identified each meter and autonomously transferred cumulative consumption data to the Powersoft software. Subsequently, this data was relayed to a database for storage, individually for each farm. The milk cooling system, milking machine, water heating and the total farm electricity consumption, including miscellaneous consumption, were metered on all farms. Data recording by these meters commenced in the first quarter of 2020 and concluded in the first quarter of 2022. For the model development process, one full year of data (August 2020 – July 2021) was used to ensure seasonality of milk production and climatic cycles were accounted for while minimizing computational cost. The mean farm herd size was 182 dairy cows. On average, the farms produced 1,157,874 L of milk, consumed 38,649 kWh of electricity annually and achieved an average milking efficiency rate of 85 cows/hour (Table 2). In addition to electricity consumption data, infrastructural data were gathered via on-site surveys, milk production data were gathered from the Irish Cattle Breeding Federation (ICBF) database (ICBF, 2021), meteorological data were sourced from Met Éireann (Met.Éireann, 2023), and the milking process was observed to determine row times and milking efficiency metrics. All farms included in this paper used herringbone type milking parlours as they are the most commonly used type of milking parlour in a study of 666 Irish dairy farms conducted by Cearbhaill et al. (2024) (under review). Details of technologies and milking infrastructure are presented in Table B1 in Appendix B. Milking

Table 2
Population description and key performance indicators for milk yield, no. dairy cows, energy consumption and efficiency, and milking efficiency of the dairy farms included in this study (n = 9).

Variable	Unit	min	mean	SD	median	max
Milk yield	L	566,622	1,157,874	473,549	887,293	1,894,265
Dairy cows	n	96	182	85	139	330
Electricity consumption	kWh	22,851	38,649	16,285	32,262	75,733
Electricity per kg milk	Wh/kg_{milk}	21.46	33.21	5.48	33.54	39.22
Electricity per cow	kWh/Cow	121	224	47	229	290
Milking Efficiency	Cows/hour	49	85	31	73	161

L = litres, n = number, Wh/kg_{Milk} = Watt-hours per kg of milk produced, kWh/Cow = kilowatt-hours per dairy cow.

process data were extracted from video recordings as described by Prendergast et al. (2023) and Buckley et al. (2023). All farms in this study operated spring calving grass-based systems and used herringbone milking parlours.

2.1. Data pre-processing

2.1.1. Outlier detection

Instances in the data where the electricity consumption was negative (<0.001 % of the dataset) were identified and removed. Errors in the metering equipment occasionally resulted in an apparent increase in electricity consumption over a 15-minute period by an unrealistically large amount. To identify and remove these events, any data points in the top 99th percentile of electricity consumption, were identified, observed and unrealistic values removed. Finally, as the data were not normally distributed, a modified z-score was used to identify and if necessary, remove any remaining outliers. A limit of +/-3.5 standard deviations from the median absolute deviation was implemented. All data points which were removed as outliers during this process were replaced using linear interpolation. In total, less than 0.1 % of the data were identified as outliers, removed and replaced.

2.1.2. K-means Clustering analysis

As dairy farms differ in terms of herd sizes, parlour sizes, and milking efficiency levels, it was necessary to ensure the model would generalise well across multiple farms. To achieve this, the database used for this study was divided into distinct clusters, and a representative farm from each cluster was selected for use in model calibration and validation. A variety of methodologies and statistical techniques have been used to typify large groups of farming and livestock systems into near homogeneous clusters. The multivariate statistical approach is one of the most common methods used for this process (Todde et al., 2016; Shine and Murphy, 2022). This approach uses qualitative and quantitative variables to sort farms into similar clusters. The primary criteria used for cluster creation was the number of dairy cows in the herd. To account for differences in milk production efficiency and energy efficiency of farms with similar herd sizes, the following criteria were also included for cluster creation: annual milk yield, the number of milking units in the parlour and annual electricity consumption. These criteria were selected as they have a strong correlation with energy consumption and energy efficiency (Buckley et al., 2023; Shine et al., 2018c). A breakdown of these categories for the nine farms is provided in Table 3.

To prevent any of the characteristics having a larger impact on the clustering process than others, the data were scaled. The scale function in R version 4.2.1. was used to create a scaled value for each of the observations in Table 3. The scale function scales the data by subtracting the mean from each observation and dividing by the standard deviation allowing for comparison between variables (equation (1).

$$z_i = \frac{x_i - \bar{x}}{sd} \# \quad (1)$$

Where x_i is an observation within the sample, $\bar{x}$ is the sample mean, *sd* is the sample standard deviation and z_i is the scaled value.

Table 3
Farm characteristics and cluster assignment.

	Farm no.	No. Dairy Cows	Milk Yield (kg)	No. Clusters	Annual kWh	Milking Efficiency (cows/ hour)
Cluster 1	2	330	1,951,093	30	75,733	106
	6	329	1,852,425	26	39,757	161
Cluster 2	1	191	1,350,951	20	41,491	68
	7	196	1,647,391	24	55,248	92
Cluster 3	8	96	583,621	14	22,851	67
	3	136	899,580	20	28,318	64
	4	139	913,912	16	32,262	83
	5	99	733,031	20	28,747	73
	9	121	801,489	20	23,432	49

A principal component analysis was carried out once scaled values had been determined for each observation. This analysis used the scaled observations from the dataset and simplified them into two-dimensional principal components to allow for clustering in a two-dimensional space. The optimum number of clusters for this data set was found to be three clusters using a within groups sum of squares plot.

The k-means clustering method was used to separate the farms into three distinct groups (Table 3). In this case, clusters were formed mainly on herd size as the four criteria largely depend on herd size.

To determine which farm in each cluster best represented that cluster, the absolute distance from the cluster centroid for each criterion was calculated for each farm. The representative farms for cluster 1, 2 and 3 were found to be farms 6, 1 and 5, respectively.

2.2. Model development and definition

The model defined in this paper is a grey-box model called the Farm Electricity System Simulator (FESS). Grey-box models are widely used in energy modelling applications and are mechanistic in nature with physics-based calculations simplified using empirically defined relationships. Through these simplifications, the number of parameters is reduced, making FESS better suited to automatic parameter tuning.

FESS consists of three main sub-models: a milk cooling model; a milking machine model; a water heating model. FESS includes a milking process sub-model which determines the milking duration and flow of milk into the bulk tank. A miscellaneous category is also included which is comprised of smaller electricity consumers such as lighting and scrapers.

Fig. 1 depicts a layout of the main energy consuming systems, how they interact with one another and different energy sources. In Fig. 1, the hot water tank represents the water heating system and the bulk tank represents the milk cooling system. The PV, battery, hot water diverter, and Gas/Oil, systems in Fig. 1 are included to show how they can be integrated with FESS but are faded as they are not being modelled in this paper. The gear symbols depict systems which include parameters which were tuned during model training.

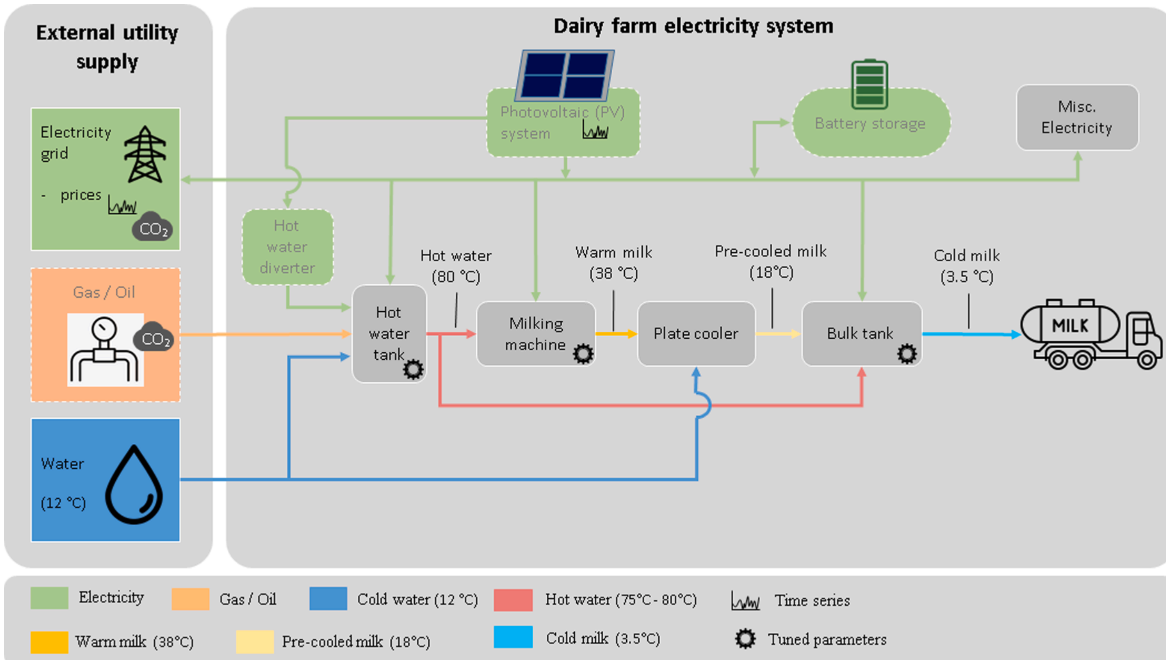

Fig. 1. Schematic of main energy consuming subsystems, external utilities, and solar PV system. The solar PV system, battery, hot water diverter, and the gas/oil, system are faded as they are not being modelled in this paper.

2.2.1. *Milking process sub-model*

The milking process sub-model determined the milking duration and the mass of milk entering the bulk tank at each time step. It was assumed that the number of cows in each row was equal to the number of clusters in the parlour, until the last row of milking, when the number of cows in the row was equal to the number of cows which had yet to be milked. Equation (2) determined the number of cows in each row at time t.

$$NC_r = \begin{cases} M, M < NC_{herd} - NC_{F(t)} \\ NC_{herd} - NC_{F(t)}, M > NC_{herd} - NC_{F(t)} \end{cases} \tag{2}$$

Where NC_r was the number of cows in the row, M was the number of clusters in the milking machine, NC_{herd} was the number of milking cows in the herd, $NC_{F(t)}$ was the number of cows which finished milking at time t.

The mass of milk entering the bulk tank at time t was calculated using equation (3).

$$m_{m(t)} = \frac{(NC_r)(m_{m,k})(\Delta t)}{(NC_{herd})(\bar{t}_r)} \tag{3}$$

Where $m_{m(t)}$ was the mass of milk which entered the bulk tank at time step t, $m_{m,k}$ was the known mass of milk produced from the given milking (kg), Δt was the time step (15 min) and $\bar{t}_r$ was the mean time taken to milk a row of cows (minutes) (Prendergast et al., 2023).

The number of cows which finished milking at time t was determined using equation (4).

$$NC_{f(t)} = NC_{f[t-\Delta t]} + \left[(NC_r)\left(\frac{\Delta t}{\bar{t}_r}\right) \right] \tag{4}$$

2.2.2. *Milk cooling sub-model*

The coefficient of performance (COP) of the refrigeration system was estimated using equation (5).

$$COP_{(t)} = \left(\frac{T_{m,b(t)} - C_c}{(T_{a(t)} + C_h) - (T_{m,b(t)} - C_c)} \right) n_c \tag{5}$$

Where $COP_{(t)}$ was the coefficient of performance of the refrigeration compressors at time t, $T_{m,b(t)}$ was the temperature of milk within the bulk tank (K), C_c was the cold temperature adjustment constant of refrigerant in the evaporator (K), $T_{a(t)}$ was the ambient temperature at time t (K), C_h was the hot temperature adjustment constant of refrigerant in the condenser (K) and n_c was the COP adjustment factor.

Equation (6) calculated the mass of milk within the bulk tank.

$$m_{m,b(t)} = m_{m,b(t-\Delta t)} + m_{m(t)} \tag{6}$$

Where $m_{m,b(t)}$ was the mass of milk in the bulk tank (kg).

Heat gained from the environment was calculated using equation (7).

$$Q_{g(t)} = \left(\frac{(U)(A)\left(T_{m,b(t)} - T_{a(t)}\right)}{1000} \right) \left(\frac{\Delta t}{60}\right) \tag{7}$$

Where $Q_{g(t)}$ was the thermal energy gain through the bulk tank walls (kWh), U was the U-value of the bulk tank insulation (W/m^{2}K), A was the surface area of the bulk tank (m^2), $T_{a(t)}$ was the ambient temperature at time t (K), and $\frac{\Delta t}{60}$ is the time step (minutes) divided by 60 to convert to hours.

Heat removed by the refrigeration system was calculated using equation (8).

$$Q_{c(t)} = (\dot{Q}_{comp})(COP_{(t)})(\Delta t/60) \tag{8}$$

Where $Q_{c(t)}$ was the thermal energy removed from the milk in the bulk tank by the refrigeration system at time t (kWh) and $\dot{Q}_{comp}$ was the power rating of the refrigeration compressor(s) (kW).

Equation (9) described the temperature change of the milk in the bulk tank due to heat gained by the environment, heat removed by the refrigeration system and heat gained due to warm milk entering the tank.

$$T_{m,b(t)} = \left(\frac{Q_{g(t)} - Q_{c(t)}}{(m_{m,b(t)})(C_m)} \right) + \left(\frac{\left((m_{my(t)})(T_{m,pre(t)})\right) + \left((m_{m,b(t-\Delta t)})(T_{m,b(t-\Delta t)})\right)}{(m_{m(t)}) + (m_{m,b(t-\Delta t)})} \right) \tag{9}$$

Where $T_{m,b(t)}$ was the temperature of the milk in the bulk tank due to heat gained from the environment and heat removed by the refrigeration system at time t (K), C_m was the specific heat capacity of milk (3900 J/kg K), and $T_{m,pre(t)}$ was the temperature of milk leaving the plate cooler (K).

The electrical energy consumed for cooling milk was calculated using equation (10). The refrigeration compressor(s), agitator motor and cooling fans were all assumed to be operating while hot milk was in/entering the system. If the compressor(s) were capable of cooling the milk to the set point temperature within a given time step, then the power draw required to reach the set point was the average power across that step.

$$Q_{cooling(t)} = \begin{cases} (\dot{Q}_{comp} + \dot{Q}_{fan} + \dot{Q}_{ag})(\Delta t/60), \dot{Q}_{comp} < \dot{Q}_{sp(t)} \\ (\dot{Q}_{sp(t)} + \dot{Q}_{fan} + \dot{Q}_{ag})(\Delta t/60), \dot{Q}_{sp(t)} \geq \dot{Q}_{comp} \end{cases} \tag{10}$$

Where $Q_{cooling(t)}$ was the electrical energy consumed for cooling milk at time t, $\dot{Q}_{sp(t)}$ was the average power required to be drawn from the compressor(s) across the time step to cool the milk in the bulk tank to the required set point temperature (kW), $\dot{Q}_{fan}$ was the power rating of the cooling fan(s) (kW) and $\dot{Q}_{ag}$ was the power rating of the agitator motor (s) on the bulk tank (kW).

Perfect mixing of milk within the bulk tank was assumed.

2.2.3. Milking Machine sub-model

The milking machine was scheduled to operate while cows were being milked or if a wash cycle was taking place. Equations (11) and (12) describe the calculation for electricity consumed by the milking machine during milking and washing respectively, with and without a VSD.

$$Q_{mm(t)} = \begin{cases} (\dot{Q}_{mm})(ER_{mi}/EC_p)(NC_r/M)(\Delta t/60), VSD = 1 \\ (\dot{Q}_{mm})(NC_r/M)(\Delta t/60), VSD \neq 1 \end{cases} \tag{11}$$

$$Q_{mm(t)} = \begin{cases} (\dot{Q}_{mm})(ER_{wa}/EC_p)(\Delta t/60), VSD = 1 \\ (\dot{Q}_{mm})(\Delta t/60), VSD \neq 1 \end{cases} \tag{12}$$

Where $Q_{mm(t)}$ was the electricity consumed by the milking machine at time t (kWh), $\dot{Q}_{mm}$ was the power rating of the milking machine (kW), ER_{mi} was the effective reserve for milking (litres/minute), EC_p was the estimated capacity of the vacuum pump (litres/minute), and ER_{wa} was the effective reserve for washing (litres/minute).

2.2.4. Water heating sub-model

The mass of hot water in the tank was assumed to be constant. Water heating continued until the water reached the required temperature for washing (80 °C). Perfect mixing of hot and cold water in the tank was assumed. During a hot wash, 10 L of water were assumed to be required for washing each cluster in the milking machine. The amount of hot water required for washing the bulk tank was assumed to equal 1 % of the volume of the bulk tank. Equation (13) calculated the thermal energy added to the hot water tank at time *t*.

$$Q_{h(t)} = \left(\dot{Q}_h\right)(n_{hw})(\Delta t/60) \tag{13}$$

Where $Q_{h(t)}$ was the thermal energy added to the tank by the heating system at time t (kWh),$\dot{Q}_h$ was the power rating (kW) of the water heating system and n_{hw} was the efficiency of the water heating element.

Heat loss from the tank to its surroundings was calculated using equation (14).

$$Q_{l(t)} = ((U)(A)\left(T_{w,tank(t)} - T_{a(t)}\right)/1000)(\Delta t/60) \tag{14}$$

Where $Q_{l(t)}$ was the thermal energy lost from the tank to the environment at time t (kWh),U was the U-value of the hot water tank (W/m^{2}K),A was the surface area of the hot water tank (m^2),$T_{w,tank(t)}$ was the temperature of the water within the tank at time t (K), and $T_{a(t)}$ was the ambient temperature (K).

Heat removed from the tank to be used for washing is described in equation (15).

$$Q_{u(t)} = (m_w)(C_w)\left(T_{w,wa} - T_{w,i}\right)/\left(3.6 \times 10^6\right) \tag{15}$$

Where $Q_{u(t)}$ was the thermal energy removed from the tank as hot water was used (kWh),m_w was the mass of water required (kg), C_w was the specific heat capacity of water (4,180 J/kg K), $T_{w,wa}$ was the temperature of water required for a hot wash (K), and $T_{w,i}$ was the temperature of water entering the system (K).

Equation (16) describes the change in temperature of water in the tank due to heat lost to the environment, heat added by the heating element and heat removed for washing.

$$\Delta T_{w,tank} = \frac{Q_{h(t)} - (Q_{l(t)} + Q_{u(t)})}{\left((C_w)\left(m_{w,tank}\right)\right)/\left(3.6 \times 10^6\right)} \tag{16}$$

Where $\Delta T_{w,tank}$ was the change in temperature of water in the tank (K), and $m_{w,tank}$ was the mass of the water contained within the tank (kg).

The temperature of water in the tank at time *t* was determined using equation (17).

$$T_{w,tank(t)} = T_{w,tank(t-\Delta t)} + \Delta T_{w,tank(t)} \tag{17}$$

The control system for water heating is described in equation (18).

$$Q_{heating(t)} = \begin{cases} (\dot{Q}_h)(\Delta t/60), T_{w,tank(t)} < T_{w,sp} \\ 0, T_{w,tank(t)} \geq T_{w,sp} \end{cases} \tag{18}$$

Where $Q_{heating(t)}$ was the electrical energy (kWh) consumed by the water heating system at time *t* and $T_{w,sp}$ was the temperature set point for the water heating system (K).

2.2.5. Miscellaneous

2.2.5.1. Lighting.
The lighting system was assumed to be active during the milking process and for 14 min before milking starts and 25 min after milking finishes to account for preparation and clean up time (Prendergast et al., 2023). The energy consumed by the lighting system is described in equation (19).

$$Q_{li(t)} = (\dot{Q}_{li})(L)(\Delta t/60) \tag{19}$$

Where $Q_{li(t)}$ was the electricity (kWh) consumed by the lighting system at time t, $\dot{Q}_{li}$ was the power rating (kW) of the luminaires used in the parlour, and L was the number of luminaires in the parlour.

2.2.5.2. Milk Pump.
The milk pump was assumed to be in constant operation while cows were being milked. Equation (20) describes the electricity consumption of the milk pump.

$$Q_{mp(t)} = (\dot{Q}_{mp})\left(\frac{NC_r}{\mathrm{M}}\right)(\Delta t/60) \tag{20}$$

Where $Q_{mp(t)}$ was the electricity (kWh) consumed by the milk pump at time t, $\dot{Q}_{mp}$ was the power rating (kW) of the milk pump, M was the number of clusters in the milking machine.

2.2.5.3. Scrapers.
The scraper sub-model operates on a scheduled timer. Start times and duration were determined by the user. The scraper sub-model includes all scrapers present on farms including in winter

housing sheds and scrapers used in the milking parlour. The electricity consumed by the scrapers is calculated using equation (21).

$$Q_{sc(t)} = (\dot{Q}_{sc})(S)(\Delta t/60) \tag{21}$$

Where $Q_{sc(t)}$ was the electricity (kWh) consumed by the scrapers at time t, S is the number of scrapers and $\dot{Q}_{sc}$ was the power rating (kW) of the scrapers.

2.3. Data partitioning for model calibration and validation

The repeat hold-out cross-validation method as described by Cerqueira et al. (2020), was used to calibrate and validate FESS as it is the most used method for dairy farming decision support applications (Shine and Murphy, 2022). The electricity consumption, meteorological, milk yield and stocking data for each of the three representative farms were partitioned into 12 sets of approximately equal length. These sets each coincided with a month of the year to account for seasonality present in milk production and meteorological data. Each set was divided into training and validating sets with the first 75 % of each set used for training and the final 25 % of the set used for validating. Fig. 2 illustrates the hold-out procedure. A description of the training and validating data sets for each farm is presented in Table A1 in Appendix A.

2.4. Model calibration and validation

2.4.1. Calibration

In total, nine parameters were selected as tuning parameters for calibration. These parameters and their minimum, maximum and initial values are presented in Table 4. The sum of the squared errors (SSE) was employed as the cost function (equation (22). The Levenberg-Marquardt algorithm was used to minimize the SSE during model training similar to cognate studies (Murphy et al., 2021, Murphy et al., 2015).

$$SSE = \sum_{i=1}^{N} \left(Q_{Fi,M_i} - Q_{Fi,S_i}\right)^2 \tag{22}$$

The SSE was selected as it heavily penalizes large residuals, where the error was the difference between simulated farm electricity consumption (Q_{Fi,S_i}) and the measured farm electricity consumption (Q_{Fi,M_i}). The value of N is equal to total the number of 15-minute observations present in the calibration dataset used for training (28,319). The algorithm stopping criteria were a convergence value of 1 x 10^{-3} and a maximum limit of 1,000 iterations (Murphy et al., 2021).

These nine parameters were selected as tuning parameters as they impact accuracy and would be difficult to determine manually. Prior to the automatic calibration process, the authors set the parameters to the most plausible initial values. Upper and lower limits were set to reasonable minimum and maximum values, constraining the calibration, and preventing unrealistic values being selected by the tuning algorithm.

2.4.2. Validation

Five metrics were used for validation: mean absolute percentage error (MAPE), root mean squared error (RMSE) (kWh)), mean percentage error (MPE), the coefficient of determination (R^2), and relative prediction error (RPE). An RPE of less than 10 % indicates a satisfactory performance, between 10 % and 20 % indicates a relatively acceptable prediction and greater than 20 % suggests poor prediction (Fuentes-Pila et al., 1996). Model precision was evaluated according to the coefficient of determination R^2, which measures the variance between the simulated and measured values (Kvålseth, 1985). Including a correlation metric for validation purposes was important as it revealed if FESS captured the underlying dynamics of the system being modelled. The MAPE calculates the absolute error between the simulated and measured values (Beaumont et al., 1984). Model bias and precision were calculated using RMSE and RPE. The MAPE, MPE, RMSE and RPE were calculated in 24-hour steps while the R^2 was determined in 15-minute steps to assess the ability of FESS to accurately simulate the electricity load profile of the farm. Total electricity consumption and the main submodels (milk cooling, water heating and the milking machine) were included in the validation process. Smaller electricity consumer models (such as lighting and scrapers) were included in the miscellaneous category of the total electricity consumption during validation.

Table 4
Parameters selected as tuning parameters for model calibration.

System	Parameter	Symbol	Unit	min	max	Initial
Milk Cooling	Bulk tank U-value	U	W/ m^2K	0.01	0.2	0.1
	Temperature offset (evaporator)	C_h	K	274	293	283
	Temperature offset (condenser)	C_c	K	274	293	283
	COP effectiveness factor	η_c	n/a	0.2	0.6	0.3
Milking Machine	Effective reserve for washing	ER_{wa}	l/ min	500	2500	1200
	Effective reserve for milking	ER_{mi}	l/ min	500	1500	600
	Estimated capacity (vacuum pump)	EC_p	l/ min	2000	4000	3000
Water Heating	Hot water tank U-value	U	W/ m^2K	0.01	0.2	0.1
	Water heating element efficiency	η_{wh}	n/a	0.85	0.99	0.9

2.5. Model demonstration

To demonstrate the usefulness of FESS we configured the model to the specifications of Farm 1. The electricity consumption of Farm 1 was simulated for 12 months in 15-minute steps. Milk yield, the number of dairy cows, ambient air temperature and solar irradiance data from 2021 and details of the electricity consuming equipment present on the farm were used as inputs into FESS. To demonstrate the ability of FESS to integrate RES, a 29 kWp solar PV system was included in the simulations. The PV system was sized to match the typical maximum import capacity of a three-phase dairy farm in the Republic of Ireland (29 kVA). The PV model described by Pfenninger and Staffell (2016) was used in this demonstration. An export tariff of €0.21 / kWh for excess PV

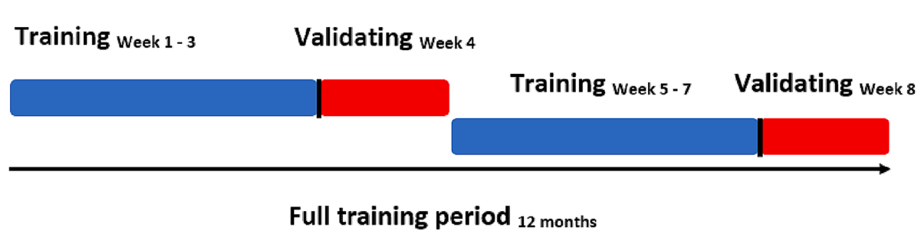

Fig. 2. Repeat hold-out methodology used for data partitioning, model training and validation where the full dataset of 12 months for each of the representative farms was broken into 12 sets of approximately four weeks. The first 75 % of each set was used for model training while the final 25 % was used for model validating.

generated electricity was used (Electric Ireland, 2023a).

Two scenarios were included in the demonstration. Scenario 1 was a baseline scenario, simulating the electricity consumption and costs of Farm 1 for 12 months with a flat rate electricity tariff. The cost per kWh of electricity for the flat rate tariff was set as €0.41 (Electric Ireland, 2023b). Scenario 2 simulated the electricity consumption of Farm 1 for 12 months with a time of use (TOU) pricing scheme for electricity. This pricing scheme had three different electricity tariffs in effect during different periods of the day (Night: midnight – 8am, Day: 8am – 5 pm / 7 pm – midnight, and Peak: 5 pm – 7 pm). The cost per kWh of electricity during the night, day and peak periods was set to €0.23, €0.43, and €0.46 respectively (Electric Ireland, 2023c). The purpose of this demonstration was to highlight FESS's ability to assess the impact of TOU electricity pricing on farm energy costs, easily integrate with RES models and provide insights into potential DSM opportunities.

3. Results

3.1. Model validation

FESS was validated against 12 weeks of data gathered from three farms (Farm 6, Farm 1, and Farm 5). Table 5 presents the average validation results across all three representative farms.

FESS simulated total daily electricity consumption with an RMSE of 7.65 kWh, an MAPE of 7.10 %, and RPE of 7.56 % across the three farms. FESS slightly underestimated the total daily electricity consumption of the farms by −0.86 % (MPE). FESS achieved an R^2 value of 0.77 for total electricity consumption (Table 5).

Table 6 presents the results of the validation for total electricity consumption and the three largest electricity consuming sub-models for each of the three representative farms.

Farm 5 had the highest MAPE value, for total daily electricity consumption, of 8.09 %. The highest RMSE observed for total daily electricity consumption was 8.58 kWh on Farm 6. Farm 1 had the lowest R^2 value for total electricity consumption ($R^2 = 0.66$). FESS underestimated the total daily electricity consumption on Farms 6 and 1 by −2.32 % and −0.86 % respectively and overestimated by 0.60 % on Farm 5.

Fig. 3 compares measured and simulated total parlour consumption profiles for Farm 6. Graphs a, b, c and d (of Fig. 3) depict representative days of quartile 1, quartile 2, quartile 3 and quartile 4, in terms of daily electricity use, respectively.

3.2. Model demonstration

Table 7 describes the annual electricity consumption, simulated by FESS, milk production and energy efficient technologies present on Farm 1 which were included in the model demonstration.

Table 8 presents the electricity generated from the solar PV model and the percentage of PV generated electricity consumed on-farm. The simulated annual electricity costs, after subtracting PV contributions, and night, day and peak rate percentages for Scenario 2 are also presented.

Table 5
Validation results (RMSE, MAPE, R^2, MPE, and RPE) averaged across the three representative farms for 12 weeks of data. RMSE, MAPE, and RPE were calculated using daily electricity consumption to assess FESS's ability to accurately simulate daily electricity usage for all sub-models, while R^2 was calculated using 15-minute steps to assess FESS's ability to capture the underlying dynamics for each sub-model.

	RMSE (kWh)	MAPE (%)	R^2	MPE (%)	RPE (%)
Total	7.65	7.10	0.72	−0.86	7.56
Milk Cooling	4.88	12.44	0.67	0.25	5.29
Milking Machine	0.98	7.25	0.76	0.93	0.46
Water Heating	3.41	13.79	0.69	8.27	1.37

Table 6
Results of the validation process for 12 weeks of data on three farms. The MAPE, RMSE, R^2, MPE, and RPE are presented for each of the main electricity consuming sub-models (milk cooling, milking machine, and water heating) as well as total electricity consumption. RMSE, MAPE, MPE, and RPE were calculated using daily electricity consumption while the R^2 was calculated in 15-minute intervals.

Farm I. D.	System	RMSE (kWh)	MAPE (%)	R^2	MPE (%)	RPE (%)
Farm 6	Total	8.58	7.37	0.79	−2.32	9.05
	Milk Cooling	7.55	13.48	0.71	−1.12	6.32
	Milking Machine	0.75	5.92	0.76	2.31	0.29
	Water heating	3.18	23.37	0.64	2.69	0.68
Farm 1	Total	7.78	5.84	0.70	−0.86	8.43
	Milk Cooling	4.86	10.35	0.71	7.11	4.77
	Milking Machine	1.01	7.72	0.75	4.76	0.40
	Water heating	4.65	8.51	0.62	0.88	2.81
Farm 5	Total	6.59	8.09	0.66	0.60	5.21
	Milk Cooling	2.23	13.48	0.59	−5.26	4.77
	Milking Machine	1.17	8.10	0.76	−4.27	0.68
	Water heating	2.40	9.50	0.83	21.25	0.63

The PV model simulated annual electricity production of 32,692 kWh. When integrated with FESS, 39 % of this electricity was determined to be consumed on-farm. With a flat rate electricity tariff (Scenario 1), the farm's annual electricity costs were simulated to be €7,319. When the TOU electricity tariff was introduced (Scenario 2), the annual electricity costs reduced to €4,664, a reduction of 36 %. This reduction of electricity costs was due to the farm consuming 60 % night rate electricity, which is cheaper than flat rate electricity. Four 24-hour load profiles of total electricity consumption and generation from renewables, simulated by FESS, are presented in Fig. 4. The four plots in Fig. 4 (a, b, c and d) depict representative days of quartile 1, quartile 2, quartile 3 and quartile 4, in terms of daily electricity production from the PV model, respectively.

4. Discussion

4.1. Model validation

4.1.1. Model comparison

In this section, the accuracy achieved by FESS in terms of total electricity consumption, and each of the sub-models, is discussed and compared to models which are available in the literature. Sources of potential error are also described and discussed. FESS's validation could not be compared to all published models, as FESS operates in 15-minute time steps, unique among existing energy models of dairy farms, resulting in many commonly used error metrics being unsuitable for comparison. For example, the R^2 achieved by FESS was calculated by comparing 35,040 (one year) observed data points to an equal number of points simulated by FESS. In comparison, a model which worked in monthly time steps would calculate an R^2 value through the comparison of 12 (one year) observed data points to 12 simulated points.

4.1.1.1. Total electricity. FESS was found to have good accuracy when compared to other models in the literature. FESS achieved an MAPE of 7.10 %, a satisfactory RPE of 7.56 % and an MPE of −0.86 %. In comparison, the ANN model (NAIDEA) described by Shine et al. (2022) achieved an MAPE of 15 % and an RPE of 18 % while the MLR model described by Shine et al., (2018a) achieved an MPE of −2.2 %, and an RPE of 11.9 %. The DEP model described by Todde et al. (2017) achieved an RPE of 11.42 %. Finally, the MECD model described by Upton et al. (2014) achieved an RPE of 7.37 %. Compared to previous models, FESS performed well in terms of accuracy while operating at a much finer time step, offering additional functionality in terms of RES

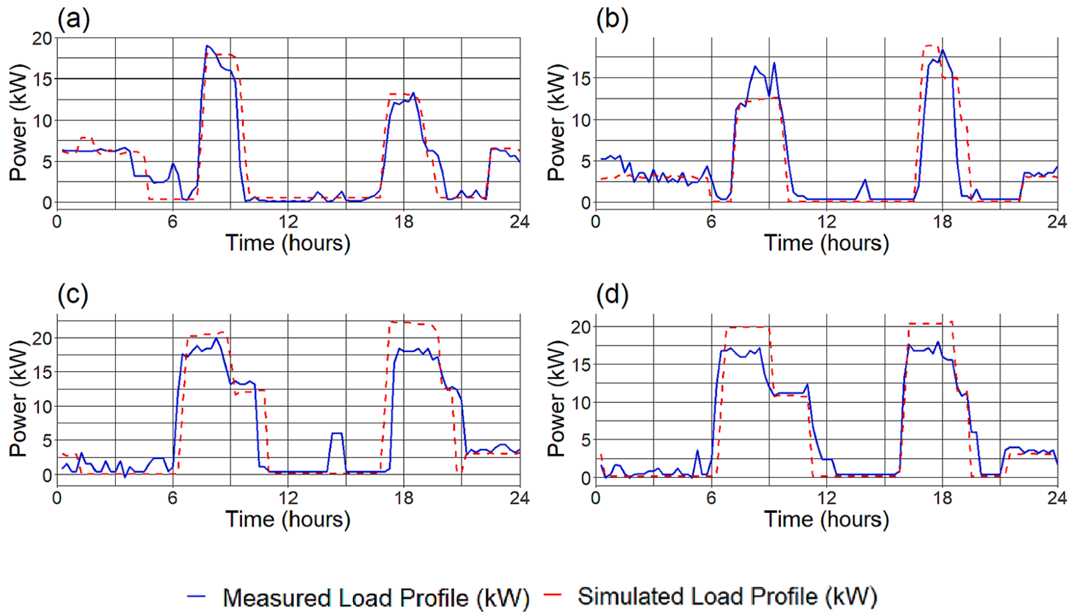

Fig. 3. Measured vs simulated Total load profiles for Farm 6, on four representative days. Each day was selected based on electricity consumption quartiles. (a) – Representative of quartile 1 (16/12/2020). (b) – Representative of quartile 2 (04/03/2021). (c) – Representative of quartile 3 (15/07/2021). (d) – Representative of quartile 4 (10/06/2021).

Table 7
Milk production, electricity consumption, simulated by FESS, and energy efficient technologies from Farm 1.

Herd Size	No. Units	Annual Milk Production (kg)	Annual Electricity Consumption (kWh)	Hot Wash per Day	VSD	PHE	HR	Export Tariff (€/kWh)
191	20	1,350,951	41,491	1	Yes	Yes	No	€0.21

VSD = Variable Speed Drive, PHE = Plate Heat Exchanger, HR = Heat Recovery.

Table 8
RES contribution, electricity costs and Night/Day/Peak rate percentage breakdown from 12 months of simulated electricity consumption. Scenario 1 used a flat rate electricity tariff (€0.41 per kWh). Scenario 2 used a TOU electricity tariff (night rate = €0.23 per kWh, day rate = €0.43 per kWh, peak rate = €0.46 per kWh).

Scenario	Solar PV Output (kWh)	PV Consumption (%)	Annual Elec. Cost (€)*	Night Rate %	Day Rate %	Peak Rate %
Scenario 1	32,692	39 %	€7,319	–	–	–
Scenario 2	32,692	39 %	€4,664	60 %	24 %	16 %

*Net of PV contribution: Scenario 1 = €9,605, Scenario 2 = €9,771.

integration and DSM. To achieve this, FESS had to account for the dynamic load profile of milking parlours, while previous models only accounted for daily, monthly or even annual changes in electricity consumption.

The highest R^2 (0.79) achieved for total electricity consumption by FESS was achieved on the largest of the three representative farms (Farm 6) which milked 329 cows in a 26-unit parlour. The lowest MAPE (5.84 %) was achieved on Farm 1, the middle of the representative farms with a herd size of 191 cows and a 20-unit parlour. The lowest RMSE (6.59kWh), MPE (0.60 %), and RPE (5.21 %) for total electricity consumption were achieved on the smallest of the representative farms (Farm 5) with a herd size of 99 cows and a 20-unit parlour. These results show good accuracy across farm size. On farms 1 and 5, domestic electricity use was included in the miscellaneous electricity category which is a source of additional error for the total electricity validation. The inclusion of domestic electricity on these two farms did not impact the training or validation process for the sub-models as it was confined to the miscellaneous category.

4.1.1.2. Milk cooling Sub-Model. Of the three sub-models, the milk cooling sub-model had the highest RMSE (4.88 kWh), the lowest R^2 (0.67) and the second highest MAPE (12.44 %). The milk cooling sub-model achieved a satisfactory RPE of 5.29 %. In comparison, the milk cooling model developed by Shine et al. (2022), achieved an MAPE of 31 % and an RPE of 23 %. Unscheduled operation of the agitator motor and/or the compressors, caused by heat gained from the environment, complicated the load profile of the milk cooling system by introducing small transient spikes in electricity consumption. These spikes are difficult to simulate and had a disproportionately large impact on the accuracy metrics achieved by the milk cooling sub-model during validation. An example of these spikes can be seen in Fig. 3(a) just after 12:00 pm.

4.1.1.3. Milking Machine Sub-Model. The milking machine sub-model achieved the lowest RMSE (0.98 kWh) and MAPE (7.25 %) as well as the highest R^2 (0.76) of all sub-models while achieving an RPE of 0.46 %. The milking machine sub-model described in this paper had a lower MAPE and RPE than the model described by Shine et al. (2022) (MAPE = 21 % RPE = 22 %). The low RMSE value achieved by the milking machine sub-model was due in part to it consuming a lower percentage of total electricity (13 %) than the milk cooling (26 %) and water heating (34 %) sub models when averaged across the three representative farms. The relatively low MAPE and high R^2 achieved by the milking machine sub-model were due to the consistent electricity demand of the system during operation and the predictable operation times. Much of the error associated with the milking machine sub-model was due to the delay between milking and the washing cycle of the milking machine. This delay can vary milking-to-milking, where the vacuum pumps would remain running for a period of time after milking had finished,

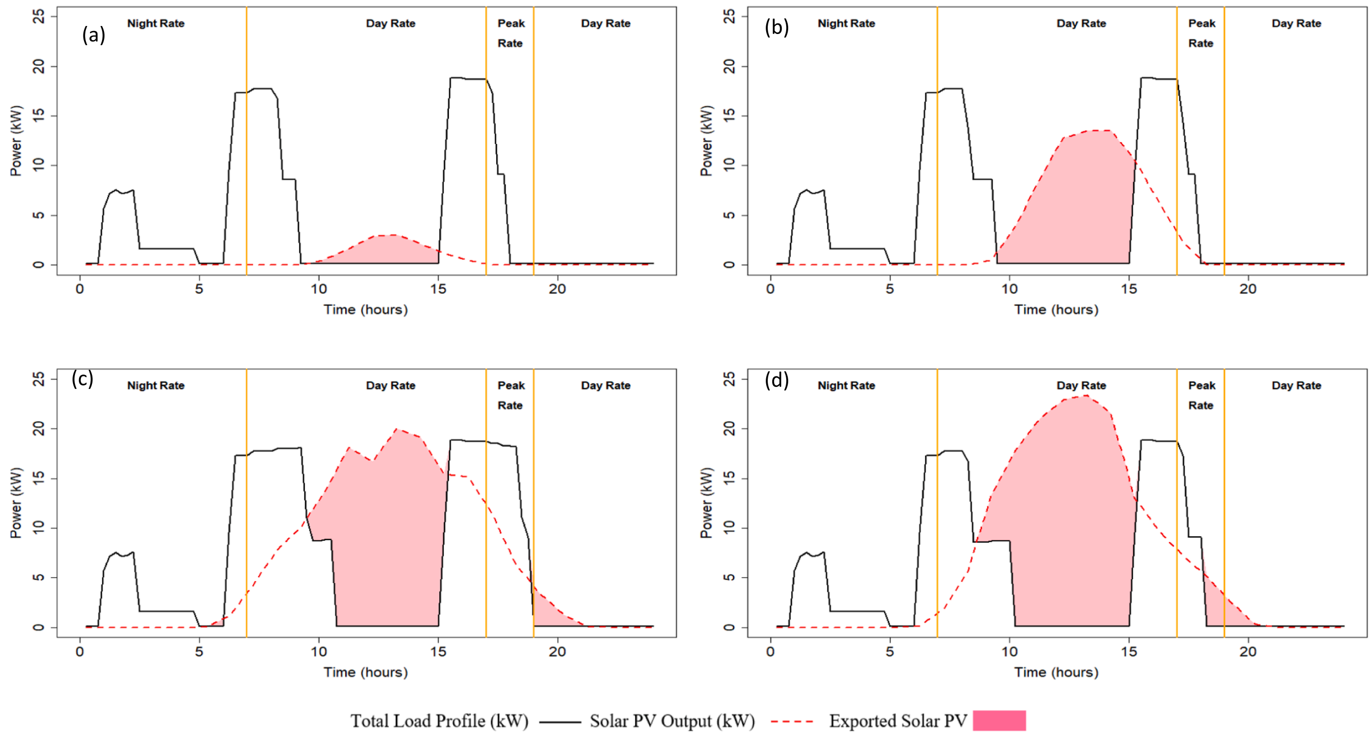

Fig. 4. Simulated Total load profiles from 4 days of the period simulated for the demonstration for Farm 1. Each day was selected based on electricity production quartiles from the PV model. (a) Representative of quartile 1 (02/12/2021), (b) Representative of quartile 2 (05/11/2021), (c) Representative of quartile 3 (08/07/2021), (d) Representative of quartile 4 (03/05/2021). The night, day and peak rate times are separated by vertical lines and are labelled in the figures.

consuming a small amount of electricity, before the washing cycle started complicating the load profile of the sub-model.

4.1.1.4. Water heating Sub-Model. The water heating sub-model achieved an MAPE of 13.79 % and a satisfactory RPE of 1.37 %. Though this was the highest MAPE achieved by any of the sub-models defined in this paper, it is still lower than the water heating model described by Shine et al. (2022) which achieved an MAPE of 48 % and an RPE of 34 %. A sizeable proportion of the error observed in this sub-model was due to the assumptions made regarding the volume and temperature of hot water required (10 L per cluster for the milking machine and 1 % of the bulk tank volume at 80 °C). Furthermore, similar to the milk cooling sub-model, heat lost from the hot water tank to the environment resulted in the heating element automatically turning on for short, unscheduled periods to maintain the set point temperature, resulting in small transient spikes in electricity demand. These spikes, being particularly difficult to accurately simulate, resulted in validation errors disproportionate to the amount of energy consumed by the spikes. An example of these spikes can be seen in Fig. 3(c) just after 12:00 pm.

4.1.2. Seasonality

The accuracy of FESS varied throughout the milking season. Table A2 in Appendix A presents the results for the three representative farms for each of the 12 weeks used for model validating. Fig. 5 presents the mean RMSE achieved by FESS, across all three farms, over 12 months. The RMSE is plotted against the mean milk production across all three farms to highlight how the RMSE changes with seasonality. As can be seen in Fig. 5, FESS achieved the lowest RMSE (6.04 kWh) in May when milk production was at its highest (170,111 L). The highest RMSE observed was in December (11.39 kWh) the second lowest month of milk production (59,249 L). FESS was most accurate during the main milk production season (March to October) which also corresponds with the period of highest electricity consumption (70 % of total annual electricity consumption).

4.2. Model demonstration

The purpose of this demonstration was to highlight FESS's ability to identify opportunities for farmers to take advantage of TOU electricity

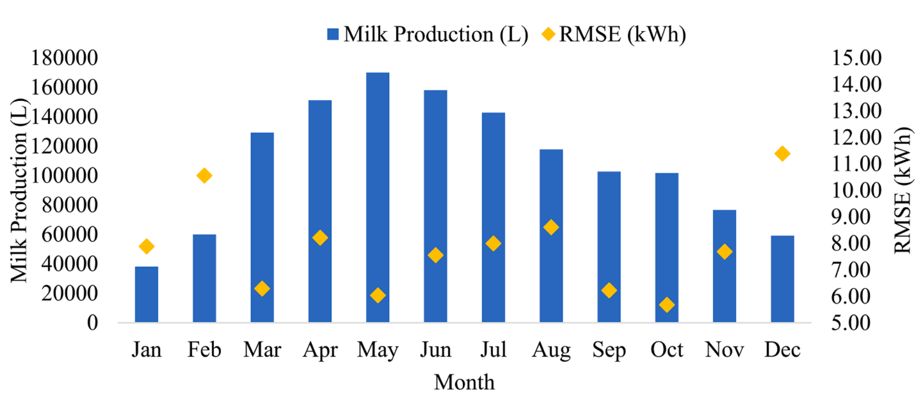

Fig. 5. Mean model accuracy (RMSE) and mean milk production across all three farms over a 12-month period.

pricing tariffs through DSM and to integrate existing RES models.

A study by Upton et al., (2015b) assessed the impact of a variety of pricing tariffs on Irish dairy farms. When a TOU tariff, similar in structure to the TOU tariff in our demonstration, was compared to a flat rate tariff on a dairy farm with 195 dairy cows, electricity costs were found to be between 17 % and 19 % lower using the TOU tariff (Upton et al., 2015b). This contrasts with 36 % difference in electricity costs observed in our demonstration. This difference was due in part to the PV system included in our demonstration which reduced the amount of day and peak rate electricity consumed by the farm.

Farm 1, used in this paper for model demonstration purposes, began morning and evening milking's at 06:00am and 15:00 pm respectively. This resulted in the morning milking consuming some day rate electricity and the evening milking consuming some peak rate electricity. If this farm was to begin morning milking's at 5:00 am, it could result in a reduction in electricity costs due to the consumption of less day rate electricity. It could also reduce the total amount of energy consumption associated with morning milking's (Upton et al., 2015b). To maintain a consistent interval between milking's, the evening milking's would have to begin at 14:00. This could also reduce energy costs associated with the evening milking's by reducing the amount of peak rate electricity consumed, however, it could increase the amount of energy required by the evening milking's (Upton et al., 2015b). Furthermore, practical factors must be considered when changing milking times. Breen et al. (2021) found the most common morning and evening milking start times, on a set of 46 Irish dairy farms, to be 7:00am and 17:00 pm respectively. Breen et al. (2021) noted that improvements in after-tax net profit, as a result of altering milking times to reduce energy costs, were relatively minor, and so was unlikely to be considered as an option by farmers. However, Breen et al. (2021) also noted that future TOU tariffs could increase the monetary gains for farmers willing to alter milking times and cited this as a potential avenue for further research. Similarly, a study by Dew et al. (2021) on 6 New Zealand dairy farms concluded that energy savings of $7,428 over a 287 day milking season could be achieved by avoiding periods of high electricity prices, however it was noted that this may be unpopular among dairy farmers as it would require the morning milking to commence between 4 am and 5am on most days.

This demonstration highlights how different electricity pricing tariffs can help to improve the financial viability of PV systems for dairy farms. Such tariffs could be used by policy makers to encourage the uptake of PV systems, reducing the carbon intensity of the agricultural sector and electricity generation at a national level.

In Fig. 4 a disconnect can be seen between the times when electricity demand was high on the farm and when PV generation was at its peak. This resulted in 61 % of electricity generated from the PV system being exported to the grid. FESS could be used to investigate DSM methods to maximise self-consumption of PV electricity by exploiting the energy flexibility of dairy farms and through the use of thermal and electrical energy storage.

Thus, FESS can provide insights into the effect of different electricity pricing structures on total farm energy costs. This ability is useful for farmers so that they can make informed decisions when selecting electricity providers or considering DSM practices. It is also useful for policy makers, as TOU pricing schemes could be used as a method to encourage dairy farmers to alter their energy consumption profiles. Furthermore, in the demonstration, FESS was integrated with an existing solar PV model highlighting its ability to assess the viability of RES on a farm-by-farm basis.

4.3. Future applications of FESS

FESS was developed to simulate electricity consumption of herringbone dairy farms which use certain common equipment. A study conducted by Chearbhaill et al. (2024) (under review) on 666 Irish dairy farms reported that 92.1 % of the farms in their study operated herringbone milking parlours. Specifically, dairy farms which use herringbone milking parlours, a direct expansion (DX) milk cooling system, and electricity for water heating. Due to the modular nature of FESS, sub-models, such as the milk cooling sub-model, can be replaced with models of different systems, such as an ice-bank model. FESS can also be adapted to simulate other types of milking machines, such as rotary or robotic milking parlours. This feature will allow FESS to be adapted and used for future studies which investigate technologies not included in FESS originally. However, any such adaptations would require revalidation of FESS for that application.

From a practical perspective, FESS can provide decision support for farmers that are planning, for example, to install solar PV in an effort to reduce energy costs and related emissions. As shown in the demonstration, FESS can provide accurate information relating to the self-consumption rates of solar PV systems on dairy farms. It can also calculate the financial performance of PV systems helping farmers to make informed decisions when sizing potential PV systems. Furthermore, farmers can investigate different management strategies, such as altering milking times or water heating times, to improve energy efficiency or self-consumption of PV generated electricity.

4.4. Limitations

Though the objectives of this paper, to define, validate and demonstrate FESS, have been achieved, there are limitations which should be noted. FESS was trained and validated using data from dairy farms operating herringbone milking parlours with a DX milk cooling system and electric water heating. Due to the wide range of combinations of technologies and types of milking parlours in use, it was necessary to limit the scope of this paper to one standard system. The system chosen is the most common system currently in use in the Republic of Ireland. FESS can be adapted to simulate electricity consumption of other types of milking machines, such has automatic milking systems or larger rotary parlours, however, this would require revalidation.

5. Conclusion

- This paper defined, validated, and demonstrated a grey-box model (FESS) for simulating dairy farm electricity consumption in 15-minute time steps.
- With an MAPE of 7.10 %, a satisfactory RPE of 7.56 % and an MPE of −0.86 %, FESS performed well in terms of accuracy when compared to previous models described in the literature while offering additional functionality in terms of RES and DSM. Additionally, FESS achieved an R^2 of 0.72 while operating in 15-minute steps.
- FESS was found to be accurate when validated across three dairy farms of varying size, representative of the small, medium and large farms in our dataset.
- The demonstration showed the ability of FESS to be integrated with existing RES models, investigate electricity tariff scenarios, and provide the user with information regarding the energy performance, RES contributions and DSM opportunities.
- We conclude that FESS is sufficiently accurate for the proposed application of simulating dairy farm electricity consumption across varying herd and parlour sizes.

CRediT authorship contribution statement

F. Buckley: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **J. Upton:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **R. Prendergast:** Writing – review & editing, Investigation, Data curation. **L. Shalloo:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization. **M.D. Murphy:** Writing –

review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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Appendix A

Table A1. Descriptive statistics of data from the training and validating datasets for the three representative farms.

Farm		1	5	6	Average
Peak power (kW)	Training Data	23.60	28.33	23.60	25.18
	Validating Data	22.40	24.00	24.40	23.60
Minimum Daily Electricity Consumption (kWh)	Training Data	38.10	75.50	77.81	63.80
	Validating Data	30.60	87.40	89.24	69.08
Average Daily Electricity Consumption (kWh)	Training Data	135.82	119.61	115.49	123.64
	Validating Data	133.45	119.66	120.42	124.51
Max Daily Electricity Consumption (kWh)	Training Data	192.00	207.50	163.03	187.51
	Validating Data	204.10	180.90	151.23	178.74

Each training and validating dataset consisted of 28,319 and 7,968 data points respectively.

Table A2. Average validation results from three representative farms by month.

	RMSE (kWh)	MAPE	R^2	MPE (%)	RPE (%)
Jan	7.88	12.25	0.63	1.70	2.59
Feb	10.56	9.56	0.71	6.64	5.51
Mar	6.29	5.65	0.78	−0.04	7.65
Apr	8.22	6.77	0.79	−3.58	9.18
May	6.04	4.78	0.80	−3.97	8.67
Jun	7.55	6.05	0.76	0.13	8.94
Jul	8.00	7.29	0.72	3.80	8.47
Aug	8.61	7.66	0.69	−11.96	8.94
Sep	6.23	5.62	0.66	−1.06	7.85
Oct	5.68	4.98	0.65	−2.90	6.65
Nov	7.69	8.03	0.72	3.90	5.25
Dec	11.39	13.10	0.73	−7.27	4.12

Appendix B

Table B1. Milking start times, durations and description of milking parlour technologies and facilities present on all farms in this study (Prendergast et al., 2023).

Farm	AM milking start time	AM milking duration (hours)	PM milking start time	PM milking duration (hours)	B. G.	A. G.	R. E.	C. L.	A.C. R.	A. F.	HY Area (m^2)
1	06:28	02:53	16:02	02:17	0	1	0	1	1	1	180
2	05:34	03:45	14:23	02:34	1	1	0	1	1	1	314
3	07:10	01:55	15:55	01:32	0	0	0	0	1	0	170
4	06:11	01:57	16:16	01:50	0	1	0	1	1	0	175
5	08:04	01:18	16:53	01:04	0	1	0	1	1	0	125
6	07:01	02:06	16:30	01:52	1	1	1	0	1	1	272
7	06:55	02:56	16:44	02:37	0	0	0	0	1	1	256
8	05:56	02:03	15:57	01:39	0	0	0	0	0	0	104
9	06:37	01:41	16:17	01:35	0	0	0	1	1	0	200

B.G. = backing gate, A.G. = Automatic exit/entry gates, R.E. = rapid exit, C.L. = conventional lift, A.C.R. = automatic cluster removers, HY = holding yard

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