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A mechanistic model for electricity consumption on dairy farms: Definition, validation, and demonstration

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ABSTRACT

Our objective was to define and demonstrate a mechanistic model that enables dairy farmers to explore the impact of a technical or managerial innovation on electricity consumption, associated CO_2 emissions, and electricity costs. We, therefore, (1) defined a model for electricity consumption on dairy farms (MECD) capable of simulating total electricity consumption along with related CO_2 emissions and electricity costs on dairy farms on a monthly basis; (2) validated the MECD using empirical data of 1 yr on commercial spring calving, grass-based dairy farms with 45, 88, and 195 milking cows; and (3) demonstrated the functionality of the model by applying 2 electricity tariffs to the electricity consumption data and examining the effect on total dairy farm electricity costs. The MECD was developed using a mechanistic modeling approach and required the key inputs of milk production, cow number, and details relating to the milk-cooling system, milking machine system, water-heating system, lighting systems, water pump systems, and the winter housing facilities as well as details relating to the management of the farm (e.g., season of calving). Model validation showed an overall relative prediction error (RPE) of less than 10% for total electricity consumption. More than 87% of the mean square prediction error of total electricity consumption was accounted for by random variation. The RPE values of the milk-cooling systems, water-heating systems, and milking machine systems were less than 20%. The RPE values for automatic scraper systems, lighting systems, and water pump systems varied from 18 to 113%, indicating a poor prediction for these metrics. However, automatic scrapers, lighting, and water pumps made up only 14% of total electricity consumption across all farms, reducing the overall impact of these poor predictions. Demonstration of the model showed that total farm electricity costs increased by between 29 and 38% by moving from a day and night tariff to a flat tariff.

Key words: energy, electricity, milk production, mechanistic model

INTRODUCTION

Grass-based production of 1 L of milk leaving the farm gate (i.e., including on-farm energy consumption and energy consumption of farm inputs) requires a total energy input of about 2.5 MJ (Upton et al., 2013). On Irish farms, about 12% of this energy use is represented by electricity consumption, of which 60% is used in the period with the highest tariff (i.e., from 0900 to 2400 h).

Innovations that reduce on-farm electricity consumption might not only reduce total energy consumption of milk production but also electricity costs and CO_2 emissions related to energy consumption. Reducing electricity costs might be attractive to farmers, because electricity prices have increased by 32% in the last 5 yr for European farmers (Eurostat, 2013). Moreover, European dairy farmers are approaching a period of change driven by the removal of the milk quota regimen. Without a quota regimen, farmers are allowed to produce milk unrestrictedly, which is expected to cause increased volatility of the milk price, ultimately resulting in volatility in farm profitability (Lips and Rieder, 2005).

An increase in price volatility warrants attention for cost price minimization. By 2020, however, 80% of all electricity consumers in Ireland are expected to be connected to the smart grid (CER, 2011). The new Irish electricity grid infrastructure implies a pricing system based on the electricity demand on the national grid, resulting in higher electricity rates during peak periods of consumption and lower rates during off-peak periods. Peak demand is currently from 1700 to 1900 h. If dairy farmers carry out their evening milking during this peak period, they may be exposed to increases in energy costs under the dynamic pricing structure. This dynamic pricing structure, however, could also

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present opportunities to reduce overall energy costs if equipment is managed intelligently to optimize energy consumption in off-peak periods (currently from 0000 to 0900 h) (Upton et al., 2013). Evaluation of the potential effect of electricity pricing tariff changes on dairy farm electricity costs requires the development of a specific electricity consumption model.

Similarly, changing one technology in favor of another (e.g., the addition of a water-cooled plate heat exchanger to precooled milk) or one management strategy over another (e.g., milking once or twice per day), however, not only affects electricity costs of producing milk but also energy consumption and associated CO_2 emissions. A model that supports decision making of one innovation over another, therefore, should not only evaluate the impact of technology, management practices, and pricing structures on the electricity costs of a farm, but also predict the impact of that innovation on energy consumption and associated CO_2 emissions. To our knowledge, such a decision-support model has not been reported. The aim of this study was to define and demonstrate a mechanistic model that enables dairy farmers to explore the impact of a technical or managerial innovation on electricity consumption, associated CO_2 emissions, and electricity costs. We, therefore, first defined the model for electricity consumption on dairy farms (**MECD**). Subsequently, we validated this model by comparing model outputs with empirical data on farm electricity consumption gathered through a physical auditing process. Finally, we demonstrated an application of the model by evaluating the effect of 2 electricity pricing tariffs on total dairy farm electricity costs.

MATERIALS AND METHODS

Model Definition

The model described in this paper was developed to predict the electricity consumption, associated CO_2 emissions, and electricity costs on dairy farms. The model is a mechanistic mathematical representation of the electricity consumption under the following key headings: milk-cooling system, water-heating system, milking machine system, lighting systems, water pump systems, and winter housing facilities (Figure 1). A monthly time step was chosen because milk production information is available from all commercial farms at the end of each month.

Electricity Consumption Calculations

The model used key inputs such as monthly herd milk yield, number of cows, and farm infrastructure details (e.g., milk tank size and vacuum pump size, among others) and management practices (e.g., grazing season length), and calculated the electricity consumed by each of the 7 infrastructural systems for 24 h on 1 d each month. Further key inputs of electricity pricing tariff structure and CO_2 emission factors were then applied to compute component running costs and CO_2 emissions on a monthly basis. All inputs, calculations, and outputs were based on a month × daily hour (12 × 24) matrix structure.

Milk Cooling. The milk-cooling electricity consumption was computed using Equation 1:

$$Q_{mc}(i,j) = \frac{C_m \times \Delta T(i,j) \times M_m(i,j)}{COP(i,j) \times 3{,}600}, \quad [1]$$

where

$$\Delta T(i,\ j) = T_{bulk}(i,\ j) - T_{final} \quad [2]$$

and

$$COP(i,j) = \left[\frac{T_{evap}}{T_{amb}(i,j) - T_{evap}}\right] \times a, \quad [3]$$

where $Q_{mc}(i,\ j)$ = predicted energy consumption for milk cooling in month i (1–12) and hour j (1–24; kWh), C_m = specific heat capacity of milk [kJ/(kg·°C)], and $\Delta T(i,\ j)$ = difference in temperature between the milk entering the storage tank [$T_{bulk}(i,\ j)$] and the milk tank set point (T_{final}; °C). The $T_{bulk}(i,\ j)$ was calculated using information about plate cooling from Upton et al. (2010) assuming a milk:water flow ratio of 1:2 in the plate cooler using ground water temperatures from a 100-m borehole well from Goodman et al. (2004). The variable $M_m(i,\ j)$ was the mass of milk in month i and hour j to be cooled (kg). It was assumed that 60% of the milk was extracted in the morning milking (O'Callaghan and Harrington, 2000). The variable $COP(i,\ j)$ was the milk-cooling system coefficient of performance (**COP**; dimensionless). A submodel was developed to compute the cooling system COP based on a modified Carnot cycle (ideal refrigeration cycle) formula, as described by Henze and Krarti (1998). This approach allows the COP of a specific cooling system to vary according to ambient temperature. It was not designed to represent exactly the vapor compression refrigeration cycle performance of an individual cooling system but rather provide a dynamic element to the COP value of a generalized direct expansion (**DX**) or ice bank (**IB**) cooling system. The variable T_{evap} was the evaporator temperature of the refrigeration system [assumed to be 268 Kelvin (K) for DX and 265 K for

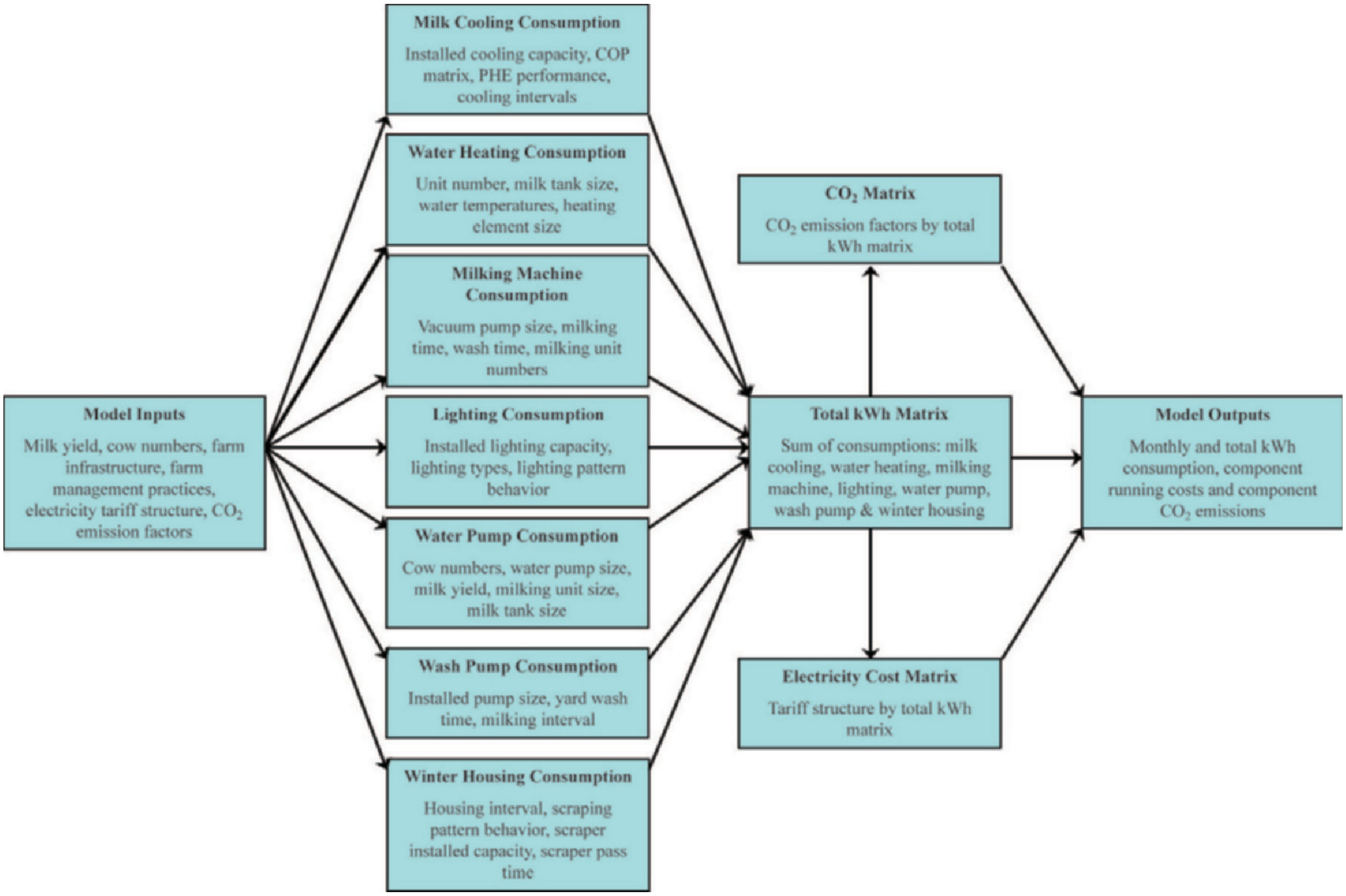

Figure 1. Schematic of milk production electricity consumption model showing the 4 primary sections, illustrated from left to right: (1) inputs, (2) consumption matrix calculations for the 7 main infrastructural systems, (3) consumption summing and tariff application, and (4) outputs. COP = coefficient of performance; PHE = plate heat exchanger. Color version available in the online PDF.

IB] and T_{amb} (K) was the hourly ambient temperature for 2011 from Met Éireann (Dublin, Ireland; Irish meteorological service); the farms used in the validation of this model were within a 20 mile radius of this weather station. Finally, a was an adjustment factor to account for inefficiencies in real-world systems (assumed 0.10 for this analysis). This approach yielded a range in COP for a DX system of 1.2 to 4.1 and 1.1 to 2.7 for an IB system.

The start time of the cooling system coincided with the time of milking (which was a model input). The duration of cooling was computed with knowledge of the necessary cooling consumption (Equation 1) as well as the installed capacity of the cooling system (Equation 4):

$$t_m(i,\ j) = Q_{mc}(i,\ j)/C_{cap}, \quad [4]$$

where $t_m(i,\ j)$ = time taken to cool the milk (h) and C_{cap} = capacity of the milk-cooling compressors (kW). However, on any given day, Q_{mc} can vary due to the ambient temperature effect on the COP, which in turn, varies t_m. To combat this issue, an approximation of the COP (average COP value across all times and seasons), was used as a first iteration. This allowed the electricity consumption to be placed in the relevant time horizon, which in turn, allowed the final appropriate COP value to be assigned to the cooling consumption on an hourly basis.

Water Heating. The electricity consumed to heat water on a dairy farm was described by Equation 5:

$$Q_{wh}(i,j) = \frac{C_w \times \Delta T(i,j) \times M_w(i,j)}{\varepsilon \times 3,600}, \quad [5]$$

where

$$\Delta T(i,\ j) = T_{hot} - T_{cold}(i,\ j) \quad [6]$$

and $Q_{wh}(i,\ j)$ = predicted energy consumption for heating cleaning water in month i (1–12) and hour j (1–24) (kWh), C_w = specific heat capacity of water (kJ/kg·°C), $\Delta T(i, j)$ = difference in temperature between the water entering the storage tank [$T_{cold}(i, j)$] and the water heater set point (T_{hot}; °C). Borehole water temperatures from Goodman et al. (2004) were used to determine T_{cold}. Guidelines for hot water temperatures and recommended water volumes per milking cluster were taken from the Teagasc Milk Quality Handbook (O'Brien, 2008), and used for T_{hot}. The mass of water to be heated was represented by $M_w(i, j$; kg) and ε was the efficiency of the heating system (dimensionless) taken at 0.90 from Upton et al. (2010). The time taken to heat the water was computed using Equation 7:

$$t_w(i, j) = Q_{wh}(i, j)/P_{wh}, \quad [7]$$

where $t_w(i, j)$ = time taken to heat the water (h), which was used to determine the specific hours the water-heating system was used, and P_{wh} = installed capacity of the water-heating system (kW). Water heating commenced at 0000 h (midnight) to coincide with night rate electricity tariffs if the heating system was controlled with a timer, otherwise heating commenced after each milking.

Milking Machine. Electricity consumption of the milking machine was described by the following formula:

$$Q_{mm} = [\text{Roundup}(N_{cows}/N_{cluster}) \times t_{row} + t_{wash}] \times Pp, \quad [8]$$

where Q_{mm} = predicted electricity consumed by the milking machine for 1 milking (kWh), N_{cows} = number of cows milked, $N_{cluster}$ = number of milking clusters in the milking parlor, t_{row} = cycle time needed to milk $N_{cluster}$ of cows (h), Pp = installed capacity of the milking machine pumps (kW), and t_{wash} = time required to wash the milking machine clusters and pipes with cleaning fluid after milking. Roundup indicates that the number of cycles needed was rounded to the first integer above the outcome of $N_{cows}/N_{cluster}$.

Lighting. Electricity is consumed by lighting on a dairy farm in 3 main areas: (1) milking area, (2) housing facilities, and (3) outdoor areas. Electricity consumed by lighting was then described by Equation 9:

$$Q_l(i, j) = N_{lm} \times Q_{lm} \times T_{lm}(i, j) + N_{hf} \times Q_{lhf} \times T_{lhf}(i, j) + N_{lod} \times Q_{lod} \times T_{lod}(i, j), \quad [9]$$

where $Q_l(i, j)$ = predicted electricity consumed by lighting for month i and hour j (kWh); N_{lm} = number of light fittings in the milking facility; Q_{lm} = installed capacity per light unit in the milking facility (kWh), which is calculated using a lookup table of light types; and $T_{lm}(i, j)$ = operating time of lights in the milking facility (h), which was assumed to be equal to the milking time [i.e., Roundup($N_{cows}/N_{cluster}$) × t_{row} + t_{wash}]. This was similar for the remaining variables, where hf = housing facility and od = outdoor area. $T_{lhf}(i, j)$ and $T_{lod}(i, j)$ were specified as inputs to the model and describe the operating times of the lights in the housing facilities and the outdoor areas during the months when animals are housed indoors.

Water Pump and Wash Pump. The predicted electricity consumed by the water pumps in month i and hour j, $Q_{wp}(i, j$; kWh), was described by the following equation:

$$Q_{wp}(i, j) = \{[V_{mc}(i, j) + V_{dc}(i, j) + V_w(i, j)]/P_c\} \times P_{wp}, \quad [10]$$

where $V_{mc}(i, j)$ = volume of water consumed by the milking cows (L), which was pumped to water troughs for drinking, and $V_{dc}(i, j)$ = volume of water consumed by the dry cows (L); V_{mc} and V_{dc} were taken from Beede (1992); $V_w(i, j)$ = water used for washing and cleaning (L), which was calculated using a combination of data from Beede (1992) and De Boer et al. (2013); P_c = total pump capacity (L/hour); and P_{wp} = total pump power (kW), which are model inputs.

Winter Housing. The predicted electricity consumption of the automatic scraping systems in month i and hour j [$Q_{as}(i, j)$; kWh] was described by the following equation:

$$Q_{as}(i, j) = S_{st} \times S_f(i, j) \times S_p \times (D_{in} - D_{out}), \quad [11]$$

where S_{st} = scraper sweep time (hours), S_f = scraping events in month i and hour j (dimensionless), S_p = scraper power (kW), D_{in} = housing date of animals (mo), and D_{out} = turnout date of animals (mo). The months of housing and turnout are converted to integers for the purposed of Equation 11.

Cost and CO_2 Calculations

The 7 electricity consumption matrices described above were summed for month i and hour j to give the total dairy farm consumption matrix ($\mathbf{M_t}$). Based on the user model inputs, a 12 × 24 matrix was populated for electricity tariffs. Tariffs were compiled from electricity suppliers of the farmers. The CO_2 emission factors for electricity production were taken from Howley et al. (2011) and used to populate a 12 × 24 matrix. These matrices were multiplied by $\mathbf{M_t}$ to yield the cost matrix ($\mathbf{M_c}$) and emission matrix ($\mathbf{M_e}$).

Model Validation

To validate the performance of the model, the energy consumption of 3 Irish farms were simulated and compared with actual farm data: a small farm (**SF**) with 45 milking cows, a medium farm (**MF**) with 88 milking cows, and a large farm (**LF**) with 195 cows. Farms chosen had spring calving herds in grass-based milk production systems with low supplementary feed input. Actual data from these farms were based on Upton et al. (2013), which yielded detailed electricity consumption data for all major infrastructural systems for all months in 2011, such as milking equipment, milk cooling, manure-handling equipment, water pumps, and winter housing facilities. Details of the farms scale and production levels are presented in Table 1.

Evaluating Model Bias and Precision

The following parameters were computed to evaluate model bias and precision.

Mean Square Prediction Error. The mean square prediction error (**MSPE**) comprises the mean bias, line bias, and random variation, and is defined by Equation 12 (Bibby and Toutenburg, 1977):

$$\mathrm{MSPE} = (A_m - P_m)^2 + S_P^2(1 - b)^2 + S_A^2(1 - \mathrm{r}^2), \quad [12]$$

where A_m and P_m = means of the actual and predicted electricity consumption data, respectively; S_A^2 and S_P^2 = variances of the actual and predicted electricity consumption data, respectively; b = slope of the linear regression of actual on predicted; and r = correlation coefficient of actual and predicted. A mean bias ($A_m - P_m$) different from zero indicates that predicted values are respectively consistently higher or lower than the actual values. A low line bias, which is the deviation of the slope of the regression of actual on predicted from unity ($1 - b$), indicates that the model will underpredict at low actual values and overpredict at high actual values, or vice versa. The results of mean bias, line bias, and random variation were calculated as a proportional contribution to each of the 3 components to the total MSPE. The proportional contribution of the mean bias, line bias, and random variation was calculated as the mean bias, line bias, and random variation divided by the MSPE. The relative contribution of the random variation around the regression line ($1 - \mathrm{r}^2$) is high if the MECD is predicting electricity consumption with a high level of accuracy. This random variation is due to electricity consumption variation due to farmer and equipment operating behavior.

The Root Mean Square Error. The root mean square error (**RMSE**; Bibby and Toutenburg, 1977) was calculated as follows:

$$\mathrm{RMSE} = \sqrt{\mathrm{MSPE}}. \quad [13]$$

The RMSE provides information on the accuracy of the simulation by comparing term by term the actual and predicted data.

Relative Prediction Error. The relative prediction error (**RPE**; Rook et al., 1990) was calculated as follows:

$$\mathrm{RPE} = \left(\frac{\mathrm{RMSE}}{A_m}\right) \times 100, \quad [14]$$

where A_m is the mean value of the actual data. The RPE is an expression of the RMSE as a percentage of the actual data. According to Fuentes-Pila et al. (1996), an RPE lower than 10% indicates a satisfactory prediction, between 10 and 20% a relatively acceptable prediction, and an RPE greater than 20% suggests a poor model prediction.

On-Farm Data Used for Model Validation

In 2011, actual milk production was 255,278 L for SF, 499,898 L for MF, and 774,089 L for LF, whereas the actual electricity consumption was 8,791 kWh for

Table 1. Mean values of characteristics for 3 farms: small farm (SF), medium farm (MF), and large farm (LF)

	Farm		
Farm characteristic[1]	SF	MF	LF
Farm area (ha)	48	70	110
Dairy herd size	45	88	195
Stocking density (LU/ha)	1.68	1.90	2.43
Milk production (L/yr)	255,278	499,898	774,089
Milk production (kg of MS/yr)	21,429	39,286	62,199
Production intensity (kg of MS/ha)	446	561	565
Milk solids per cow (kg of MS/cow)	476	446	319

[1]LU = livestock units, where 1 LU is equivalent to 1 adult dairy cow; MS = milk solids.

Table 2. Empirical electricity consumption of each infrastructural component, total consumption and costs for a small farm (SF), medium farm (MF), and large farm (LF) as measured in 2011 (Upton et al., 2013)

	Farm		
Parameter	SF	MF	LF
Milk cooling (kWh)	3,473	5,450	16,288
Water heating (kWh)	2,336	7,175	7,992
Milking machine (kWh)	2,150	3,673	5,714
Wash pump (kWh)	NA[1]	149	NA
Water pump (kWh)	87	1,994	2785
Automatic scrapers (kWh)	563	1,653	NA
Lighting (kWh)	183	983	483
Electricity consumption (Wh/L)	34	42	43
Total electricity consumption (kWh)	8,791	21,099	33,262
Electricity costs (€/L)	0.0043	0.0058	0.0051
Annual electricity costs (€)	1,097	2,900	3,942

[1]NA = not applicable.

SF, 21,099 kWh for MF, and 33,262 kWh for LF. Table 2 shows the actual electricity consumption (kWh) for each of the 7 main infrastructural systems on each of the 3 farm sizes. On average, milk cooling made up 40% of the total electricity consumption across all 3 farms (range: 26–49%), water heating: 28% (range: 24–34%), milking machine: 18% (range: 17–24%), wash pump: 0.3% (range: 0–0.7%), water pump: 8% (range: 1–9%), automatic scrapers: 4% (range: 0–8%), and lighting: 3% (range: 1–5%).

The actual electricity consumption and electricity costs per liter of milk were lowest for the SF (i.e., 34 Wh/L and €0.0043/L), with 62% of electricity consumed on the day rate electricity tariff (from 0900 to 2400 h). Electricity consumption values were 42 Wh/L for MF and 43 Wh/L for LF, whereas electricity costs were €0.0058/L for MF and €0.0051 €/L for LF, with 75 and 68% of the electricity being consumed on the day tariff, respectively.

Model Demonstration

To demonstrate the functionality of the model 2 existing tariff matrices were applied to the $\mathbf{M_t}$. First, the farm electricity costs were computed using the farm electricity tariffs from 2011. This took the form of a day and night tariff matrix, where the price of electricity changed from day to night rate at 0000 h and from night to day rate at 0900 h (as applied in Ireland in 2013), and a flat-rate tariff of €0.18/kWh, which corresponds to the rate for a medium-duty consumer (with consumption of approximately 15,000 kWh of electricity per year) in 2013. This demonstrates the ability of the model to react to changes in the electricity pricing structure. The model also has the ability to evaluate changes in technology applied to each of the 7 infrastructural systems on a dairy farm as well as the ability to evaluate managerial changes, such as once-per-day milking. However, it is outside the scope of this paper to demonstrate all of the functionality of the model.

RESULTS

Model Predictions

SF. The model predicted a total electricity consumption of 8,498 kWh, total electricity costs of €1,108, and electricity-related emissions of 4,633 kg of CO_2 (Table 3). Predictions were made for 5 of the 7 infrastructural systems on a monthly basis (Table 3). This farm did not use a wash pump for cleaning purposes. Moreover, the water supply of the SF was sourced, for the majority of the year, from a gravity-fed borehole that did not require pumping. During periods of dry weather or especially high water demand, a secondary pumped supply was used, which consumed only 87 kWh of electricity in 2011 (1% of the overall electricity consumption). Therefore, no prediction was made for this water pump electricity consumption due to the sporadic nature of its operation. The model underpredicted the total electricity consumption of the SF by 293 kWh (3.3%) and overpredicted the electricity costs by €11.50 (1%). The MSPE of the total electricity consumption prediction was 5,233 kWh^2. The proportion of variation made up by the mean bias, line bias, and random variation were 0.11, 0.01, and 0.88 (see Table 4), whereas the RMSE was 72.3 kWh and the RPE was 9.9%. Further details relating to the quality of predictions for the SF are presented in Table 4.

MF. The model predicted a total electricity consumption of 20,779 kWh, total electricity cost of €2,896, and electricity-related emissions of 11,329 kg of CO_2. Predictions were made for all of the 7 infrastructural systems on a monthly basis (Table 5). The model underpredicted the total electricity consumption of the MF by 320 kWh (1.5%) and underpredicted the total electricity costs by €4.10 (0.1%). The MSPE of the total electricity consumption prediction for the MF was 7,127 kWh^2; the proportion of variation made up by the mean bias, line bias, and random variation were 0.10, 0.02, and 0.88; the RMSE was 84.4 kWh; and the RPE was 4.8%. Further details relating to the quality of predictions for the MF are presented in Table 4.

LF. The model predicted a total electricity consumption of 32,326 kWh, total cost of €3,922, and total electricity-related emissions of 15,147 kg of CO_2. The LF did not use a standalone wash pump; instead, the main water pump was used for washing purposes. The LF did not use automated scrapers in the winter facility.

The model underpredicted the total electricity consumption by 936 kWh (2.8%) and underpredicted total electricity costs by €20.40 (0.5%). Further details of the model predictions of the LF are shown in Table 6. The MSPE of the total electricity consumption prediction for the LF was 47,997 kWh^2; the proportion of variation made up by the mean bias, line bias, and random variation were 0.13, 0.00, and 0.87 (Table 4); the RMSE was 219.1 kWh; and the RPE was 7.9%. Further details relating to the quality of predictions for the LF are presented in Table 4.

Model Bias and Precision

Table 4 shows the MSPE, RMSE, and RPE for the 7 infrastructural systems along with the actual and predicted electricity consumption values. The model was most accurate on the MF prediction, delivering an RPE of 4.8% (RMSE of 84.4 kWh) for total electricity consumption. About 88% of the variation was accounted for by the random variation. The RPE for total electricity consumption were 9.9% for SF (RMSE of 72.3 kWh) and 7.9% for LF (RMSE of 219.1 kWh). The random variation accounted for a large portion of the MSPE (i.e., 0.88 for SF and 0.87 for LF). The model prediction of milk-cooling consumption, water-heating consumption, and milking-machine consumption all yielded RPE of less than 20%. These consumptions made up 86% of total electricity consumption across all 3 farms, which made them the most important items to predict accurately. Automatic scraper consumption, lighting consumption, and water pump consumption proved more difficult to predict. The RPE values varied between 20 and 30% for water pump predictions, between 42 and 58% for automatic scraper consumption, and between 18 and 113% for lighting consumption. However these consumptions, when totaled, made up 14% of the total electricity consumption of the 3 farms.

Model Demonstration

Results of the demonstration of the model are presented in Table 7. For this analysis $\mathbf{M_t}$ was multiplied

Table 3. Model predictions for monthly and annual total kilowatt hour consumption, electricity costs (€), and electricity-related CO_2 emissions for the 7 main infrastructural components for the small farm (SF)

Model output for SF	January	February	March	April	May	June	July	August	September	October	November	December	Total
Milk cooling (kWh)	0	172	380	406	419	400	396	372	340	277	161	0	3,322
Water heating (kWh)	0	256	283	274	275	266	251	228	221	208	183	0	2,444
Milking machine (kWh)	0	175	262	221	228	221	228	228	221	228	122	0	2,131
Wash pump (kWh)	NA[1]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Water pump (kWh)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Automatic scrapers (kWh)	145	131	0	0	0	0	0	0	0	0	0	145	422
Lighting (kWh)	36	39	9	8	8	8	8	8	8	8	4	36	179
Total electricity consumption (kWh)	181	772	934	908	930	894	883	836	789	721	469	181	8,498
Electricity per liter (Wh/L)	0	69	26	24	28	27	28	32	35	39	80	0	33
Total electricity costs (€)	26	100	130	127	121	115	111	107	98	89	57	26	1,108
Electricity (kg of CO_2)	99	421	509	495	507	487	481	456	430	393	256	99	4,633

[1]NA = not applicable.

Table 4. Mean square prediction error (MSPE), root mean squared error (RMSE), and relative prediction error (RPE) for the 7 main infrastructural components in the electricity consumption prediction model as well as the prediction of total electricity consumption for the 3 modeled farms: small farm (SF), medium farm (MF), and large farm (LF)

Item	Actual (A; kWh)	Predicted (P; kWh)	Bias (P − A; kWh)	MSPE (kWh)^2	Proportion of MSPE: Mean bias	Line bias	Random variation	RMSE (kWh)	RPE (%)
SF									
Milk cooling	3,473	3,322	−151	745	0.21	0.35	0.44	27.3	9.4
Water heating	2,336	2,444	108	1,096	0.07	0.02	0.90	33.1	17.0
Milking machine	2,150	2,131	−18	601	0.00	0.23	0.77	24.5	13.7
Wash pump	NA[1]	NA	NA	NA	NA	NA	NA	NA	NA
Water pump	87	NA	NA	NA	NA	NA	NA	NA	NA
Automatic scrapers	563	422	−141	393	0.35	0.06	0.59	19.8	42.2
Lighting	183	179	−4	294	0.00	0.20	0.80	17.1	112.6
Total electricity consumption	8,791	8,498	−293	5,233	0.11	0.01	0.88	72.3	9.9
MF									
Milk cooling	5,450	5,353	−97	939	0.07	0.01	0.92	30.6	6.7
Water heating	7,175	7,294	119	702	0.14	0.18	0.68	26.5	4.4
Milking machine	3,673	3,628	−45	839	0.02	0.00	0.98	29.0	9.5
Wash pump	149	145	−4	4	0.02	0.03	0.94	2.0	16.3
Water pump	1,994	1,832	−162	1,110	0.16	0.74	0.10	33.3	20.1
Automatic scrapers	1,653	1,533	−120	6,284	0.02	0.10	0.88	79.3	57.6
Lighting	983	994	11	227	0.00	0.17	0.83	15.1	18.4
Total electricity consumption	21,099	20,779	−320	7,127	0.10	0.02	0.88	84.4	4.8
LF									
Milk cooling	16,288	14,898	−1,391	63,934	0.21	0.30	0.49	252.9	18.6
Water heating	7,992	8,303	311	11,652	0.06	0.04	0.90	107.9	16.2
Milking machine	5,714	6,124	411	4,450	0.26	0.46	0.28	66.7	14.0
Wash pump	NA	NA	NA	NA	NA	NA	NA	NA	NA
Water pump	2,785	2,452	−333	4,818	0.16	0.05	0.79	69.4	29.9
Automatic scrapers	NA	NA	NA	NA	NA	NA	NA	NA	NA
Lighting	483	493	10	55	0.01	0.00	0.99	7.4	18.4
Total electricity consumption	33,262	32,326	−936	47,997	0.13	0.00	0.87	219.1	7.9

[1]NA = not applicable.

by 2 different electricity price matrices to compute 2 different cost matrices. This approach yielded a model prediction for total farm electricity costs of €1,108 for SF, €2,896 for MF, and €3,922 for LF. Second, applying a flat-rate tariff of €0.18/kWh demonstrated the effect on total electricity costs if farms were to use a flat-rate electricity tariff instead of the day-and-night-rate tariff. Total electricity costs then increased to €1,530 for SF, €3,844 for MF, and €5,046 for LF.

DISCUSSION

Model Structure

Many models have been developed to simulate a range of important impacts of innovations at the farm level. Examples are biophysical and economic impacts on dairy farms (Shalloo et al. 2004; Baudracco et al., 2013), greenhouse gas effects at beef and dairy production systems (O'Brien et al., 2010; Foley et al., 2011), and pasture production effects in grazing systems (O'Neill et al., 2013). At this time, none of these models contains a dedicated electricity consumption submodel, probably because its financial impact was deemed insignificant when energy prices were low and environmental efficiency was not deemed important. However, to evaluate the impact of rising energy prices, or changes to pricing structure, or implementation of technical and managerial innovations on farm profitability and to estimate the environmental effects, a dedicated electricity model is required. Similarly if the MECD were integrated with a whole-farm modeling system, such as in Shalloo et al. (2004), the impact of scenarios such as once-per-day milking versus twice-per-day milking on energy efficiency and energy costs could be examined along with other management strategies, such as spring versus autumn calving or changes in breeding practices by the farmer (e.g., crossbreeding with Jersey cows, which may produce lower milk volumes but similar milk solids per animal).

The mechanistic modeling approach taken in the current study is similar to that taken by Henze et al. (1997), who used a mechanistic approach to describe the operating performance of an ice building system. Other modeling techniques exist, such as pattern recognition regression modeling, which are widely accepted as technologies offering alternative ways to tackle complex and ill-defined problems (Kalogirou, 1999). However, regression models are a generalization tool and are not useful in the analysis of innovations in an

Table 5. Model predictions for monthly and annual total kilowatt hour consumption, electricity costs (€), and electricity-related CO_2 emissions for the 7 main infrastructural components for the medium farm (MF)

Model output for MF	January	February	March	April	May	June	July	August	September	October	November	December	Total
Milk cooling (kWh)	51	308	623	866	672	592	532	485	436	373	294	121	5,353
Water heating (kWh)	591	563	624	603	624	619	640	640	635	640	549	567	7,294
Milking machine (kWh)	216	282	360	349	360	349	360	360	349	312	209	120	3,628
Wash pump (kWh)	12	11	12	12	12	12	12	12	12	12	12	12	145
Water pump (kWh)	101	109	184	192	185	222	153	145	159	118	128	136	1,832
Automatic scrapers (kWh)	315	284	315	0	0	0	0	0	0	0	305	315	1,533
Lighting (kWh)	66	82	103	91	94	91	94	94	91	82	64	41	994
Total electricity consumption (kWh)	1,352	1,640	2,221	2,113	1,947	1,885	1,792	1,737	1,682	1,538	1,560	1,312	20,779
Electricity consumption per liter (Wh/L)	129	63	38	34	32	26	37	38	33	49	66	106	42
Total electricity costs (€)	173	232	328	330	278	267	244	235	225	200	217	167	2,896
Electricity (kg of CO_2)	737	894	1,211	1,152	1,062	1,028	977	947	917	838	850	715	11,329

Table 6. Model predictions for monthly and annual total kilowatt hour consumption, electricity costs (€), and electricity-related CO_2 emissions for the 7 main infrastructural components for the large farm (LF)

Model output for LF	January	February	March	April	May	June	July	August	September	October	November	December	Total
Milk cooling (kWh)	56	682	1,121	1,739	2,275	1,870	2,034	1,779	1,739	1,102	398	101	14,898
Water heating (kWh)	669	633	709	675	701	699	717	717	699	717	683	685	8,303
Milking machine (kWh)	570	515	570	552	570	552	570	570	552	510	320	271	6,124
Wash pump (kWh)	NA[1]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Water pump (kWh)	7	116	280	325	377	305	282	241	221	174	106	20	2,452
Automatic scrapers (kWh)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Lighting (kWh)	77	70	41	40	41	40	41	41	40	37	23	0	493
Total electricity consumption (kWh)	1,379	2,016	2,722	3,331	3,965	3,466	3,645	3,348	3,251	2,540	1,530	1,132	32,326
Electricity consumption per liter (Wh/L)	589	55	31	32	33	36	41	44	47	46	46	182	42
Total electricity costs (€)	148	243	337	430	494	433	457	415	400	295	160	112	3,922
Electricity (kg of CO_2)	553	910	1,272	1,615	1,953	1,681	1,773	1,611	1,564	1,171	630	413	15,147

[1]NA = not applicable.

Table 7. Total electricity costs (€) and electricity costs per liter of milk produced (€/L) for a small farm (SF), medium farm (MF), and large farm (LF) for 2 tariff schemes[1]

	Farm					
	SF		MF		LF	
Model demonstration	Flat	Day and night	Flat	Day and night	Flat	Day and night
Total electricity costs (€)	1,530	1,108	3,844	2,896	5,046	3,922
Electricity cost per liter of milk (€/L)	0.0060	0.0043	0.0077	0.0058	0.0065	0.0051

[1]The tariff schemes were as follows: (1) a flat-rate tariff of €0.18/kWh was used, which corresponds to the flat rate for a medium-duty consumer in 2013; and (2) a day and night rate, where the price of electricity changed from day to night rate at 0000 h (midnight) and from night rate to day rate at 0900 h (as applied in Ireland). Day and night tariffs were compiled from electricity suppliers of the farms. The average day rate was €0.18/kWh and the average night rate was €0.09/kWh.

existing system. For example, it would be possible to forecast electricity use at the farm level, given a forecasted milk yield using a regression model. Many tools exist for the purpose of forecasting milk yields, such as those described by Grzesiak et al. (2006), Olori et al. (1999), and Quinn et al. (2005). However, a regression-based electricity prediction model would only be valid if the infrastructure installed on the farm remained static because these models are trained to predict the future based on historic performance. For these reasons, a mechanistic approach was taken in this study.

Model Validation

Relative prediction error values of less than 10% (9.9, 4.8, and 7.9% for the SF, MF, and LF, respectively) suggest that the MECD described in this paper can be classified as providing acceptable prediction accuracy for total electricity consumption (Fuentes-Pila et al., 1996). This level of accuracy is satisfactory for the intended use of this model as a decision-support tool for dairy farmers because the practical significance of the errors are low (i.e., prediction errors of total annual electricity costs amounted to approximately €11.50 for SF, €4.10 for MF, and €20.40 for LF). Moreover, the random variation accounts for >87% of the MSPE of the total electricity consumption predictions, indicating that the majority of errors in prediction are due to chance or random causes. This is preferred to having a large portion of errors accounted for by mean or line bias, which would indicate consistent steady-state errors or inadequacies in the structure of the model, respectively. The subpredictions of the 7 infrastructural systems generated mixed-accuracy levels. The milk-cooling consumption RPE values were 9.4% for SF, 6.7% for MF, and 18.6% for LF, which also can be classified as satisfactory prediction accuracy (i.e., <20% RPE). The water-heating consumptions were predicted with RPE values of 17.0% for SF, 4.4% for MF, and 16.2% for LF; this can be classified as satisfactory prediction accuracy. Similar satisfactory prediction accuracy was achieved for the milking machine consumptions, as the RPE values were 13.7% for SF, 9.5% for MF, and 14.0% for LF.

Some poor prediction accuracies were achieved for the water pump, automatic scraper, and lighting consumptions (details in Table 4). These components together, however, made up only 14% of the total electricity used across the 3 farms; hence, the poor RPE values achieved (especially for automatic scrapers) only slightly influenced the overall model accuracy. However, if this model were to be applied to a confinement dairy system where cows were housed indoors all year round and where the scrapers and lights made up a higher proportion of the total electricity consumption, then the overall accuracy could decline in a more significant fashion.

Sources of Variation

Variations in prediction accuracy were found with this modeling approach. Here, we will explain how some of the variations might have arisen.

Milk Cooling. The milk-cooling consumption (Q_{mc}) for a given volume of milk is driven largely by the COP of the cooling system (Equation 3). It is very common for modelers to assume a COP based on manufacturers performance data (Henze et al. 1997; Halvgaard et al. 2012; O'Dwyer et al. 2012; Hong et al. 2012). In the MECD, we accounted for the variation in ambient temperatures. It is possible, however, that the weather data used, which were sourced from a weather station approximately 20 miles away from the farms, did not present the ambient temperature of the air at the cooling compressor on the farms. The largest effect on milk-cooling energy predictions, however, were expected to be due to variations in effectiveness of the milk precooling system throughout the year. If ground water temperatures varied dramatically throughout the year, this would affect prediction accuracies.

Water Heating. Water-heating electricity consumption (Q_{wh}) is governed by hot water consumption, initial water temperature, and final hot water temperature. Many farmer-related sources of variation and equipment-related variations exist in this system. The frequency of washing of the milking machine with hot water is a fixed model input (i.e., it remains constant throughout the year). This may not reflect the true washing frequency, which may vary from season to season, causing prediction errors.

Milking Machine. The electricity consumed by the milking machine is influenced primarily by the time spent milking, which is influenced by size of the herd (N_{cows}), size of the milking machine ($N_{clusters}$), and the operator row time (**RT**). Row time can be approximated according to whether the farmer fully or partially prepares the cow teats before milking, as described by O'Brien et al. (2012). However, the model only uses 1 value throughout the year for RT. It is likely that a farmer would adjust RT throughout the year according to weather conditions and stage of lactation. This would introduce errors in the prediction of Q_{mm}.

Lighting. The model requires input on the types (e.g., T8 fluorescent, T5 fluorescent, sodium, halogen, and metal halide) and numbers of fittings located in the milking facility, outdoor areas, and winter housing facility. The model assumes that lighting in the milking facility is turned on during milking. A lighting behavior chart is a required model input and this allows the run times of the housing facility lights and outdoor area lights to be quantified. Naturally, the behavior of the farmer with regard to lighting will not follow these patterns in reality, resulting in prediction errors.

Water Pumping. The quantity of electricity consumed by the water pumps is influenced by the quantity of water consumed by the milking facility during and after milking, the water consumed by the dairy cows, and the maintenance water for stock during the year. Drinking water consumed by the dairy herd will vary from day to day and season to season, which will not be picked up by the model, resulting in prediction errors of this metric.

Winter Facilities. Electricity is consumed in the winter housing facilities by automatic manure-handling equipment. An automatic scraper behavior chart is a required model input and this allows the run times of the scraping equipment to be quantified. However, if the scrapers run more or less frequently in reality, then variation will be introduced.

Model Applications

Farmers are presented with a plethora of alternative technologies and strategies when upgrading infrastructure (especially around milk harvesting technology). The MECD has been developed with an adaptable infrastructure approach in mind, allowing for alternative technologies and managerial changes to be evaluated. Moreover, the MECD could be used to optimize the decision-making process for new technologies at the farm level. Similarly, the effect of milking speed on electricity costs could be evaluated, with variations arising from variations in milking parlor size, milking routine among farmers, or variations in cow type.

Countries such as Estonia, Finland, France, Ireland, Italy, Malta, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom are all classified as "dynamic movers" in relation to the implementation of smart grid infrastructure. Within these countries, either the mandatory rollout is already decided or major pilot projects are underway to evaluate the feasibility of smart grids (Hierzinger et al., 2012). Countries such as Australia and New Zealand have recognized smart metering as a method of improving resource use efficiency and have carried out some early-stage feasibility studies and cost-benefit analysis calculations (DRET, 2008; Energy Federation of New Zealand, 2010). These developments heighten the importance of energy efficiency and, moreover, increase the need for further analysis of the impact of smart grids on dairy farming, especially in countries where milk production is a substantial or expanding industry. The MECD could be used to account for time of use tariffs or dynamic pricing tariffs, which would provide guidelines to farmers on how best to use these new pricing structures to their advantage.

CONCLUSIONS

A model was built that simulated the total yearly electricity consumption, electricity consumption of the 7 main infrastructural systems, total electricity costs, and total electricity-related CO_2 emissions. This model was validated by comparing the simulated results against actual farm data, using empirical data of farms of varying scale. The model delivered an acceptable RPE of <10% for total electricity consumption, with over 87% of the MSPE of total electricity consumption being accounted for by random variation. These levels of accuracy make the model suitable for application as an advice tool for farmers to improve their energy efficiency and reduce milk-production costs. The usefulness of the model was demonstrated through an electricity tariff change (i.e., from day-and-night rate to flat rate), which showed that total electricity costs would increase by over 30% if farmers were to use a flat-rate tariff instead of a day and night tariff. This methodology could be used to assess the impact of various time-of-use tariffs or even a dynamic pricing system on total electricity costs in the future.

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