

Review

Energy Consumption on Dairy Farms: A Review of Monitoring, Prediction Modelling, and Analyses

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Abstract: The global consumption of dairy produce is forecasted to increase by 19% per person by 2050. However, milk production is an intense energy consuming process. Coupled with concerns related to global greenhouse gas emissions from agriculture, increasing the production of milk must be met with the sustainable use of energy resources, to ensure the future monetary and environmental sustainability of the dairy industry. This body of work focused on summarizing and reviewing dairy energy research from the monitoring, prediction modelling and analyses point of view. Total primary energy consumption values in literature ranged from 2.7 MJ kg⁻¹ Energy Corrected Milk on organic dairy farming systems to 4.2 MJ kg⁻¹ Energy Corrected Milk on conventional dairy farming systems. Variances in total primary energy requirements were further assessed according to whether confinement or pasture-based systems were employed. Overall, a 35% energy reduction was seen across literature due to employing a pasture-based dairy system. Compared to standard regression methods, increased prediction accuracy has been demonstrated in energy literature due to employing various machine-learning algorithms. Dairy energy prediction models have been frequently utilized throughout literature to conduct dairy energy analyses, for estimating the impact of changes to infrastructural equipment and managerial practices.

Keywords: dairy; energy; review; modelling; efficiency; sustainable agriculture; machine-learning

1. Introduction

The Food and Agriculture Organization of the United Nations has forecasted the global consumption of milk and dairy produce to increase by 19%, to 99 kg person⁻¹ year⁻¹ by 2050, compared to 2005–2007 levels [1]. This increase is largely due to an increased forecasted demand from developing countries (fueled by projected Gross Domestic Product (GDP) growth), where a 46% increase is projected across Latin America, Sub-Saharan Africa, South Asia, East Asia, and Near East/North Africa [1]. Thus, a 22% growth in global milk production is forecasted in the ten year period between 2018 and 2027 [2]. In 2018, the European Union (EU-28) was the largest producer of milk worldwide producing 153 billion liters of milk, producing a 59% greater volume of milk than the USA [3]. Since 2015, milk production volumes increased by 6% in the EU and USA to help supply increased global demand [3]. From an environmental perspective, the increased dairy herd and consequent increased milk production comes with its own significant challenges regarding the consumption of on-farm energy resources and related greenhouse gases (GHG) [4,5].

Energy consumption on dairy farms is composed of direct (on-farm energy use) and indirect energy use (energy required to produce farm inputs; e.g. concentrate feed) [4,6]. Thus, energy use can be attributed to electricity consumption, liquid fuel use, fertilizer application, concentrate feed, and other miscellaneous energy consumption. Naturally, an increase in milk production will result in an increased energy consumption unless changes to management strategies and/or farm infrastructure are carried out. The magnitude and efficiency (energy use per kg of milk produced or per head) of energy consumption on dairy farms will vary according to a number of factors including (but not limited to): type of production system (e.g. grazing, confined, conventional, organic, calving pattern, etc.), type of milking system (e.g. conventional or automatic milking system (AMS)), milking schedules, installed infrastructure, climate, etc. [4,5,7,8]. The importance of dairy energy consumption is twofold: 1) environmentally, the use of grid-sourced electricity, liquid fossil energy (e.g. kerosene, diesel), and natural gas on dairy farms have a related GHG intensity with negative environmental impact. While the production of milk, processing, and transport of dairy products contribute to 4% of global anthropogenic emissions, the dairy industry must respond to recent increased scrutiny by minimizing its environmental impact across all stages of the dairy supply chain [9]. 2) economically, grid-sourced electricity may be exposed to rising energy costs, increasing financial concerns for dairy farmers, and increasing interest in energy efficient and renewable energy technologies to help improve energy independence and minimize energy usage [4,6].

The expansion of dairy farms globally must be met with considerations regarding minimizing energy consumption to insure the future sustainability of dairy farms. Dairy energy research will become increasingly important as researchers aim to identify new technologies and methods to improve the energy efficiency of producing milk and dairy products. Recently, Baldini et al. [10] focused on reviewing life cycle analyses strategies in the dairy industry. However, there exists a lack of secondary research (literature review) which focuses specifically on energy use. This review focused on critically assessing published literature related to the monitoring, prediction modelling and analyses of energy consumption in dairy farming. In particular, this review placed specific emphasis on the portion of energy consumption that can be controlled by the farmer, although research focusing on indirect energy use is also incorporated. This review incorporated two primary components; 1) review of research studies, which focusing on dairy energy assessment, prediction modelling and analyses; and 2) a discussion highlighting common trends throughout the dairy energy literature.

2. Dairy Energy

Research regarding energy on dairy farms has primarily focused on life cycle assessment (LCA), developing prediction models, and analyzing various strategies to reduce energy consumption, related costs, and GHG emissions. Interest regarding the energy intensity of dairy farming is due in part to conflicting targets regarding increasing milk production and reducing GHG emissions (i.e. the EU aims for a 30% reduction in GHG emissions by 2030, compared to 2005 levels) [11,12]. Concurrently, due to the volatile nature of milk pricing, dairy farmers should adequately prepare for periods of reduced revenue through minimizing the costs of all aspects of production. Monitoring and effectively reducing the energy intensity of the milk production process may offer significant environmental benefits, increase profits for dairy farmers and improve the long-term sustainability of the global dairy industry. In this review, dairy energy related research studies will be differentiated according to whether they report results from conventional, organic, confined or pasture-based systems [5]. This literature review covers international studies related to dairy energy measurement and assessment, prediction modelling, and the conservation/analysis of energy on dairy farms.

2.1. Dairy Energy Assessment

Total energy consumption on dairy farms can be categorized as direct and indirect energy use [4,6,13]. Direct energy is composed of energy consumption carried out directly on the farm. For example, electrical energy consumption and the consumption of liquid/gaseous fuels. Indirect energy is

composed of those energy uses whereby the direct energy use occurs outside the farm boundaries [13]. More specifically, indirect energy is the energy embodied in the products used on the farm. Examples of indirect energy sources include the energy required to produce and transport feed, fertilizers, and agricultural chemicals, which are produced outside the farm, but consumed on the farm.

In 2017, Baldini et al. [10] conducted a critical review of the recent evolution of LCA when applied to milk production. They noted inconsistencies between functional units defined throughout international literature and suggested the definition of a common functional unit. This would allow for direct comparison between the results of international studies, with different assumptions. This inconsistency was found throughout the dairy energy literature whereby functional units included energy corrected milk (ECM), fat and protein corrected milk (FPCM), milk solids (MS), kg of milk, fat-corrected milk (FCM), and liters of milk. The authors noted that the most common functional unit throughout the literature was ECM, thus when possible, ECM was utilized for comparative purposes. Key performance indicators, which utilized the remaining functional units were then converted to their ECM equivalence when milk fat and protein percentage values were available. If milk fat and protein values were unavailable in a research paper, the corresponding authors were contacted directly via email.

2.1.1. Total Energy

A summary of 23 studies that were utilized for calculating average energy usage values (MJ kg^{-1} ECM), as displayed in Table 1. In total, 36 studies were gathered across 17 countries, however, 13 of these studies presented energy consumption values relative to either MJ kg^{-1} , MJ kg^{-1} FPCM, or MJ kg^{-1} FCM, without reporting corresponding fat and protein percentage values to convert to MJ kg^{-1} ECM using Equation (A1), Equation (A2), and Equation (A3). Further details related to the 36 research findings are available in Appendix B.

Total primary energy use was 54% greater on conventional farms compared to organic farms, as shown in Table 1. This was primarily due to increased indirect energy use on conventional farms, as conventional farms used 75% greater indirect energy, while organic farms used 13% less direct energy, on average.

Table 1. Mean energy consumption and characteristics of studies found in literature.

Title Characteristic	Conventional		Organic	
	Conv-g *	Conv-c	Org-g	Org-c
No. of studies	5	11	5	2
No. of countries	4	11	4	2
Mean no. farms per study	37	43	5	9
Total Energy (MJ kg^{-1} ECM)	2.8	4.7	2.9	2.1
	4.1		2.7	

* Conv-g = conventional grazing farm; Conv-c = conventional confinement farm; Org-g = organic grazing farm; Org-c = organic confinement farm.

Across the 16 studies that reported energy use (MJ kg^{-1} ECM) on conventional dairy farms, an average of 4.1 MJ kg^{-1} ECM was calculated. Conventional confinement farming systems (Conv-c) had an average of 4.7 MJ kg^{-1} ECM across the literature, while conventional grazing farming systems (Conv-g) had an average of 2.8 MJ kg^{-1} ECM. Thus, Conv-c dairy farms required 68% greater energy resources compared to Conv-g dairy farms. Differences in energy requirements between Conv-c and Conv-g dairy farms will be discussed further in Sections 2.1.2 and 2.1.3.

Across the seven studies that reported energy use on organic dairy farms, an average of 2.7 MJ kg^{-1} ECM was calculated. Organic confinement farming systems (Org-c) studies had an average of 2.1 MJ kg^{-1} ECM across the literature, while organic grazing or pasture-based systems (Org-g) studies reported an average of 2.9 MJ kg^{-1} ECM. Interestingly, the mean energy consumption of Org-g farms

was only 4% greater than that of Conv-g farms. In contrary to conventional dairy farms, Org-c dairy farms required 28% less energy resources compared to Org-g dairy farms. Differences in energy requirements between Org-c and Org-g dairy farms will be discussed further in Sections 2.1.2 and 2.1.3.

2.1.2. Indirect Energy

Indirect energy consumption is sectioned into two categories: ancillary and embodied, as shown in Tables 2 and 3. Ancillary energy encompasses energy utilized for the production of agricultural products utilized on farm, such as fertilizer and feed. Concurrently, embodied energy refers to the energy consumed in the mining of raw materials for, and production of capital dairy farm inputs averaged across their expected working life, assuming straight-line depreciation [14]. Embodied energy sources include buildings and facilities, and machinery and equipment. Due to the lack of available data, embodied energy calculations are rarely included in LCA [10].

Ancillary Energy

On average, studies that reported on ancillary energy requirements on conventional dairy farms (Conv-g or Conv-c) reported an average of 3.0 MJ kg⁻¹ ECM, as may be calculated using data shown in Table 2.

Table 2. Ancillary energy values found in literature.

	Study	System	Country	MJ kg ⁻¹ ECM
Fertilizer	Meul et al. [15]	Conv-c	BEL	0.82
	O'Brien et al. [5]	Conv-c	IRL	0.49
	Pagani et al. [16]	Conv-c	ITA/USA	0.21
	Todde et al. [17]	Conv-c	ITA	0.84
	O'Brien et al. [5]	Conv-g	IRL	1.09
	Pagani et al. [16]	Conv-g	ITA / USA	0.30
	Upton et al. [4]	Conv-g	IRL	1.34
	Wells [14]	Conv-g	NZ	0.66
	Pagani et al. [16]	Org-c	ITA	0.00
	Pagani et al. [16]	Org-g	USA	0.00
	Fertilizer mean	Conv-c	n/a	0.59
	Fertilizer mean	Conv-g	n/a	0.85
Feed	Aguirre-Villegas et al. [18,19]	Conv-c	USA	1.54
	Meul et al. [15]	Conv-c	BEL	0.24
	Pagani et al. [16]	Conv-c	ITA / USA	2.28
	Sefeedpari et al. [20,21]	Conv-c	IRN	6.30
	Todde et al. [17]	Conv-c	ITA	3.90
	Pagani et al. [16]	Conv-g	ITA / USA	1.44
	Upton et al. [4]	Conv-g	IRL	0.49
	Pagani et al. [16]	Org-c	ITA	0.85
	Pagani et al. [16]	Org-g	USA	1.22
		Feed mean	Conv-c	n/a
	Feed mean	Conv-g	n/a	0.96

Key performance indicators were converted to ECM using Equation (A1), Equation (A2) and Equation (A3).

On these conventional farms, the use of fertilizer was responsible for 0.7 MJ kg⁻¹ ECM, while the production of feed required 2.3 MJ kg⁻¹ ECM. On the only study involving organic dairy farms (Org-c and Org-g) [16], fertilizer required 0.0 MJ kg⁻¹ ECM. The production of feed utilized on conventional farms required 131% greater energy to produce compared to the value of 1.0 MJ kg⁻¹ ECM calculated by Pagani et al. [16] on organic farms (Org-c and Org-g).

Comparing ancillary energy requirements of confinement and grazing system dairy farms, fertilizer used on Conv-g farms required 44% greater energy to produce compared to Conv-c farms, on average. Regarding the energy required for feed, Conv-c farms required 196% greater energy

compared to Conv-g farms. This difference in feed energy requirements is due to large portions of cattle feed being met by pasture on Conv-g farms as opposed to concentrated feed. On organic farms, the energy required for fertilizer production required 0.0 MJ kg^{-1} ECM for both the Org-c and Org-g systems. Regarding feed, Pagani et al. [16] found that feed consumed by dairy cows on Org-g farms required 43% greater energy for production compared to Org-c farms. Overall, Conv-c farms reported 90% greater ancillary energy compared to Conv-g farms.

Embodied Energy

Embodied energy requirements on conventional dairy farms (Conv-g or Conv-c) reported in literature averaged 0.8 MJ kg^{-1} ECM, as may be calculated using data shown in Table 3.

Table 3. Embodied energy values found in literature.

	Study	System	Country	MJ kg^{-1} ECM
Buildings and Facilities	Kraatz [22]	Conv	DEU	0.10
	Todde et al. [17]	Conv	ITA	0.29
	Wells [14]	Conv	NZ	0.25
	Buildings and facilities mean	Conv	n/a	0.21
Machinery and Equipment	Kraatz [22]	Conv-c	DEU	0.57
	Meul et al. [15]	Conv-c	BEL	1.27
	Pagani et al. [16]	Conv-c	ITA / USA	0.24
	Sefeedpari et al. [20,21]	Conv-c	IRN	0.08
	Todde et al. [17]	Conv-c	ITA	1.08
	Pagani et al. [16]	Conv-g	ITA / USA	0.27
	Pagani et al. [16]	Org-c	ITA	0.39
	Pagani et al. [16]	Org-g	USA	0.62
Machinery and equipment mean	Conv-c	n/a	0.65	

Key performance indicators were converted to ECM using Equation. (A1), Equation (A2) and Equation (A3).

On these conventional farms, embodied energy contained in the production of building and facilities equaled 0.2 MJ kg^{-1} ECM, while no studies for organic farms were reported in literature. Embodied energy contained within machinery and equipment equaled 0.6 MJ kg^{-1} ECM on conventional farms, greater than the value of 0.50 MJ kg^{-1} ECM calculated by Pagani et al. [16] on organic farms (Org-c and Org-g).

Regarding the energy embodied within dairy farm buildings and facilities, Conv-g farms contained 27% greater embodied energy compared to the Conv-c farm. Regarding the energy embodied within machinery and equipment, the single Org-g farm had 60% greater energy embedded in machinery and equipment compared to the single Org-c farm. On Conv-c farms, 0.6 MJ kg^{-1} ECM were embodied within machinery and equipment, while 0.3 MJ kg^{-1} ECM were embodied on Conv-g farms. Overall, Conv-c farms had 62% greater embodied energy compared to Conv-g farms.

2.1.3. Direct Energy

A summary of total on-farm electricity consumption usage metrics is displayed in Table 4. Electrical energy is directly consumed on farm through milk cooling (refrigeration), milk harvesting (vacuum pumps), water heating, water pumping, lighting, as well as other miscellaneous usage throughout the farm. The other major source of direct energy use includes the consumption of liquid/gaseous fuels such as diesel, kerosene, natural gas, liquefied petroleum gas (LPG), and lubricants. Liquid fuels may be utilized on-farm for water heating or for powering mechanical machinery (e.g. tractors).

Electrical energy

On average, 48.9 watt-hours of electrical energy are consumed per kg of milk (Wh kg^{-1}) ($n = 4$) on conventional dairy farms, as shown in Table 4. On conventional farms (Conv-c and Conv-g), milk

cooling was the largest consumer of electrical energy on dairy farms, consuming 15.3 Wh kg⁻¹ on average. Milk harvesting was found to be the second largest consumer of electricity (14.0 Wh kg⁻¹) followed by water heating (9.5 Wh kg⁻¹), and water pumping (3.3 Wh kg⁻¹). However, Edens et al. [24] (n/a), Hörndahl [25] (n/a), and Todde et al. [29] (23%) found milk harvesting to be the largest consumer of electricity, while additionally, although no specific electricity consumption values were reported, Hartman and Sims [30] found water heating to be the largest consumer of electrical energy, consuming 31%, followed by milk cooling (21%), milk harvesting (18%), water pumping (18%), and miscellaneous usage throughout the farm (12%).

Table 4. Electrical energy consumption breakdown statistics of studies found in literature (Wh kg⁻¹).

Study	System	Country	Total	Milk Cooling	Milk Harvesting	Water Heating	Water Pumping
Calcante et al. [23]	AMS-c	ITL	n/a	n/a	11.13	n/a	n/a
Edens et al. [24]	Conv-c	USA	n/a	21.17	22.82	13.50	n/a
Hörndahl [25]	Conv-c	SWE	n/a	16.70	23.01	4.85	n/a
Hörndahl [25]	AMS-c	SWE	n/a	13.20	20.49	5.05	n/a
Murgia et al. [26]	Conv-c	ITA	42.84	9.85	8.14	3.43	4.71
Rajaniemi et al. [27]	Conv-c	FIN	n/a	21.70	12.00	16.30	1.51
Rajaniemi et al. [27]	AMS-c	FIN	n/a	21.90	29.30	2.20	n/a
Shine et al. [8]	Conv-g	IRL	38.68	11.24	6.91	7.66	1.51
Shortall et al. [28]	AMS-g	IRL	60.78	10.97	20.10	4.27	2.62
Todde et al. [29]	Conv-c	ITA	73.00	13.87	16.79	10.95	6.57
Upton et al. [4]	Conv-g	IRL	41.11	12.64	8.19	9.54	2.07
Mean	AMS-c	n/a	n/a	17.45	14.54	10.67	1.51
Mean	Conv	n/a	48.91	15.32	13.97	9.45	3.28
Mean	Conv-c	n/a	57.92	16.68	16.54	9.80	4.27
Mean	Conv-g	n/a	39.89	11.94	7.55	8.60	1.79

Concurrently, the one study that calculated total electricity consumption of AMS farms found 60.8 Wh kg⁻¹ were consumed (24% greater than conventional farms) [28]. Four AMS farms reported on sub-metered energy consumption values, whereby on these farms (AMS-c and AMS-g), milk harvesting was the largest consumer of electrical energy, consuming 20.2 Wh kg⁻¹. Milk cooling was found to be the second largest consumer of electricity (16.4 Wh kg⁻¹) followed by water heating (3.2 Wh kg⁻¹), and water pumping (2.6 Wh kg⁻¹). All four studies [23,25,27,28] found milk harvesting to be the greatest consumer of electricity on AMS farms. Although none of the farms included in Table 4 are organic farms, electrical energy on organic farms is of greater importance compared to conventional farms because it represents 26% of total primary energy usage, compared to 17% on conventional farms (calculated using energy values in Table A1). In Ireland, Upton et al. [4] found that electricity consumption was the largest source of total direct energy use (60%), representing 12% of total energy consumption on Irish dairy farms. They found that electricity use was the third largest contributor to total energy use behind indirect energy related to fertilizer application (57%) and concentrates feed (21%). On the 22 Irish study farms, Upton et al. [4] found 41.1 Wh kg⁻¹ were consumed on average in 2011. Shine et al. [8] carried out a more focused assessment of dairy electricity consumption on Irish dairy farms by utilizing 43 dairy farms monitored throughout the 2015 calendar year. Shine et al. [8] reported an electricity usage value of 38.7 Wh kg⁻¹, thus 6% less than Upton et al. [4]. Using a day/night pricing tariff (day tariff of 0.18 € kWh⁻¹; night tariff of 0.08 € kWh⁻¹ from 00:00 to 09:00 h), Upton et al. [4] calculated a mean cost of 0.51 € cent L_m⁻¹ in 2011, while Shine et al. [8] calculated a mean cost of 0.55 € cent L_m⁻¹ in 2015. With production costs averaging 21.8 cent L_m⁻¹ in 2016 [31], and using values calculated by Shine et al. [8], electricity costs are responsible for 2.5% of overall production costs, on average. Hartman and Sims [30] calculated electricity costs of between \$0.06 per cow⁻¹ day⁻¹ and \$0.12 per cow⁻¹ day⁻¹, equaling between 1.5% and 3.0% of total costs. However, they employed an assumed electricity tariff of \$0.17 kWh⁻¹, as opposed to a day/night or day/night/peak pricing tariff.

To the authors' knowledge, no other studies directly assessed with the monetary aspect of electrical energy consumption on dairy farms, possibly due to varying electrical energy costs between countries. However, Todde et al. [32] developed the dairy energy prediction (DEP) model, which allowed for the estimation of diesel and electricity energy usage, CO₂ emissions, and monetary costs (static electricity price). This model is discussed further in Section 2.2.2.

In Italy, Murgia et al. [26] conducted a partial LCA to quantify the energy intensity associated with electricity and diesel use on 20 dairy farms in 2011 (mean herd size = 320 cows; range = 158 – 500 cows). They found electricity use contributed 30% to direct energy consumption (401 kWh per lactating cow, 42.84 Wh kg_m⁻¹), thus less than the average of 47% found between international studies. Concurrently, Todde et al. [29] analyzed the direct energy use of 285 Italian dairy farms through a detailed survey of electricity, diesel and liquefied petroleum gas consumption and related on-farm activities and processes. They calculated an electricity consumption value of 73 Wh kg_m⁻¹. Similar to Murgia et al. [26] electricity accounted for 27% of direct energy use. Additionally, in Italy, utilizing 60 dairy farms in the Emilia Romagna region in 2009, Rossi et al. [33] calculated values of 510 kWh cow⁻¹ year⁻¹ and 64 Wh kg_m⁻¹, again, representing greater electricity consumption values than Murgia et al. [26].

Meul et al. [15] utilized a representative set of Flemish farms to analyze the energy use efficiency of dairy, arable and pig farms between the 1989–1990 and 2000–2001 periods. They found that energy usage per hectare reduced significantly during the considered timeframe. They also showed greater energy efficiency associated with more intense dairy farming practices, while electricity use contributed to 9.5% of overall dairy farm energy use across the 2000 to 2001 period.

Similar to Upton et al. [4] and Shine et al. [8], Kraatz [22] found that milking equipment (vacuum pumps, milk bulk tanks, and water heaters) were the major electricity consumers on German dairy farms. In Finland, Rajaniemi et al. [27] calculated electricity consumption associated with milk production (milk-cooling, milk harvesting and water-heating) to vary between 37 and 67 Wh kg_m⁻¹ when analyzing three dairy farms (mean herd size = 82 cows), one farm of which employed an AMS. Rajaniemi et al. [27] reported milk harvesting and milk-cooling as the largest electricity consumers on the AMS farm, (29% and 22%, respectively), while on the two Conv-c farms, milk-cooling and water-heating were the two largest electricity consuming processes (22% and 16%, respectively). In Denmark, Brøgger Rasmussen and Pedersen [34] analyzed the electricity consumption within the milking parlor on 17 dairy farms, which each employed an AMS between June 2003 and February 2004, making comparisons with a conventional herringbone parlor and 26-stall rotary milking parlor. Across four AMS brands, Brøgger Rasmussen and Pedersen [34] found AMS to consume between 15.2 and 86.0 Wh kg_m⁻¹ (values converted from liters of milk using milk volumetric mass density value equal to 1.03 kg per liter), while the conventional milking parlors consumed between 19.0 and 21.5 Wh kg_m⁻¹. Concurrently, Brøgger Rasmussen and Pedersen [34] found (in diminishing order (no specific values reported)) the vacuum pump, milk-cooling, electric water heater and automatic washing system to be the greatest electricity consuming processes on AMS dairy farms.

Hörndahl [25] measured and analyzed the electricity consumption of two Swedish dairy farms (herd sizes: 150 cows and 202 cows), finding that milk harvesting (24.4 Wh kg_m⁻¹), milk-cooling (17.7 Wh kg_m⁻¹), and water-heating (5.2 Wh kg_m⁻¹) were the three largest electricity consuming processes. Additionally, Edens et al. [24] conducted a thorough energy analysis of the four major energy components on USA based dairy farms (vacuum pumps, refrigeration compressors, water heaters (with water preheater), and an air compressor). Utilizing 14 years of data for a single farm (herd size = 160 cows), they calculated the kWh requirement per 100 pounds of milk produced (values were converted to Wh kg_m⁻¹ using milk volumetric mass density of 1.03 kg L_m⁻¹). They found milk harvesting (24.2 Wh kg_m⁻¹) to be the largest consumer of electrical energy, followed by milk cooling (22.5 Wh kg_m⁻¹), and water heating (14.3 Wh kg_m⁻¹). Concurrently, Hartman and Sims [30] measured the electrical energy consumption on three New Zealand dairy farms. They found that on average, total energy use amounted to 47 MJ kg⁻¹ MS, whereby 30% was associated to electricity (163 kWh cow⁻¹

year⁻¹). As they calculated and presented total energy use in MJ kg⁻¹ MS and electricity efficiency as kWh cow⁻¹ year⁻¹, without reporting milk production, protein, and fat content values, it is difficult to make comparisons with cognate studies. However, they did breakdown electricity consumption, whereby water heating (31%) was the largest consuming process, followed by milk cooling (21%), water pumping (18%), milk harvesting (18%), and miscellaneous usage (12%).

Liquid Fuel Energy

Liquid fuel energy usage values are summarized in Table 5. All studies presented in Table 5 focused on conventional dairy systems, except for one study that reported diesel use for farms that had AMS installed. On average, 0.73 MJ kg⁻¹ ECM of energy is required on conventional dairy farms (Conv-c and Conv-g) in the form of diesel fuel. Conv-c farms consume 1.0 MJ kg⁻¹ ECM, while Conv-g farms consume 0.2 MJ kg⁻¹ ECM. However, this comparison contains only a small number of farms, thus making it difficult to make useful conclusions. This is particularly important as diesel consumption would be expected to be greater on pasture-based farms due to the increased tractor requirement for larger pasture production, as found by Cederberg and Mattson [35] when comparing conventional and organic dairy farms. Cederberg and Mattson [35] also found that the use of crude oil was greater on conventional dairy farms compared to organic farms. However, Cederberg and Mattson [35] did not report on exact liquid fuel consumption values. For conventional dairy farms (both Conv-c and Conv-g), diesel use equaled 0.7 MJ kg⁻¹ ECM, lubricants equaled 0.03 MJ kg⁻¹ ECM, LPG equaled 0.02 MJ kg⁻¹ ECM, while kerosene equaled 0.02 MJ kg⁻¹ ECM. Thus, in total, liquid fuels were responsible for 0.92 MJ kg⁻¹ ECM.

Table 5. Liquid energy consumption breakdown statistics of studies found in literature.

Fuel	Study	System	Country	MJ kg ⁻¹ ECM
Diesel	Hospido et al. [36]	AMS-c	ESP	0.16
	Meul et al. [15]	Conv-c	BEL	0.79
	Sefeedpari et al. [20,21]	Conv-c	IRN	1.09
	Thomassen et al. [37]	Conv-c	NLD	0.29
	Todde et al. [17]	Conv-c	ITA	1.89
	Upton et al. [4]	Conv-g	IRL	0.19
	Diesel mean	Conv-c	n/a	1.01
Kerosene	Sefeedpari et al. [20,21]	Conv-c	IRN	0.04
	Upton et al. [4]	Conv-g	IRL	2.28x10 ⁻³
LPG	Todde et al. [17]	Conv-c	ITA	0.02
Lubricants	Meul et al. [15]	Conv-c	BEL	0.05
	Upton et al. [4]	Conv-g	IRL	2.47x10 ⁻³

LPG = liquefied petroleum gas. Key performance indicators were converted to ECM using Equation (A1), Equation (A2), and Equation (A3).

In addition to Table 5, Murgia et al. [26] found diesel fuel contributed 70% to the total direct energy consumption (92 kg per cow, 0.021 kg diesel kg⁻¹ FPCM). Concurrently, Todde et al. [29] calculated a liquid fuel consumption of 40 kg per tonne of milk produced. Similar to Murgia et al. [26], diesel fuel accounted for 72% of total direct energy requirement. Wells [14] calculated liquid fuels to be responsible for 20% of total primary energy consumption on the average New Zealand dairy farm, equating to 0.40 MJ kg⁻¹ ECM. Concurrently, O'Brien et al. [5] calculated the liquid energy consumption of both Conv-c and Conv-g dairy systems, finding that liquid fuels were responsible for 4.6% and 12.7% of total primary energy, respectively. This equated to 0.18 MJ kg⁻¹ ECM and 0.30 MJ kg⁻¹ ECM for Conv-c and Conv-g systems, respectively.

2.1.4. Dairy Energy Assessment Summary

A breakdown of total primary energy for conventional and organic farming systems is displayed in Figure 1.

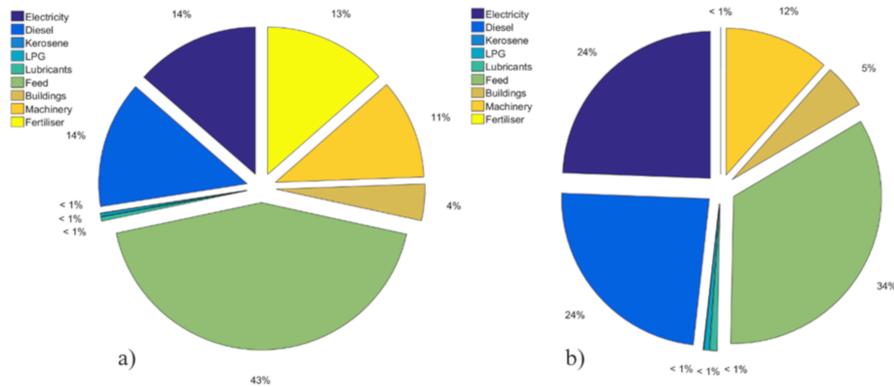


Figure 1. Pie charts showing the breakdown of total primary energy consumption on: a) conventional dairy farm systems and b) organic systems (b).

Balance equations were used for the development of pie chart in Figure 1, while liquid fuel usage values, energy embodied in buildings, and facilities were assumed to be equal on conventional and organic farms, due to unavailability of data for organic farms. These pie charts contain energy consumption associated with electricity, diesel, kerosene, LPG, lubricants, fertilizer, feed, buildings and facilities, and machinery and equipment. In summary, across the studies considered in this review, the production of feed requires the greatest energy consumption on both conventional and organic dairy systems, requiring 43% and 34%, respectively. On conventional dairy farms, electricity and diesel use were both the second greatest consumers of energy, each responsible for 14% of total energy, followed by the energy required for the production of fertilizer (13%), and energy embodied in machinery and equipment (11%), and buildings and facilities (4%). On organic farms, electricity and diesel use were each responsible for 24% of total primary energy, followed by energy embodied in machinery (12%) and energy embodied in buildings and facilities (5%). On conventional farms, direct energy use was responsible for 28% of total primary energy whereby, electrical energy use was responsible for 48% of direct energy use. On organic farms, direct energy use was responsible for 50% of total primary energy, whereby electrical energy use was found responsible for 49% of direct energy use.

It is clear from the literature that numerous international research studies have focused on quantifying energy consumption both directly and indirectly related to the production of milk. However, albeit useful for comparing cognate studies, averaged electricity consumption per liter of milk produced (or FPCM, kg_m , etc.) is a generalized consumption metric. This may be problematic when single farm consumption predictions may be required, whereby consumption per liter of milk can vary considerably depending upon country, milk-cooling equipment, hot water-heating strategies, vacuum pump types, managerial strategies, etc. Concurrently, LCAs often require the physical metering of dairy farm inputs such as liquid fuel usage and electricity consumption. Often, the installation of metering equipment may require high capital and maintenance costs and can be quite time consuming. Thus, literature has also covered the development of prediction models for dairy farm-related energy consumption.

2.2. Dairy Energy Prediction Modelling

Many methods have been utilized for the prediction of energy consumption on dairy farms. Methods that are covered in this review include: mechanistic modelling, energy balance modelling, multiple linear regression (MLR), polynomial regression, and machine-learning. Similar to the varying functional units utilized for assessing energy consumption (as detailed in Section 2.1), there also exist

a number of different model assessment criteria and methods used in dairy energy literature. The most common model assessment criteria were the coefficient of determination (R^2), root mean square error (RMSE), and relative prediction error (RPE). Other common accuracy metrics included (but not presented) are mean absolute percentage error (MAPE) and mean percentage error (MPE).

2.2.1. Mechanistic Modelling

A mechanistic model for electricity consumption on dairy farms (MECD) was developed in 2014, capable of predicting electricity consumption, cost and related GHG emissions [38]. The MECD was developed through Microsoft Excel as a mathematical representation of the seven major infrastructural systems on a dairy farm (milk-cooling, water-heating, milk harvesting, lighting, water pumping, wash pumping, and winter housing). Due to the MECD calculating electricity consumption from first principals, a large number of input variables are required, including but not limited to: milk to water ratio, water temperatures, milking times, milk collection interval, hot water temperature set point, and water pump motor sizes. Mathematical equations representing the seven infrastructural systems were constructed using a 12-month \times 24-hour matrix structure and the accuracy of the MECD was validated on three farms sizes (small (45 cows)–medium (88 cows)–large (195 cows)). The MECD was found to predict annual electricity consumption to less than 10% (RPE). This level of prediction accuracy represented excellent prediction capability according to Fuentes-Pila et al. [39]. The model accuracy scale proposed by Fuentes-Pila et al. is commonly utilized throughout the dairy domain [40–45], whereby additionally, RPE values between 10% and 20% represent acceptable levels of prediction error, while values greater than 20% suggest poor prediction capability.

Breen et al. [46] adapted the MECD model [38] to include wind turbine and solar photovoltaic models. They assessed the applicability of installing solar photovoltaic modules and wind turbines on a dairy farm across four technology scenarios (i.e. four different dairy farm infrastructural situations) using three electricity tariffs, and three feed-in-tariffs. They found that for wind turbine and photovoltaic systems, a farm with an ice bank (IB) milk-cooling system, nighttime electric water-heating schedule using a day/night electricity tariff was the optimum scenario for all three feed-in-tariffs considered. Additionally, monetary savings attributed to wind turbines were highly sensitive to feed-in-tariffs, while savings associated with photovoltaic cells varied depending upon the technology scenario (i.e. electrically heated water start time). It was found that the electricity output of the photovoltaic system matched the load profile of the direct expansion (DX) scenario well, which resulted in a grid connected photovoltaic system having similar monetary savings to a standalone system.

Murphy et al. [47] developed a decision support system for energy use on dairy farms (DSSSED) to open-source the work carried out by Upton et al. [38] and Breen et al. [46] in Ireland. DSSSED allows dairy farmers, policymakers, academics, and other stakeholders to assess the potential monetary payback (ROI), and environmental impact (CO_2 emissions) of various energy efficient and renewable energy technologies. Users may assess the financial or environmental applicability of a plate cooler, variable speed drive (VSD), heat recovery system, solar thermal water heating system, solar photovoltaic system, and/or a wind turbine. DSSSED allows for various user inputs to be adjusted, so that calculations are carried out unique to each farm scenario. User inputs related to dairy farm infrastructure, managerial procedures, energy technology parameters (e.g. solar PV size (kWp)), investment cost, and the level of available grant aid, inflation rate, feed-in-tariff, and electricity tariff rates may be adjusted. Shine et al. [48] carried out a hypothetical case study utilizing DSSSED, assessing the applicability of a solar PV system on a hypothetical farm with 210 dairy cows. They found that under the hypothetical conditions, the solar PV system would save over 96 tons of CO_2 over the course of 20 years, with a calculated payback period of 6.1 years.

2.2.2. Regression Modelling

Regression models has been widely applied in literature in order to find a pattern for energy use in dairy farming systems. Sefeedpari et al. [21] used linear regression to predict output energy (energy

of milk produced and outputted cow manure) via inputs related to the fossil fuel and electrical energy consumption of 50 Iranian dairy farms between 2011 and 2012. However, linear regression was found to be an inadequate method of predicting dairy farm output energy, with a resulting R^2 value equaling 0.11.

Edens et al. [24] utilized empirical modelling, developing four multiple linear regression (MLR) models to predict the annual electricity consumption of each major electricity component in the USA. These included vacuum pumps, water heaters, refrigeration compressors, and air compressors, as well as a fifth MLR model to predict their combined consumption. Using data from a single farm (herd size = 160 cows) throughout a 14 year period, Edens et al. [24] developed the MLR models using data related to the volume of milk produced, the number of lactating cows, the percentage of butterfat in milk, pounds of fat-corrected milk, monthly low temperature, monthly high temperature, average monthly high temperature, and average monthly low temperature. They utilized five variable selection methods to help maximize the prediction capability of each MLR model to predict monthly unseen electricity consumption for each individual component. The five variable selection methods were: 1) forward variable selection, 2) backward variable selection, 3) stepwise regression, 4) R-squared, and 5) Mallows Cp. The final subset of variables selected for each component was then utilized for MLR model development through SAS software [49]. For the vacuum pumps, milk production alone was capable of explaining 44% of the variation ($R^2 = 0.44$), as shown in Table 6.

Table 6. Summary of models developed for predicting energy consumption on dairy farms.

Study	Country	Model Type	Res	Prediction Variable	Validation Method	R^2	RMSE	RPE (%)
Edens et al. [24]	USA	MLR	M	Milk harvesting (kWh)	n/a	0.44	n/a	n/a
Edens et al. [24]	USA	MLR	M	Milk cooling (kWh)	n/a	0.74	n/a	n/a
Edens et al. [24]	USA	MLR	M	Water heating (kWh)	n/a	0.34	n/a	n/a
Edens et al. [24]	USA	MLR	M	Air compressors (kWh)	n/a	0.18	n/a	n/a
Edens et al. [24]	USA	MLR	M	Combined (kWh)	n/a	0.62	n/a	n/a
Sefeedpari et al. [50]	IRN	ANN	A	Output energy of milk (MJ Cow ⁻¹)	Test set (20%)	0.88	0.015	n/a
Upton et al. [38]	IRE	Mech	M	Total electricity use (kWh)	3 typical farms	n/a	125.0	7.5
Sefeedpari et al. [20]	IRN	Linear	A	Output energy of milk (MJ Cow ⁻¹)	Test set (20%)	0.11	0.2	n/a
Sefeedpari et al. [20]	IRN	ANFIS	A	Output energy of milk (MJ Cow ⁻¹)	Test set (20%)	0.79	0.1	n/a
Mhundwa et al. [51]	SA	MLR	D	Morning milk cooling (kWh)	Test set (30%)	0.92	n/a	n/a
Mhundwa et al. [51]	SA	MLR	D	Evening milk cooling (kWh)	Test set (30%)	0.90	n/a	n/a
Todde et al. [32]	ITL	PR	A	Total electricity use (kWh)	LOOCV	n/a	n/a	11.4
Todde et al. [32]	ITL	PR	A	Total diesel use (kg)	LOOCV	n/a	n/a	15.0
Shine et al. [41]	IRE	MLR	M	Total electricity use (kWh)	10-fold CV	0.72	543.0	16.1
Shine et al. [40]	IRE	SVM	M	Total electricity use (kWh)	10-fold CV	0.94	241.0	12.0

USA = United States of America; IRN = Iran; IRE = Ireland; Sa = South Africa; ITL = Italy. 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. Res = prediction resolution; M = monthly; A = annual; D = daily. LOOCV; leave-one-out cross-validation; 10-fold CV = 10-fold cross-validation. n/a = information not available

Regarding milk-cooling, milk production and monthly high temperature together were capable of explaining 74% of the variation in electricity consumption of the refrigeration compressors. Regarding the electricity consumption of the water heater, a large proportion of the variability could not be explained, with all variables only capable of explaining 34% of the total variability. Concurrently, milk production and the number of lactating cows explained only 18% of the variability of energy consumed by the air compressors. They noted leaks in the air system could have been the primary cause of the poor predictive capability of the data. Finally, regarding the total energy use of the major components, the number of cows milked, the pounds of milk produced, the monthly average high temperature the monthly high temperature, and together explained 62% of the total variability of electricity consumption. They concluded that the quantity of milk had a greater impact on dairy farm electricity consumption over quality of milk produced with the number of cows milked and ambient temperature having lesser statistical impacts. The specific model coefficients for each major electrical energy consuming process were not presented by Edens et al. [24].

Shine et al. [41] also employed MLR modelling to predict dairy electricity consumption. As opposed to predicting annual electricity consumption, they predicted monthly electricity consumption data remotely monitored on 56 dairy farms throughout the January 2014–May 2016 period in conjunction with farm details related to milk production, cow numbers (herd size and number of lactating cows), farm infrastructural equipment, managerial processes, and environmental conditions. This resulted in 12 individual regression model equations being developed for each month, allowing for consumption trends throughout the year to be modelled. In total, 15 farm variables were assessed for their ability to predict dairy farm electricity consumption. The subset of farm variables that maximized the prediction accuracy of unseen electricity consumption was selected through applying a univariate variable selection technique and Variance Inflation Factor (VIF) in conjunction with all subsets' regression and 10-fold cross validation. The final subset of variables was found to be herd size, the volume of milk produced, whether an IB or DX milk bulk tank was used, whether ground water was utilized for pre-cooling milk, the number or air compressors, the frequency of hot washing (HzHW), and the total water heater volume. This MLR model was found to predict monthly dairy electricity consumption to within 26% (RPE). Through a standardized regression analysis, milk production and herd size had the largest impact on electricity consumption. Mhundwa et al. [51] developed MLR models to predict the milk-cooling related electricity consumption of a DX bulk tank without pre-cooling, utilizing a single South African dairy farm (mean of 500 lactating cows) monitored over three months. Two MLR models were developed; the first predicted the electricity requirements of the morning milking, while the second predicted the electricity requirements of the evening milking. The MLR models were developed using input data related to the volume of milk produced (liters), the milk temperature ($^{\circ}\text{C}$), bulk tank room temperature ($^{\circ}\text{C}$), ambient temperature ($^{\circ}\text{C}$), and relative humidity. Model development was carried out using a 70% of the overall dataset, while the remaining 30% was utilized as a test set to calculate model accuracy. They report R^2 values of 0.92 and 0.90 for the MLR models to predict the milk-cooling related electricity consumption of the morning and evening milking, respectively. The developed MLR models to predict the milk-cooling related electricity consumption of the morning and evening milking are shown in Equations (1) and (2), respectively.

$$E_{AM} = 23.7 + 0.33 \times T_{amb} - 6.4 \times 10^{-2} \times RH + 9.0 \times 10^{-3} \times V_m + 0.22 \times T_m - 0.64 \times T_r \quad (1)$$

$$E_{PM} = 12.0 + 1.53 \times T_{amb} - 0.30 \times RH + 7.0 \times 10^{-3} \times V_m + 2.2 \times T_m - 0.62 \times T_r \quad (2)$$

where E_{AM} and E_{PM} are the milk-cooling electricity consumption of the morning and evening milking, respectively, T_{amb} is the ambient temperature, RH is the relative humidity, V_m is the volume of milk harvested, T_m is the milk temperature, and T_r is the temperature of the bulk tank room.

Todde et al. [32] developed the dairy energy prediction (DEP) model (polynomial regression models) for predicting annual electricity and diesel fuel consumption on Italian dairy farms using empirical data from 285 farms. For polynomial regression model development, they considered herd

size, the number of lactating cows, milk production (kg FPCM) and land area (hectares) as input variables for both electricity and diesel models. Unlike Edens et al. [24], their methodology employed a univariate statistical method (correlation matrix) for variable selection and analyzed second and third order polynomial terms for herd size and number of lactating cows. The inclusion of the second and third order polynomial terms for herd size and number of lactating cows were assessed through Akaike Information Criterion (AIC) and VIF. Todde et al. [32] prescribed a maximum VIF value of ten. As a result, the final electricity polynomial regression model only included the number of lactating cows as an input variable, as shown in Equation (3).

$$TE_i^T = 14.3 + 0.19 \times LC_i - 1.9 \times 10^{-6} \times LC_i^3 \quad (3)$$

where TE_i^T represents the annual electricity consumption (kWh) of the i^{th} farm, LC_i is the number of lactating cows on the i^{th} farm, and LC_i^3 is number of lactating cows cubed on the i^{th} farm.

Leave-one-out cross-validation (LOOCV) was employed to measure the capability of the developed models to predict unseen electricity consumption (data not used for model development). Through this LOOCV method, the electricity model was found to predict annual electricity consumption of the Italian farms to within 11.4% (RPE).

Using an identical methodology, Todde et al. [32] also developed a polynomial regression model to predict diesel energy consumption (kg) on Italian dairy farms, as shown in Equation (4). Using LOOCV, their diesel model was found to predict annual diesel consumption of the Italian farms to within 15.0% (RPE).

$$TF_i^T = 23.5 + 0.18 \times TC_i - 1.3 \times 10^{-7} \times TC_i^3 + 0.34 \times Land_i + 15.4 \times MF \quad (4)$$

where TF_i^T represents the annual diesel usage (kg) of the i^{th} farm, TC_i is the total number of cows on the i^{th} farm, and TC_i^3 is the total number of cows cubed on the i^{th} farm, $Land_i$ is the total hectares (ha) of land used, and MF is the presence (1) or absence (0) of feed mechanization.

Concurrently, Todde et al. [17] developed a polynomial regression model to predict the embodied energy per year per farm, as shown in Equation (5). Using LOOCV, their model was found to predict annual diesel consumption of the Italian farms to within 13.3% (RPE).

$$EE_i^T = 90.4 + 0.52 \times TC_i - 8.5 \times 10^{-7} \times TC_i^3 \quad (5)$$

where EE_i^T represents the annual embodied energy (MJ) of the i^{th} farm, TC_i is the total number of cows on the i^{th} farm, and TC_i^3 is the total number of cows cubed on the i^{th} farm.

2.2.3. Machine-Learning

Studies by Sefeedpari et al. [50] and Sefeedpari et al. [20] also applied machine-learning to predict energy output on Iranian dairy farms. These studies involved the development of an artificial neural network, and an adaptive neural-fuzzy inference system (ANFIS) model. The data for model development were attained through detailed questionnaires including: the amount of fossil fuel (diesel, gasoline, kerosene, natural gas) and electricity consumed, milk produced, amount of cow manure, farm area, and cow numbers. The total energy consumption values were then calculated using energy intensity values found in literature. Each model was developed and tested utilizing a milk production year equal to the lactation period of 305 days to improve the prediction capabilities of each model. For model training, Sefeedpari et al. [50] refers to 60% of the original dataset used for model training, 20% used for validation and 20% for testing. Sefeedpari et al. [38] found that the artificial neural network model with 16 hidden neurons in the hidden layer with the Levenberg–Marquardt training algorithm maximized the prediction accuracy of energy consumption with a R^2 value of 0.88. When considering the R^2 values of the developed models, values of 0.79 and 0.11 were calculated for the ANFIS and MLR models, respectively [20].

Shine et al. [40] also looked at the capability of improving the prediction accuracy of dairy farm electricity consumption achieved by MLR modelling through employing various machine-learning algorithms. Using the same dataset to Shine et al. [8], Shine et al. [40] assessed the applicability of predicting monthly dairy farm electricity consumption using a support vector machine algorithm, a CART decision tree algorithm, a random forest ensemble algorithm, and an artificial neural network. Their methodology excluded variables that added little predictive power through employing backward sequential variable selection. Additionally, hyper-parameter tuning was carried out in conjunction with nested cross-validation to calculate the capability of each model to predict unseen electricity consumption. Backward sequential variable selection allowed for those variables with little predictive power to be removed, while hyper-parameter tuning allowed for a machine-learning model that generalized well on unseen data. They found the support vector machine algorithm maximized prediction accuracy of dairy farm electricity consumption, resulting in an RPE value of 12% (an improvement of 54% compared to MLR modelling). Shine et al. [40] commented on the improved capabilities of machine-learning algorithms to improve prediction accuracy stems from their ability to quantify non-linearities and interactions between input variables while offering an increased flexibility regarding data multicollinearity, input data distributions, missing data points and pattern recognition compared to standard statistical methods (such as MLR). Shine et al. [52] further assessed the ability of the support vector machine model to predict dairy farm electricity consumption at an annual resolution, both at the farm-level and catchment-level (combined consumption of multiple farms). They found a negative correlation between prediction resolution and RPE. More specifically, prediction error (RPE) reduced from 12%, to 10%, and to 5%, as the prediction resolution increased from predicting monthly consumption, to annual farm-level consumption, and to annual catchment-level consumption, respectively. This result demonstrated the models' potential effectiveness as a simulation tool for macro-level analyses.

2.2.4. Prediction Modelling Summary

It is clear from the literature that numerous international research studies have focused on developing prediction models for dairy farm energy and/or electricity consumption. These prediction models vary from mechanistic, MLR, polynomial regression, balance equation-based models, to machine-learning models. In conjunction with different data from different countries being employed for model training, the methods utilized for the development of these energy models vary. These methods vary from the response variable considered (i.e. dairy farm electricity consumption or diesel consumption), to the number of farms utilized for model training, to variable selection and model validation methods. Thus, reported accuracies throughout the dairy energy prediction modelling literature also vary. Therefore, it is difficult to determine which methodology provides the greatest prediction capability for a particular objective. There is a need for a common methodology for model development and assessment to be developed. However, the development of a prediction model for a particular purpose is highly problem specific. Thus, defining a common methodology would be difficult. However, a minimum methodology standard may be defined to ensure, at the very least that the accuracy of a prediction model is not over-estimated. Although model prediction accuracy may not be maximized in all cases, these prediction models may still offer adequate capability when forecasting the potential impact of various strategies to reduce dairy energy consumption in different scenarios.

2.3. Dairy Energy Analysis

With increasing electricity demand, there exists the potential for improvements in efficiency (usage per liter of milk) as dairy farm facilities may not be optimally configured for milk production increases [4,27]. For example, utilizing the MECD [38], Upton et al. [53] found a farm with a herd size of 88 dairy cows had a 24% greater electricity consumption per liter compared to a farm with a herd size of 45 cows. Additionally, in Ireland, through carrying out a detailed statistical analysis, Shine et al. [8] calculated that farms that employed ice chiller or IB milk cooling systems consumed

32% greater electricity compared to farms that employed DX systems. Thus, consideration for electricity consumption per liter of milk produced must be considered, especially during periods of milk production expansion.

Hartman and Sims [30] conducted an analysis of potential energy reduction strategies on three New Zealand dairy farms. They highlighted that the majority of farms could reduce their electrical energy usage and costs by between 10% and 20% through implementing various electrical energy reduction and load shifting strategies. They highlighted that as electricity is a minor component of overall production cost, simply reducing electrical energy usage may have a marginal impact on profit. However, relatively inexpensive methods of load shifting or levelling may result in a greater return on investment, especially as electricity pricing tariffs that charge different prices depending on the time of day become more commonplace. To improve energy efficiency, they suggested that a 70% reduction in milk harvesting energy use (20% of total electricity use) could be achieved by employing a VSD. Concurrently, they highlighted the significant impact of pre-cooling milk prior to entry into the milk bulk tank, as 90% of the energy required for milk chilling is used for initial milk cooling, while the remaining 10% is required to maintain the milk temperature below 4°C. More specifically, each 1 °C drop in milk temperature set point prior to entry to the milk bulk tank would result in a 5–7% reduction in chiller load [30]. Additionally, Hartman and Sims mention potential water heating energy savings due to installing a heat recovery system to pre-heat the cold inlet water by: 1) extracting heat from the milk flow, 2) using a small heat exchanger on the chiller condenser coils, or 3) recycling residual heat from the used washing water. Regarding diesel fuel savings, they identify the importance of dairy farmers learning the correct use of the hydraulic systems, keeping the machinery well maintained, matching tractor size and ballast to the task in hand, and checking tyre pressures. Although Hartman and Sims mentioned the greater potential for energy cost savings due to load shifting or load levelling, they only identify the use of heat recovery and storage systems in conjunction with IBs for the production and storage of heated and chilled water.

Barnett and Russell [13] reviewed strategies to reduce energy use on dairy farms. They highlighted an increase in the proportion of total energy use associated with direct sources from 41% to 53% due to irrigation practices on New Zealand farms [14]. They listed potential strategies to reduce water heating, water cooling, milk harvesting, water pumping, and lighting energy usage and costs on dairy farms. They report that the implementation of these strategies may reduce dairy energy usage by 43.6%. Barnett and Russell [13] also assessed the potential for alternative energy supplies including: methane from manure (anaerobic digestion), wind power, hydro-electric power (small-scale), solar water heating, and bio-diesel. They highlight that anaerobic digestion is more economically suited to confinement dairy systems, whereby nearly 100% of the manure can be digested, compared to between 10% and 20% in outdoor grazing systems. Thus, confinement systems require a minimum herd size of between 250 and 300 cows to be economically viable, whereby an outdoor grazing system requires a minimum herd size of 1,000 cows. Regarding wind power, they report that small-scale wind energy (example used: 10kW) is not economical in the short to medium term. Barnett and Russell also reported that small-scale hydroelectric power generation would only be suitable for very few dairy farms that have the required flow capable of generating the magnitude of electricity required to be economically viable. Regarding solar water heating, the potential for a 50% reduction in energy required for water heating on a typical dairy farm is reported, however, the economic viability is not discussed. Although they mention the potential for biodiesel to reduce fossil fuel consumption and emission of GHGs, they fail to mention any studies that directly focus on this aspect of dairy energy reduction. They conclude their study by mentioning that although energy savings are oftentimes given low priority, this is likely to change in the future as the cost of energy rises and greater incentive is given to reduce GHG emissions.

Rajaniemi et al. [27] highlighted that milk-cooling related electricity savings of approximately 30% may be achieved through modest improvements to plant infrastructure such as: improving the ventilation of the milk tank room, placing the refrigeration condenser outside the building to improve

the operational COP, and installing milk pre-cooling and heat recovery systems. However, it should be noted that these calculations were carried out through utilizing only three dairy farms, while electricity saving potential was calculated using an un-validated model. Improvements in animal welfare, growth, and milk production were reported by Crill et al. [54], whereby increases in cow milk production of between 5% and 16% were calculated when exposed to between 16 and 18 hours of adequate light over cows exposed to less than 13.5 hours of adequate lighting in a confinement system. Harner and Smith [55] also recommend subjecting lactating cows to between 16 and 18 hours of continuous light. In addition, Rajaniemi et al. [56] recommended illumination intensity of the milking parlor of 200–250 lux, in line with lighting level recommendations by Harner and Smith [55], who suggested illumination levels of 215 lux (20 foot-candles). However, the lighting level of the milking pit must also be considered, whereby ASABE [57] recommend an illumination level of 500 lux to ensure adequate lighting for controlling hygiene and the attachment of milking clusters. In either case, the energy intensity of the lighting equipment must be considered, whereby the installation of energy efficient lighting may reduce overall electricity consumption by 9% [58].

Regarding milk harvesting, Dunn and Butler [59] reported milk harvesting savings of between 40% and 50% due to the installation of VSD for milk harvesting in the United Kingdom, while Ludington et al. [58] calculated milk harvesting savings of 33% across 32 dairy farms in the United States. Similarly, on Danish AMS farms, Brøgger Rasmussen and Pedersen [34] highlighted farms that employed a VSD for milk harvesting had 20 kWh lower electricity consumption per 24 hours compared to regular vacuum pumping systems. In Ireland, Upton et al. [60] reported that the installation of a VSD for milk harvesting reduced milking costs by 60%, on average. Conventional vacuum pumps are primarily designed to operate at higher air flows than is required for milking due to higher air flows being required for the adequate washing of milking equipment. This may result in air bleeding within the system and energy wastage [61]. As highlighted by Rajaniemi et al. [56], Upton et al. [62], and Morison et al. [61], VSDs reduce electricity consumption over conventional milking machine vacuum pumps due to their ability to vary the speed of the motor to balance the rate of air flow removed from the system and admitted to the system, while still producing adequate vacuum stability. In addition, the installation of a VSD allows for milk pre-cooling to be carried out with a greater efficiency, whereby Morison et al. [61] reported an improvement of 5 °C.

With regards to milk-cooling, Ludington et al. [58] calculated milk-cooling energy reduction of 15% due to the installation of a pre-cooling system, whereby milk was pre-cooled prior to entry to the milk bulk tank, reducing the electrical energy required for cooling, i.e. reducing the temperature differential. Similarly, Karlsson and Nordman [63] measured a reduction in milk temperature from 37 °C to 17 °C, resulting in about a 50% reduction in milk-cooling electricity consumption when pre-cooling milk through a PHE using a 1:1 milk to water flow rate [56]. This is comparable to similar results in Ireland, whereby Upton et al. [62] recommended milk to water ratios of between 1:1 and 1:3 with the optimum ratio depending upon the size of the PHE and power of the milk pump.

Upton et al. [53] employed the MECD to investigate the impact of dynamic pricing environments on dairy farm electricity costs. Electricity usage on Irish dairy farms is primarily bi-modal during the milking season, due to the common 2-day milking schedule of dairy cows (once early in the morning and once late in the afternoon) [4]. With 62% of daily electricity consumption occurring during the peak electricity demand period (17:00–19:00), the impact of dynamic pricing tariffs may result in increased electricity costs whereby higher tariffs are imposed on times of high consumption on the electricity grid which may coincide with evening milking [4,53]. In response, Upton et al. (2015) found that for a twice a day milking strategy, adjusting milking times to milk earlier in the morning and later at night offered the greatest scope for energy and cost savings (flat, day/night, two time of use tariffs, and a real time pricing tariff) due to variations in milk-cooling system COP. More specifically, adjusting milk starting times (from default milking times) on a time-of-use tariff (€0.13 kWh⁻¹ (range 0.08–0.23 € kWh⁻¹)) resulted in electricity cost reduction of 39%, 34%, and 33% for small (herd size = 45 cows), medium (herd size = 88 cows), and large (herd size = 195 cows) sized representative farms, respectively [53].

However, a real-time pricing environment may also offer opportunities for dairy farmers that have IB milk bulk tanks installed, whereby pre-designed ice charging strategies may be employed to minimize milk-cooling costs [64]. IB storage units may offer the electricity grid operators a variable load for demand side management purposes during periods of high or low grid frequency or system voltage, in particular with an increased penetration of intermittent power sources (e.g. wind and solar energy systems) to the electricity grid [64].

In conjunction with defining electricity usage metrics, Shine et al. [8] also conducted a detailed statistical analysis to determine key relationships between dairy farm characteristics as well as potential differences between 45 dairy farms. A correlation analysis found that electricity consumption was largely associated with milk production, herd size, and the number of lactating cows. They found that across IB and DX systems, employing ground water for milk pre-cooling reduced electricity consumption by 25% on average. They also found interesting results associated with employing IB milk bulk tanks for milk-cooling. More specifically, they found that systems that utilized ice chiller units or IB milk tanks consumed 21% less electrical energy during day-time hours due to their load shifting capabilities (thus taking advantage of lower electricity rates). However, this decrease was met with a 32% increased energy consumption per liter resulting in no difference in milk cooling cost per liter of milk when under a day and night electricity tariff (day tariff of 0.18 € kWh⁻¹; night tariff of 0.08 € kWh⁻¹ from 00:00 to 09:00 h).

Shine et al. [52] utilized the support vector machine model [40] to conduct a macro-level analysis, whereby the impact of increased milk production on electricity use was assessed on 16 Irish dairy farms. Relative to a base scenario (no change in infrastructural equipment as milk production increased), they found the greatest reduction in electrical energy requirement per liter of milk occurred when all farms pre-cooled milk in conjunction with the installation of two additional parlor milking units. The addition of two parlor units resulted in electricity savings due to reduced milking times, which outweighed the increased electricity usage of the additional vacuum units.

Breen et al. [65] developed an optimization strategy to maximize return on investment in dairy farm infrastructural equipment over a specific time horizon. This was referred to as the discrete infrastructure optimization model for economic assessment on dairy farms (DIOMOND) and assessed the performance of five optimization algorithms. These included: Dynamic Programming, the Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing, and Tabu Search. The Genetic Algorithm was found to offer greater efficiency and performance compared to the other optimization algorithms for a test scenario involving a 195-cow farm. The optimal combination of farm technology, management practices, and electricity tariff was identified, resulting in a 26.3% improved return on investment over a ten year time horizon compared to a base investment scenario. Concurrently, Breen et al. [44] developed a multi-objective optimization (DAIRYMOO) method (employed similar methods to those used for DIOMOND) to identify farm infrastructure and managerial practices to 1) maximize farm net profit and 2) minimize farm electricity related CO₂ emissions, over a ten year time horizon. This study incorporated solar thermal heating and heat recovery models developed and validated using empirical data. However, heat recovery systems were only selected in the optimal scenario when the combined objective function was weighted heavily towards minimizing CO₂ emissions, while solar thermal heating was never selected in the optimal farm configuration. These results suggested poor financial performance for both heat recovery and solar thermal heating technologies.

Previous studies have utilized prediction models to quantify the impact of numerous methods to reduce energy/electricity consumption and related costs on dairy farms such as: altering the placement of the refrigeration system, heat recovery, installation of VSDs, milk pre-cooling, and the installation of an IB milk-cooling system to allow for load shifting of electricity consumption to cheaper cost rates. Pre-cooling milk with water through a PHE can reduce milk temperature from 37 °C to 17 °C, substantially reducing energy demand and reducing the time taken to reduce milk temperature to below 4 °C. However, consideration must be given to the impact on the related water consumption,

as increases in milk production can result in unsustainable levels of water consumption during periods of high stress.

3. Discussion and Perspective

The expansion of the global dairy industry poses challenges regarding minimizing environmental impacts while ensuring dairy farmers can adjust their farming strategies to minimize production costs in the volatile milk price environment [66]. Thus, literature related to the consumption of energy on dairy farms was reviewed under the headings of monitoring, prediction modelling and analyses.

The monitoring of dairy farm energy consumption is well documented in numerous LCA research articles. Although consumption metrics vary between studies (e.g. L_m , FPCM, ECM, kg_m , etc.), the reporting of fat and protein percentage values of the milk production used in the respective studies allowed for the effective comparison between international studies. Concurrently, although reporting energy usage metrics are useful for international comparisons, monitoring consumption can be quite time-consuming, financially expensive and not offer much in terms of prediction accuracy on a particular farm. Thus, literature has also focused on developing effective prediction models to predict dairy farm electricity and water consumption.

Numerous prediction and analyses methodologies have been employed to predict dairy farm energy consumption. Prediction modelling has involved mechanistic modelling, MLR modelling, polynomial regression modelling and machine-learning. Thus, prediction modelling has largely focused on empirical prediction modelling over mechanistic modelling. Although highly suitable to simulating single dairy farms, a mechanistic model such as the MECD [38] may not be suitable to predict large-scale dairy energy consumption (which may be required for environmental reporting) due to requiring a large number of input variables that dairy farmers may not know without the use of specialized equipment (i.e. milk to water ratio, water temperatures, water pump motor sizes, etc.). However, empirical modelling can replace metering equipment and/or mathematical models (that require a large number of input variables) with a small number of empirically derived coefficients, or black box machine-learning models. It should be noted that the final developed models are country specific due to the unique climatic conditions and farming practices

Balancing coarse input variables with acceptable prediction accuracy is difficult through standard regression methods such as MLR, polynomial regression etc. Thus, recent research carried out by Shine et al. [40] looked at the applicability of machine-learning algorithms to provide the dual benefit of requiring a reduced number of input variables compared to mechanistic modelling without compromising on prediction accuracy. Further work may look towards applying a larger range of machine-learning algorithms to dairy farm energy consumption data collected internationally, potentially stemming to deep-learning algorithms if/when applicable (large number of data points required). Concurrently, the development of a global database containing international dairy energy consumption values and descriptive variables could be developed, and models built to generate a global dairy energy model. If such a model were to be developed, each country would require a cohort of dairy farms to be selected that are representative of the country's dairy farm demographic. These farm's energy consumption could then be monitored in conjunction with farm characteristics, managerial strategies, and environmental data, and all collected data shared to a central database for model development. This would greatly reduce any financial cost associated with calculating the energy consumption on dairy farms globally as well as offer a means for international comparison. In conjunction with national surveys carried out throughout each country (to collect data required for energy and water models), such a model would offer countries the opportunity to continually monitor dairy energy consumption per liter of milk while also assessing the continual impact of various strategies aimed to reduce energy use on dairy farms.

Some studies have focused on identifying the most significant areas for reducing overall energy consumption associated with the production of milk. For example, Wells [14] identified the following areas as most important to consider for improving overall energy efficiency on New Zealand dairy

farms: fertilizer management, water management (irrigation), farm vehicle selection and operation, insulation of hot water cylinders, and pre-cooling milk to reduce electrical energy use and related costs. It is difficult to quantify the potential energy savings due to the implementation of best practice methods on dairy farms as all farms are unique (i.e. the potential energy savings will vary from farm to farm). However, from analyzing dairy energy literature, some conclusions can be made. More specifically, the literature shows that on average, switching from conventional farming system to organic farming system, will result in a 31% reduction in energy required per kg ECM. However, further analyses may be required on a country-wide basis to calculate the economic viability of switching to an organic farming system. If switching to an organic farming system is unfeasible, another option for some conventional confinement dairy farms could be to switch to a pasture-based farming system (if possible). On average, literature shows that energy consumption may be reduced by 37% by switching from a conventional confinement system to a pasture-based system. This switch may also result in financial savings, whereby Finneran et al. [67] identified a cost saving of 61% in switching a cows diet from concentrate to grazed grass.

4. Conclusions

Literature related to the consumption of energy on dairy farms was reviewed with respect to monitoring, prediction modelling, and data analyses. The future of the global milk production must be sustained through the minimal impact to energy resources, while ensuring dairy farmers adjust their farming strategies minimize production costs. Total primary energy consumption values ranged from 2.7 MJ kg⁻¹ ECM on organic dairy farming systems to 4.1 MJ kg⁻¹ ECM on conventional dairy farming systems, whereby variances in energy intensity between farms that employed either confinement or pasture-based farming systems were also identified. Across all studies (conventional and organic farms), direct energy consumption was responsible for 32% of total primary energy. On average, electrical energy made up 48% of direct usage, while other liquid fuels were responsible for the remaining 52%. Concurrently, indirect energy sources were responsible for the remaining 68% of total energy consumption. On conventional dairy farms, ancillary energy is responsible for 56% of total energy needs on average across the literature, whereby feed is responsible for 76% of ancillary energy representing the largest energy requirement on dairy farms. As the largest consumer of energy, altering dairy cow feed practices may offer the greatest reduction to dairy energy requirements. For example, a conventional confinement dairy farm may reduce feed energy requirements by 66% by switching to a pasture-based system (if possible). Concurrently, considerable energy savings may be achieved by switching from conventional farming to an organic farming system, whereby studies have calculated minimal energy requirements associated with organic fertilizer production. Other strategies to reduce dairy farm energy consumption include technologies which aim to reduce on-farm electricity consumption, including pre-cooling milk through a plate cooler, variable speed drives, improving hot water tank insulation, switching to energy efficient lighting, etc. Developed prediction models in literature have largely focused on predicting dairy farm electrical energy consumption, however, some studies have focused on modelling output energy, as well as diesel use and embodied energy on dairy farms. In addition, varying modelling techniques have also been employed including mechanistic, regression, and machine-learning models. It is difficult to determine which method is most applicable to simulate dairy energy consumption on dairy farms, instead, the most applicable modelling technique is largely dependent on its intended application. For example, to simulate farm-level electrical energy consumption, whereby a large number of input data are available, mechanistic modelling may be desirable. Concurrently, to simulate dairy farm energy consumption on a large scale, whereby a small number of easily attainable input data are desirable, then regression or machine-learning methods would be best suited. From a research perspective, increased prediction capabilities of dairy energy prediction models associated with the utilization of machine-learning algorithm, will result in an increased confidence in predictions, while also potentially allowing for a greater number of dairy farms to be included in future lifecycle analyses as the need for electricity monitoring equipment is reduced.

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Appendix A

A range of usage metrics relating to milk analyses are utilized throughout dairy energy consumption literature. These include: liters of milk (L_m), kilograms of milk (kg_m) (Equation (A1)), fat and protein corrected milk (FPCM) (Equation (A2)) [68], and energy corrected milk (ECM) (Equation (A3)) [69]. The units of FPCM and ECM are commonly utilized for international comparisons as it assures a fair evaluation between farms with different breeds or feed regimes [68]. However, studies utilizing different usage metrics may be compared through reporting of milk data variables such as the mean percentage of fat (% or g/kg), the percentage of protein (% or g/kg), and/or the amount of lactose (g/kg), depending on the key performance indicator required.

$$kg_m = L_m \times (\text{milk volumetric mass density}) \quad (\text{A1})$$

$$\text{FPCM} = kg_m \times ((0.1226 \times \% \text{ Fat}) + (0.0776 \times \% \text{ Protein}) + 0.2534) \text{ kg} \quad (\text{A2})$$

$$\text{ECM} = L_m \times ((0.383 \times \% \text{ Fat}) + (0.242 \times \% \text{ Protein}) + 0.7832)/3.1138 \text{ kg} \quad (\text{A3})$$

where milk volumetric mass density equals 1.03 kg per liter of milk, L_m is the volume of milk in liters, % Fat is the percentage of fat in milk, % Protein is the percentage of protein in milk.

Appendix B

In total, 36 research findings related to total, direct and electrical energy usage on dairy farms is presented in Table A1. These studies were carried out across 17 countries including: Belgium (BEL), Canada (CAN), France (FRA), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), Great Britain (GBR), Iran (IRN), Ireland (IRL), Italy (ITA), Japan (JPN), the Netherlands (NTL), New Zealand (NZL), Sweden (SWE), and the United States of America (USA). The mean number of farms per study was 24, while some studies (notated by “n/a” in Table A1) used national or regional level parameters with no on-site analysis. The exact energy sources considered when calculating total energy consumption in each study may be identified within each article, as some energy sources (such as machinery and facilities) may not be considered due to unavailability of data. Energy values from 11 studies are presented in MJ kg^{-1} , one finding is presented in MJ kg^{-1} FPCM, while one finding is presented in fat-corrected milk (FCM) due to unavailability of fat and protein percentage values for conversion purposes. When possible (i.e. when fat and protein percentage values were available), energy values per liter of milk, kg of milk, kg of MS, or kg of FPCM were converted to MJ kg^{-1} ECM using Equations (A1), (A2), and (A3). Where direct or electrical energy consumption was given as a percentage of the overall energy value, these values were calculated accordingly. Where electrical energy values were presented in terms of electrical energy (i.e. kWh, Wh, etc.), these values were converted to MJ using 3.6 MJ kWh^{-1} [22], in conjunction with either country specific or average EU-28 primary energy factor of electricity values [70,71]. Therefore, reporting of fat and protein percentage values when describing the energy intensity of dairy farming is critical to ensure future provision of comparisons between international studies.

Table A1. Energy consumption (MJ kg⁻¹ ECM unless stated otherwise) values found in literature.

Study	System ⁵	Country	n	Total Energy	Direct	Electrical
Arsenault et al. [72]	Conv-c	CAN	1	4.87 ¹	n/a	n/a
Arsenault et al. [72]	Conv-g	CAN	1	4.99 ¹	n/a	n/a
Basset-Mens et al. [73]	Conv-g	NZL	1	1.51 ^{1,4}	n/a	n/a
Cederberg and Flysjö [74]	Org-g	SWE	6	2.10	n/a	0.74
Cederberg and Flysjö [74]	Conv-c	SWE	17	2.66	0.93	0.59
Cederberg and Mattson [35]	Org-g	SWE	1	2.51	n/a	n/a
Cederberg and Mattson [35]	Conv-c	SWE	1	3.55	n/a	n/a
Frorip et al. [75]	Conv-c	EST	1	5.36	n/a	n/a
Haas et al. [76]	Org-g	DEU	6	1.20 ¹	n/a	n/a
Haas et al. [76]	Conv-g	DEU	6	1.30 ¹	n/a	n/a
Haas et al. [76]	Conv-g	DEU	6	2.70 ¹	n/a	n/a
Hartman and Sims [30]	Conv-g	NZL	62	3.90 ³	2.03	1.17
Hospido et al. [36]	AMS-c	ESP	2	6.03 ¹	0.73	0.58
Kraatz [22]	Conv-c	DEU	n/a	3.54	1.24	0.39
Meul et al. [15]	Conv-c	BEL	74	3.58 ¹	1.20	0.34
Mikkola and Ahokas [77]	Conv-c	FIN	n/a	3.20 ¹	1.60	0.70
Nguyen et al. [78]	Conv-g	FRA	1	3.97 ⁷	n/a	n/a
O'Brien et al. [5]	Conv-g	IRL	1	2.37	0.30	n/a
O'Brien et al. [5]	Conv-c	IRL	1	4.02	0.21	n/a
Ogino et al. [79]	Conv-c	JPN	1	5.53 ⁸	n/a	n/a
Pagani et al. [16]	Org-c	ITA	3	1.97	0.80	n/a
Pagani et al. [16]	Org-g	USA	3	4.07	2.23	n/a
Pagani et al. [16]	Conv-c	ITA/USA	5	4.32	1.62	n/a
Pagani et al. [16]	Conv-c	ITA/USA	4	3.35	1.38	n/a
Refsgaard et al. [80]	Org-c	DNK	14	2.16	n/a	0.66
Refsgaard et al. [80]	Conv-c	DNK	17	3.34	n/a	0.66
Sefeedpari et al. [20,21]	Conv-c	IRN	50	8.05	1.57	0.26
Thomassen et al. [37]	Conv-c	NLD	10	5.15	0.62	0.35 ⁶
Thomassen et al. [37]	Org-g	NLD	11	3.19	0.99	0.55 ⁶
Todde et al. [17,29]	Conv-c	ITA	285	8.91	2.60	0.27
Upton et al. [4]	Conv-g	IRL	22	2.37	0.48	0.29
Van der Werf et al. [81]	Org-g	FRA	6	2.68	n/a	n/a
Van der Werf et al. [81]	Conv-c	FRA	41	2.88	n/a	n/a
Wells [14]	Conv-g	NZL	96	1.98	0.87	0.47
Williams et al. [82]	Conv-g	GBR	n/a	2.44 ^{1,2,4}	n/a	n/a
Williams et al. [82]	Conv-g	GBR	n/a	1.55 ^{1,2,4}	n/a	n/a

¹ Values from study are in MJ kg⁻¹ milk. ² Value converted from liters to kg using milk volumetric mass density of 1.03 kg L⁻¹. ³ Value provided by Pagani et al. [16]. ⁴ Value provided by Upton et al. [4]. ⁵ Conv-c = conventional confinement farm; Conv-g = conventional grazing farm; Org-c = organic confinement farm; Org-g = organic grazing farm; AMS-c = conventional automatic milking system. ⁶ Converted from Wh kg⁻¹ ECM using 3.6 MJ kWh⁻¹ [22] and mean EU-28 primary energy efficiency factor between 2010 and 2013 [71] 9 and using standard equations. ⁷ Values from study are in MJ kg⁻¹ FPCM. ⁸ Values from study are in MJ kg⁻¹ FCM (Fat-corrected milk)

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