

## **Annual electricity consumption prediction and future expansion analysis on dairy farms using a support vector machine**

P. Shine <sup>a</sup>, T. Scully <sup>b</sup>, J. Upton <sup>c</sup>, M. D. Murphy <sup>a,\*</sup>

<sup>a</sup> Department of Process, Energy and Transport Engineering, Cork Institute of Technology, Cork, Ireland

<sup>b</sup> Department of Computing, Cork Institute of Technology, Cork, Ireland

<sup>c</sup> Animal and Grassland Research and Innovation Centre, Teagasc Moorepark Fermoy, Co. Cork, Ireland

Corresponding Author: Michael D. Murphy

Address: Department of Process, Energy and Transport Engineering, Cork Institute of Technology, Bishopstown, Co. Cork, Ireland.

Tel: +353214326747

E-mail: [michaeld.murphy@cit.ie](mailto:michaeld.murphy@cit.ie)

### **Abstract**

This study utilised a previously developed support vector machine (SVM) (trained using empirical data from 56 dairy farms) for predicting and analysing annual dairy farm electricity consumption to help improve the sustainability of the projected expansion of milk production in Ireland. Firstly, the capability of the SVM to predict annual electricity consumption was investigated at both a farm and catchment-level (combined consumption). Electricity consumption data were attained from 16 pasture-based, Irish dairy farms between June 2016 and May 2017 in conjunction with farm data related to herd size, milk production, infrastructural equipment and managerial tendencies, required to generate predictions using the SVM. The SVM predicted annual electricity consumption of dairy farms to within 10.4% (relative prediction error). Concurrently, catchment-level electricity consumption was predicted with an error value less than 5.0%. Secondly, an investigation was carried out to assess the impact of increasing herd size and milk production on dairy farm related electricity consumption at a catchment-level across ten hypothetical infrastructural scenarios. The dairy expansion analysis showed electricity economies of scale across all ten infrastructural scenarios. The greatest reduction in electricity consumption per litre was observed when all farms employed ground water for pre-cooling milk with two additional parlour units, reducing by 4% in 2018, relative to a

base scenario (no change to infrastructural equipment). The results presented in this article demonstrate the potential effectiveness of the SVM as a macro-level simulation forecast tool for dairy farm electricity consumption that may be used to quantify the impact of milk production on electricity resources, or to offer decision support to dairy farmers.

Keywords: energy, milk production, machine-learning, dairy expansion, sustainability, SVM

## 1. Introduction

The dairy sector was Ireland's strongest agricultural export performer in 2017, increasing by 19% to represent a third (€4 billion) of overall export value (Bord Bia, 2018). The increased production and exportation of Irish dairy products may be attributed to the abolishment of European Union (EU) milk quotas in April 2015. In 2017, Ireland produced 7.3 billion litres of milk ( $L_m$ ), representing a 45% increase over 2007-09 levels, or 90% towards the 2020 target of 7.5 billion litres of milk, set out in 2010 (CSO, 2018; DAFM, 2010). The increased dairy herd, milk production and exportation of dairy products comes with its own significant challenges with regard to Ireland's 2030 EU target requiring a 30% reduction in greenhouse gas (GHG) emissions, compared to 2005 levels (European Commission, 2016; Lanigan et al., 2018). The agri-sector is responsible for 33% of Ireland's national GHG emissions and 44% of the non-Emission trading sectors (non-ETS) (Lanigan et al., 2018). Thus, the improved sustainability of the agri-sector is imperative to ensure Ireland's 2030 targets are achieved to minimise financial penalties and safeguard the clean green image of Ireland's agri-sector internationally (DAFM, 2016; Donnellan et al., 2018). However, Ireland's GHG emissions are set to be between 4% and 6% below 2005 levels by 2020, far away from the targeted 20% reduction (EPA, 2017). Furthermore, it is predicted that without considerable mitigation actions, Ireland's 2030 agricultural related GHG emissions will increase above 2005 levels (Donnellan et al., 2018). Donnellan et al. (2018) highlighted three categories for GHG mitigation: 1) agricultural mitigation (reduced agricultural activity), 2) land use mitigation (increase  $CO_2$  removal through land use changes), and 3) energy mitigation (improved energy efficiency, displacement of fossil fuels etc.). As reducing agricultural activity would negatively affect Ireland's GDP (Gross Domestic Product) and land use mitigation actions may require a number of years to have any substantial impact, one potential area for improvement is to reduce the impact of increasing milk production on indirect GHG emissions related to the consumption of electricity on dairy farms. Empirical modelling can offer an efficient means to quantify electricity consumption on dairy farms. These models may be utilised to quantify potential savings due to changes in infrastructure or managerial practises, or used to calculate the sustainability of Ireland's agri-sector at a national level. This is of particular interest in the current

volatile milk price climate, whereby previously developed technologies such as control systems to optimise the production of ice in a dynamic pricing environment may be utilised in future scenarios to minimise milk production costs (Murphy et al., 2015). More recently, research in this domain has also focused on economic and environmental optimisation on dairy farms (Breen et al., 2019).

In Italy, Todde et al. (2017) developed polynomial regression models to predict the annual farm-level diesel use (15% relative prediction error (RPE) for diesel) and electricity use (11% RPE). These models were developed using variables related to herd size, farm size (hectares) and data related to feed mechanisms. The advantage of regression modelling is its simplicity and ease of deployment for researchers, government bodies and dairy farmers for predicting consumption figures. However, these polynomial regression models are not capable of forecasting monthly consumption trends throughout the year (due to calculating regression coefficients using annualized figures), and also may not be used for decision support purposes because they do not consider variations in energy consumption due to varying infrastructural equipment.

Extensive research has been carried out regarding the prediction of electricity consumption on Irish dairy farms. Upton et al. (2014) developed a mechanistic model capable of predicting electricity consumption to less than 10% (RPE). However, this mechanistic model required large-scale data collection related to specific plate cooler ratios, water temperatures, milking times etc., and is thus not suited to large-scale macro analysis. However, machine-learning models may be highly suited to carry out macro analyses due to their ability to offer satisfactory prediction accuracy using relatively coarse input variables, which may be attained without the use of specialised equipment. Machine-learning algorithms have been applied to a wide range of applications within agricultural literature. These include milk production forecasting using artificial neural networks (Murphy et al., 2014; Zhang et al., 2016), comparing the performance of a random forest, a support vector machine (SVM) and extremely randomised trees for discriminating between grassland types in Ireland (Barrett et al., 2014), and predicting global and regional crop yield predictions using a random forest (Jeong et al., 2016). Machine-learning algorithms in the form of an artificial neural networks and an adaptive neural-fuzzy inference system have previously been employed to improve the prediction accuracy

when modelling the energy output of dairy farms in Iran (Sefeedpari et al., 2014, 2013). Furthermore, Shine et al. (2018a) developed and validated a support vector machine model (using empirical data from 56 dairy farms) capable of predicting monthly electricity consumption to within 12% (RPE), representing a 54% improvement in prediction accuracy over standard multiple linear regression method (Shine et al., 2018b). However, Shine et al. (2018a) did not consider the ability of the SVM to predict annual farm-level electricity consumption and/or catchment-level consumption, which may be required for macro-level environmental analysis. Catchment-level predictions may offer government bodies or milk processors the ability to conduct large-scale analysis for calculating the impact of dairy farming on electrical power resources for life-cycle assessment.

The objectives of the work presented in this article were twofold: 1) assess the annual prediction accuracy of the SVM model at an individual farm-level, and catchment-level (combined consumption of 16 study farms). 2) utilise the SVM model to hypothetically analyse the impact of increasing herd size and milk production on related electricity consumption across multiple infrastructural scenarios. This hypothetical study was designed to highlight the effectiveness of the SVM model for investigating electricity consumption across different infrastructural scenarios during a period of dairy expansion. Thus, certain assumptions were made related to the dairy expansion projections, which allowed for the impact of increasing herd sizes and milk production levels along their current trajectory to be assessed. To the authors' knowledge, no previous studies have been carried out that: 1) compare and contrast the ability of an empirical model to predict dairy energy consumption across both a farm-level and a catchment-level and 2) conduct a hypothetical analysis related to the impact of expanding dairy activities on energy consumption.

## 2. Materials & Methods

### 2.1. Study farms

Table 1 Electricity consumption statistics, herd size, milk production levels infrastructure equipment and managerial procedures across the 16 study farms

Farm Characteristic	mean	median	SD	min	max
Electricity consumption (kWh)	20,314	19,087	6,919	11,747	36,722
Wh $L_m^{-1}$	36.54	38.15	8.01	22.85	50.51
kWh $cow^{-1}$	195	197	48	116	310
Herd size (no. dairy cows)	104	101	22	71	159
Milk production ( $L_m$ )	557,413	542,094	145,125	315,150	955,205
No. of air compressors	0.3	0.0	0.5	0.0	1.0
HzHW (hot washes / month)	8.3	8.0	6.7	1.0	30.0
No. parlour units (n)	12.3	10.0	3.6	8.0	20.0
Bulk tank volume (L)	8,688	8,884	2,680	3,100	13,000
Water heater volume (L)	209	174	82	150	400
No. of scrapers	2.75	2.50	2.72	0.00	8.00
Cows / parlour unit	8.7	8.2	1.6	6.7	12.1
Milk production ( $L_m$ ) / dairy cow	5,354	5,436	634	3,728	6,135
Milk cooling system	DX (16)   IB (0)				
Milk pre-cooling system	No (2)   Yes (14)				

HzHW = Frequency of hot washing  
 IB = Ice bank milk-cooling system  
 DX = Direct expansion milk-cooling system

This study utilised the SVM model trained and validated by Shine et al. (2018a), capable of predicting monthly electricity consumption to within 12% (RPE). A description of the 16 study farms utilised to test the annual and catchment-level prediction accuracy of the SVM model, as per their farm characteristics throughout the June 2016 to May 2017 period, is shown in Table 1. Electricity consumption data were recorded through a remote monitoring system installed on a study sample of 16 pasture-based, Irish dairy farms between June 2016 and May 2017. The June 2016 to May 2017 period represents a timeframe of 12 months after the final month used for training and validating the SVM model. Data related to these 16 study farms did not exceed the remit (lower or upper limits (with respect to herd size) of the training data) of the SVM model, ensuring no extrapolation when generating predictions in the dairy expansion analysis (section 3.2). This description covers the range of input variables to the SVM model required for predictions, the acquisition of which is described in detail by Shine et al. (2018c). These variables are related to milk production and stock, infrastructural equipment and managerial procedures. The average observed electricity consumption on the selection

of dairy farms equalled 20,314 kWh ranging from a minimum of 11,747 kWh and maximum consumption of 36,722 kWh. The average observed electricity consumption per litre of milk equalled  $36.5 \text{ Wh L}_m^{-1}$ , ranging from  $22.9 \text{ Wh L}_m^{-1}$  to  $50.5 \text{ Wh L}_m^{-1}$ , while the average measured electricity consumption per dairy cow per year equalled  $195 \text{ kWh cow}^{-1}$ , ranging from  $116 \text{ kWh cow}^{-1}$  to  $310 \text{ kWh cow}^{-1}$ . The 16 study farms had a median herd size of 101 dairy cows, 40% greater than the national average of 72 dairy cows in 2016 (Teagasc, 2016). The 16 study farms had a median annual milk production of 542,093  $\text{L}_m$  throughout the analysis period, producing 8.9 million  $\text{L}_m$  combined, representing 0.12% of the milk produced nationally over the same 12 month period (CSO, 2018). All 16 study farms utilised direct expansion (DX) systems, whereby two farms did not employ ground water (gW) for the pre-cooling of milk. Concurrently, the study farms had an average of nine cows per parlour unit (range; 7 – 12 cows per parlour unit), with milk production per cow equalling  $5,354 \text{ L}_m \text{ cow}^{-1} \text{ year}^{-1}$  (range  $3,727 - 6,134 \text{ L}_m \text{ cow}^{-1} \text{ year}^{-1}$ ), essentially equalling the national average of  $5,316 \text{ L}_m \text{ cow}^{-1} \text{ year}^{-1}$  in 2016 (Teagasc, 2016).

## **2.2. The support vector machine**

SVMs operate through the non-linear mapping of input data to higher dimensional variable space whereby linearity can be exhibited, and a linear separator can be calculated, which can be controlled via the tuning of SVM parameters (Basak et al., 2007; Smola & Schölkopf, 2004; Vapnik, 1995). The methodology employed for model selection included various variable selection techniques, outlier extraction, grid-search hyper-parameter tuning, and nested cross-validation. A comprehensive description of the methods employed for developing and assessing the SVM model is presented in Shine et al. (2018a). The SVM regression model was trained and validated through MATLAB 2016b, thus, all consequent analyses were also carried out through MATLAB 2016b (MathWorks, 2018). The final developed SVM model was trained using monthly electricity data collected between Jan 2014 and May 2016 from 56 Irish pasture-based dairy farms. The final developed SVM model utilised 11 variables: month number, the total number of dairy cows, milk production, the number of parlour units, the total water heater volume, the frequency of hot washing (HzHW), the milk-cooling system, the milk pre-cooling system, the bulk tank volume, the number of air compressors and the total number of

scrapers. The SVM algorithm was found to offer the greatest prediction accuracy when compared to an artificial neural network, a CART decision tree and a random forest (Shine et al., 2018a). The SVM with a rbf kernel, a C parameter value equalling 10,000 and  $\gamma$  value equalling 1.92 offered the greatest prediction accuracy of electricity consumption for a single 10-fold cross-validation loop. The SVM model was found to provide the greatest prediction accuracy when compared to the MLR model, artificial neural network, CART decision tree and random forest algorithms. Shine et al. (2018a) found this SVM model capable of predicting monthly dairy farm electricity consumption to within 11.9% (RPE), on average overpredicting by 2.2% (mean percentage error (MPE) = -2.2%). This suggested the SVM model performed more accurately when predicting across a number of farms and months compared to predicting the monthly electricity consumption of a single farm. However, Shine et al. (2018a) did not consider the prediction performance of the SVM when predicting annual consumption figures for large scale dairy farm electricity prediction.

Thus, the present study builds on prior knowledge by analysing the SVM model for the predicting annual and overall catchment-level electricity consumption of a selection of 16 study farms using consumption data in the 12-month period post model development (June 2016 – May 2017). All predictions were carried out at a monthly resolution, with related annual and catchment-level accuracies calculated thereafter. Consideration was given to ensure that data related to the 16 study farms did not exceed the lower or upper limits (with respect to herd size) of the training data, ensuring no extrapolation took place when generating electricity predictions for accuracy calculations or generating predictions for the dairy expansion analysis. This is important as machine-learning models are trained to quantify interactions and/or non-linearity's of data within a specific remit of its training data, as generating predictions based on data outside of the training data limits may be highly inaccurate.

### **2.3. Prediction accuracy analysis**

Shine et al. (2018a) found encouraging results related to improvements in prediction accuracy when predicting the cumulative monthly prediction across a large number of monthly predictions. More specifically, the SVM model resulted in a MPE value of -2.2% representing a considerably lower

error value when compared to the absolute value (11.9% (RPE)) for predicting electricity consumption on a single farm. This was primarily due to electricity consumption overprediction on a particular farm and/or month being equalised by the underprediction of electricity consumption on another farm and/or month, resulting in an improved accuracy value (e.g. MPE) for the collection of dairy farms. Thus, this study focused on calculating the prediction performance of the SVM model across two areas: 1) annual electricity consumption prediction per dairy farm was analysed whereby prediction accuracy may be improved compared to a monthly resolution as areas of overprediction and underprediction may be equalised on each individual farm. 2) cumulative electricity consumption predictions were investigated whereby the annual prediction accuracy of all 16 study farms combined may be further improved as areas of overprediction and underprediction are balanced throughout the year and between the farms themselves.

For presenting prediction accuracy results of the SVM model a number of criteria were calculated. Prediction bias across all study farms were evaluated according to calculated mean percentage error (MPE (%)). Positive MPE values represented model underprediction, while negative values represented overprediction, with the absolute MPE value representing the scale of under or overprediction. Absolute model precision was evaluated according to root mean squared error (RMSE) (square root of MSPE) (Bibby and Toutenburg, 1977), relative prediction error (RPE (%)) (RMSE expressed as a percentage of the dependent mean) (Rook and Gill, 1990) while prediction agreement was measured via the concordance correlation coefficient (CCC) (Lin, 2016). These criteria are in line with previous studies analysing model prediction in agriculture (Hanrahan et al., 2017; Upton et al., 2014a).

## **2.4. Dairy expansion analysis**

A hypothetical analysis pertaining to the relationship between increased herd sizes and milk production levels on Irish dairy farms and the resulting impact on electricity consumption was carried out. This analysis was not to test the accuracy of the model. Instead, the impact of increasing dairy cow numbers and milk production levels on associated electricity consumption was investigated

through a catchment-level analysis across a base scenario (assuming current dairy farm infrastructural equipment) and nine additional infrastructural scenarios.

For each study farm ( $n = 16$ ), the slopes of monthly herd size and milk production were calculated using monthly data from Jan 2014 to Aug 2017. More specifically, 12 individual linear slopes were calculated (one for each month (Jan – Dec)), for each farm. These were used to generate herd size and milk production figures for 2018, 2019, 2020 and 2021 at a monthly resolution. These herd size and milk production figures for each dairy farm were hypothetical, assuming increases in herd size and milk production continued along their current trajectory. This allowed the dairy expansion analysis to be carried out, while also allowing for changes in milk production trends to be considered (e.g. potential increased milk production in winter), specific to each farm. This method assumed milk production per dairy cow continued on the current trajectory in line with increasing cow numbers. More specifically, this method assumed either an increased availability of pasture due to increased acreage and/or increased concentrate feed, proportional to the increase in cow numbers, in line with the current expansion trajectory on each study farm. This method assumed dairy cow parity proportions of each dairy herd, concurrent with average levels throughout the Jan 2014 to Aug 2017 period.

With monthly herd size and milk production figures calculated for 2018, 2019, 2020 and 2021, totalised electricity consumption per litre of milk was firstly calculated for the dairy farm catchment to provide the base scenario (i.e. no change to dairy farm infrastructure). To avoid extrapolation, it was ensured that data utilised to generate predictions during the dairy expansion analysis did not exceed the upper limits (with respect to herd size) of the training data, for each scenario. The SVM has been trained to quantify interactions and/or non-linearity's of data within a specific remit of its training data. Thus, predictions were carried out using data within the lower and upper ranges of the training data as generating predictions based on data outside of the training data limits may be highly inaccurate. This was particularly important for this analysis whereby the impact of expanding milk production on electricity consumption was being assessed.

Nine additional hypothetical infrastructural scenarios were assessed consisting of varying milk-cooling systems, milk pre-cooling systems, increasing parlour units and hot washing frequency across the study farms. The data utilised for training the SVM model contained each of the scenarios included in the analysis (as described in Table 2). The nine infrastructural scenarios included: Scenario 1) a 100% IB scenario whereby all farms that employed DX milk bulk tanks were altered to employ IB milk-cooling systems. The benefit of IB milk-cooling systems are threefold: a) milk can be cooled faster than DX systems, thus minimising bacterial growth, improving milk quality (Murphy et al., 2013; Paludetti et al., 2018). b) IB bulk tanks allow for load shifting capabilities, whereby reduced electricity prices during off-peak hours may be taken advantage of to reduce milk-cooling related electricity costs (Shine et al., 2018c; Upton et al., 2014b). c) Increasing the load shifting capacity on the electricity grid is beneficial to grid operators, as the potential for demand side management is increased; this is particularly significant with the increased penetration of intermittent renewable energy sources (Finn and Fitzpatrick, 2014). Thus, this scenario assumes a large uptake of IB milking systems as a means of improving milk quality, reducing milk-cooling related electricity costs and helping to improve electricity grid conditions. Scenario 2) 0% GWPHE (milk pre-cooled via gW through a plate heat exchanger), whereby no farms were assumed to pre-cool milk with gW. Pre-cooling milk via gW through a plate heat exchanger can reduce milk-cooling related electricity consumption by 21%, by reducing the temperature of milk prior to entry to the bulk tank (Shine et al., 2018c). Thus, this 0% GWPHE scenario may calculate the impact of pre-cooling throughout the dairy expansion. Scenario 3) a 100% GWPHE scenario whereby all farms that did not pre-cool milk with gW were changed to assume that all farms pre-cooled milk. Understanding the impact of pre-cooling milk while expanding dairy operations may help dairy farmers and researchers minimise electricity consumption per litre of milk. The next four hypothetical scenarios include: Scenario 4) a base + 2 units, Scenario 5) a 100% IB + 2 units, Scenario 6) 0% GWPHE + 2 units, and Scenario 7) 100% GWPHE + 2 units, which each assessed the addition of two parlour units to each study farm in conjunction with the dairy expansion. Increasing the number of parlour units (or clusters) will improve a farm's milk-harvesting efficiency (i.e. cows milked per hour). The addition of a parlour unit will increase electricity consumption as additional milk-harvesting equipment is used. However,

overall electricity consumption may also decrease as the milking period is reduced due to dairy cows being milked quicker, resulting in less wasted electricity consumption between milking cows. Thus, understanding the impact of adding parlour unit infrastructure in conjunction with dairy expansion may aid in minimising electricity consumption per litre of milk. Scenario 8) a 100% GWPHE & 100% IB, which assumes all farms employing IB milk bulk tanks, while pre-cooling milk through a plate heat exchanger. This scenario may quantify the impact of additional milk pre-cooling on farms that solely employ IB milk bulk tanks as opposed to DX based milk-cooling systems (as in scenario 3). The final hypothetical scenario: Scenario 9) HzHW  $\geq$  12, incorporated a minimum hot washing frequency amongst the dairy catchment to maintain hygienic requirements of milking equipment throughout the dairy expansion. Currently, the study farms hot washed their parlour equipment 8.3 times per month equating to less than twice per week. Infrequent hot washing may lead to issues surrounding bacterial counts and milk residues in milking equipment, which may affect milk quality as milking equipment may not be properly sanitised. Imposing a minimum hot washing frequency of 12 hot washes per month equates to around three hot washes per week, in line with an every-other-day milking schedule, (all 16 study farms have every-other-day milk collections schedules). The recommended frequency of hot washing depends on the cleaning product used, and thus, will vary from farm to farm (O'Brien, 2008). This hot washing frequency allows all milking equipment to be hot washed with no milk in the bulk tank. A concise description of the ten scenarios is presented in Table 2.

Table 2 Concise descriptions of the ten hypothetical infrastructural scenarios assessed

Scenario	Description
Base Scenario	No change to dairy farm infrastructural equipment
1. 100% IB	All farms employing IB bulk tanks
2. 0% GWPHE	No farms pre-cooling milk with gW
3. 100% GWPHE	All farms pre-cooling milk with gW
4. Base + 2 units	Base scenario with each farm having 2 additional parlour units
5. 100% IB + 2 units	All farms employing IB bulk tanks and 2 additional parlour units
6. 0% GWPHE + 2 units	No farms pre-cooling milk with gW and having 2 additional parlour units
7. 100% GWPHE + 2 units	All farms pre-cooling milk with gW and having 2 additional parlour units
8. 100% GWPHE & 100% IB	All farms employing IB bulk tanks and pre-cooling milk with gW
9. HzHW $\geq$ 12	All farms hot washing a minimum of 12 times per month

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IB = Ice bank  
gW = Ground water  
GWPHE = Milk pre-cooled via gW through a plate heat exchanger  
HzHW = Frequency of hot washing

### 3. Results and Discussion

#### 3.1. Model performance

##### 3.1.1. Farm-level prediction

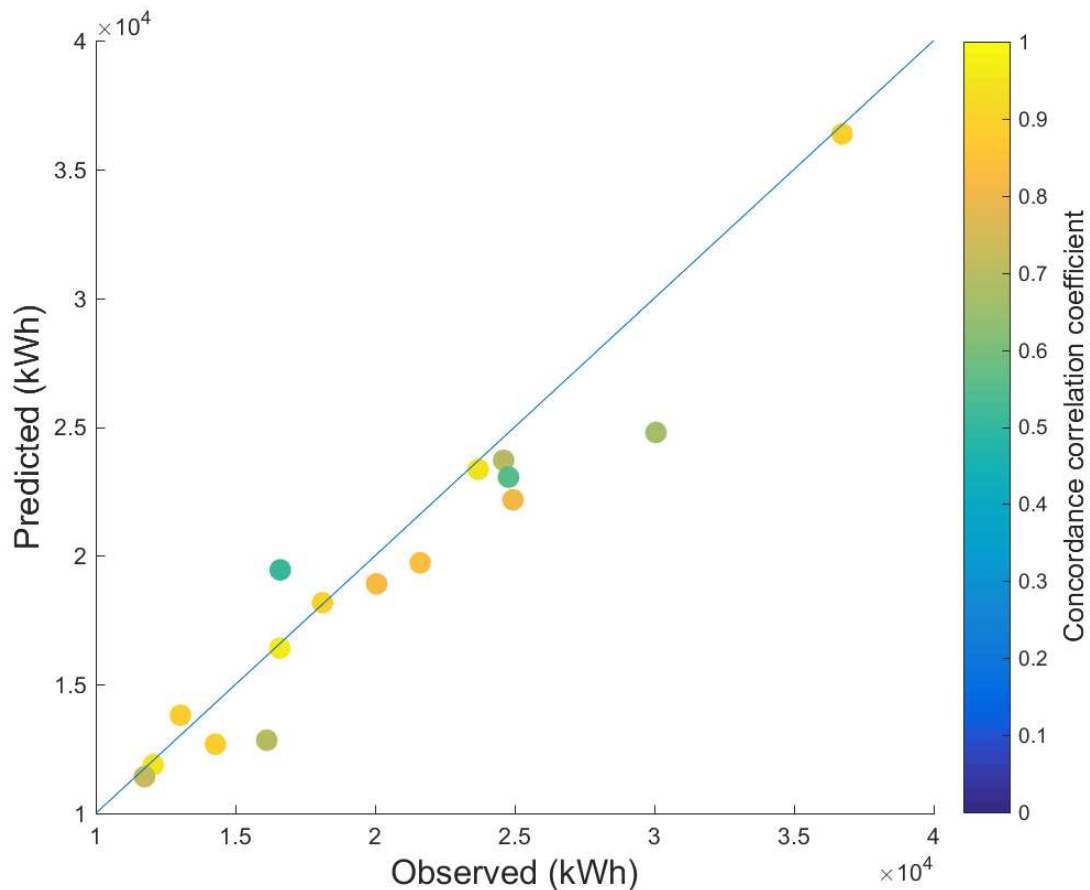


Fig. 1 Scatter plot showing annual observed and predicted electricity values graduated according to the concordance correlation coefficient between monthly observed and predicted values on each farm

Annual observed and predicted electricity values for the SVM model are shown in Fig. 1. Concurrently, calculated CCC values are presented as a measure of the agreement of monthly observed and predicted monthly values on each study farm (i.e. the calculated CCC between 12 observed values and 12 predicted values on each farm). The lowest CCC value calculated from the SVM model predictions was 0.51 (herd size = 104 cows, milk production = 628,384 L<sub>m</sub> year<sup>-1</sup>, DX bulk tank with pre-cooling, annual electricity consumption = 16,660 kWh, annual prediction error = 17.2%).

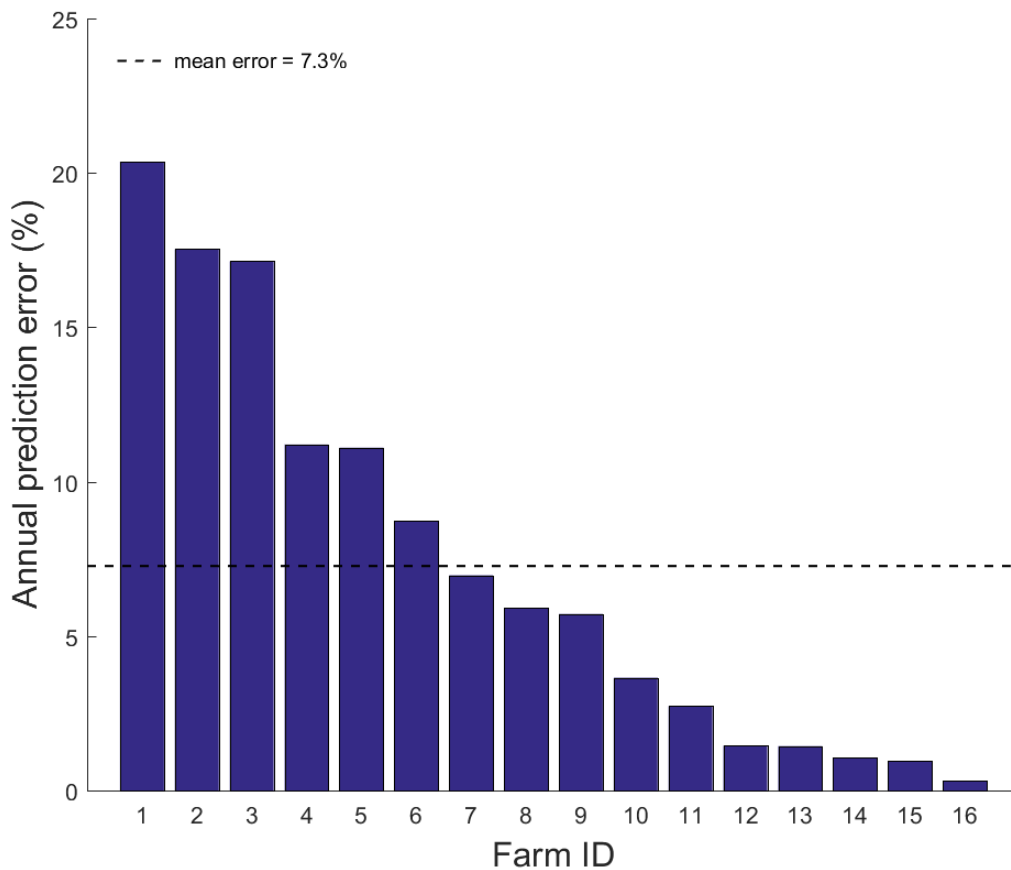


Fig. 2 Annual farm-level absolute prediction errors of the 16 study farms and mean absolute error line

Absolute annual percentage errors from the SVM model ranged from 0.3% to 20.4%, as shown in Fig. 2. The mean absolute percentage error across the 16 study farms equalled 7.3% (mean absolute error = 1,476 kWh), suggesting improved prediction capabilities when predicting electricity consumption of a group of farms.

Table 3 Farm-level annual prediction accuracy statistics for the SVM model across the 16 study farms

Farm-level	RPE	CCC	MAPE	MAE	MPE	r	RMSE
	10.4%	0.95	7.3%	1,476 kWh	4.3%	0.97	2,040 kWh

RPE = relative prediction error; CCC = concordance correlation coefficient; MAPE = mean absolute percentage error; MAE = mean absolute error; MPE = mean percentage error; r = Pearson's correlation coefficient; RMSE = root mean square error

The annual prediction accuracy statistics for the 16 study farms (farms whose data is within the remit of the SVM model during the June 16 – May 17 period), is presented in Table 3. Farm-level electricity consumption was predicted with error of 10.4% (RPE) and CCC value of 0.95 was calculated with MPE of 4.3% (i.e. underprediction). Shine et al. (2018a) found the SVM model could

predict monthly electricity consumption to within 11.9% (RPE). Thus, this suggested that the SVM model may offer greater functionality as a prediction tool across an annual timeframe compared to monthly resolution for farm-level predictions. This reduced error may be due to a balance between monthly underprediction and overprediction values throughout the year. I.e. months that the SVM model overpredicted electricity were cancelled out by other months that the SVM model underpredicted electricity consumption.

### 3.1.2. Catchment-level prediction

Table 4 Catchment-level prediction performance of the SVM model across the 16 study farms

No. of farms	Observed (kWh)	Predicted (kWh)	Error (%)
16 study farms	325,028	308,755	5.0%

The catchment-level (combined annual consumption of the 16 study farms) measured electricity consumption (summed electricity consumption of study farms), predicted electricity consumption from the SVM model and prediction error value, are presented in Table 4. In total 325,028 kWh was consumed between the 16 study farms. The SVM model predicted an overall consumption of 308,755 kWh, resulting in a percentage error value of 5.0%. Thus, the usefulness of the SVM model is further demonstrated when utilised as a catchment-level prediction tool for dairy farm electricity consumption. Thus, it was observed that the SVM model balanced overprediction and underprediction when predicting at the monthly resolution across farms as well as at the annual resolution across farms. I.e. farms that the SVM model overpredicted electricity were cancelled out by other farms that the SVM model underpredicted electricity consumption.

### 3.2. Hypothetical dairy expansion

Table 5 Dairy expansion characteristics and SVM electricity projections for 16 study farms across ten infrastructural scenarios

Dairy expansion characteristics	2018	2019	2020	2021
Milk production (million L)	10.3	11.0	11.6	12.3
Average herd size (n)	114	119	124	129
Dairy farm scenario	Wh L <sub>m</sub> <sup>-1</sup>			
Base scenario (farms as is)	32.6	31.9	31.1	30.3
1. 100% IB	36.8 (13%)*	35.1 (10%)	33.4 (7%)	31.9 (5%)
2. 0% GWPHE	35.9 (10%)	34.7 (9%)	33.4 (7%)	32.1 (6%)
3. 100% GWPHE	31.3 (-4%)	30.6 (-4%)	29.9 (-4%)	29.1 (-4%)
4. Base + 2 units	32.6 (0%)	31.6 (-1%)	30.8 (-1%)	29.9 (-1%)
5. 100% IB + 2 units	37.2 (14%)	35.4 (11%)	33.6 (8%)	32.1 (6%)
6. 0% GWPHE + 2 units	35.7 (9%)	34.4 (8%)	33.1 (7%)	31.8 (5%)
7. 100% GWPHE + 2 units	31.5 (-4%)	30.5 (-4%)	29.8 (-4%)	29.0 (-4%)
8. 100% GWPHE & 100% IB	36.3 (11%)	34.5 (8%)	32.9 (6%)	31.4 (4%)
9. Base HzHW ≥ 12	33.3 (2%)	32.5 (2%)	31.7 (2%)	30.9 (2%)

\*Values in brackets represent the percentage deviation from the base scenario, in each year

Combined projected expansion figures (herd size and milk production) for 2018, 2019, 2020 and 2021 for the dairy farm catchment (comprising of 16 study farms whose projected dairy expansion (relative to herd size) was within the remit of the SVM model training data), are presented in Table 5. Electricity consumption per litre of milk for the dairy farm catchment (current base scenario) and nine hypothetical infrastructural scenarios are also shown in Table 5 in conjunction with the projected dairy expansion. Compared to the June 2016 – May 2017 period, a 24% increase in the average herd size (from 104 to 129 dairy cows) and a 38% increase in milk production (from 8.9 to 12.3 million L<sub>m</sub>) was calculated in the 2021 calendar year across the 16 study farms. These figures assumed the expansion of the study farms between 2014 and 2017 continues on the current trajectory, which has been largely influenced by the abolishment of milking quotas in April 2015.

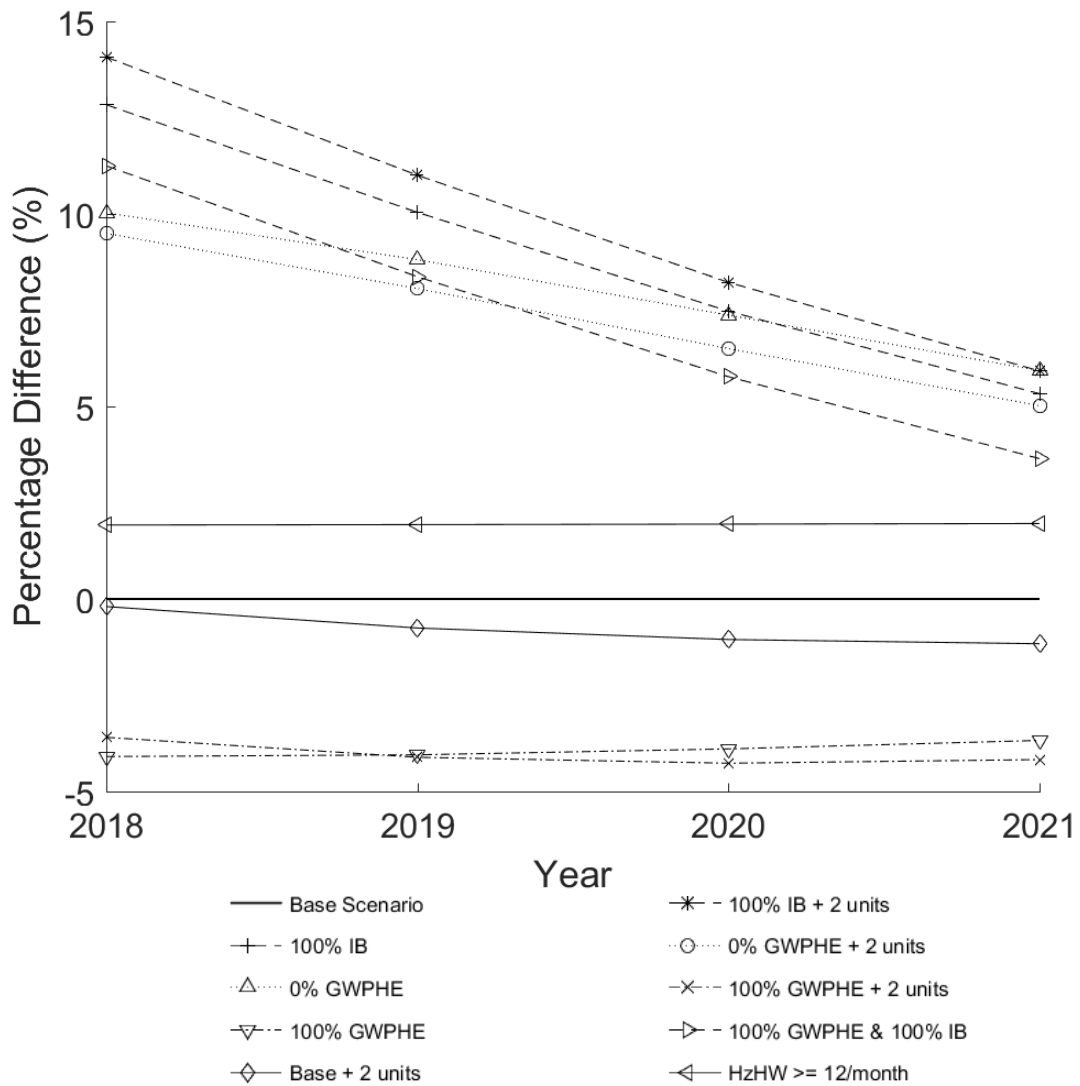


Fig. 3 Percentage comparison of electricity consumption per litre of milk between the base scenario (zero line) and the nine hypothetical infrastructural scenario across four expansion years

Regarding the base scenario (no change to infrastructural equipment), the SVM model calculated economies of scale due to increasing production, with electricity consumption per litre of milk reducing by 7.3% from 32.6 Wh L<sub>m</sub><sup>-1</sup> to 30.3 Wh L<sub>m</sub><sup>-1</sup>. More specifically, the proportional increase in electricity consumption was less than the proportional increase in milk production. This was potentially due to a dilution of non-milking (milk-cooling and milk-harvesting) related electricity consumption, such as: water heating, lighting, water pumping and other miscellaneous usage throughout the farm which contribute to 53% of total electricity consumption (Shine et al., 2018c).

Nine additional infrastructural scenarios were assessed and compared to the base scenario (as discussed in section 2.4), whereby economies of scale were observed for all nine scenarios when comparing the 2018 and 2021 years, as shown in Table 5 and Fig. 3.

Scenario 1 (100% IB) increased the proportion of study farms that employed IB milk bulk tanks with pre-cooling from 0% to 100% (i.e. DX milk bulk tanks on all 16 farms were replaced by IB bulk tanks). Compared to the base scenario, 2018 electricity consumption per litre of milk in scenario 1 increased by 13%, whereby in 2021, an increase of 5% was observed. Thus, the difference in electricity consumption per litre of milk (compared to the base scenario (zero line)) reduced as cow numbers and milk production increased from 2018 to 2021. Concurrently, the 100% IB scenario resulted in a reduction of  $2.38 \text{ Wh L}_m^{-1}$  from 2018 to 2021 in line with the dairy expansion. This reduction is displayed in Fig. 3, whereby the percentage difference between  $\text{Wh L}_m^{-1}$  between the base scenario and the nine hypothetical infrastructural scenario across each of the four expansion years is presented. Increasing electricity consumption due to the installation of IB milk bulk tank was an expected projection of the SVM model. IB bulk tanks have been shown to consume  $3.1 \text{ Wh L}_m^{-1}$  more electricity for milk-cooling than DX systems (Shine et al., 2018c), thus lower than the  $4.2 \text{ Wh L}_m^{-1}$  reduction (compared to base scenario) calculated in 2018 for scenario 1. However, this value may vary depending upon the pre-cooling methodology employed (Shine et al., 2018c), and water-to-milk ratio (Murphy et al., 2013).

Scenario 2 (0% GWPHE) reduced the proportion of study farms that pre-cooled milk with gW through a plate cooler from 87.5% to 0% (i.e. milk pre-cooling systems on 14 of the 16 farms were removed). Compared to the base scenario, 2018 electricity consumption per litre of milk increased by 10%, whereby in 2021, electricity consumption per litre of milk increased by 6%. A reduction of  $3.9 \text{ Wh L}_m^{-1}$  was observed from 2018 to 2021 in line with the dairy expansion, as shown in Fig. 3.

Scenario 3 (100% GWPHE) increased the proportion of study farms that pre-cooled milk with gW through a plate cooler from 87.5% to 100% (i.e. milk pre-cooling systems installed on the 2 farms with no milk pre-cooling system). Compared to the base scenario, 2018 electricity consumption per litre of milk reduced by 4%, while in 2021, electricity consumption per litre of milk also reduced by

4%. A reduction of 2.2 Wh L<sub>m</sub><sup>-1</sup> was observed from 2018 to 2021 in line with the dairy expansion, as shown in Fig. 3.

Scenario 4 (Base + 2 units) added two parlour units to each study farm, assuming all other infrastructural equipment remained consistent with the base scenario. Compared to the base scenario, 2018 electricity consumption per litre of milk remained the same (from 32.6 Wh L<sub>m</sub><sup>-1</sup>). However, in the fourth expansion year (2021), electricity consumption per litre of milk reduced to a level 1% lower than the base scenario. This suggested that a level of expansion was only reached after 2018, whereby the advantages associated with two additional parlour units on each farm outweighed disadvantages due to increased electricity consumption of the additional milking equipment. A reduction of 2.7 Wh L<sub>m</sub><sup>-1</sup> was observed from 2018 to 2021 in line with the dairy expansion, as shown in Fig. 3.

Scenario 5 (100% IB + 2 units) increased the proportion of study farms that employed IB milk bulk tanks from 0% to 100% (like scenario 1), while also adding two additional parlour units. Compared to the base scenario, 2018 electricity consumption per litre of milk increased by 14%, while 2020 electricity consumption per litre of milk increased by 6%, as shown in Fig. 3. In comparison to scenario 1 (100% IB), the addition of two parlour units did not result in a reduction of electricity consumption per litre of milk in any of the expansion years. Instead, electricity consumption per litre of milk increased by 1% and 1% in 2018 and 2021, respectively, compared to scenario 1. Additionally, a reduction of 5.2 Wh L<sub>m</sub><sup>-1</sup> was observed for scenario 5 from 2018 to 2021 in line with the dairy expansion, thus slightly greater than the 5.0 Wh L<sub>m</sub><sup>-1</sup> observed for scenario 1.

Scenario 6 (0% GWPHE + 2 units) reduced the proportion of study farms that pre-cooled milk with gW through a plate cooler from 87.5% to 0% (like scenario 2), while also adding an additional two parlour units on each study farm. Compared to the base scenario, 2018 electricity consumption per litre of milk increased by 9% while in 2021, electricity consumption per litre of milk increased by 5%, as shown in Fig. 3. In comparison to scenario 2 (0% GWPHE), the addition of two parlour units reduced electricity consumption per litre of milk in each expansion year. Electricity consumption per litre of milk reduced by less than 1% and 1% in 2018 and 2020, respectively, compared to scenario 2.

Additionally, a reduction of  $4.0 \text{ Wh L}_m^{-1}$  was observed from 2018 to 2021 in line with the dairy expansion, thus slightly greater than the  $3.9 \text{ Wh L}_m^{-1}$  observed for scenario 2.

Scenario 7 (100% GWPHE + 2 units) increased the proportion of study farms that pre-cooled milk with gW through a plate cooler from 87.5% to 100% (like scenario 3), while also incorporating two additional parlour units on each study farm. Compared to the base scenario, 2018 electricity consumption per litre of milk reduced by 4%, while in 2021, electricity consumption per litre of milk was reduced by 4%. In comparison to scenario 3 (100% GWPHE), the addition of two parlour units failed to reduce electricity consumption per litre of milk in the 2018 expansion year. Electricity consumption per litre of milk increased by 1% and reduced by 1% in 2018 and 2021, respectively, compared to scenario 3. Thus, electricity consumption per litre of milk for scenario 7 was the lowest observed for each of the three scenarios (scenario 4 to 7), which involved the addition of two parlour units. Additionally, a reduction of  $2.5 \text{ Wh L}_m^{-1}$  was observed from 2018 to 2021 in line with the dairy expansion, thus greater than the  $2.2 \text{ Wh L}_m^{-1}$  observed for scenario 3 (100% GWPHE).

Scenario 8 (100% GWPHE & 100% IB) increased the proportion of study farms that employed IB milk bulk tanks with pre-cooling from 0% to 100%, while also increasing the proportion of study farms that pre-cooled milk with gW through a plate cooler from 87.5% to 100%. Compared to the base scenario, 2018 electricity consumption per litre of milk in scenario 8 increased by 11%, whereby in 2021, an increase of 4% was observed. Thus, similar to scenario 1, the difference in electricity consumption per litre of milk (compared to the base scenario) reduced as cow numbers of milk production increased from 2018 to 2021. Concurrently, the 100% GWPHE & 100% IB scenario resulted in a reduction of  $5.0 \text{ Wh L}_m^{-1}$  from 2018 to 2021 in line with the dairy expansion, equalling the reduction calculated in scenario 1. Compared to scenario 1, 2018 electricity consumption per litre of milk in scenario 8 reduced by 1%, whereby in 2021, an increase of 2%. Thus, similar to scenario 3, this shows to calculated benefit of increased milk pre-cooling adoption.

Scenario 9 ( $\text{HzHW} \geq 12$ ) incorporated a minimum hot washing frequency (12 hot washes per month) amongst the dairy catchment. This increased to hot washing frequency on 75% of the 16 study farms, increasing the average HzHW from 8.3 hot washes per month to 13.1. Compared to the base scenario,

2018 electricity consumption per litre of milk increased by 2%, while in 2021, an increase of 2% was also observed. Thus, the increase in electricity consumption due to the increased hot washing is constant throughout the expansion of milk production in this analysis. This is retrospective of the electricity consumption related to hot washing of parlour equipment not having any interactions with farm variables included in the SVM model. More specifically, results presented in scenario 9 displays how the HzHW does not interact with herd size or milk production within the SVM model, as expected.

### **3.3. Discussion overview**

The SVM was capable of accurately capturing interactions between input variables and dairy farm electricity consumption to provide an effective macro-level simulation tool, as shown in Fig. 3. More specifically, the SVM captured four primary interactions to model dairy farm electricity consumption. Firstly, the effect of installing an IB milk-cooling system was accurately quantified by the SVM model, whereby electricity consumption increased by  $4.2 \text{ Wh L}_m^{-1}$  (in 2018) due to the installation of an IB milk bulk tank on each dairy farm, as shown in scenario 1. Secondly, the effect of milk pre-cooling was effectively quantified by the SVM model, whereby the 0% GWPHE scenario (scenario 2) had a  $4.6 \text{ Wh L}_m^{-1}$  greater electricity consumption than the 100% GWPHE scenario (scenario 3), greater than the  $2.9 \text{ Wh L}_m^{-1}$  calculated by Shine et al. (2018c). The effect of installing IB milk-cooling systems (100% IB) in conjunction with milk pre-cooling systems (100% GWPHE) on all farms were shown in scenario 8 (100% GWPHE & 100% IB), whereby as expected,  $\text{Wh L}_m^{-1}$  in all four expansion years were found to be less than the 100% IB scenario, and greater than the 100% GWPHE scenario. Thirdly, the effect of adding two additional parlour units to each farm across each dairy expansion scenario was captured, and effectively shown in the Base + 2 units scenario (scenario 4). In scenario 4, a level of expansion was achieved in 2019 and onwards, whereby the advantages associated with two additional parlour units (decreased milking timeframe) on each farm outweighed disadvantages due to increased electricity consumption of the additional milking equipment. Lastly, the effect of increasing the HzHW in conjunction with the expansion of dairy farms was accurately captured by the SVM model as no interactions were evident. More specifically, the difference in

electricity consumption due to increasing HzHW was constant throughout the dairy expansion analysis (2018 – 2021) as hot washing is independent of the milk production process (i.e. increasing milk production had no impact on the electricity consumption related to hot washing of milking equipment). These interactions (or lack thereof) captured by the SVM allow for macro-level simulations and sensitivity analyses to be carried out for a large number of dairy farms (provided farms are within the remit of the data used for training the SVM). These simulations and/or analyses may be performed using easily attainable farm information, which may be collected without the use of specialised equipment. This method of simulating dairy farm electricity consumption contrasts that of the mechanistic model for electricity consumption on dairy farms developed by Upton et al. (2014), which requires large-scale data collection related to specific plate cooler ratios, water temperatures, milking times etc..

Using the 16 study farms as a test-set, the SVM model predicted annual farm-level electricity consumption to within 10.4% (RPE). This represented a 13% reduced prediction error compared to the monthly prediction error value of 11.9% calculated by Shine et al. (2018a) using the stratified nested k-fold cross validation method. The SVM model was found capable of predicting combined electricity consumption of the 16 study farms to within 5.0% (error). This result concurred with that of the mechanistic model for dairy farm electricity consumption, whereby the average annual error across three test farms equalled 2.6%, which was less than the average monthly error value of 7.5% (RPE) (Upton et al., 2014a). This improved the confidence threshold of the SVM model for macro scale analyses.

The method employed to quantify the dairy expansion was biased towards a large expansion due to the abolishment of milking quotas in April 2015. The dairy expansion analysis was useful to quantify electricity consumption effects on the current milk expansion trajectory. However, the calculated herd size and milk production figures for each dairy farm were hypothetical, with exact figures subject to model assumptions related to the availability of pasture, concentrate feed and dairy cow parity proportions, which have been defined in section 2.4. The key finding from the hypothetical dairy expansion analysis lies with the electricity economies of scale over time and the effect of the different

infrastructural scenarios over time in line with the dairy expansion. Previous research presented by Upton et al. (2015) showed varied electricity consumption per litre of milk figures between small (herd size = 45), medium (herd size = 88) and large (herd size = 195) farms, whereby figures of  $40.9 \text{ Wh L}_m^{-1}$ ,  $50.5 \text{ Wh L}_m^{-1}$  and  $42.2 \text{ Wh L}_m^{-1}$  were calculated, respectively. Upton et al. (2015) could not comment on possible economies of scale as their analysis involved three hypothetical farms with varying infrastructural equipment. In comparison, the dairy expansion analysis carried out in this paper included constant infrastructural equipment using the SVM model for dairy farm electricity consumption.

Benefits related to milk pre-cooling were shown in scenario 2 (0% GWPHE) and scenario 3 (100% GWPHE) of the dairy expansion analysis. Reducing electricity consumption due to the installation of milk pre-cooling systems was an expected projection of the SVM model as milk pre-cooling has been shown to reduce milk-cooling related electricity consumption per litre of milk by 21% ( $2.9 \text{ Wh L}_m^{-1}$ ), on average, varying depending upon whether a DX or IB milk bulk tank was installed (Shine et al., 2018c). Concurrently, Ludington et al. (2003) reported milk-cooling savings of 15% due to the installation of a milk pre-cooling system. Reducing the number of farms that pre cooled milk to zero (0% GWPHE) allowed for electricity consumption savings due to pre cooling milk to be quantified. This was carried out by comparing scenario 2 (0% GWPHE) to the base scenario (whereby 87.5% of farms pre-cooled milk) and scenario 3 (100% GWPHE). Comparing scenario 2 and 3 projections,  $\text{Wh L}_m^{-1}$  savings due to increased milk pre-cooling adoption, decreased between 2018 and 2021 expansion years. More specifically, in 2018, savings due to milk pre-cooling equalled  $4.6 \text{ Wh L}_m^{-1}$ , while in 2021, savings reduced to  $2.9 \text{ Wh L}_m^{-1}$ . Increasing the adoption of milk pre-cooling may not necessarily equal a linear electricity saving with increased milk production as the operation of plate coolers could be time based as opposed operating for the entire duration of milking. I.e. a plate cooler could be operated for a fixed period during milking, whereby if milk production increases, increased electricity savings will not occur. This plate cooling constraint may be due to water conservation or farm management purposes, whereby after pre-cooling milk, plate cooler water is stored in a buffer tank and used for yard washing. The size of the buffer tank may therefore be a milk pre-cooling

constraint (if not of adequate size) if water wastage to be minimised, as any additional water will have to go to waste. Quantifying energy savings due to the utilisation of gW for pre-cooling milk may be useful for future analyses related to the energy-water-food nexus (Shine et al., 2018c; Wu et al., 2017).

Compared to the base scenario, scenario 7 (100% GWPHE + 2 units) resulted in the greatest reduction in electricity consumption per litre of milk. This scenario showed the benefit of adding 2 parlour units (as well as scenario 8), whereby the electricity savings due to reduced milking times outweighed increases in electricity due to increased vacuum units. This suggested that a milk production level was achieved across the dairy farm catchment, where the advantages associated with the increased number of parlour units (reduced milking periods, reduction in wasted electricity between milking cows and a dilution of non-milking related electricity consumption) outweighed disadvantages related to the increased electrical load. Additionally, due to the increased number of parlour units, milking occurs faster, therefore potentially increasing electricity savings due to pre-cooling as more milk can be harvested before the buffer tank constraint is achieved (assuming fixed period plate cooler operation), as previously discussed.

#### **4. Conclusion**

This paper utilised a previously developed support vector machine to predict annual and catchment-level electricity on dairy farms and provided future hypothetical projections across multiple farm infrastructural scenarios in line with the current dairy expansion trajectory of a selection of Irish dairy farms. Results showed reduced prediction capabilities as the prediction resolution decreased (i.e. annual electricity prediction error was 13% (relative prediction error = 10.4%) less than the monthly prediction error (relative prediction error = 11.9%)). This study therefore improved the confidence of the SVM model as a prediction tool for catchment-level electricity consumption on dairy farms. Moreover, further improved accuracy (error = 5.0%) was observed when predicting annual electricity consumption across a larger number of farms as areas of model overprediction and underprediction

balanced throughout the year on each farm as well as between overall annual predictions across the 16 dairy farms.

The hypothetical dairy expansion analysis was carried out to assess the impact of increasing cow numbers and milk production across six infrastructural scenarios (one base (current infrastructural scenario) and nine hypothetical scenarios). This method calculated a 24% increase in the average herd size and a 38% increase in milk production by 2021, compared to the June 2016 – May 2017 period. Furthermore, results showed economies of scale across all nine infrastructural scenarios, with the base scenario (no change to infrastructural equipment with dairy expansion) having a 7.3% reduction in electricity consumption per litre of milk produced in line with a 19% calculated increase in milk production between 2018 and 2021.

The results presented in this paper reinforce the importance of assessing and refining model applicability across various prediction applications. More specifically, a model found to offer a specific prediction accuracy for a particular application (i.e. monthly farm-level predictions) may offer a greater applicability for macro-level applications (i.e. annual farm-level or catchment-level predictions), and thus, must be assessed accordingly. These results demonstrate the effectiveness of the SVM as a macro-level simulation forecast tool for dairy farm electricity consumption. The tool may be implemented at a national level to quantify the electrical energy contribution to greenhouse gas emissions associated with the production of milk in Ireland. This information could be utilised for government reporting, marketing of dairy products abroad and/or as an input to a carbon footprint based grant system for Irish dairy farms. Additionally, research utilising actual dairy farmers' future plans regarding changes to infrastructural equipment in line with a milk production expansion could be collected by dairy catchments or government bodies quantify the impact on electricity consumption to help achieve EU environmental targets.

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