An Optimal Milk Production Model Selection and Configuration System for Dairy Cows

Fan Zhang

*Cork Institute of Technology*

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AN OPTIMAL MILK PRODUCTION MODEL

SELECTION AND CONFIGURATION SYSTEM FOR

DAIRY COWS

A thesis presented for the award of

Doctor of Philosophy

BY

Fan Zhang

Supervisor: Dr. Michael D. Murphy

Department of Process, Energy and Transport Engineering

Cork Institute of Technology, Cork, Ireland

November 2017
DECLARATION

I declare that this thesis has not previously been submitted for a degree at Cork Institute of Technology, Ireland or any other university. I declare that the work contained in this thesis is my own.

Fan Zhang

November, 2017
DEDICATION

Nanos gigantum humeris insidentes

-- Bernardus Carnotensis

If I have seen further, it is by standing on the shoulders of giants.

-- Sir Isaac Newton

To all the people, who guide me, inspire me and support me.
ACKNOWLEDGEMENTS

First of all I would like to acknowledge Cork Institute of Technology and Teagasc for the opportunity they provided me with to conduct my PhD research. Without the Rísam Scholarship, the on-farm dairy data and the advice from my supervisors, I would not have been able to finish my PhD research and final thesis.

I am deeply grateful to my supervisor Dr. Michael D. Murphy. Thanks for his help, support and supervision during this study. He is the first person to lead me to the research field of dairy because the truth is that I had never seen a real dairy cow before I came to Ireland. I am fortunate that I can open a door, not only to a new life, more importantly, to science.

I would like to thank my Teagasc supervisors Dr. Laurence Shalloo and Dr. John Upton for sharing their time and expertise along with Dr. Elodie Ruelle, of the Animal & Grassland Research and Innovation Centre, Teagasc. Thank you for your help, comments, suggestion and answering my questions about the dairy industry during my study.
I would like to thank all researchers whose paper I have ever read, for their contribution to this discipline, for their generous sharing of academic resources, without this I could not get any clue or idea of the research field.

I would like to thank people from CIT, Nimbus and Teagasc for their warm help, especially to me, a young man from a country on the other edge of the world and have never ever enjoyed so much of drizzle in the winter.

I would like to thank Philip Shine for helping me to improve my ‘Chinglish’. I would like to thank Damilola Asaley, An Phan Quang, Stefan Reis and Dr. Conor Lynch for sharing their experiences and news from different countries. I would like to thank my Chinese friends: Dr. Haiyang Li and his family, Dr. Guangbo Hao and his family. We come from different regions of China and become friends in Ireland.

Finally, I would like to express my deepest appreciation to my wife, for her support in the daily life. I thank my parents, in-laws, grandparents, brothers and sisters for their concern and all the sacrifices they made for my family.
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<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>Artificial neural network</td>
</tr>
<tr>
<td>ASSA</td>
<td>Adaptive stratified sampling approach</td>
</tr>
<tr>
<td>BCS</td>
<td>Body condition score</td>
</tr>
<tr>
<td>DHMY</td>
<td>Daily herd milk yield</td>
</tr>
<tr>
<td>DIM</td>
<td>Days in milk</td>
</tr>
<tr>
<td>DMY</td>
<td>Daily milk yield</td>
</tr>
<tr>
<td>DNN</td>
<td>Dynamic neural networks</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
</tr>
<tr>
<td>GUI</td>
<td>Graphical user interface</td>
</tr>
<tr>
<td>MD</td>
<td>Meteorological data</td>
</tr>
<tr>
<td>MLR</td>
<td>Multiple linear regression</td>
</tr>
<tr>
<td>MPFOS</td>
<td>Milk production forecast optimization system</td>
</tr>
<tr>
<td>MY</td>
<td>Milk yield</td>
</tr>
<tr>
<td>NARX</td>
<td>Nonlinear auto regressive model with exogenous input</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
<tr>
<td>---------</td>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td>NCM</td>
<td>Number of cows milked</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean squared error</td>
</tr>
<tr>
<td>RPE</td>
<td>Relative prediction error</td>
</tr>
<tr>
<td>$R^2$</td>
<td>Coefficient of determination</td>
</tr>
<tr>
<td>POD</td>
<td>Percentage of difference</td>
</tr>
<tr>
<td>SANN</td>
<td>Static artificial neural networks</td>
</tr>
<tr>
<td>SD</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>SSE</td>
<td>Summed square of residual errors</td>
</tr>
</tbody>
</table>
ABSTRACT

Milk production forecasting in the dairy industry has been an independent research topic since the early 20th century. The accurate prediction of milk yield can benefit both the processor (creameries) and the producer (dairy farmer) through developing short-term production schedules, planning long-term road maps, facilitating trade and investment in the dairy industry, improving business operations, optimising the existing infrastructure of the dairy industry, and reducing operating costs. Additionally, due to the innate characteristics of the milk production process, the accurate prediction of milk yield has been a challenging issue in the dairy industry. With the abolishment of EU milk quotas in 2015, the business requirements of milk production forecasting from the dairy industry has become increasingly important. However, to date, most of the existing modelling techniques are data dependent and each case study utilises specific data based on unique conditions. Consequently, it is difficult to compare the prediction performance of each candidate model for forecasting milk as both the data types and origins are independent from study to study. This body of work proposes an integrated forecasting framework.
concentrating on milk production forecasting using heterogeneous input data combinations based on animal data, milk production, weather variables and other possible records that can be applied to milk yield forecasting on either the herd level or the individual cow level. The first objective of this study concerned the development of the Milk Production Forecast Optimisation System (MPFOS). The MPFOS focused on data processing, automated model configuration and optimisation, and multiple model comparisons at a global level. Multiple categories of milk yield prediction models were chosen in the model library of the MPFOS. Separated databases existed for functionality and scalability in the MPFOS, including the milk yield database, the cow description database and the weather database. With the built-in filter in MPFOS, appropriate sample herds and individual cows were filtered and processed as input datasets for different customised model simulation scenarios. The MPFOS was designed for the purpose of comparing the effectiveness of multiple milk yield prediction models and for assessing the suitability of multiple data input configurations and sources. For forecasting milk yield at the herd level, the MPFOS automatically generated the optimal configuration for each of the tested milk production forecast models and benchmarked their performance over a short (10-day), medium (30-day) and long (365-day) term prediction horizon. The MPFOS found the most accurate model for the short (the NARX model), medium and long (the surface fitting model) terms with $R^2$ values equalling 0.98, 0.97 and 0.97 for the short, medium and long term, respectively. The statistical analysis demonstrated the effectiveness of the MPFOS as a model configuration and comparison tool. For forecasting milk yield at the individual cow level, the MPFOS was utilised to conduct two exploratory analyses on the effectiveness of adding exogenous (parity and meteorological) data to the milk production modelling
procedure. The MPFOS evaluated the most accurate model based on the prediction horizon length and on the number of input parameters such as 1) historical parity weighting trends and 2) the utilisation of meteorological parameters. As the exploratory analysis into utilising parity data in the modelling process showed, despite varying results between two cow groups, cow parity weighting profiles had a substantial effect on the success rate of the treatments. Removal of the first lactation and applying static parity weight were shown to be the two most successful input treatments. These results highlight the importance of examining the accuracy of milk prediction models and model training strategies across multiple time horizons. While the exploratory analysis into meteorological data in the modelling process demonstrated that based on statistical analysis results, 1) the introduction of sunshine hours, precipitation and soil temperature data resulted in a minor improvement in the prediction accuracy of the models over the short, medium and long-term forecast horizons. 2) Sunshine hours was shown to have the largest impact on milk production forecast accuracy with an improvement observed in 60% and 70% of all predictions (for all test cows from both groups). However, the overall improvement in accuracy was small with a maximum forecast error reduction of 4.3%. Thus, the utilisation of meteorological parameters in milk production forecasting did not have a substantial impact on the overall forecast accuracy. One possible reason for this may be due to modern management techniques employed on dairy farms, reducing the impact of weather variation on feed intake and lessening the direct effect on milk production yield. The MPFOS architecture developed in this study showed to be an efficient and capable system for automatic milk production data pre-processing, model configuration and comparison of model categories over varying prediction horizons. The MPFOS has proven to be a
comprehensive and convenient architecture, which can perform calculations for milk yield prediction at either herd level or individual cow level, and automatically generate the output results and analysis. The MPFOS may be a useful tool for conducting exploratory analyses of incorporating other exogenous data types. In addition, the MPFOS can be extended (addition or removal of models in the model library) and modularised. Therefore the MPFOS will be a useful benchmark platform and integrated solution for future model comparisons.
1 INTRODUCTION
1.1 The Irish dairy industry

As one of the most important indigenous industries, the Irish dairy industry is a prospering sector and comprises the vital part of food and beverage exports, according to the annual report from the Irish Department of Agriculture, Food and the Marine (2016). The Irish dairy industry accounted for 30% of Food and Beverages exports between 2014 and 2015 (as shown in Table 1-1), and has a reputation for high quality and nutritious dairy products, due to a sustainable, pasture-based milk production system (Central Statistics Office, 2017). With the abolishment of the European Union (EU) milk quotas in April 2015, Irish dairy farmers were able to freely increase milk production. As a result, Irish annual milk yield increased by 13.3% between 2014 and 2015 (Table 1-2 and Figure 1-1). Due to the grass-based dairy system, the monthly milk yield varies seasonally throughout the year (as shown in Figure 1-1), as cows are kept indoors during the winter months. From 2010 to 2015, annual milk production in Ireland increased by almost 25%, on the other hand, the Peak to Trough Ratio (PTR) has increased from 4.7 to 5.7, while the UK has a relatively stable PTR of 1.2 over the same period (Central Statistics Office, 2017).
Table 1-1 Food and beverage exports of Ireland between 2014 and 2015 (Data source: Central Statistics Office).

<table>
<thead>
<tr>
<th>Category</th>
<th>2014</th>
<th>2015</th>
<th>Rank</th>
<th>Change</th>
<th>Share of Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dairy Products</td>
<td>€3,105</td>
<td>€3240</td>
<td>1</td>
<td>4%</td>
<td>30%</td>
</tr>
<tr>
<td>Beef</td>
<td>€2,280</td>
<td>€2,410</td>
<td>2</td>
<td>6%</td>
<td>22%</td>
</tr>
<tr>
<td>Others</td>
<td>€5,085</td>
<td>€5,157</td>
<td>-</td>
<td>-</td>
<td>48%</td>
</tr>
<tr>
<td>Total</td>
<td>€10,470</td>
<td>€10,825</td>
<td>-</td>
<td>3%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 1-2 Comparison of milk production yield and trend between 2014 and 2015 in different countries (Data source: Department of Agriculture Food & the Marine).

<table>
<thead>
<tr>
<th>Milk Production (thousand tonnes)</th>
<th>Ireland</th>
<th>Rest of EU</th>
<th>Total EU</th>
<th>USA</th>
<th>New Zealand</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>5,816</td>
<td>142,602</td>
<td>148,418</td>
<td>93,460</td>
<td>21,843</td>
<td>9,513</td>
</tr>
<tr>
<td>2015</td>
<td>6,589</td>
<td>145,043</td>
<td>151,632</td>
<td>94,571</td>
<td>21,533</td>
<td>9,605</td>
</tr>
<tr>
<td>% change</td>
<td>13.30%</td>
<td>1.70%</td>
<td>2.20%</td>
<td>1.20%</td>
<td>-1.40%</td>
<td>1.00%</td>
</tr>
</tbody>
</table>
In addition to macro-level milk production figures, the average annual performance level (litres/cow) varied by between -4% and 5% in Ireland, as shown in Table 1-3 (Teagasc, 2011). Additionally, milk price variances and other feed and farm management related costs have considerable effects on net margin. By 2016, there were approximately 15,639 Irish dairy farms with an average income of €51,809, according to Teagasc National Farm Survey Results (Teagasc, 2016). The average income of dairy farms has declined continuously in 2015 and 2016, as shown in Table 1-4, due to the reduction in milk price and gross output (Teagasc, 2016). Despite this reduction in the average dairy farm income, dairy farms still have the opportunity to recover by practising positive technical and
financial methods, including expanding milk production, increasing system efficiency on farms and reducing total costs.

Table 1-3 Average milk production yield (litres per cow), milk price (cent per litre) and net margin (cent per litre) of Irish dairy industry and annual changes (%) (2011-2016) (Data source: Teagasc).

<table>
<thead>
<tr>
<th>Year</th>
<th>Average Yield</th>
<th>Average Price and Margin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Production (litres/cow)</td>
<td>Milk Price (cent/litre)</td>
</tr>
<tr>
<td></td>
<td>5,166</td>
<td>4,968</td>
</tr>
<tr>
<td>Change (%)</td>
<td>0</td>
<td>-4%</td>
</tr>
</tbody>
</table>

Table 1-4 Income of Irish dairy farms (2014-2016): total number of dairy farms, average gross output (Euro), average total costs (Euro), average income (Euro) and annual changes (%) (2014-2016) (Data source: Teagasc).

<table>
<thead>
<tr>
<th>Year</th>
<th>No. of Dairy farms</th>
<th>Gross Output (€)</th>
<th>Total Costs (€)</th>
<th>Average Income (€)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>17,000</td>
<td>15,588</td>
<td>15,639</td>
<td>185,685</td>
</tr>
<tr>
<td>Change (%)</td>
<td>0</td>
<td>-3%</td>
<td>-7%</td>
<td>0</td>
</tr>
</tbody>
</table>
Milk production within the EU has been restricted since the introduction of milk quotas in 1984 under the Dairy Produce Quota Regulations 1984. After three decades, the EU milk quota system was abolished in April 2015. As a free market, milk yield and price fluctuations pose a logistical challenge for both milk producers (farmers) and processors (creameries). The reporting of milk production statistics frequently use averaged values derived from cumulative milk yield over a relative fixed period (i.e. monthly, annual) at the herd level. According to the Food Wise 2025 report (Department of Agriculture Food & the Marine, 2016) and the Dairy Road Maps (Teagasc 2008, 2013, 2016), total number of dairy cows, average milk yield and net margin are the three major indicators of economic forecasting and comparison, as well as reference points of targets and achievements on the Dairy Road Maps (as shown in Table 1-5). This can be seen to result in a disjunction between targets (estimated values) from regulators and achievements (actual values) from industry. e.g. differences between achievements and targets of average milk yield and net margin on all three Road Maps indicates that targets were far from fulfilled: even the achievements in 2016 were still below the targets in the Road Map 2018 which was made in 2008 (as shown in Figure 1-2). In a future scenario, a situation may arise whereby milk yield cannot be predicted precisely, potentially leading to overcapacity, under capacity and/or milk price volatility. With this, both milk producers and processors may benefit from accurate milk production information via practical forecasting methods. Accurate milk production forecasts would allow farmers to predict on farm thermal cooling loads, plant capacity sizing, plant operations and optimization (Breen et al., 2015; Murphy et al., 2015, 2014, Upton et al., 2015, 2014).
On the other hand, regarding precision agriculture and animal welfare, precise forecasts of milk yield for a specific cow at the individual cow level could be beneficial within the dairy industry. Such beneficial applications include: 1) monitoring disease and the condition of a cow’s health, i.e.: mastitis detection (Andersen et al., 2011), conception interval prediction (Madouasse et al., 2010). 2) cow milking performance prediction (Nielsen et al., 2010; Rémond et al., 1997), decision support for advanced milking parlours and milking machines (André et al., 2010; Thomas and DeLorenzo, 1994). 3) precision input for herd simulation models (Petek and Dikmen, 2006; Ruelle et al., 2016). These applications will have direct or indirect effects on the milk yield of an individual cow. Consequently, as time goes on, the performance of the herd milk yield can be improved, as well as the prediction accuracy and precision of both herd and individual cow milk yield.
Table 1-5 Summary of Irish Dairy Road Maps (2018, 2020 and 2025) (Data source: Teagasc and Central Statistics Office).

<table>
<thead>
<tr>
<th>Key Figures of Dairy Road Maps</th>
<th>Road Map 2018</th>
<th>Road Map 2020</th>
<th>Road Map 2025</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dairy Farm Numbers</td>
<td>_</td>
<td>15,500</td>
<td>_</td>
</tr>
<tr>
<td>Dairy Cows Numbers (million) (by December)</td>
<td>1.104</td>
<td>1.382</td>
<td>1.082</td>
</tr>
<tr>
<td>Average Herd Size</td>
<td>_</td>
<td>89</td>
<td>_</td>
</tr>
<tr>
<td>National Milk Production (million tonnes)</td>
<td>_</td>
<td>7,101</td>
<td>_</td>
</tr>
<tr>
<td>Average Milk Delivered per Farm (kg)</td>
<td>_</td>
<td>458,123</td>
<td>_</td>
</tr>
<tr>
<td>Milk Yield (kg/cow)</td>
<td>4,661</td>
<td>5,140</td>
<td>4,902</td>
</tr>
<tr>
<td>Net Margin (€/ha)</td>
<td>-42</td>
<td>821</td>
<td>-25</td>
</tr>
</tbody>
</table>

Notes: total dairy cows, annual average milk yield (kg/cow), net margin (€/ha) are three major indicators of economic forecasting on the Dairy Road Maps.
1.2 Problem statement

With milk production levels expected to increase to 7.5 billion litres by 2020 (from a base of 4.9 billion litres in 2008-09), along with an increase in the national average herd size, accurate milk production forecasts would allow individual farmers to predict increased on-farm thermal cooling loads and to optimize the sizing and configurations of plant infrastructure (Department of Agriculture Food & the Marine, 2016). Concurrently, accurate milk production forecasts will be useful for farm management support and analysis for herd management, energy utilization and economic prediction (Shalloo et al., 2011, 2004; Murphy et al., 2013; Upton et al., 2015).
There exists a plethora of milk production forecast models in the literature. Each study has found that a particular model is best suited for a specific situation at a specific time for the available level of data. E.g. the Ali-B model (Quinn et al., 2005) for Irish pasture-based systems, the log-quadratic model (Adediran et al., 2012) for grass-based systems in Tasmania, Australia. Similarly, there have been several studies on the applicability of regression modelling and artificial neural networks (ANN) for milk production forecasting. Therefore, a solution that will find the most suitable model for a specific application and that can also test multiple training inputs in an efficient manner will be very useful. A number of features regarding the milk prediction timeframe resolution, input data and model application must be considered to optimize the applicability of such a solution. The solution must: 1) automatically select the most suitable model for predicting milk production at both the herd and individual cow level. 2) predict milk production for an annual, monthly and weekly resolution. 3) optimize the selection of input data, simplify the data input process. 4) be able to compare the performance of multiple milk production forecast models along with the ability to analyse the effectiveness of varying model input configurations.

1.3 Research objective

The following section describes the primary objectives of this thesis. The first objective concerns the development of a Milk Production Forecast Optimisation System that was later employed to carry out the following objectives.
(1) Develop a milk production forecast model selection configuration and optimization system. This system must be capable of evaluating the accuracy of multiple models across multiple categories for varying data inputs. The system must also be able to analyse the effectiveness of introducing additional data combinations to the modelling process.

(2) Compare the effectiveness of multiple herd milk yield prediction models for an Irish pasture-based dairy herd for different prediction horizons.

(3) Develop, compare and evaluate pre-processing input treatments designed to factor parity information into the milk prediction model configuration process and compare the knock-on effect on milk production prediction accuracy.

(4) Conduct an exploratory analysis of adding multiple combinations of meteorological information to the training process of milk production forecast models and analyse the effect the introduction of this data has on the effectiveness of the milk production models.

1.4 Thesis framework

This thesis is comprised of seven chapters. Each chapter contains specific results and conclusions related to the research carried out within the chapter. Following the introduction, the remainder of this thesis is presented as follows:

- **Chapter 2** provides a comprehensive literature review of milk yield prediction models and external factors related to milk yield production.

- **Chapter 3** presents a description of the Milk Production Forecast Optimization System (MPFOS) and the forecasting of milk yield at herd level including evaluation of model performance.
• **Chapter 4** illustrates the impact of applying parity weighting for milk yield prediction at the individual cow level with results, comparison and evaluation. The models analysed included curve fitting and auto-regressive models.

• **Chapter 5** examines the effect of applying weather variables for milk yield prediction at the individual cow level. Prediction results of auto-regressive category and regression category models were compared and evaluated.

• **Chapter 6** presents the global discussion on the output of this thesis.

• **Chapter 7** presents a global conclusion and the future work.
2 LITERATURE REVIEW
2.1 Introduction

This literature review focuses on milk yield prediction models and additional aspects related to milk yield modelling such as grassland and grazing, the impact of weather data, and data variation. A number of authors have developed lactation curve models in a variety of ways, such as empirical curve fitting models, multiphasic models, semiparametric models and regressive procedures. In addition to these conventional modelling techniques, the artificial neural network has proved successful in non-linear function fitting and time series prediction of milk production in recent decades. The first section of this chapter will investigate and discuss the models related to milk yield modelling, followed by the statistical criteria for model performance comparison that have been utilised in other published studies in this domain.

The second section of this review will introduce and investigate various factors found to influence the prediction of milk yield, as specified in previous research. These factors may be categorised into three sections: 1) physiological factors including: breed, parity, calving season etc., 2) geographic region and management factors including ambient environment conditions, grazing management and etc. and 3) long term and short term variations in milk production records.

2.2 Modelling milk yield

Historically, studies have been undertaken regarding milk production prediction techniques where diverse equations have been developed for the purpose of describing a lactation curve based on past milk yield data. These equations include curve fitting models,
regression models and auto-regressive models and mechanistic models. Each one of these models has been successfully applied to predict cow/herd level milk production, based on specific datasets. Each statistical model offers separate advantages related to their ease of deployment and ability to effectively quantify the non-linear nature of the lactation curve.

In relation to curve fitting models algebraic equations are utilised for fitting lactation curves using empirical data, usually requiring one variable as input data, such as daily or weekly cumulative milk yield at herd or individual cow level. Curve fitting models have performed well in numerous studies, taking many different forms including parabolic exponential (Sikka, 1950), incomplete gamma (Wood, 1967), polynomial (Ali and Schaeffer, 1987), exponential (Wilmink, 1987), Cubic splines (Green and Silverman, 1993), Legendre polynomial (Kirkpatrick et al., 1994) and log-quadratic (Adediran et al., 2012). Due to the variety of mathematical functions available to model lactation profiles, curve fitting models have two sub-categories: 1) empirical models (linear or nonlinear) and 2) semiparametric models which show their flexibility in fitting time-series for events with various curves (Schaeffer, 2004; Sherchand et al., 1995). However, lack of flexibility and adaptation is a common weakness of curve fitting models when dealing with significant fluctuations in yield within and between years (Jones, 1997).

Regression models have been found to perform well statistically over a wide variety of milk yield datasets. Auto-regressive neural network models were introduced for milk yield prediction and found to more accurately forecast milk yield when compared with static neural network models (Murphy et al., 2014). Mechanistic models offer more biological details and take account milk yield models, paddock models and grass conditions (Ruelle et al., 2016).
2.2.1 Empirical algebraic models

Empirical algebraic models have been utilised in research to forecast milk yield over the course of the lactation cycle (lactation curve) since early 20th century. Numerous studies have attempted to describe lactation curves using algebraic formula, these include Brody et al. 1923; Sikka 1950; Wood 1967; Wilmink 1987; Ali and Schaeffer 1987; Guo and Swalve 1995; Noreen Quinn 2005.

The curve-fitting model developed by Brody et al. (1923) was the first gamma model to forecast milk yield over the lactation cycle for four breed of cows in the US including, Holstein, Jersey, Guernsey and Scrub. In Brody et al.’s original formula:

$$Y_n = ae^{-bn}$$

(Equation 2-1)

Where $Y_n$ is the milk yield during the $n^{th}$ month, a is the theoretical value of the milk yield at the time of parturition, and $b$ is coefficient. The initial aim of this model was to describe the declining phases of the whole lactation. Hence, this model first proposed the concept of a constant relative rate of decline in milk yield of $b$ kg per month from an initial value of $a$.

One year later, Brody et al. (1924) proposed a more complex model which uses two exponential functions to describe not only the declining phases but also the whole lactation for 119 US Holstein-Friesian cows. The model of Brody et al. (1924) was the first gamma model on the prediction of whole lactation yield research, the formula of which equalled:

$$Y_n = ae^{-bn} - ae^{-cn}$$

(Equation 2-2)

Where $Y_n$ is the milk produced during the $n^{th}$ month, $a$ is the theoretical value of the milk yield at the time of parturition, and $b$ and $c$ are coefficients. However, although this model
was the state-of-art in that era, this model was later found to have underestimated in the mid lactation and overestimated in the late lactation.

A study investigating the effect of heredity and environment factors on milk yield was conducted by Sikka, L. C. (1950). The data used this study was obtained from five herds of Ayrshire cows and involved 2392 lactations during the period 1920 - 1939. Through utilising the multiple regression technique, Sikka concluded that any given lactation can be predicted much more accurately by using the following formula:

\[ Y_n = ae^{(bn - cn^2)} \]

(Equation 2-3)

Where \( Y_n \) is milk production during the \( n \)th month, \( a \) is the theoretical value of the milk yield at the time of parturition, and \( b \) and \( c \) are coefficients. The model developed by Sikka et al. was found to have a better performance for the first lactation compared with the predictions of latter lactations due to the symmetric estimated yield around the peak yield.

Wood’s model (1967) is the most commonly used model to predict milk yield throughout the whole lactation cycle and has been used as the base for consequent studies involving empirical equations of lactation curves. Wood’s model was the first equation that presented the lactation curve in a reasonable accuracy using the following equation:

\[ Y_n = an^b e^{-cn} \]

(Equation 2-4)

Where \( Y_n \) is the average daily yield in the \( n \)th week, \( a \) is a scaling factor associated with the average yield, and \( b \) and \( c \) are related to pre-peak curvature and post-peak curvature, respectively. Wood’s model utilised the least squares method to get its regression parameters \( a \), \( b \) and \( c \). According to the prediction of Wood’s model, the peak yield of
\( a(b/c)^{e-b} \) will occur at the \((b/c)\)th week. However Wood’s model was inherently non-linear and it was computationally expensive to perform nonlinear regression in 1960’s.

A logarithmic transformation of Wood’s model was a more popular technique, which makes the model’s linear equation as follows (Equation 2-5 or Equation 2-6):

\[
\log_e(Y_n) = \log_e(a) + b\log_e(n) - cn
\]

(Equation 2-5)

\[
\ln(Y_n) = \ln(a) + b\ln(n) - cn
\]

(Equation 2-6)

In certain circumstances, a lack of fit was found in the predictions developed by Wood’s model. As a consequence, Wilmink (1987) proposed a non-linear exponential model to predict milk yield with four parameters. In Wilmink’s study, test-day records of 14,275 purebred Dutch Friesians were analysed by generalized least squares. In Wilmink’s model:

\[
Y_n = a + bn + ce^{-dn}
\]

(Equation 2-7)

Where \(Y_n\) is the yield in lactation day \(n\), where \(a\), \(b\), \(c\) and \(d\) are coefficients. The exponential term tends to zero as \(n\) increases, while after the peak, the decline in yield eventually equates the straight line \(a + bn\). Although Wilmink (1987) claimed this non-linear model offered a greater representation of the lactation curve, other studies reported that a reduced \(d\) parameter value offered a simplified model with a similar level of forecasting accuracy (Olori et al., 1999; Brotherstone and White, 2000).

Concurrently, Ali and Schaeffer (1987) proposed the first polynomial regression model based on empirical data from 775 Canadian Holstein-Friesian cows in 42 herds (1964-1984), the formula of which is as follows:
\[ Y_n = a + b\gamma + c\gamma^2 + d\omega + e\omega^2 + f \]  
\hspace{1cm} (Equation 2-8)

Where \( Y_n \) is the milk yield in lactation day \( n \), \( \gamma = n/305 \), \( \omega = \ln(305/n) \), \( f \) is the residual error and \( a, b, c, d, e \) are regression coefficients. In this formula, \( a \) is associated with peak yield, \( b \) and \( c \) are associated with the decreasing slope of the curve, \( d \) and \( e \) are associated with the increasing slope, and \( f \) is the residual error for this model. Ali and Schaeffer’s model requires test data to estimate five parameters which is a disadvantage for some applications. Thus, this model could only be applied on milk yield data from a limited length lactation, and it was not suitable for extending part of the lactation. Moreover, the concave shape of Ali and Schaeffer’s formula resulted in limitations as it could only be applied on milk yield forecast. The Ali and Schaeffer model has shown to be one of the most effective milk yield predictors over the last 30 years. A recent study found that the Ali and Schaeffer model performed better on the highly heterogeneous data, in contrast to the Wilmink model (Melzer et al., 2017).

Based on the Ali and Schaeffer model, Quinn et al. (2005) proposed the Ali-B model which have showed better forecasting performance than the original Ali and Schaeffer model based on data of 4336 Irish dairy cows from 79 spring-calving herds. After removing parameter \( b \), the modified Ali and Schaeffer’s model (the Ali-B model) was the most accurate model for predicting total and weekly milk yield. The Ali-B formula is as follows:

\[ Y_n = a + c\gamma^2 + d\omega + e\omega^2 + f \]  
\hspace{1cm} (Equation 2-9)
Where $Y_n$ is the daily milk yield in lactation day $n$, $\gamma = 7n/305$, $\omega = \ln(305/7n)$, $f$ is the residual error and $a$, $b$, $c$, $d$, $e$ are the regression coefficients. Peak yield is associated with the coefficient $a$, $b$ and $c$ are associated with the decreasing slope, $d$ and $e$ are associated with the increasing slope of the curve.

Guo and Swalve (1995) proposed a mixed logarithmic model, the formula equalling:

$$Y_n = a + b\sqrt{n} + c\ln(n)$$

(Equation 2-10)

Where, $n$ is the number of weeks in lactation, and $a$ and $b$ are coefficients. Quinn et al. (2005) analysed the prediction performance of this model to those models developed by Wood (1967), Wilmink (1987), Ali and Schaeffer (1987) and Ali-B (2005) and found that the Ali-B model was the most consistent at satisfying the assumptions and prediction of weekly and total lactation individual milk yield.

Adediran et al. (2012) proposed Log-quadratic model for Australian pasture-based dairy systems (Equation 2-11). The data used including 9,505 lactations from 154 Holstein-Friesian herds collected from 2005-2007. This recent log-quadratic model has the peculiar ability to fit both inclining and declining lactation rates according Adediran et al.’s research results. The author stated that the developed model performed well for both the average lactation and individual cow lactations. However, the tested data of individual cows was the average of a selected group of cows due to the actual diversity of the individual cows. This limitation is ubiquitous for all empirical algebraic lactation models.

$$Y_n = \exp[a(b - \log n)^2 + c]$$

(Equation 2-11)
2.2.2 Semiparametric approach

Recently, semiparametric functions including Legendre polynomial and Cubic spline have been applied for lactation curve modelling due to their flexibility in fitting time-series for events with various curves. Kirkpatrick et al. (1994) created the Legendre polynomial model which are nth degree polynomial functions. The equation describing a single observation equals:

\[ Y_n = \sum_{i=0}^{n} \alpha_i \varphi_i(\omega) \]

(Equation 2-12)

\[ \omega = 2 \left( \frac{t - t_{\text{min}}}{t_{\text{max}} - t_{\text{min}}} \right) - 1 \]

(Equation 2-13)

Where \( \omega \) is lactation time unit ranging from -1 to +1, \( t \) is the test day, \( t_{\text{min}} \) (5 day) is the earliest days in milk (DIM) and \( t_{\text{max}} \) (305 day) is the latest DIM (Schaeffer, 2004).

\[ \varphi_i(\omega) = \sqrt{\frac{2n+1}{2}} P_n(\omega) \]

(Equation 2-14)

Where \( P_n(\omega) \) is a polynomial of degree \( n \) and \( \varphi_i(\omega) \) is the normalized polynomial. The first 5 Legendre polynomials functions of standardized units of time (\( \omega \)) are defined below, according to Spiegel (1971).

\[ P_0 = 1 \]

\[ P_1(\omega) = \omega \]

\[ P_2(\omega) = \frac{1}{2} (3 \omega^2 - 1) \]
Different normalized Legendre polynomial functions of standardized units of time ($\omega$) and coefficients $\alpha$ with different degrees require different data from observations by lactation. E.g. degree 2, 3, 4 requires a minimum 4, 5, 6 observations by lactation respectively, which implies that they were not applicable to all the data of sampling groups. According the study from Silvestre et al. (2006), the Legendre polynomial functions with different degrees generated totally different accuracy results. Particularly, the Legendre polynomial functions were more accurate for describing the lactation curve when the first test day was recorded late in lactation than models developed by Wood, Wilmink and Ali and Schaeffer. These results supported the authors’ hypothesis that the performances of Wood, Wilmink and Ali and Schaeffer models were greatly affected by both the sample properties and sample dimension.

The second semiparametric model is the Cubic spline fitting which was proposed by Green and Silverman (1994). The original normal formula is:

$$Y_k(x) = \sum_{i=0}^{k} \frac{\alpha_i x^i}{i!} + \sum_{j=1}^{n-1} \frac{\beta_i (x-x_j)^k}{k!}$$

(Equation 2-16)

Where $(x-x_j)^k = \begin{cases} (x-x_j)^k, & x \geq x_j \\ 0, & x < x_j \end{cases}$. Recently, the Cubic spline model was used to describe the lactation curve (Silvestre et al., 2005; White et al., 1999). The Cubic spline
model requires a minimum of three observations for each record, and the formula for each record can be written as:

\[ Y_n = a_i + b_i (n - n_i) + c_i (n - n_i)^2 + d_i (n - n_i)^3, \text{ for } n_i < n < n_{i+1} \]

(Equation 2-17)

According to other studies, the Cubic spline model fitted the lactation data best and had the additional advantage of describing the lactation curve adequately with fewer observations than was required for the Legendre polynomial model (Adediran et al., 2012; Silvestre et al., 2006). Although, semiparametric functions including Legendre polynomial and Cubic spline are not always the most accurate, these functions were found to work well using an appropriate data set as a previous study implied that a single outlier data point could greatly distort the curve, in particular for small data sets with few data points where the impact of outlier data is enhanced (Motulsky and Ransnas, 1987).

2.2.3 Surface fitting model

The surface fitting method creates a surface fit to the data in the x, y, and z planes. In this study, three training data matrices which were deemed the most accessible data for commercial dairy farms including number of cows milked (NCM), days in milk (DIM) and daily herd milk yield (DHMY) were chosen as the input datasets. In this study, the expression of the surface fitting method can be written as:

\[ Z(x,y) = \epsilon + p_1x + p_2y + p_3x^2 + p_4xy + p_5y^2 + p_6x^3 + p_7x^2y + p_8xy^2 + p_9y^3 \]

(Equation 2-18)
Where $Z_{(x,y)}$ is the DHMY and the dependent variable, $x$ is the independent variable DIM and $y$ is the independent variable NCM, $p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, \text{ and } p_9$ are the surface coefficients and $\varepsilon$ is the residual error.

2.2.4 Multiple linear regression

The Multiple Linear Regression (MLR) model has been proposed by multiple authors in cognate studies (Grzesiak et al., 2003; Kerr et al., 1998; Zar, 1984). The MLR model was chosen for milk yield prediction for two reasons. Firstly, the MLR model was proved to be successful in milk yield forecasting at the herd level (Dongre et al., 2012; Grzesiak et al., 2003; Sharma et al., 2007; Smith, 1968). Secondly, the MLR model can use more input variables than the curve fitting models, which can only use DIM and DHMY. Research carried out by Smith (Smith, 1968) has successfully demonstrated that the addition of rainfall and temperature data as additional input variables can improve the annual milk yield forecasting accuracy of a MLR model. For the purpose of forecasting herd level milk yield using most accessible data from commercial farms, Murphy et al. (2014) utilised a practical expression of the MLR model which only takes two inputs:

$$Y_n = \varepsilon + \alpha_1 NCM_n + \alpha_2 DIM_n$$

(Equation 2-19)

Where $Y_n$ is the daily herd milk yield and the dependent variable, NCM and DIM are independent variables, $\alpha_1$ and $\alpha_2$ are the regression coefficients and $\varepsilon$ is the residual error.
2.2.5 ANN modelling approach

An artificial neural networks (ANN) is a computational model based on the operating principles of the human nervous system and brain. An ANN is configured and applied to specific applications, such as function approximation, including non-linear function fitting (Esen et al., 2008; Kalogirou and Bojic, 2000; Specht, 1991), classification, including pattern recognition (Fukushima, 1988; Lyons et al., 2004), numerical control applications (Jung and Kim, 2007; Kim and Lewis, 2000) and time series prediction. Previous studies have applied ANN modelling in the forecasting domain (Hocaoğlu et al., 2007; Kalogirou and Bojic, 2000; Khoshnevisan et al., 2013; Kim et al., 2004; Pahlavan et al., 2012; Voyant et al., 2011; Wong et al., 2010; Zarzalejo et al., 2005).

In this section, the ANN architectures and related algorithms are reviewed. The basic component of a neural network is a node (or neuron), which is designed to mimic the understanding of the functionality of a neuron in the human brain. Each node forms the basic block of a neural networks. Figure 2-1 shows the structure of a neuron node.
Figure 2-1 The structure of a neuron node.

The calculation flow of neuron node is as follows:

- The inputs $x_j$ to a node are the measurements or the outputs from other nodes. Each input could be treated as a connection or a link with synaptic weights $w_{kj}$.

- Each node is characterized by an additive threshold value $b_k$ and an activation function $f(v)$. The threshold is used as an offset.

- The node sums the weighted inputs and the threshold value and passes the result through its characteristic nonlinearity to produce the output $y_k$.

The summation of the weighted input signals is described as:
\[ v_k = \sum_{j=1}^{m} w_{kj} x_j \]

Where \( x_j \) are input vectors, \( w_{kj} \) are the synaptic weights of neuron \( k \), \( v_k \) is the linear summation of the weighted input vectors.

This allows the neuron node output to be written as:

\[ y_k = f(v_k + b_k) \]

(Equation 2-20)

Where \( v_k \) is the linear summation of the weighted input vectors, \( b_k \) is the bias, \( f(v) \) is the activation function and \( y_k \) is the neuron output.

The common types of activation functions include step, sign, saturating, linear, and sigmoid etc. (Figure 2-2).

![Typical activation functions](image)

**Figure 2-2 Typical activation functions.**
• Step function:

\[
f(x) = \begin{cases} 
1, & x \geq t \\
0, & x < t 
\end{cases}
\]

• Sign function:

\[
f(x) = \begin{cases} 
1, & x \geq 0 \\
-1, & x < 0 
\end{cases}
\]

• Saturating function:

\[
f(x) = \begin{cases} 
1, & x > t \\
t, & -t \leq x \leq t \\
-1, & x < -t 
\end{cases}
\]

• Linear function:

\[
f(x) = t
\]

• Sigmoid function:

\[
f(x) = \begin{cases} 
\frac{1-e^{-x}}{1+e^{-x}}, & for \ -1 \leq f(x) \leq 1 \\
\frac{1}{1+e^{-x}}, & for \ 0 \leq f(x) \leq 1 
\end{cases}
\]

A typical neural networks usually consists of a three-layer architecture including an input layer, a hidden layer and an output layer (as shown in Figure 2-3). Input layer nodes and
output layer nodes are accessible from the external environment. However, the hidden layer nodes are not directly accessible from the external environment, meaning that all input and output connections of these nodes are associated with nodes within the ANN only (black box). In addition, the external inputs to the network are usually not weighted while all interconnections within the network are weighted. There are two basic architectures for ANN: 1) the feedforward architectures and 2) the feedback architectures. Figure 2-3 demonstrates a typical static feedforward ANN. This type of ANN is commonly referred to as a Multilayer Neural Networks (MNN). The signals between the nodes of the feedforward ANN only flow in the forward direction. Nodes of a layer could have inputs from nodes of any of the earlier layers.

![Diagram of a typical feedforward ANN.](image)

**Figure 2-3** A typical feedforward ANN.
In the feedback ANN (also named recurrent ANN), the output signal from a node is allowed to flow in the forward and backward directions, potentially feeding back as an input to the same node itself in the input layer.

In comparison with other modelling approaches discussed in previous sections, the advantage of the ANN model is that neural networks can be trained by supervised learning methods and error updating rules. Hence, the ANN prediction performance can be improved due to synaptic weights adjustment and better outputs selection.

A number of studies have reported that the ANN technique can be utilized for milk yield forecasting (Dongre et al., 2012; Gorgulu, 2012; Grzesiak et al., 2006, 2003; Ince and Sofu, 2013; Khazaei and Nikosiar, 2005; Kominakis et al., 2002; Salehi et al., 1998; Sanzogni and Kerr, 2001; Sharma et al., 2007; Torres et al., 2005). However, the common disadvantage of these proposed milk prediction ANN models is the requirement of a large amount of detailed information for model inputs. One model developed by Sharma et al. requires 12 individual traits of each cow (genetic group, DMY, season of birth, period of birth, birth weight, age at maturity, weight at maturity, season of calving, period of calving, age at calving, weight at calving, peak yield, days to attain peak yield). Similarly, An ANN model developed by Lacroix et al. (1995) requires 16 parameters for input to the model (logarithm of somatic cell count, energy fed on test day, protein fed on test day and dry matter fed on test day etc.). The disadvantage of these models is that they require too many biological parameters requiring a large scale, expensive and time consuming data recording and collection scheme. Unfortunately, this data is unavailable for typical pasture-based dairy farms at the practical level limiting the usability of these ANN models.
2.2.6 Dynamic ANN model

Neural networks are generally classified into two types: static (non-recurrent) and dynamic (recurrent) networks (Medsker and Jain, 2001). In contrast to static neural networks, dynamic neural networks (DNN) may result in good time-series prediction performance due to their embedded memory capability (retaining information to be used at later time step) (Connor et al., 1994; Von Zuben and de Andrade Netto, 1995). The internal strategy of a static feedforward (FFD) multilayer ANN is that all outputs are generated from current inputs, however, outputs of a DNN are based on both current and previous inputs and outputs. This short-term memory mechanism may enhance the whole networks’ performance on learning and recognition. Figure 2-4 shows a typical DNN with a feedback loop from the output back to the input layer.

![Figure 2-4 A typical DNN (Murphy et al., 2014).](image_url)
Tapped delay lines (TDL) are placed before the input and the feedback loop from the output to the hidden layer, and used to delay the input signal by a number of time steps. In many applications to date, dynamic neural networks are referred to as the nonlinear auto-regressive model with exogenous input (NARX) due to the exogenous (external data) feedback element and TDLs. The mathematical representation of a NARX model is as follows:

$$\chi(t + 1) = f(\chi(t), \chi(t - 1), ..., \chi(t - n), \kappa(t), \kappa(t - 1), ..., \kappa(t - n))$$

(Equation 2-21)

The embedded short term memory within the NARX model allows for an increased efficiency in back propagating gradient information compared to other ANN models. In particular, NARX models have been shown to perform well at recognising short-term patterns in the input data (Lin et al., 1997, 1998).

The NARX model has been proven to be a powerful tool for short term time series analysis in chaotic and noisy environments (Diaconescu, 2008a; Mirzaee, 2009) and time series prediction (Barbounis et al., 2006; El-Shafie et al., 2012; Khoshnevisan et al., 2014; Paoli et al., 2010; Voyant et al., 2011).

The NARX model could be presented as a more accurate alternative to conventional regression modelling techniques, especially for short-term milk yield predictions (Murphy et al., 2014). The study of Murphy et al. demonstrated that the NARX model was successful in milk production forecasting at the herd level with training data consisting of herd DMY, DIM and the NCM. In this study, the NARX model was compared with a static ANN model and a MLR model using three years of historical milk production data. The result comparison was based on prediction of the total daily herd milk yield over a whole
lactation using different forecast horizons. The NARX was found to increase the prediction accuracy as the horizon was shortened from 305 to 50, 30 and 10 days, while the other two models could not reduce error to the same extent due to lack of ability to dynamically learn from their errors from previous predictions. On the other hand, this study claimed that it is difficult to compare the effectiveness of models for individual cows due to lack of specific information, especially for a dairy farm without the use of a sophisticated computerized milk recording system. In addition, this study also indicated that each mentioned study used case-specific data to predict milk yield for a herd or cow at the unique conditions and it was probably difficult to conduct comparisons over different studies.

2.2.7 Mechanistic approach

Mechanistic approaches offer insights into the mammary gland physiological processes and thus, offer an increase in biological parameters (Grossman and Koops, 2003; Neal and Thornley, 1983; Pollott, 2000). However, according to study of Pollott (2000), one limitation of mechanistic models is that they cannot fit the data well based on current monthly milk records and are often over parameterized. A recent study proposed an explanatory mathematical and biological model based on udder physiology which could be tested and validated using empirical data (Gasqui and Trommenschlager, 2017). The author claimed that this model could both predict lactation traits (such as the length of peak lactation, peak milk yield, and total milk yield), explore a physiological process and pinpoint potential problems. This model enhanced Wood’s model, which does not have a clear biological interpretation.
Recently, a mechanistic model was proposed by Baudracco et al. (2012) to predict milk production of a pasture-based dairy cow. This model comprised of three previously published models including an ‘INTAKE’ model that predicts herbage dry matter (DM) intake by grazing dairy cows, a ‘MILK’ model that predicts potential milk yield and a ‘LIPID’ model that predicts genetically driven live weight (LW) and body condition score (BCS). The highlight of this model is that it could give prediction results with satisfactory accuracy (concordance correlation coefficient value equalling 0.76 for milk yield), under the conditions that all input parameters for three sub-models should be provided meaning this model requires large amounts of detailed input information.

Another recent mechanistic model was proposed by Ruelle et al. (2015) to predict milk production of pasture-based dairy herd. This model integrates three components, including a herd dynamic milk model that predicts the production of standard milk at 4.0% fat and 3.1% protein, a paddock model that predict grass conditions and grazing management rules that simulate the impact of dairy farm management rules. The advantage of this model is that it is able to take into account the management effect on dairy farms and has the ability to integrate updated grass growth models and bring wider usability. However, with the same innate characteristics as that of Baudracco et al.’s model, the requirement of embracive on farm data may reduce the practicability and limit the application of model.

2.2.8 Standard lactation curve method in Ireland

The Standard Lactation Curve (SLAC) method was proposed by Olori and Galesloot (1999) and is currently used in Ireland for predicting milk yield. This method was developed through interpolating 341,652 lactations from 121,179 cows in 5,225 herds,
which has a library of three equations as follows (Equation 2-22, 2-23, 2-24). The SLAC method involved three developmental steps. Step 1) standard lactation curves were derived for each contemporary group of cows defined to suit the production environment (Equation 2-22). Step 2) 15 milk yield values were predicted at 20 day intervals between the 10th and 290th lactation day using the derived lactation curve (Equation 2-23) and step 3) the lactation curve was expanded by calculating the milk yields in the unknown sections of the curve based on neighbouring fixed days (Equation 2-24).

\[ Y_n = E(Y_n) + b_1[Y_{p305} - E(Y_{p305})] + b_2[Y_k - E(Y_k)] \]  

(Equation 2-22)

Where \( Y_n \) is the predicted yield for day \( n \) of the lactation in progress, \( E(Y_n) \) is the expected yield on day \( n \) from the SLAC, \( Y_{p305} \) is the realised 305-day yield of the previous lactation, \( E(Y_{p305}) \) is the expected 305-day yield of the previous lactation, \( Y_k \) is the yield on the last test day \( k \) of the lactation in progress, \( E(Y_k) \) is the expected yield on the last test day \( k \) from the SLAC, and \( b_1 \) and \( b_2 \) are the lactation projection factors. Projection factors were derived by recurrent regression analyses involving the deviation of the yield on the last test and the previous lactation from their expectations. Additionally, for predicting fixed days before the first test by back prediction, a revised equation is used where \( Y_k \) is equal to the yield on the first test day.

The prediction yield for the fixed DIM is calculate by interpolation using following equation:

\[ Y_n = G_n + [(Y_2 - Y_1) - (G_2 - G_1)] / [(X_2 - X_1) * (X_n - X_1)] + (Y_1 - G_1) \]  

(Equation 2-23)
Where \( Y_n \) is the yield to be predicted, \( Y_2 \) and \( Y_1 \) are the observed daily yields, \( X_1 \) and \( X_2 \) are the days when \( Y_1 \) and \( Y_2 \) were measured respectively, \( X_n \) is the day for which a yield is to be predicted where \( X_1 < X_n < X_2 \), and \( G_n, G_1, G_2 \) are the expected yields \( E(Y) \) on days \( n, 1 \) and \( 2 \), respectively.

Once the yields of each of the fixed days have been calculated, the cumulative 305-day milk production (fat or protein) yield can be calculated using Equation 2-24:

\[
Y_{305} = \sum_{i=1}^{n} 0.5 \left[ Y_i \ast (\text{int}_i - 1) + Y_{i+1} \ast (\text{int}_i + 1) \right]
\]

(Equation 2-24)

Where \( Y_{305} \) is the 305-day milk production yield, \( Y_i \) is the yield of day \( i \), \( \text{int}_i \) is the interval in days between the daily yields \( Y_i \) and \( Y_{i+1} \), \( n \) is total number of daily yields (measured and predicted).

As states above, results of the SLAC method were based on a large number of sample data and confirmed that the correlations between projected and actual whole lactation yields increased with progressing length of records. The projection process was able to differentiate cows with potential from those without potential to produce further in projecting short lactations.

2.3 Model application and comparison

Several studies have been carried out comparing the milk yield prediction performance of the modelling techniques discussed in section 2.2. Similar studies have been carried out comparing the forecast accuracy of each individual model category. In particular, numerous works have been carried out comparing model performance within two
categories, across different modelling techniques and results evaluation platforms (Adediran et al., 2012; Bhosale and Singh, 2017; Cole et al., 2009; Druet et al., 2003; Gandhi et al., 2010; Grzesiak et al., 2003; Murphy et al., 2014; Olori et al., 1999; Otwinowska-Mindur et al., 2013; Quinn et al., 2005; Sharma and Kasana, 2006; Silvestre et al., 2006).

Olori et al. (1999) analysed five empirical models for milk yield forecasting of stall fed cows between 1990 and 1994 in the UK. These five standard lactation curve models were developed and analysed for their prediction capabilities of the average daily milk yield of 325 first lactation cows in a single herd. Weekly averages of daily milk yield were obtained from a single Holstein-Friesian herd, and used for developing the standard lactation curve models. Hence, this study focused on analysing model performance with a relatively low data variance. Based on the adjusted R-squared correlation (R²) and the root mean square error (RMSE), the herd average milk yield was predicted with a high degree of accuracy by all models (0.99 > R² > 0.94, 0.67 kg > RMSE > 0.17 kg). For predicting of individual lactations, the mean and standard deviation of R² for individual lactation predicted was 0.66±0.25, 0.69±0.24, 0.65±0.25 and 0.67±0.24 for the incomplete gamma (Wood, 1967), exponential (Wilmink, 1987), inverse polynomial (Nelder,1966; Yadav et al., 1977), and mixed log (Guo and Swalve, 1995) models, respectively. Results showed the models fitted equally well for typical lactations which peaked between the 6th and 9th week (0.76 > R² > 0.70) and fitted equally poorly for non-typical lactations (0.69 > R² > 0.20). Thus, the accuracy levels of the model predictions depended upon the variance of the data utilised for fitting the lactation curves as opposed to the specific characteristics of the model. i.e. an increased number of cows following the typical lactation pattern will
result in an increased prediction accuracy. In another words, the suitability of models predicting herd lactation curves depend on the function utilised whereas the suitability of a model predicting individual cow lactation curves depend upon the biological nature of the training lactation data which varies randomly between cows. In order to analyse the performance of curve fitting models for milk yield prediction, high resolution data is required because all models performed equally well.

Druet et al. (2003) compared splines with traditional polynomial models (polynomial regression (Ali and Schaeffer, 1987), exponential (Wilmink,1987), Legendre polynomial, regression splines (White et al., 1999)) for modelling the fixed part of the lactation curve as well as the genetic parameters of Holsteins cows using 1.69 million first lactation records between 1994 and 2000 in France. The evaluation of each model was based upon the model fitting accuracy and flexibility and computational difficulty. Different performance rankings were obtained according to two criterions used in this study: fixed classes curves performed better than the others based on the mean sum of squares of the residuals (MSSE = 1187 kg), while the regression spline were the best based on the mean residual (<1 in each 305 DIM). As the authors mentioned, the size of a milk yield dataset may explain differences between the results of this study (0.8 million records in the first lactation) and contemporaneous studies. Thus, it is difficult to compare the accuracy of these lactation curve models to those developed utilising a smaller number of cows, due to the scale of this study. In particular, this is relevant from an Irish perspective where the overall number of dairy cows equalled 1.3 million by the end of December 2016 (Central Statistics Office, 2017). Even though a recent model comparison study utilising 4.5 million milk records of Polish Holstein-Friesian cows from 530,425 lactations (Otwinowska-
Mindur et al., 2013) may have been compared with the study of Druet et al. (2003). Five models were compared in the study in Poland, including exponential (Wilmink, 1987), polynomial regression (Ali and Schaeffer, 1987), mixed log (Guo and Swalve, 1995), third-order Legendre polynomials, and fourth-order Legendre polynomials. According to two criterions used in Druet et al.’s study (the mean absolute error (MAE) and the mean square error (MSE)), the polynomial regression model performed best for either the 305-day lactations (1.32 kg - 1.55 kg in MAE and 3.52 kg - 4.93 kg in MSE) or extended 400-day lactations (1.39 kg - 1.62 kg in MAE and 4.33 kg - 5.63 kg in MSE). Both studies failed to compare similar models, thus, results from each study are highly unique and case-specific, different studies analysing different number of milking records impedes the ability to compare research results. Beyond objective limitation, model selection in each study was subjective and attended by more or less preference of the author, hence not all studies utilise the same models. This is the second constraint of comparison of outputs from different studies.

Similarly, Quinn et al. (2005) compared 14 empirical algebraic models for Irish pasture-based milk yield data (14,965 records) between 1995 and 2001. Tested models consist of the most commonly used models in previous studies, i.e. including exponential (Wilmink, 1987), polynomial regression (Ali and Schaeffer, 1987), mixed log (Guo and Swalve, 1995), incomplete gamma (Wood, 1967), exponential (Wilmink, 1987), inverse polynomial (Yadav et al., 1977) and etc. The mean square prediction error (MSPE) and $R^2$ value were used to compare the model performance. The polynomial regression model was found to be the best on the basis of its MSPE (501.7) and $R^2$ (0.68) with the 5,937 kg estimated annual yield and percentage deviation (3.9%), in contrast, the Ali-B model
which was proposed in this study, has a relative level of MSPE (520.9) and $R^2$ (0.67), but has the smallest difference between the 5,795 kg estimated annual yield and the actual average annual yield (5,702 kg) and percentage deviation (1.6%). Quinn et al. found that using a curve fitting model to predict the milk yield for an individual cow always required parameter adjustments due to many regional effects such as climate, soil quality and environment. Beyond model comparison, differences of parameter estimates for the same model resulting from differences between datasets from experimental herds and commercial herds have been considered. The author demonstrated that there were two significant differences in prediction results based on two training datasets obtained from experimental herds in 1978 and commercial herds in 2003: 1) average annual yield per cow has increased from 2,364 kg to 5,448 kg and 2) the week where peak yield occurred shifted from week six to week eight.

Silvestre et al. (2006) reviewed seven models including polynomials, Legendre polynomials and cubic splines models using data from stall based dairy cows collected between 1999-2001 in Portugal. The dataset consisted of 144 complete lactations (305-days) of 139 cows and the criteria consisted of mean error, standard deviation (SD) of error correlation, the quotient (Q) between the error sum of squares and the observed sum of squares, and etc. The cubic splines model showed better prediction performance (mean error <1, SD of error < 5, R > 0.83 and mean of Q < 4.1, SD of Q < 4.0), when compared to the including exponential (Wilmink, 1987), polynomial regression (Ali and Schaeffer, 1987), incomplete gamma (Wood, 1967) models. All seven models achieved better prediction using shorter interval data from calving to first test day (less than 30-day vs more than 60 day), and these results showed that the differences in prediction accuracy
between models became more significant as the amount of data decreased and the timing of the initiation of data collection was delayed. In particular, the polynomial models were highly affected by the reduction the sample dimension. This study agrees that the performance of polynomial models depends on both the sampling properties and the variability between each individual cow within test samples. Also, the limitation of the data collection frequency from an economical view was mentioned, however, the impact of this limitation may be reduced as more advanced automatic milking systems are deployed in modern dairy farms (O’Brien et al., 2015).

For forecasting milk yields during long lactation cycles (>= 500 days) Cole et al. (2009) utilised 152,734 cows as sample consisting of six breeds. After editing, 348,123 lactation records were used for parameter estimation and random samples of one million records from US Holsteins were abstracted for validation purposes. In this study, the 7-day average milk yield was used as the daily milk data. Average milk yield and SD at any DIM were estimated by utilising an incomplete gamma (Wood, 1967) and compared with actual observation yields using correlations. As a result, cows with long lactations had different shapes compared to those of 305-day lactations and the author stressed that using only 305-day lactation records may produce opposite results and data used in this study should be as least 500-day. In contrast, the same data were used in another study of modelling long lactations based on the comparison of 305-day and 999-day lactations (Dematawewa et al., 2007). This study compared nine models including incomplete gamma (Wood, 1967), exponential (Wilmink, 1987) based on several criteria such as: error of squares (SSE), square root of mean square error (RMSE), adjusted squared correlation ($R^2$). The results showed that the prediction of incomplete gamma model for 999-day were the best
with respect to RMES and $R^2$ (7.175 kg, 0.076 for 305-day lactations of first parity cows, 9.380 kg, 0.270 for 305-day lactations of cows in other parities, 7.811 kg, 0.210 for 999-day lactations of first parity cows, 9.623 kg, 0.367 for 999-day lactations of cows in other parities). However, the point is that the possible comparison can be conducted based on the results from jointing these two studies which have common test data and that’s the most valuable contribution for any follow-up study.

Grzesiak et al. (2003) presented a comparison between the static ANN model and the MLR model for 305-day lactation yield predictions using data from 902 Polish Holstein-Friesian cows during 1994 to 1999. For the purpose of training the ANN model and the MLR model, each cow was described with a group of seven input variables, including average cumulative lactation milk yield, DIM, average milk yield of first four months, and numerical month of calving (1-12). Model evaluation based on criteria included RMSE, SD, relative mean error of prediction (MEP) and $R^2$. By training these data, both the MLR model and static ANN model obtained good prediction performance with an $R^2$ value of 0.87 for the MLR and 0.88 for the ANN model. The SD ranged between 0.36 and 0.39 for the MLR model, while the SD ranged between 0.34 and 0.35 for the ANN model. These results implied the ANN model can be an alternative to the conventional MLR model.

Another study carried out by Grzesiak et al. (2006) compared the static ANN model with Wood’s gamma model (Wood, 1967) using datasets consisting of 137,507 daily records of 320 cows over 2000-2002. In this study, the ANN model was trained with a group of five variables: the HF percentage, the age at calving in months, the numerical month of calving (1-12), DIM, and the lactation number (1-3), while the Wood’s model was only trained with DIM and average daily milk yield. Based on the same criteria as in their previous
study (RMSE, $R^2$), the $R^2$ value of the static ANN model was 0.77, in contrast to the values of the Wood’s model which ranged from 0.45 to 0.62. The forecasting improvement of the static ANN model was contributed to the ability to use additional variable inputs derived from the population of test cows. In this study, to take the same dimension of input data of the static ANN model, the pre-processing of training data for the Wood’s model was complicated. This pre-processing divided the raw dataset into different groups such as age groups, genetic groups, calving season groups, lactation groups and etc. resulting in the production of 24 equations. The authors implied that it was virtually impossible to repeat this for a single farm and the ANN model was the optimum solution for this kind of study. However there was no further test to combine these two studies, thus, the conclusions are only valid for each study respectively.

Sharma et al (2006) proposed and compared two static ANN models with a conventional MLR model based on the prediction of the first lactation 305-day milk yield using filtered data from raw records of 672 Indian Karan Fries dairy cows. In this study, the training data was collected over a period of 20 years (1982-2002) and adjusted values of input included weight at maturity, age at calving, peak milk yield and days to attain the peak milk yield. Although there may be a variation in the performance of cows due to the effect of various non-genetic factors, the variation may not be significant enough to be detected due to the small amount of sample cows distributed over 20 years. Based on percentage RMSE value, the results of this study showed that one static ANN (radial basis function neural networks, RMSE = 9.44%) performs relatively better than MLR model (RMSE = 9.46%). Similarly, the other static ANN (back propagation neural networks, RMSE = 11.22%) performs more or less equivalently. Subsequent studies found that the ANN was more accurate than MLR
model on prediction of lifetime milk yield on the basis of the first lactation traits using data of Sahiwal cattle (Bhosale and Singh, 2017) and Holstein-Friesian dairy cows (Gandhi et al., 2010), respectively. Although studies of Bhosale and Singh and the study of Gandhi et al. used RMSE and $R^2$ as comparison criterion, these studies compared ANN models and MLR models using different empirical data of multiple breeds utilising data over various periods, hence the conclusions are qualitatively consistent, however with quantitative differences in detail.

Adediran et al. (2012) analysed 16 models including empirical models and semiparametric models using data from pasture-based dairy cows collected between 1998-2007 in the Australian states of Tasmania and Victoria (96,747 records from 11,643 lactations). Both average and individual cow lactations were used for model evaluation. Based on these datasets and evaluation criteria including residual mean square (RMS), SD of RMS, mean error, SD of mean error and $R^2$, models with biologically interpretable parameters were found to have good performance, compared to the polynomial model and the gamma model. i.e. the log-quadratic model (Adediran et al., 2012) showed a high $R^2$ value (0.99) of prediction for individual cow lactations, with a low $R^2$ (0.18) value for the incomplete gamma (Wood, 1967), and in addition, the RMS values for these two models were 0.03 and 16.9, respectively. This study confirmed the effect of the day at the first test day and number of recorded test days on the fitting performance of lactation models. The overall goodness of fit of all lactation models were adequate while the most accurate model was the log-quadratic model which was recommended for fitting test day milk yield. However, the limitation of this study is that model accuracy was tested on data from another dairy
system (stall-based farms), thus, the robustness of the log-quadratic model was not quantified for pasture-based systems.

In a recent study by Murphy et al. (2014), the MLR model, the static ANN model and the NARX model were compared using Irish pasture-based data collected from 140 Holstein-Friesian cows between 2006 and 2010. The NARX model was introduced as an advanced ANN model compared to the conventional static ANN model. Inconsistent with the previous study (Grzesiak et al., 2003) and using the same evaluation criteria including RMSE, and $R^2$, over the full 305-day cycle with four different horizons ranging from 305-day to 10-day, the static ANN did not produce superior prediction in compared to the MLR model: the RMSE of the static ANN forecast decreased from 12.03% to 10.7% and $R^2$ increased from 0.889 to 0.911, while the RMSE of the MLR forecast ranged from 10.62% to 10.54% and $R^2$ decreased from 0.917 to 0.916. In contrast, the NARX proved to have considerably better accuracy for predicting milk yield for different horizons. In particular, the prediction error dropped monotonically in correspondence with the shortening of the prediction horizon, the RMSE of the NARX forecast decreased from 8.59% to 5.84% and $R^2$ increased from 0.936 to 0.968. In this study, the forecast accuracy of the static ANN was not better than the MLR model and this may be caused by data limitation as only DIM, NCM and DHMY were selected as the training inputs. In spite of this, the NARX still produced best prediction accuracy and the error reduced in accordance with the shortening of the prediction horizon. This attribute was due to the NARX model’s ability to adapt and update its trajectory based on past errors. The authors stated that it is difficult to compare the results of this study with previous studies due to each study using case-specific data, each uniquely impacted by environmental, grazing and feeding factors.
From the discussion above, results from these studies show varying levels of accuracy for different models with different data inputs, for specific applications. e.g., the Ali and Schaeffer model (Ali and Schaeffer, 1987) was the most accurate model for Canadian datasets in the original study, while the revised Ali-B model (Quinn et al., 2005) was found to have better performance than the original Ali and Schaeffer model. From an Irish perspective, the Ali and Schaeffer model was found better than the Ali-B model again (Zhang et al., 2014), while the log-quadratic model (Adediran et al., 2012) did not perform as well on Irish data as it did on Australian data. Concurrently, there may be a potential opportunity to discover a model which has better prediction performance than the NARX model at specific prediction horizons for Irish data. In addition, in comparing these configurations within the same model category or within cross-category may increase the complexity and time consumption of the overall development of the prediction model. Furthermore, cross category milk yield model comparisons are technically and computationally more complex than those within the same category, as discussed above. Although many studies exist comparing the prediction performance of these models using average data of individual cows (Cole et al., 2009; Madouasse et al., 2010; Van Bebber et al., 1999), a comparison focusing on an individual cow level has yet to be carried out. Milk yield forecasting at an individual cow level could be beneficial to numerous applications in dairy industry including monitoring health conditions and disease detection by monitoring individual cow milk yield, i.e. udder mastitis (Andersen et al., 2011; Gasqui and Trommenschlager, 2017); decision support for advanced milking parlours and milking machines (Thomas and DeLorenzo, 1994) and precision input for herd simulation models (Petek and Dikmen, 2006).
2.4 Model assessment

Model assessment is an essential component for the accurate comparison of milk yield prediction models and to provide numerical description of model performance on the basis of its goodness of fit to the data. Especially for the milk yield dataset, which is highly case specific and all predictions from model simulations need to be investigated and evaluated using the corresponding validation data associated with that case. Regardless, calculated comparison results should be delivered based on universal and acceptable statistical criteria, to benchmark the results and support further study and analysis. According to evaluation methods utilised within cognate studies (Baudracco et al., 2012; Fuentes-Pila et al., 1996; Jones, 1997; Murphy et al., 2014; Olori et al., 1999; Quinn et al., 2005; Ruelle et al., 2015), four statistical criteria have been considered in this thesis. These include the Summed Square of Residuals (SSE), Coefficient of Determination ($R^2$), Root Mean Squared Error (RMSE) and the Relative Prediction Error (RPE).

2.4.1 Summed square of residuals (SSE)

The summed square of residuals (SSE) value measures the total deviation of the predicted values from the observed values.

$$SSE = \sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2$$

(Equation 2-25)

Where $\hat{y}_i$ is the predicted value, $y_i$ is the observed value, $w_i$ is the weight (one by default). A SSE value closer to 0 indicates that the milk yield model has a smaller random error component, more useful for prediction. The random error is due to variation in the
measured data and predicted data. Hence, the SSE value provides the overall accuracy evaluation of the milk yield model over the specific period.

2.4.2 Coefficient of determination (R²)

The coefficient of determination (R²) value represents the goodness of fit between the observed values and the actual values. The R² is the ratio of the sum of squares of regression (SSR) and the total sum of squares (SST) as shown below:

\[
SSR = \sum_{i=1}^{n} w_i (\hat{y}_i - \bar{y})^2
\]

(Equation 2-26)

\[
SST = \sum_{i=1}^{n} w_i (y_i - \bar{y})^2
\]

(Equation 2-27)

\[
R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}
\]

(Equation 2-28)

Where for the ith record, \(\hat{y}_i\) is the predicted value, \(y_i\) is the observed value, and \(\bar{y}\) is the mean of the observed value. The SSR measures the variation in the predicted values, while the SST measures the variation in the observed values. The R² value (normally ranges from 0 to 1) indicates how much of the variability between the two variables has been accounted for, while the remaining value (1 - R²) indicates how much of the variability is still unaccounted for. For different milk yield forecasting models, the R² value provides a measure of how well observed outcomes are replicated by each model, based on the proportion of total variation of outcomes explained by the model. In particular, for
comparing different modelling techniques, the $R^2$ values could be significant between different categories, e.g. curve fitting models and regression models. According to definitions of model quality based on $R^2$ from the study of Olori et al. (1999), all tested models with different prediction horizons can be classified as ‘good’ due to all $R^2$ values were higher than 0.70.

2.4.3 Root mean squared error (RMSE)

The root mean squared error (RMSE) value is defined as the square root of the mean square error (MSE) and is an estimate of the standard deviation of the random component in the data.

$$\text{RMSE} = \sqrt{\text{MSE}}$$

(Equation 2-29)

$$\text{MSE} = \frac{\text{SSE}}{n}$$

(Equation 2-30)

The RMSE value represents the average variation between predicted values and observed values. The lower the RMSE value, the more accurate the model prediction, where a value closer to 0 indicates that the model is more useful for prediction. Due to the square root of MSE and with the same units as the predictions, the RMSE value is easy to accentuate errors of milk yield forecasting.
2.4.4 Relative prediction error (RPE)

According to Fuentes-Pila et al. (Fuentes-Pila et al., 1996), the relative prediction error (RPE) value is defined as follows:

\[
RPE = \left( \frac{RMSE}{\bar{y}} \right) \times 100\%
\]

(Equation 2-31)

The RPE is an expression of the RMSE as a percentage of the actual data. A RPE value lower than 10% indicates a satisfactory prediction, between 10% and 20% indicates relatively acceptable prediction, and the RPE value greater than 20% suggests a poor model prediction.

2.5 Influence of grazing management and weather factors on milk yield

2.5.1 Brief profile of Irish pasture resource

On Irish dairy farms, cows are housed indoors in winter and grazed from early spring to late autumn. Grass is the primary feeding resource for dairy cows and effective grass utilization plays an essential role in the efficiency of the Irish dairy industry (Dillon, 2006; Gauly et al., 2013). Table 2-1 shows the percentage of grassland in agricultural land (Utilised Agricultural Area by land use referred to as AA) in different EU countries (Eurostat, 2012). There is a large difference of grassland coverage among EU countries. For example in Malta and Finland, the percentage of AA coverage is below 30%, while the percentage is very high and in Ireland, where 50.6% of AA is covered by grassland.
Table 2-2 shows the average annual milk production per cow in different EU countries (2010) (Eurostat, 2012). When comparing the average milk yield per cow with percentage of grassland among different EU countries, UK has a similar level of grassland coverage with Ireland (45.9% in UK and 50.6% in Ireland). However the average milk yield in the UK is 60% greater than that in Ireland. One possible explanation is that UK dairy cows require more nutrient-dense feed to produce high milk yields, hence, cows are fed more concentrates and less forage in the UK. A FAO (Food and Agriculture Organization) report found the Irish dairy farms are well managed at pasture-based production systems (O’Mara 2008). Thus, the milk yield in Ireland is highly correlated with pasture conditions.
Table 2-1 The percentage of grassland in agricultural land (AA) in different EU countries (2010) (Data source: Eurostat).

<table>
<thead>
<tr>
<th>Country</th>
<th>Area Total 1000 ha</th>
<th>Utilized AA %</th>
<th>Permanent grassland %</th>
<th>Area Total 1000 ha</th>
<th>Utilized AA %</th>
<th>Permanent grassland %</th>
</tr>
</thead>
<tbody>
<tr>
<td>EU</td>
<td>412</td>
<td>40.3</td>
<td>13.2</td>
<td>50,537</td>
<td>47.9</td>
<td>12.5</td>
</tr>
<tr>
<td>MT</td>
<td>32</td>
<td>36.2</td>
<td>0</td>
<td>35,713</td>
<td>46.8</td>
<td>13</td>
</tr>
<tr>
<td>FI</td>
<td>33,842</td>
<td>6.8</td>
<td>0.1</td>
<td>11,100</td>
<td>45.5</td>
<td>15.3</td>
</tr>
<tr>
<td>CY</td>
<td>925</td>
<td>12.7</td>
<td>0.4</td>
<td>2,027</td>
<td>23.8</td>
<td>14.1</td>
</tr>
<tr>
<td>SE</td>
<td>45,030</td>
<td>6.8</td>
<td>1</td>
<td>3,053</td>
<td>44.5</td>
<td>16.4</td>
</tr>
<tr>
<td>EL</td>
<td>13,198</td>
<td>27.9</td>
<td>1.3</td>
<td>63,795</td>
<td>45.9</td>
<td>15.4</td>
</tr>
<tr>
<td>DK</td>
<td>4,310</td>
<td>62</td>
<td>4.8</td>
<td>23,839</td>
<td>59.4</td>
<td>19.1</td>
</tr>
<tr>
<td>HR</td>
<td>5,659</td>
<td>23.6</td>
<td>6.1</td>
<td>9,191</td>
<td>39.9</td>
<td>19.8</td>
</tr>
<tr>
<td>EE</td>
<td>4,523</td>
<td>9</td>
<td>6.6</td>
<td>3,736</td>
<td>37.7</td>
<td>20.6</td>
</tr>
<tr>
<td>HU</td>
<td>9,303</td>
<td>57.4</td>
<td>8.2</td>
<td>3,736</td>
<td>50.1</td>
<td>21.8</td>
</tr>
<tr>
<td>LT</td>
<td>6,530</td>
<td>42.5</td>
<td>9.4</td>
<td>259</td>
<td>50.7</td>
<td>26.1</td>
</tr>
<tr>
<td>LV</td>
<td>6,456</td>
<td>28</td>
<td>9.7</td>
<td>4,129</td>
<td>36.8</td>
<td>26.1</td>
</tr>
<tr>
<td>PL</td>
<td>31,268</td>
<td>50.2</td>
<td>10.3</td>
<td>2,041</td>
<td>70.6</td>
<td>45.9</td>
</tr>
<tr>
<td>SK</td>
<td>4,904</td>
<td>39.2</td>
<td>10.5</td>
<td>7,029</td>
<td>64.9</td>
<td>50.6</td>
</tr>
<tr>
<td>IT</td>
<td>30,132</td>
<td>42.8</td>
<td>11.5</td>
<td>NO</td>
<td>_</td>
<td>_</td>
</tr>
<tr>
<td>CZ</td>
<td>7,887</td>
<td>44.7</td>
<td>11.9</td>
<td>NO</td>
<td>_</td>
<td>_</td>
</tr>
</tbody>
</table>

EU - European Union, MT - Malta, FI - Finland, CY - Cyprus, SE - Sweden, EL - Greece, DK - Denmark, HR - Croatia, EE - Estonia, HU - Hungary, LT - Lithuania, LV - Latvia, PL - Poland, SK - Slovakia, IT - Italy, CZ - Czech Republic, ES - Spain, DE - Germany, SI - Slovenia, BG - Bulgaria, FR - France, BE - Belgium, RO - Romania, PT - Portugal, AT - Austria, NL - Netherlands, LU - Luxembourg, CH - Switzerland, UK - United Kingdom, IE - Ireland, NO - Norway.
Table 2-2 The average annual milk production per cow in different EU countries (2010) (Data source: Eurostat).

<table>
<thead>
<tr>
<th></th>
<th>Cows' milk production on farms</th>
<th>Number of dairy cows</th>
<th>Average yield</th>
<th>Cows' milk production on farms</th>
<th>Number of dairy cows</th>
<th>Average yield</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1000 tonnes</td>
<td>1000 heads</td>
<td>kg/head</td>
<td>1000 tonnes</td>
<td>1000 heads</td>
<td>kg/head</td>
</tr>
<tr>
<td>EU-27</td>
<td>149,300</td>
<td>23,122</td>
<td>6457</td>
<td>NL</td>
<td>_</td>
<td>_</td>
</tr>
<tr>
<td>DK</td>
<td>4,910</td>
<td>573</td>
<td>8569</td>
<td>CY</td>
<td>151</td>
<td>23</td>
</tr>
<tr>
<td>SE</td>
<td>2,336</td>
<td>284</td>
<td>8218</td>
<td>LU</td>
<td>295</td>
<td>46</td>
</tr>
<tr>
<td>UK</td>
<td>2,862</td>
<td>349</td>
<td>8211</td>
<td>PL</td>
<td>3,258</td>
<td>533</td>
</tr>
<tr>
<td>RO</td>
<td>1,957</td>
<td>243</td>
<td>8045</td>
<td>BE</td>
<td>3,111</td>
<td>518</td>
</tr>
<tr>
<td>AT</td>
<td>11,941</td>
<td>1,518</td>
<td>7866</td>
<td>FI</td>
<td>918</td>
<td>159</td>
</tr>
<tr>
<td>HR</td>
<td>13,960</td>
<td>1,847</td>
<td>7558</td>
<td>SK</td>
<td>604</td>
<td>110</td>
</tr>
<tr>
<td>ES</td>
<td>6,357</td>
<td>845</td>
<td>7521</td>
<td>IE</td>
<td>5,350</td>
<td>1,027</td>
</tr>
<tr>
<td>CZ</td>
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<td>375</td>
<td>7146</td>
<td>EL</td>
<td>1,744</td>
<td>144</td>
</tr>
<tr>
<td>DE</td>
<td>29,594</td>
<td>4,182</td>
<td>7077</td>
<td>LV</td>
<td>831</td>
<td>164</td>
</tr>
<tr>
<td>HU</td>
<td>1,685</td>
<td>239</td>
<td>7050</td>
<td>PT</td>
<td>12,279</td>
<td>2,529</td>
</tr>
<tr>
<td>EE</td>
<td>675</td>
<td>97</td>
<td>6999</td>
<td>LT</td>
<td>1,733</td>
<td>360</td>
</tr>
<tr>
<td>IT</td>
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<td>1,746</td>
<td>6529</td>
<td>SI</td>
<td>4,500</td>
<td>1,179</td>
</tr>
<tr>
<td>FR</td>
<td>24,000</td>
<td>3,718</td>
<td>6455</td>
<td>BG</td>
<td>1,124</td>
<td>308</td>
</tr>
</tbody>
</table>

EU-27 - European Union of 27 Member States, DK - Denmark, SE - Sweden, UK - United Kingdom, RO - Romania, AT - Austria, HR - Croatia, ES - Spain, CZ - Czech Republic, DE - Germany, HU - Hungary, EE - Estonia, IT - Italy, FR - France, NL - Netherlands, CY - Cyprus, LU - Luxembourg, PL - Poland, BE - Belgium, FI - Finland, SK - Slovakia, IE - Ireland, EL - Greece, LV - Latvia, PT - Portugal, LT - Lithuania, SI - Slovenia, BG - Bulgaria.
2.5.2 Grazing management

Due to the highly seasonal grass growth in Ireland, Irish pasture-based cows are typically housed full-time from December to February and fed grass silage during the winter period, in line with a 305 days lactation period. In the subsequent calving season, all cows are fed both grass silage and specified levels of concentrate feeds (Kennedy et al., 2003). During the rest of the year (up until the next November), cows are allowed out to pasture where they feed primarily on grazed grass with additional amounts of concentrate feed when necessary.

Herd level milk yield has been modelled while taking into account farm grazing management and cow’s body conditions (O’Neill et al., 2014; Ruelle et al., 2015). In the study of Ruelle et al. (2015), the overall pasture-based herd milk model consisted of a herd model, which mainly describes cows’ body condition, a grass model and grazing management rules. The grass height was the output of the grass model, the input the herd model, as well as a significant factor of the grazing management. Although weather parameters have been shown to effect both grass growth and herbage quality, controlled levels of supplementation feed are sometimes provided to pasture based cows during periods of poor grass growth. In doing so, the effect of weather parameters on milk production levels is reduced. The feed allocation also took into account supplementary feed flexibly to simulate different scenarios.

Due to practical constraints, it is difficult to adopt a holistic approach of milk yield forecasting where detailed inputs are utilised such as grass growth, feed intake and body condition. Common milking records such as milk yield, milking date and NCM are readily accessible on commercial farms, while accurately measuring grass growth and feed intake
is very challenging. Thus, this information is currently not available on the majority of commercial dairy farms.

2.5.3 Influence of weather factors on grassland and milk yield

Previous studies based in southern Ireland have reported relationships between grass growth and weather parameters including air temperature, soil temperature, solar radiation, sunshine hours and rainfall (Hurtado-Uria et al., 2013b; Hurtado-Uria et al., 2013). Although the effects of weather parameters varied at different periods during the year, soil temperature was found to have a major influence on the grass growth all year around, while no strong relationship was found between rainfall and grass growth in any season of the year.

Over the past four decades, the influence of weather factors on dairy milk production has been explored in several studies discussed as follow. Multiple weather parameters including rainfall, temperature, humidity etc. have been proved to have different influence on milk production yield.

In Northern Nigeria (dry tropics), the relationship between weather variables and milk yield was not found to be consistent, temperature was found to have a more profound effect than humidity and rainfall (Alhassan and Buvanendran, 1985).

In Ghana (humid tropics), the relationships between milk yield and weather variables were small and inconsistent, where weather accounted for less than 2% and 1% of the variation in milk yield for imported and indigenous cows, respectively (Kabuga, 1991).

In New South Wales, Australia (subtropics), rainfall was found to have an effect on milk production in non-irrigated areas if rainfall had dominant influence on pasture growth and
pasture formed the main feed source. The seasonal availability of moisture had a sufficiently strong influence (for more than half of the tested samples) on cow milk yields (Dragovich, 1982).

In areas with temperate maritime climates such as Britain and New Zealand, cows are kept on pasture for at least part of the year, hence in certain studies meteorological data was found to have a relationship with milk yield and was employed to predict annual daily average milk yield.

In a study based in England and Wales, a linear regression model was developed to predict totalized annual milk yield on a national level for 13 years using factors based on average cow milk yield from about one third of national herd (approximately one million cows) (Smith, 1968). Smith’s predictions comprised of a three-stage piecemeal forecast of annual average daily milk yield for 13 years individual years (1954 - 1966) based on annual average daily cow production records. Stage 1) at the end of March, a twelve months ahead forecast (MLR model) was produced using milk production data and the additional mean March soil temperature with a mean percentage error of 0.53. Soil temperature data was incorporated into the model as temperature was an indicator of grass growth for the coming season. Stage 2) at the end of April an eleven months ahead forecast was produced using only milk production data with a mean percentage error of 0.56. Stage 3) at the end of June, a nine months ahead forecast was produced using milk production data and rainfall over England and Wales over the month of June with a mean percentage error of 0.31. This rainfall data was incorporated because the rainfall during the haymaking season determines the hay quality for the rest of the year. However, the impact of adding these weather parameters were not compared with forecasts solely based on milk production data. Hence,
the effect of applying weather parameters was not quantified and consequently, it is not clear what level of improvement was gained by adding these weather parameters to the milk production forecast model. The study of Smith is the sole body of work that has focused on introducing weather parameters to improve the accuracy of milk production forecasts. However, the study was limited to averaged annual figures on a countrywide production level. In addition, during the period of the selected study, grazing systems were far more susceptible to the effects of weather conditions as many of the grasslands management techniques and technologies employed today were not yet developed.

New Zealand has a similar temperate climate to that of Ireland (mild temperatures and moderate rainfall). Grass from pasture constitutes the principal feed for cows in both New Zealand and Ireland. Correlations between milk yield and 16 weather factors (including air temperature, soil temperature, sunshine hours, wind force, relative humidity, rainfall and evaporation rate and so on) were analysed and statistically significant positive associations between weather factors and milk yield were found (Roche et al., 2009). In particular, sunshine hours and soil temperature had positive correlations with milk yield, while others were found to be far less significant, such as air temperature, relative humidity, and wind speed and so on. While sunshine hours and soil temperature had positive correlations with milk yield, they were low with R values of 0.14, and 0.25, respectively. Roche et al. concluded that weather variables had only a slight effect on milk production as pasture quality was not allowed to vary greatly in well-managed farms. Since a modern farm management system was designed to eliminate subjectivity, management can overcome the effect of weather on cows’ dry matter intake (Macdonald and Penno, 1998).
In Scotland, upper levels of temperature and humidity were found to have an effect on both milk yield and composition variably depending on whether cows were kept in sheds or out on pasture. Furthermore, the effects of soil temperature was found to have a stronger fit to milk yield, in comparison to air temperature, while sunshine hours was found to have the highest correlation for milk yield among models that exclude temperature variables. However, the rainfall was found to have the second lowest correlation for milk yield (Hill and Wall, 2015). This research took into consideration animal welfare based on heat stress levels.

Previous studies have shown that grass growth is dependent on weather parameters such as temperature, radiation and rainfall in pasture based systems (Hurtado-Uria et al., 2013a; Mattern, 2005). Soil temperature has been found to have a correlation with milk yield due to both physiological (heat stress) and environmental (grazing conditions) factors (Hill and Wall, 2015; Roche et al., 2009; Smith, 1968). Sunshine hours and rainfall were also found to influence milk in cognate studies (Hill and Wall, 2015; Roche et al., 2009; Smith, 1968).

The Irish metrological service (Met Éireann) provides medium range (7 days) agricultural related weather forecasts, including rainfall, soil temperature and sunshine hours as well as access to historical records of weather data thought out Ireland. The ECMWF (The European Centre for Medium-range Weather Forecasts) model and the HIRLAM (the High Resolution Limited Area Model) numerical weather prediction (NWP) model is utilised by Met Éireann to create regional forecasts for medium-term forecasts and short-term forecasts (48 hours ahead), respectively. Despite this, no previous studies have investigated the impact of introducing metrological parameters for milk production prediction modelling in Ireland.
2.6 Data variation in milk yield

2.6.1 Long term trends of average milk yield and genetic changes

The long term trend of annual average yield has previously been investigated by Quinn et al. (2005). For milk lactation model studies conducted in 2005 and 1978, different datasets were shown to impact the generation of lactation model parameters. For the datasets from experimental herds and commercial dairy herds in 1978 and 2005, respectively, the incremental increase in annual average yield can be more than twofold from 2364 kg to 5448 kg over 26 years.

Table 2-3 shows the historical average annual milk production per cow in different EU countries (Eurostat, 2016, 2015, 2012). Figure 2-5 shows the average annual milk yield of EU countries. These show the historical long term trend in the average annual milk produced per cow for each decade. This trend is expected to remain across Ireland and other EU countries. The twofold increment of annual milk yield can be seen from several countries, including Denmark, Germany, and France.

Historical milk yield records can be used to predict future, long-term statistical trends. This trend is objective and may explain the phenomenon that the ‘optimal’ milk yield prediction models have been proposed and updated continuously, and after decades, the model prediction performance may not keep at the same level of accuracy in comparison to when they were first published.

Most milk forecasting models are based on empirical records. Empirical models allow genetic changes to be quantified as the long term trends in statistical records (As shown in Table 2-4). For example, in Ireland, prior to the 1960s, the dairy Shorthorn was the
predominant breed in dairy herds (first imported into Ireland from Great Britain in 1822). British Friesian genetics were introduced over the 1960s and 1970s. Later, in the 1990s the herd slowly made the switch to Holstein genetics due to the difficulty of sourcing top Friesian bulls from the UK. However, in the late 1990s, the genetic was back to British Friesian. Nowadays, the Holstein Friesian (HF) breed is the most popular dairy breed (representing 95% of all dairy births) in Ireland (ICBF, 2007; Mee, 2004).

The first trial of utilising the artificial insemination technique was made by Mr. Nagle in Mallow in 1946 (Cunningham, 1966). As a revolutionary technique, the national genomic selection of Holstein Friesian dairy cattle was introduced in Ireland in February 2009 (Kearney et al., 2009). Genetic correlations among milk yield, milk composition (protein and fat) and fertility traits demonstrate a strong antagonistic relationship (Berry et al., 2014). In contrast, at the herd level, Roxström et al. (2001) claimed higher yielding herds have better reproductive performance based on the study of Swedish red and white dairy cattle. However, it is the high genetic merit cows within these herds that are likely have poorer reproductive performance than low genetic merit cows. If this is neglected, those well-managed, high yielding herds can obtain good reproductive performance. From these studies, it is clear that high milk production is not always detrimental to reproduction. Hence, the genetic selection can be seen as a ‘double-edged’ sword. i.e. to implement high productiveness on both individual cows and herd will involve many subjective factors (such as farm management strategy), whereby it is difficult to balance production and reproduction, due to both being highly cost-related. Regarding the maximization of milk yield within one lactation, high production cows would be preferable, but this is highly improbable in a real commercial dairy farm due to the unpredictable reproduction in the
following years. In addition, there is a cost associated with frequent testing as discussed in the study of Berry et al. (2003), while infrequent testing may lead to inaccurate results. Meanwhile, inconsistent phenotypic correlations among milk production and fertility have been reported from different studies, i.e. positive associations (Buckley et al., 2003); negative associations (Nebel and McGilliard, 1993); or no association (Patton et al., 2007). Considering the Holstein Friesian (HF) breed is the dominant breed (95% of all dairy births) in Ireland, the variance in milk yield caused by genetic factors may be mitigated by many other factors such as feeding and grazing management.
Table 2-3 The average annual milk yield (kg/cow/year) in EU countries (Decennary average yield of 1970-2010 and annual average yield of 2011, 2014 and 2015) (Data source: Eurostat).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>EC / EU</td>
<td>2,810</td>
<td>3,624</td>
<td>4,236</td>
<td>5,733</td>
<td>5,859</td>
<td>6,051</td>
<td>6,777</td>
<td>6,898</td>
</tr>
<tr>
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<td>-</td>
<td>4,613</td>
<td>5,906</td>
<td>7,019</td>
<td>8,408</td>
<td>8,268</td>
<td>9,346</td>
<td>9,361</td>
</tr>
<tr>
<td>DE</td>
<td>2,827</td>
<td>3,274</td>
<td>3,725</td>
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<td>7,541</td>
<td>7,625</td>
</tr>
<tr>
<td>FR</td>
<td>2,410</td>
<td>3,500</td>
<td>4,581</td>
<td>5,606</td>
<td>6,283</td>
<td>6,690</td>
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<td>7,061</td>
</tr>
<tr>
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<td>7,659</td>
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</tr>
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<td>8,059</td>
</tr>
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<td>5,187</td>
<td>5,246</td>
<td>5,162</td>
<td>5,351</td>
</tr>
</tbody>
</table>

EC / EU - European Union; DK - Denmark; DE - Germany; FR - France; NL - Netherlands; UK - United Kingdom; IE - Ireland.

Table 2-4 Cow Breeds in Ireland (Data source: Cattle and Federation, 2007).

<table>
<thead>
<tr>
<th>Breeds</th>
<th>Introduced year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jersey</td>
<td>1700s</td>
</tr>
<tr>
<td>Shorthorn</td>
<td>1820s</td>
</tr>
<tr>
<td>British Friesian</td>
<td>1960s</td>
</tr>
<tr>
<td>North American Holstein-Friesian</td>
<td>1974</td>
</tr>
<tr>
<td>Montbeliarde cow</td>
<td>1990s</td>
</tr>
<tr>
<td>Meuse Rhine Issel</td>
<td>1990s</td>
</tr>
</tbody>
</table>
Figure 2-5 The historical average annual milk yield in EU countries (Data source: Eurostat). (Left: decennary average yield of 1970-2010. Right: annual average yield of 2011, 2014 and 2015).

2.6.2 Short term variation caused by parity

The short-term variation of milk yield is evident both among different lactations and during the single lactation of individual cows. Milk yield per cow has been found to be dependent on parity at the statistical level of historical Irish milk production data (Central Statistics Office, 2017). The effect of parity on dairy cow milk yield has been presented in several previous studies and the corresponding findings are in consensus. Parity has a significant effect on the milk yield due to separate genetic traits (Collins-Lusweti, 1991; Rémond et al., 1997; Silvestre et al., 2009; Ríos-Utrera et al., 2013; Storli et al., 2014;
Otwinowska-Mindur and Ptak, 2016) and DIM at peak yield varies in respect to parity (Rekik et al., 2003).

The profile of the first lactation curve is not consistent with subsequent lactations. Total and peak milk production yield of dairy cows in the first parity is lower than those of cows in the second parity and the third parity (Hansen et al., 2006; Stanton et al., 1992; Tekerli et al., 2000). This has resulted in difficulties for curve fitting models in profiling the first lactation in comparison with the second and later parities (Guo and Swalve, 1995).

The highest total yield is typically presented in the third and subsequent parities (Friggens et al., 1999; Rekik et al., 2003; Ríos-Utrera et al., 2013) and the first lactation has a slightly delayed peak yield (Mellado et al., 2011). The conclusions above indicate that the first parity is substantially different in profile and magnitude in comparison to the second, third and later parities which display similar lactation profiles.

In previous cognate studies, the variation in lactation records was treated as a fixed parameter. For example, the milk yield ratios used in the study of Hutchinson et al. (2013) for the first, second, third and fourth lactation were 0.75, 0.92, 0.98 and 1, respectively, while in the study of Ruelle et al. (2016), the milk yield ratios used for the first, second, were 0.75, 0.92 , and 1 for the rest lactations, respectively. This methodology shows the inner relationship between the parity and milk yield at the average level as the fixed ratio comes from statistical records of herds. On the other hand, the static number cannot reflect any dynamic truth of yields among lactations for each individual cows.

Lactation milk yield records may be utilised to predict short-term variations at both statistical level (i.e.: national average value: (kg milk produced/cow/year)) and individual cow level (kg/cow/lactation). The short term variation in milk yield records have caused
considerable difficulty in cognate studies when attempting to forecast milk yield at the individual cow level.

2.6.3 Relationship between body condition score and milk yield

A previous study concluded that body condition score (BCS) is a valuable tool in measuring the status of dairy cows, especially for monitoring the energy intake and body lipid change (Domecq et al., 1997; Friggens et al., 2004; Reneau and Linn, 1989). There are several BCS systems in place. According to Reneau and Linn, the BCS system in UK uses a scale of 0-5 in increments of 0.5 resulting in a functional 11 point scale. The BCS system concentrates on the accurate determination of scores between 2.0 and 4.0, which is the most vital for management decisions. Scores below 2.0 means the cow is seriously under-conditioned and need immediate attention, while a BCS score over 4.0 means the cow requires weight control. In other countries such as: the USA and Ireland, the BCS system in operation uses a BCS scale of 1-5; the Australian system uses a scale of 1-8 while the New Zealand system uses a scale of 10-point (Roche et al., 2004). Target BCS in UK and Ireland are shown in Table 2-5 (Butler, 2014; DEFRA, 2011).

Waltner et al. (1993) reported that the BCS varied quadratically with DIM in high producing US Holstein dairy cows, however, the BCS was not related to the daily milk production on a given DIM. Similarly, Loker et al. (2012) concluded that the level of association BCS has with milk production traits is not constant over the lactation (permanent environmental correlations between BCS and milk yield varied from 0.8 to -0.28 over the 305-day lactations ) in Canadian Holsters. Green et al. (2014) reported that based on a 60-day BCS recording interval, there was no strong association between milk
yield and BCS over the whole lactation in UK. According to the study based on the Irish pasture-based data, negative correlations (ranged from -0.51 to -0.14) exist between BCS levels at different stages of lactation and total lactation milk production (Berry et al., 2003). Likewise, the conclusion from the study of Domecq et al. (1997), results of studies investigating BCS and milk production yield were variable, in most cases, health status had more association with BCS than did changes in milk yield. The study of Pryce et al. (2002) in UK suggested that cows with low BCS have longer calving interval which is exacerbated by high levels of milk production (an increase of 768 kg of milk come with a reduction of 0.41 BCS units for every standard deviation change). Dechow et al. (2002) concluded that cows become genetically thinner as they are selected for higher milk production using BCS records in the US.

The change in BCS is more important than the absolute value, however the current method of measuring BCS is manual and subjective where the scores depend on the person who performs the measurements and therefore the error is un-voided (Schröder and Staufenbiel, 2006). Recently, digital image processing and analyses were used for automatic estimation of BCS in some research trials (Azzaro et al., 2011; Bercovich et al., 2013), and the result from 3-D vision monitoring was highly affected by other common factors, such as cow traffic (Van Hertem et al., 2017). However, the fully automatic BCS systems is still developing and the broad application these advanced system in commercial dairy farms is highly limited by the high resolution image acquisition module and overall cost. As shown in Table 2-6, different countries use their own scoring and measuring methods based on a visual and tactile evaluation (AHDB, 2013; Roche et al., 2004).
Too many uncertain factors hinder the application of BCS and other genetic factors on the practical milk yield forecasting. Firstly, in comparison to the milk yield records, the unavailability of BCS recording data on a large scale in a particular country may hinder the ability of BCS to be utilised for milk yield forecasting. Secondly, BCS score is not a direct observation value, but is an indirect estimate of energy balance of body fat reserves and the output of model and algorithm. Due to the long BCS recording interval (every 60-day in a 305-day lactation), the BCS is out of scope of most milk yield forecasting model so far (Green et al., 2014). Instead, relying on easy attainable variables to predict the cow and the herd level milk yield should be top-priority.

Table 2-5 Target BCS in UK and Ireland (Data source: DEFRA, Teagasc).

<table>
<thead>
<tr>
<th></th>
<th>Target BCS in Ireland and UK</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UK</td>
</tr>
<tr>
<td></td>
<td>Cows</td>
</tr>
<tr>
<td>Pre-calving</td>
<td>2.5 - 3.0</td>
</tr>
<tr>
<td>Pre-service</td>
<td>2.0 - 3.0</td>
</tr>
<tr>
<td>Drying off</td>
<td>2.5 - 3.0</td>
</tr>
</tbody>
</table>
Table 2-6 Brief difference between BCS systems (Data source: Reneau and Linn, 1989; AHDB, 2013; Roche et al., 2004).

<table>
<thead>
<tr>
<th>Country</th>
<th>Point Scale</th>
<th>Assessing Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>America</td>
<td>0 - 5.0</td>
<td>visual</td>
</tr>
<tr>
<td>Australia</td>
<td>0 - 8.0</td>
<td>visual</td>
</tr>
<tr>
<td>New Zealand</td>
<td>0 - 10.0</td>
<td>tactile</td>
</tr>
<tr>
<td>UK</td>
<td>0 - 5.0</td>
<td>visual and tactile</td>
</tr>
<tr>
<td>Ireland</td>
<td>0 - 5.0</td>
<td>tactile</td>
</tr>
</tbody>
</table>

2.7 Conclusion

A literature review related to milk yield prediction was presented and investigated within this chapter, covering different lactation modelling approaches, model application and comparison, comparison criteria, factors affecting milk yield, long-term and short-term milk yield variation. Numerous modelling techniques have been proposed and applied to milk yield forecasting, including classical curve fitting models, regressive models, auto-regressive models and mechanistic models. Due to the main limitation that specific milk yield datasets are highly case specific, most models could be the optimal model based on the specific research objects and test datasets under unique conditions. Furthermore, when excluding advanced feeding methods, new grazing management techniques, severe weather conditions and climate or genetic factors, there has been consistent growth in the average annual milk yield over the past decades, along with the variations of milk yield in the lactations of individual breeds. Therefore, researchers from similar or dissimilar regions do not have a mutual target to compare with. Most models are developed and adapted for their countries under numerous limitations. As a result, it is difficult to propose
a standard or the optimal model for dairy cows for whatever vertical comparison (different regions over the same period) or horizontal comparisons (same region over different periods). Therefore, the first objective of this research was to develop, implement and evaluate an optimal milk production model selection and configuration system for dairy cows. The implementation of this comparison platform included three key stages; 1) data gathering, where all required data was collected, stored and abstracted for both herd and individual cows. 2) Model comparison, where milk yield models were analysed and implemented using the same data input and output interfaces and 3) results analysis, for choosing the required statistical criteria. Ultimately, not only the optimal models and effect of possible factors related to milk yield forecast modelling will be investigated and analysed, also the new results can be found due to more data and models employment on this model comparison system.
3 EXPERIMENTAL PLATFORM
3.1 Introduction

As discussed in Section 2.3, there is a requirement for the forecasting of herd milk yield from an integrated information perspective where the solution can integrate multiple parameters including data gathering, storage and processing, all model configuration, simulation and optimization, results analysis and optimal prediction calculation. The aim of this chapter is to develop and demonstrate the Milk Production Forecast Optimization System (MPFOS) with the Adaptive Stratified Sampling Approach (ASSA) for automatic model configuration, comparison, optimization and validation. The MPFOS architecture was designed to calculate model parameters for curve fitting techniques, to calculate coefficients for regression models, to select optimal training algorithms and neuron architectures for neural network models and duration for auto-regressive memory. The ASSA filters and sorts the input data to ensure the training dataset is representative of the entire population. The final output of the MPFOS contains configurations for each prediction model, statistical analysis for all simulation results and the optimal milk production forecast. In short, the MPFOS selects the most effective milk production forecast model and corresponding model configuration for a specific cow population. While numerous model categories and model configurations have been found to be most effective for a particular dairy cow group in previous studies, no one model has shown to produce the most accurate milk production forecast for all circumstances. The results in this chapter demonstrate the capability and performance of the MPFOS.
3.2 The MPFOS architecture

3.2.1 Design of the MPFOS architecture

The MPFOS focuses on global data processing, automated model configuration and optimization and can accomplish multiple model comparisons at a global level. The self-adaptive capability of the MPFOS can provide automatic configurations for different modelling techniques by providing corresponding input datasets. Once various well-known models were translated into algorithms, implemented as programming code and stored in the MPFOS as specific files, all possible subsequent repetitive work is avoided, with the modelling techniques abstracted, thus requiring no further manual interventions from the user side. MPFOS can calculate parameters, coefficients or optimal training configurations for corresponding category models automatically with the same input training dataset in one multiple model comparison procedure. More importantly, all relevant data for simulation and calculation are stored in databases of the MPFOS which can be reused for future data analysis. The space requirements for the empirical data vary as different category of milk yield prediction models require various input data combinations and hence corresponding output results have differing degrees of accuracy.

As discussed in the Literature Review chapter, considering the data availability and model characteristics such as training input requirements and prediction horizons, three different categories of milk yield prediction models were chosen in the model library of the MPFOS including curve fitting models, regression models and auto-regressive models (as shown in Table 3-1). The primary reason for choosing these three model types is that in consideration of other authors’ studies and conclusions, each one of these models has been
successfully applied to cow/herd level milk production modelling, based on specific datasets. For example, the adaptive polynomial model (Quinn et al., 2005) was the best fitting model for Irish experimental study data in 2005, the log-quadratic model (Adediran et al., 2012) was optimal and recommended for Australian pasture-based data in 2012, an artificial neural networks (ANN) model was superior to the conventional MLR model (Sharma et al., 2007) and in 2014, the nonlinear auto-regressive (NARX) model was introduced for milk yield prediction and presented more accurate forecasting compared with the ANN model (Murphy et al., 2014). Therefore, nine representative models of three categories were chosen to populate the MPFOS.

The primary challenge in carrying out a model comparison between two or more model categories is that different models have unique data input formatting requirements. It should be emphasized that the optimal model was dependent on the training input dataset in many cases. For example, daily herd milk yield (DHMY) and corresponding days in milk (DIM) are essential and common training inputs for all milk prediction models and especially for curve fitting category models. Besides DHMY and DIM, number of cows milked (NCM) was selected as a data input for regression and surface fitting models. Additional input information such as calving date (McCarthy et al., 2013), parity and meteorological conditions could be incorporated into the ANN and NARX models. It is reasonable to extend the scope of model comparisons to test as many milk yield prediction models and input combinations as possible. Therefore, the MPFOS has the ability to comprehensively simulate each populated milk prediction model with all possible combinations of input data, compare the accuracy of every scenario and calculate the optimal model configuration.
Figure 3-1 shows the database design inside the MPFOS with a brief description. Three separated databases exist for functionality and scalability in the MPFOS, including the milk yield database (table), the cow description database (table) and the weather database (table). With the possibility of performing more experiments for future hypothesis, the architecture was designed to allow the database to be extended through a greater number of training data inputs, such as milk composition records including protein and fat content, feeding records and so on. The method for adding new data into the MPFOS databases in this study is using MySQL Workbench to import data from comma-separated values (CSV) files to tables in the local databases.

1) The milk yield database

The milk yield database contained information related to every daily milking yield record for each cow in the entire dataset. Essential data measurements and acquisition can be operated by either automatic recorders or manual recorders while maintaining the integrity of the records for each individual cow. In this study, milk yield and composition records came from commercial research dairy farms in the south of Ireland. As population samples, they are imported into the milk yield database (multiple tables) without any deletion to ensure objectivity, accuracy and facticity.

2) The cow description database

The cow description database contained identification and description information for all cows relevant and available to the study, as well as essential information related to treatments and calving. For example, this included the date of calving and number of
lactations. Each record in the milk yield database belonged to one cow which should be found in the cow description database (linked by a foreign key). If not, this record was regarded as abnormal and was not chosen by the configuration filter of the MPFOS automatically.

3) The weather database

Localized meteorological data from Met Eireann were stored in an independent database. The climatic variables stored in the database were: air temperature, precipitation, sunshine, wind speed, and soil temperature. The weather database in the MPFOS is dependent on the location of the herd. The weather database is automatically populated with historical observed meteorological records (as outlined in the Literature Review Chapter) from the Met Eireann meteorological station in closest proximity to the sample herd.

Figure 3-1 Overview of the database in the MPFOS.
Figure 3-3 shows the technical view of the MPFOS with the connected systems integrating three layers of components. The architecture will be discussed from a user perspective, separated into layers including: the presentation layer, application layer and data management layers. The application layer, which in the context of this paper refers to control configuration, model simulation, optimization and data processing, is further divided to corresponding function modules. Finally, data processing and management are considered.

In the presentation layer, the user is the trigger of the system and destination of logic flow. The user can set the filter for the configuration and initialize the model simulation calculation. The filter contains essential simulation settings such as scale of herd, duration of training data input, horizon of target output, selection of yield prediction models and statistical analysis criteria. After each round of calculations, the user will receive a final result including model prediction values, analysis results and optimal model configurations in both numeric values and visual representations. A demonstration of the presentation layer Graphical User Interface (GUI) is shown in Appendix A. In the application layer, upon receipt of the initial configuration from the presentation layer, the filter will fetch raw data from prepared databases in the data layer. Raw data is then processed packed in the filter as input combinations and passed on to the subsequent model simulation procedure. The model simulation procedure runs chosen models with corresponding input combinations in either parallel or serial mode depending on the model category and programming constraints. With all simulation calculations finished, final results of each model are presented to the user in the presentation layer and stored in databases with a
unique timestamp in the data layer, respectively, including model prediction yields, statistical analysis results and optimal model configurations.

Figure 3-2 Overview of the MPFOS architecture.

Figure 3-3 shows the technical view of the MPFOS containing the inside modules of the application layer. The application layer is at the core of the MPFOS and includes three primary segments: the library, the filter and the core procedure. The library consists of three sub-libraries: the rule library, the model library and the statistical criteria library and forms the foundation of the application layer. The rule library contains those scripts that connect databases and the application layer where its core mission is to fetch and pack input combinations from databases. Milk production models are stored in the model library and the statistical criteria library provides functions for comparing milk yield model prediction results within the statistical analysis. Components
of each library can be adjusted arbitrarily by the user depending on future applications. With prerequisite libraries available, the filter can select rules, models and statistical criteria from each library. Based on user settings, the databases can be accessed by the filter and modified properly using SQL statements.

The core calculating procedure of the application layer is a sequential flow structure. After being fetched from databases as a subset of original records, the raw data is transformed into several coupled input combinations. These input combinations are formatted to be ready for the development of selected milk yield prediction models from the model library, hence different subsets of combinations may be chosen by corresponding models. The model simulation calculation, which depends on the model category and constraints of programming functions, works either in a parallel or a serial mode. Generated raw results of all selected simulation models, including prediction results and configuration parameters, are encapsulated and passed on to selected criteria. The selected criteria are in charge of calculating statistical analysis for comparing the prediction result and target values for each model. Finally, result packages are delivered including prediction values, analysis results and optimal model configurations, presented to the user in both numeric values and visual representations. In addition, final results are stored in databases with a unique timestamp for future requirements such as revaluation, data mining and remote access, in other words, the core procedure can be recalculated as many times as required without any risk of data loss or over-write.
3.2.2 Use case diagrams

As discussed in the section 3.2.1, in regards to the portability and applicability of MPFOS to multiple applications, the UML (Unified Modelling Language) use case (as shown in Figure 3-4) explains the operations of the MPFOS, the databases, the data processing and the model configuration. A step by step walkthrough on how to use the MPFOS GUI was shown in Appendix A.
3.2.3 The ASSA for sample herd selection

In this study, the Adaptive Stratified Sampling Approach (ASSA) was introduced for data filtering and processing. The primary purpose of setting up the ASSA was to select appropriate sample herds as input datasets for different customized model simulation scenarios regarding four aspects: raw data quality, traditional taxonomy, simulation
requirements and the statistical sampling process. A visual representation of selecting a random sample herd by using the ASSA and the corresponding process flow chart are shown in Figure 3-5.

1) Raw data quality:

The main issue for raw data quality is its reliability and integrity. Firstly, empirical data from a research or commercial dairy farm cannot usually avoid containing corrupt data (Menendez et al., 2008) because it is obtained through automatic or manual recordings. Secondly, from a biological perspective, milking record data may lack certain records during the lactation periods due to animal illnesses of individual cows or accidents caused by extreme weather conditions, etc. Although original milking data can be assumed to be recorded as accurately as possible, significant variances can be presented among annual milk yield curves from different cows based on visual plotting. Cows taking part in scientific trials may produce abnormal lactation profiles due to modification in grazing conditions. In this case, if too many anomalous milking records from research farms are used to represent typical dairy farms, the simulation prediction result may face a risk of accuracy problems caused by unstable and unreliable data inputs. Hence it was necessary to filter out a relatively normal herd from the whole population herd to represent a conventional dairy farm.

2) Traditional taxonomy:

According to previous studies, describing or predicting milk yield at herd level always groups cows into lactation classes according to parity. For example, first parity and second
parity were in lactation class 1 and class 2, respectively, whereas, cows of parities greater or equal 3 was grouped together into class 3. (Deluyker et al., 1990; Friggens et al., 1999; Hansen et al., 2006; Kelsey et al., 2003; Sevi et al., 2000; Stanton et al., 1988). Parity refers to the number of occasions a dairy cow has had offspring. A non-linear relationship exists between parity level and milk yield and thus, must be considered when developing milk yield forecasting models.

3) Simulation requirements:

The scale of a normal herd is always dynamic and according to research statistics, most size of Irish farms concentrated in herds of 50 to 100 cows (Donnellan et al., 2011) and overall average size is over 60 cows in 2014 (Donnellan et al., 2015). To obtain prediction results for different sizes of simulation herds, input training datasets should be adjusted at corresponding levels before calculations commence.

4) Statistical sampling process:

A typical statistical sampling process comprises several stages as in (Brick and Kalton, 1996; Cochran, 1977; Pitard, 1993)

- Defining the population of study.
- Specifying a sampling frame.
- Specifying a sampling method for selecting items.
- Determining the sample size.
- Implementing the sampling plan.
Following the above stages, selecting cows’ records as an input training dataset should use a modified random method, whereby, it cannot only select a certain number of cows randomly, but also keep the same percentage scale or proportion of each parity class in the new group as the original population herd. In other words shrink or enlarge the size of a simulation herd in an equal proportion. Also, the percentage scale of each parity class can be adjusted as an experimental parameter by the user of the MPFOS for various herd simulation purposes.
Figure 3-5 A representation of selecting a random sample herd by using the ASSA (up) and the corresponding process flow chart (down).
3.3 Data used in this chapter

Empirical data including milking records and cow information was obtained from dairy farms situated in the south of Ireland which were not limited by milk quotas. Each daily milking record contained the identity number of each cow, date of milking, time of milking, and milk yield. Cow information included calving data, lactation number, and treatments. In total, 1,563,393 un-processed milking records of pasture based cows and cow information were imported into corresponding existing databases of the MPFOS in their original raw form as the total population herd data. Each record contains sequential metadata including cow id, date of milking, milking time, milk yield, maximum flow rate during milking, duration of milking, and weight of concentrate fed in sequential data flow, for example: IE197824770331 (id), 30/06/06 (date of milking), 2 (milking time), 7.6 (milk yield), 3.409 (maximum flow rate during milking), 332 (duration of milking), 2 (weight of concentrate fed) (the id in this example was randomly generated).

3.4 Simulation and configuration

A demonstration of the MPFOS architecture with the ASSA was implemented using open source database system MYSQL (Oracle, Redwood, CA) and MATLAB R2016b (MathWorks, Natick, MA) programming environment.

In this chapter, the model simulation was set at herd level and a research scenario built to simulate a sample herd generated by the ASSA in the MPFOS. The ASSA developed a sample herd of 100 cows consisting of 25 cows, 25 cows, 50 cows in parity one, parity two and parity three or more, respectively, representative of the population mean (relative to
parity) in the third simulation year. As shown in Figure 3-6, the daily number of cows milked (NCM) distribution of this sample herd were equal to the population herd. However, a non-linear relationship exists between the NCM and milk yield due to the parity level. The parity distribution in the third year and later is 25%, 25%, and 50% in parity one, parity two and parity three or more, respectively. However the NCM increases from year one to year three (as shown in Figure 3-7) by introducing new parity one cows each year. This result in a situation where both the NCM and parity distributions are varying through the training period As a result, the average daily herd milk yield (DHMY) over the five training years is slightly lower than the target year (shown in Figure 3-8). This arrangement was created as it represents an interesting simulation scenario where NCM rapidly increased and parity distributions were dynamic as the herd size grew. Models were evaluated by comparing annual daily milk yields cross the sample herd of 100 randomly selected cows. The cumulative daily milk yield of this sample herd in the last year (2009) was chosen for validation and the previous five years (2004-2008) of data were used as simulation training data inputs across all of the models evaluated. The computational power required for this 100 cow sized herd simulation was around 30 minutes on a workstation with Intel i7 six-core processors and 64 GB of RAM.
Figure 3-6 Number of cows milked (NCM) in the sample herd and the population herd.

Figure 3-7 Number of cows milked (NCM) and daily herd milk yield (DHMY) of the sample herd.
Table 3-1 shows initial calculation settings for simulations in the MPFOS and the corresponding decision tree is shown in Figure 3-8. The user may choose tested models for different scenario. e.g. If only DHMY data is available then only curve fitting models can be tested; if DHMY, DIM and NCM data are available, then regression and auto-regressive models can be tested . In this chapter, three categories of model were chosen, including the curve fitting category (#1 - #5), the regression category (#6 - #8) and the auto-regressive category (#9). The chosen sample herd information and corresponding milk production data were arranged by the ASSA. Due to the limitations of single-variable equations, only DHMY can be used as training inputs for the curve fitting category models (#1 - #5), while regression category models (#6 - #8) and dynamic category model (#9) can be trained with more input datasets such as NCM, DIM, calving date, parity and so on. Moreover, the NCM value on each milking day was readily counted from the database of the MPFOS by the ASSA based on calving date, hence NCM was selected as the second training input for regression and auto-regressive category models in this chapter.

Due to the limitation of the original population herd size (<500 cows) in this study, there is not enough cows to be utilised to generate a standard lactation curve (121,179 cows from 5,224 herds in the original study of Olori and Galesloot), therefore the SLAC method (Olori and Galesloot, 1999) was not selected in the MPFOS in this study. However, the capacity of data loading in database of the MPFOS depends on which database is adopted, i.e. in this study, the MySQL has the potential of containing about 5,000 million rows of records (Oracle Corporation, 2016) hence, the SLAC method may be analysed based upon the suitable sample data in a future study.
Adjustable prediction horizons were designed to test the performance of model prediction among specific horizons. As previously reported (Murphy et al., 2014), different model categories produce varying levels of accuracy over long and short term horizons; therefore 365-day, 30-day and 10-day prediction horizons were selected for regression category models (#6 - #8) and dynamic category model (#9). The surface fitting model (#8) has not been applied in previous studies.

As discussed in the model assessment section, four statistical criteria have been populated in the MPFOS, including Summed Square of Residuals (SSE), Coefficient of Determination ($R^2$), Root Mean Squared Error (RMSE) and Relative Prediction Error (RPE).
Table 3-1 MPFOS model library.

### 365-day Prediction Horizon

<table>
<thead>
<tr>
<th>#</th>
<th>Model</th>
<th>Author</th>
<th>Training Input</th>
<th>Statistical Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Polynomial</td>
<td>Ali and Schaeffer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Adaptive Polynomial</td>
<td>Quinn et al.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Legendre Polynomial</td>
<td>Kirkpatrick et al.</td>
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<td></td>
</tr>
<tr>
<td>4</td>
<td>Cubic Splines</td>
<td>Green and Silverman</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Log-quadratic</td>
<td>Adediran et al.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Multiple Linear Regression</td>
<td>Sharma and Kasana</td>
<td>DHMY</td>
<td>SSE, RMSE, RPE</td>
</tr>
<tr>
<td>7</td>
<td>Static Artificial Neural Networks</td>
<td>Lacroix et al.</td>
<td></td>
<td>DHMY, DIM, NCM</td>
</tr>
<tr>
<td>8</td>
<td>Surface Fitting</td>
<td>Zhang et al.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Nonlinear Auto Regressive Model</td>
<td>Murphy et al.</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>with Exogenous Input (NARX)</td>
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### 30-day and 10-day Prediction Horizon

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<td>Multiple Linear Regression</td>
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<td>DHMY</td>
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<td>Static Artificial Neural Networks</td>
<td>Lacroix et al.</td>
<td></td>
<td>DHMY, DIM, NCM</td>
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<tr>
<td>8</td>
<td>Surface Fitting</td>
<td>Zhang et al.</td>
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<tr>
<td>9</td>
<td>Nonlinear Auto Regressive Model</td>
<td>Murphy et al.</td>
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<td></td>
<td>with Exogenous Input (NARX)</td>
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</tbody>
</table>
Figure 3-8 The decision tree for model selection.
3.5 Results and discussion

Table 3-2 shows the statistical analysis of the tested prediction models’ forecasts against the validation dataset of the daily DHMY of 2009. According to definitions of model quality based on $R^2$ from Olori et al. (1999a); all tested models can be classified as ‘good’ due to all $R^2$ values were higher than 0.70. Over the 365-day horizon, the best performing prediction model is the Surface Fitting model ($R^2 = 0.97$) where the worst performing prediction model is the MLR model ($R^2 = 0.72$).

Figure 3-9 shows milk production forecasting results for curve fitting category models in the MPFOS. Curve fitting category models (#1 - #5) have an approximately similar level of performance with a distribution of $R^2$ values between 0.74 - 0.78 and RPE values between 23.4% and 25.9%, as well as a small variation in RMSE values (13.4%) and SSE values (6.9%). The Cubic Spline model (#4) ($R^2 = 0.77$, RMSE = 189.9kg, RPE = 23.4%) can be considered as the best performing model in the curve fitting category, affirming conclusions established by Green and Silverman (1994). However, the overall prediction accuracy of curve fitting category models were lower than that of the regression category models ($R^2 >= 0.93$, RPE <= 13.1%, excluding #6 the MLR model) and the dynamic category ($R^2 >= 0.96$, RPE <= 9.3%) over the 365-day horizon. One possible reason for this large contrast in prediction performance was that curve fitting category models can only use DIM and DHMY values while all other models can also utilise NCM as a training and prediction input.

Figure 3-10 shows the milk production forecast results for regression category models in the MPFOS. With a large disparity in accuracy existing among the three regression models used (#6 - #8), both the best performing model (#8 the Surface Fitting model) and the
worst performing (#6 the MLR model) over the 365-day prediction horizon can be found from the regression category models, where the RMSE values, the $R^2$ values the RPE values and the SSE values varied dramatically between them. With the highest SSE value (16,160,838kg), RMSE value (210kg) and RPE value (25.9%), and the lowest $R^2$ value (0.72) the MLR model was the least accurate among all tested models in this chapter. These results were not in accordance with other authors’ previous studies (Grzesiak et al., 2003; Sharma and Kasana, 2006). The SANN model produced more accurate results (#7, the SSE = 4,152,805kg, $R^2 = 0.93$, RMSE = 106.7kg, RPE = 13.1%) than the MLR model, while the Surface Fitting model achieved the best level of accuracy in the 305-day forecast, with an $R^2$ value of 0.97, the lowest SSE value (1,714,385kg), RMSE value (68.5kg) and RPE value (8.4%), compared with the best curve fitting models (#1, #5) and the best dynamic model (#9 the NARX model), indicating the presence of smaller residual errors in the Surface Fitting forecasts. Moreover, the Surface Fitting model showed a consistent high quality prediction performance over different time horizons ranging from 10-day to 365-day, with a 9% variance of the SSE values, 5% variance of the RMSE values, approx.0.3% variance of the $R^2$ values and 4.7% variance of the RPE values between 10-day and 365-day predictions. The demonstration of the best fitting surface is shown in Figure 3-11.

Figure 3-12 shows the milk production forecast results for a 10-day moving piecewise horizon in the MPFOS. The prediction results of the dynamic category model (#9 NARX) varied compared with the Surface Fitting model. From the 365-day to 10-day horizon, the accuracy of the NARX model increased substantially in correspondence with the shortening of the prediction horizon, where the $R^2$ value increased monotonically from
0.96 to 0.98, the RPE value dropped from 9.3% to 7.1% and the RMSE value dropped by 24% (from 75.5kg to 57.3kg). The NARX model was less accurate than the Surface Fitting model over the 365-day horizon; however, it produced the best prediction accuracy over the 10-day horizon (the SSE = 1,198,267kg, $R^2 = 0.98$, RMSE = 57.3kg, RPE = 7.1%), compared with the same 10-day forecast Surface Fitting model (the SSE = 1,543,438kg, $R^2 = 0.97$, RMSE = 65.0kg, RPE = 8%). In previous studies (Murphy et al., 2014), the NARX model was found to be the best performing model when compared with regression category models including the MLR model and the SANN model over the 365-day, 30-day and 10-day time horizons due to its ability to dynamically adapt its trajectory based on previous errors.

These forecasting performance differences in comparison to previous studies may be due to the composition of these regression models as most previous studies used case-specific data that pertained only to a specific application. It is difficult to define the absolute best performing model on a global level while the optimal model can be found for relative to a certain criterion (prediction horizon length, number of model inputs). No one model is most accurate in all scenarios. Curve fitting category models and the MLR model merely showed acceptable prediction accuracy ($0.7 < R^2 < 0.9$). Although the SANN model produced accurate forecasting ($R^2 > 0.9$, RPE = 13.1%) over the 365-day horizon, the Surface Fitting model was shown to be the most effective milk-production model even if compared with the NARX model in the same prediction horizon (365-day and 30-day). However, in correspondence with shortening of prediction horizon (10-day), the NARX model provided the most accurate prediction results. In another hand, the accuracy of different models can be seen from residual errors of Figure 3-9, Figure 3-10 and Figure 3-
12. Some models are more accurate for peak prediction while others are better for early and/or late lactation. Hence there is possibility of using model scheduling or multiple model prediction. i.e. Using the SANN model for the early lactation while using the Surface Fitting model for the late lactation (as shown Figure 3-10).

The simulation outputs of DHMY in this study were based on the sample herd selected from the original population herd. As the NCM increased during the first two years, the DHMY also increased over the five years (as shown in Figure 3-7). Concurrently, the difference between the annual yield and the average annual yield of the training data also increased (as shown in Figure 3-9). This could explain the reasoning behind why all curve fitting category models were shown to under estimate the DHMY, compared to the actual milk yield. The curve fitting category models are based upon average DHMY of the training years, only taking into account DIM and DHMY. Although a relationship exists between the actual DHMY and the NCM, the prediction accuracy was limited by the average yield of previous years, not taking into account the increasing NCM. In addition, as the NCM is dynamic in the sample herd, as well as the parity distribution, the MLR model cannot take into account the nonlinear relationship between the NCM and DHMY and as a result, produced rigid prediction values at the later stage of the lactation period (as show in Figure 3-10). However, the surface fitting model was shown to capture this nonlinear relationship as the final prediction accuracy was not affected (as shown in Figure 3-11). Although the same performance can be seen from predictions of the static ANN model and the NARX model, the surface fitting model is a more simpler and robust model which may act as an alternative to the conventional ANN models for predicting 365-day DHMY.
Table 3-2 Statistical analysis results of tested model predictions.

<table>
<thead>
<tr>
<th>#</th>
<th>Model</th>
<th>SSE</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>RPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Polynomial (365-day)</td>
<td>13,535,376</td>
<td>0.77</td>
<td>192.6</td>
<td>23.7%</td>
</tr>
<tr>
<td>2</td>
<td>Adaptive Polynomial (365-day)</td>
<td>15,006,422</td>
<td>0.74</td>
<td>202.8</td>
<td>25.0%</td>
</tr>
<tr>
<td>3</td>
<td>Legendre Polynomial (365-day)</td>
<td>14,045,097</td>
<td>0.76</td>
<td>196.2</td>
<td>24.2%</td>
</tr>
<tr>
<td>4</td>
<td>Cubic Splines (365-day)</td>
<td>13,158,072</td>
<td>0.77</td>
<td>189.9</td>
<td>23.4%</td>
</tr>
<tr>
<td>5</td>
<td>Log-quadratic (365-day)</td>
<td>13,509,082</td>
<td>0.77</td>
<td>192.4</td>
<td>23.7%</td>
</tr>
<tr>
<td>6</td>
<td>Multiple Linear Regression (365-day)</td>
<td>16,160,838</td>
<td>0.72</td>
<td>210.4</td>
<td>25.9%</td>
</tr>
<tr>
<td>7</td>
<td>Static Artificial Neural Networks (365-day)</td>
<td>4,152,805</td>
<td>0.93</td>
<td>106.7</td>
<td>13.1%</td>
</tr>
<tr>
<td>8-1</td>
<td>Surface Fitting (365-day)</td>
<td>1,714,385</td>
<td>0.97</td>
<td>68.5</td>
<td>8.4%</td>
</tr>
<tr>
<td>8-2</td>
<td>Surface Fitting (30-day)</td>
<td>1,610,491</td>
<td>0.97</td>
<td>66.4</td>
<td>8.2%</td>
</tr>
<tr>
<td>8-3</td>
<td>Surface Fitting (10-day)</td>
<td>1,543,438</td>
<td>0.97</td>
<td>65</td>
<td>8.0%</td>
</tr>
<tr>
<td>9-1</td>
<td>NARX (365-day)</td>
<td>2,081,906</td>
<td>0.96</td>
<td>75.5</td>
<td>9.3%</td>
</tr>
<tr>
<td>9-2</td>
<td>NARX (30-day)</td>
<td>1,920,547</td>
<td>0.97</td>
<td>72.5</td>
<td>8.9%</td>
</tr>
<tr>
<td>9-3</td>
<td>NARX (10-day)</td>
<td>1,198,267</td>
<td>0.98</td>
<td>57.3</td>
<td>7.1%</td>
</tr>
</tbody>
</table>
Figure 3-9 Prediction results (up) and residual errors (down) for curve fitting models in the MPFOS.
Figure 3-10 Prediction results (up) and residual errors (down) for regression models in the MPFOS.
Figure 3-11 The demonstration of the surface fitting method.
Figure 3-12 Prediction results (up) and residual errors (down) for a 10-day moving piecewise horizon in the MPFOS.
3.6 Conclusion

Multi-simulation prediction results including 365-day, 30-day and 10-day prediction horizons, statistical analysis (SSE, $R^2$, RMSE and RPE), optimal model parameters and configurations were generated by the MPFOS through one single operation. This comprehensive approach provided a direct and effective cross-category model comparison mechanism for the forecasting of daily herd milk yield. The MPFOS can find the most accurate model for just DIM and DHMY input (Cubic Spline), the most accurate model over a long term horizon (Surface Model) and the most accurate model over a short term horizon (NARX). The above results demonstrate the effectiveness of the MPFOS as a model configuration and comparison tool.

The MPFOS architecture developed in this chapter showed to be an efficient and capable system for automatic milk production data pre-processing, model configuration and comparison of model categories over varying prediction horizons. The MPFOS has proven to be a comprehensive and convenient architecture, which can perform simulation calculations for milk yield prediction at herd level and automatically generate the output results and analysis. In addition, the MPFOS can be extended (addition or removal of models in the model library) and modularized. The MPFOS will be a useful benchmark platform for future model comparisons as it is an integrated solution for data processing, model configuration, optimization and analysis.
4 EFFECT OF PARITY WEIGHTING ON MILK PRODUCTION FORECAST MODELS
4.1 Introduction

As detailed in the Literature Review chapter, the ability to accurately forecast the lactation profile of an individual is a great benefit to farm management. The effect of parity on dairy cow lactation has been presented in several previous studies and the corresponding findings are in consensus. Parity has a significant effect on the milk yield (Collins-Lusweti, 1991; Rémond et al., 1997; Silvestre et al., 2009; Ríos-Utrera et al., 2013; Storli et al., 2014; Otwinowska-Mindur and Ptak, 2016) and DIM at peak yield varies in respect to parity (Rekik et al., 2003). The profile of the first lactation curve is not consistent with subsequent lactations. Total and peak milk production yield of dairy cows in the first parity is lower than those of cows in the second parity and the third parity (Hansen et al., 2006; Stanton et al., 1992; Tekerli et al., 2000). The highest total yield is typically presented in the third and subsequent parities (Dematawewa et al., 2007; Friggens et al., 1999; Rekik et al., 2003; Ríos-Utrera et al., 2013) and the first lactation has a slightly delayed peak DIM and lower peak yield (Jamrozik et al., 1998; López et al., 2015). The profile of the first lactation has been shown to introduce difficulties for lactation curve fitting models, in comparison with the second and later parities (Guo and Swalve, 1995). Hence, first lactation is substantially different in profile and magnitude of yield in comparison to the second, third and later parities which display similar lactation profiles. Hence in this chapter, milk yield of the first lactation was tested as a treatment parameter of the control groups to check whether removing this will improve the model prediction accuracy.

There are two primary objectives of this chapter: 1: To compare prediction accuracy of both the Ali and Schaeffer model and the NARX model at the individual cow level. 2: To develop, compare and evaluate six input data pre-processing treatments designed to factor
parity information into the model configuration process to predict individual animal milk production.

4.2 Data used in this chapter

The selected models were trained and validated using daily milk yield (DMY) and days in milk (DIM) records which were deemed the most accessible data for commercial dairy farms in Ireland. Empirical data comprising 1,344,318 milking records of pasture based cows were collected from dairy farms situated in the south of Ireland for a five year period (2004 - 2008). Each daily milking record contained: date of milking, time of milking, milk yield, and cow identification number. In this chapter, the model simulations and evaluations were set at the individual cow level and sample cows were selected using the MPFOS. The MPFOS was designed to calculate optimal model parameters, statistical evaluation and milk production forecasts for each chosen model using input data combinations based on individual milk production records stored in the database.

The tested subjects in this chapter were individual cows and three selection rules were applied to select the test cows. The following conditions had to be satisfied for each cow: 1, started the first lactation in the first model training input year; 2, had a minimum of four continuous lactations; 3, milking records of the fourth lactation were complete. All cows that met the above criteria were selected for analysis. Integrity of milking records in the last lactation was particularly vital as they were employed for both prediction validation and model forecasting performance comparisons. The selection rules were applied to the raw data which consisted of 1,098 cows over a span of five years (2004 to 2008). Of these,
307 cows calved in 2004, 64 of these 307 cows were in the first lactation. Of these 64 first lactation cows, 18 cows had full datasets for four or more successive lactations and these 18 cows were selected as the test group that began lactation in 2004. For the test group that began lactating in 2005, 21 cows were eligible based the same methodology described above.

In total, 39 cows were selected by the MPFOS in the form of two groups which were used to examine the effect of prediction year on prediction accuracy. Grass based systems can be influenced by many time dependent external factors; hence two groups were desirable to test the temporal robustness of the treatments. All 39 cows selected had four consecutive years of milk production from first to fourth lactation, some of which were incomplete lactations (less than 305 days). The daily milk yield of the forth lactation was chosen for model validation while the first three lactation records were used as model training inputs.

4.3 Model input

In this chapter, DMY and DIM were chosen as the model inputs. This chapter focused on parity weight at the individual cow level as opposed to herd level. The inclusion of the parity weight at this level was chosen in order to preclude forecast aggregation effects that may occur at herd level (averaging of milk production figures between cows). By operating the models at the individual cow level, we may investigate the impact of applying parity weight to the milk production prediction for each cow and then calculate the average values. As previous studies proposed, the daily herd milk yield can be viewed as a time series that is being driven by DIM and number of cows milked at the herd level (Murphy et
al., 2014). Similarly, the DMY can be viewed as a time series that is being driven by DIM. The DIM was factored in by chronologically applying a day number (1 - 305) relative to the beginning of calving date for the individual cow. Traditional modelling methods usually assume time series applications are stationary (Box et al., 2008; Chatfield, 2004; Kim et al., 2004). However, in real world applications, most time series applications exhibit some degree of nonstationary behaviour which is a major reason for degradation of the prediction performance (Virili and Freisleben, 2000), such as the annual record of DMY for an individual cow. The most common method of modelling a nonstationary time series dataset is to transform the data to a stationary series (Trapletti et al., 2000). A typical real world time series usually displays both long-term trends and irregularity components. Previous studies proposed the method of improving the modelling performance, which included removing trends (Butler and Kazakov, 2011; Montesino Pouzols and Lendasse, 2010). As shown in Figure 4-1, daily milking records of a representative individual cow shows the trend of milk yield from the first to the third lactation. Essentially, forecasting of milk production is to describe the behaviour of dairy cows and the innate profile of the lactation curve. Hence in the present study, removing trends (long-term) and removing irregular components (extraordinary) were adopted to improve stationarity of milking records when configuring simulation training inputs.

Although the genetic level also affects the trend in annual milk production as discussed in the Literature Review chapter (Section 2.6.1), also due to the limitation of experimental data availability. In this study, we hypothesized that both the irregularity and trends in the time series are primarily due to parity (as shown in Figure 4-1). The irregularity in the series appears in the first lactation and the magnitude of the DMY increases in a seasonal
trend as the lactation number increases from one to three. The milking records of the first lactation may be identified as noise in the training data and this chapter focused on the prediction of the fourth lactation. To remove irregular components, the removal of the first lactation records from training inputs was tested as one of the pre-processing treatments. To remove trends, two types of parity weight (described below) were applied to original DMY to generate training input data (DMY\text{training}) to keep the three lactation records at an equivalent level as shown in Figure 4-2.

![Figure 4-1 Daily milking records of a representative individual cow showing the trend of milk yield from the first to the third lactation.](image-url)
Figure 4-2 Demonstration of differences between standard model milk yield input and adjusted milk yield input using static (SPW) and dynamic parity weight (DPW) for one cow (cow #27).

Parity weight was configured as an array of ratios which normalized the first and second cumulative lactation milk yields with respect to the cumulative 3rd lactation. There were four lactation records for each cow. The first three lactation records were set as training data and the fourth lactation was set as the target year and should be unknown before calculation, therefore the cumulative milk yield in this lactation was assumed equal to that of the third lactation (i.e. the parity weight was 1). For instance, the historical total milk yield of the first three lactations may be 4,000kg, 4,500kg and 5,000kg then the parity weight would be 1.25, 1.11 and 1 respectively, and milk yield of the fourth lactation would
be unknown and assumed to be 5000kg based on the findings of previous research (see Introduction).

Two types of parity weight were applied including: 1) the static parity weight (SPW, Equation 4-1) where the values were selected from previous studies (conducted in Irish pastures based systems) indicated by historical average ratios of cumulative milk production yields between the first, second and third lactations (Hutchinson et al., 2013; Ruelle et al., 2016) and: 2) the dynamic parity weight (DPW, Equation 4-2) where the unique ratio set was generated from the recorded data of each individual cow before every prediction calculation.

The historical milk yield training data were pre-processed in six different treatments in relation to parity, including: #0 standard input (original data without any parity weight), Equation 4-3; #1 static parity weight, Equation 4-4; #2 removed the first lactation record, Equation 4-5; #3 removed the first lactation record and apply static parity weight, Equation 4-6; #4 dynamic parity weight, Equation 4-7; #5 removed the first lactation record and apply dynamic parity weight, Equation 4-8. The treatments were designed to normalize the training inputs and remove noise. Figure 4-2 shows the training data for three treatments: standard, static parity weight and dynamic parity weight.

$$DYM_{training} \begin{bmatrix} L_1 \\ L_2 \\ L_3 \end{bmatrix} = DYM_{original} \begin{bmatrix} L_1 \\ L_2 \\ L_3 \end{bmatrix} \cdot SPW \begin{bmatrix} SPW_1 \\ SPW_2 \\ SPW_3 \end{bmatrix}$$

(Equation 4-1)
\[
\text{DMY}_{\text{training}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = \text{DMY}_{\text{original}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} \cdot \text{DPW} \begin{pmatrix} DPW_1 \\ DPW_2 \\ DPW_3 \end{pmatrix}
\]

(Equation 4-2)

Where \( L_1, L_2 \) and \( L_3 \) is the daily milk yield in the first, second and third lactation.

**#0 standard input**

\[
\text{DMY}_{\text{training}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = \text{DMY}_{\text{original}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix}
\]

(Equation 4-3)

**#1 static parity weight**

\[
\text{DMY}_{\text{training}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = \text{DMY}_{\text{original}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} \cdot \text{SPW} \begin{pmatrix} SPW_1 \\ SPW_2 \\ SPW_3 \end{pmatrix}
\]

(Equation 4-4)

**#2 removed the first lactation**

\[
\text{DMY}_{\text{training}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = \text{DMY}_{\text{original}} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} \cdot \text{SPW} \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}
\]
#3 removed the first lactation and apply static parity weight

$$DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} \cdot SPW \begin{pmatrix} 0 \\ SPW_2 \\ SPW_3 \end{pmatrix}$$

(Equation 4-5)

#4 dynamic parity weight

$$DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} \cdot DPW \begin{pmatrix} DPW_1 \\ DPW_2 \\ DPW_3 \end{pmatrix}$$

(Equation 4-6)

#5 removed the first lactation and apply dynamic parity weight

$$DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} \cdot DPW \begin{pmatrix} 0 \\ DPW_2 \\ DPW_3 \end{pmatrix}$$

(Equation 4-7)
4.4 Model configuration

4.4.1 The curve fitting model

The Ali and Schaeffer model has shown to be one of the most effective milk yield predictors over the last 30 years. Based on the Ali and Schaeffer model, Quinn et al. (2005) proposed the Ali-B model which was shown to have better forecasting performance than the original Ali and Schaeffer model for Irish dairy cows. However in later studies, the Ali-B model’s prediction accuracy at herd level was found to be less accurate than the original model (Zhang et al., 2016). Hence the Ali and Schaeffer model was chosen as the representative of curve fitting models in this chapter.

4.4.2 The auto-regressive model

In this chapter, for the purpose of milk production forecasting at the individual cow level, the actual NCM value was either one or zero, the NCM was adopted in the form of Boolean values to mark if a cow was milked on the corresponding DIM or not. This was introduced to accommodate incomplete lactations (less than 305 days) in the model training process. Hence, the NARX model was trained using individual cow DMY as the predicted time series with the DIM and the NCM was fed in as corresponding time series. The best final NARX configuration for each cow was calculated by the MPFOS including the number of neurons in the hidden layer, the number of delays, the training function and the transfer function.
4.5 Evaluation criteria

In this chapter the evaluation criteria were chosen and configured from the MPFOS including: Summed Square of Residuals (SSE), Coefficient of determination ($R^2$) and Root Mean Squared Error (RMSE) (as shown in the model assessment section).

In addition, the percentage of difference (POD) was introduced as an indicator of increase or decrease in prediction accuracy. The POD was calculated as follows:

$$POD = \left( \frac{RMSE_{\text{standard}} - RMSE_{\text{control group}}}{RMSE_{\text{standard}}} \right) \times 100\%$$

(Equation 4-9)

Where the POD of treatment #0 for each cow was set to 1 as the base line, a positive POD value of treatment (from treatment #1 to treatment #5) shows how the prediction improved in the form of decreasing (positive) RMSE values. Similarly, a negative POD value shows how the prediction worsened in the form of increasing RMSE values.

4.6 Results and discussion

4.6.1 Model comparison

The statistical results of the NARX model and the Ali and Schaeffer model forecasts against the validation dataset of 39 individual cows’ DMY are shown in Table 4-5 (see Section 4.8). The statistical summary of Table 4-5 is shown in Table 4-1 (One-way ANOVA between treatments). The training inputs were milk yield records of the first three lactations and records of the fourth lactation were used for evaluation. According to
definitions of model quality based on $R^2$ from Olori et al. (1999a), both tested models can be classified as ‘good’, due to $R^2$ values greater than 0.70 in most cases (37 of 39 cows, 94.9%, see Table 4-5). In addition, for treatment #0 with standard input, the NARX model had a high level of performance with a distribution of $R^2$ values between 0.47 - 0.95 (8 of 39 $R^2$ values were lower than 0.7), in comparison, the Ali and Schaeffer model had a distribution of $R^2$ values between 0.43 - 0.92 (10 of 39 $R^2$ values were lower than 0.7). It was observed that the NARX model had absolute better performances than the Ali and Schaeffer model for all 39 cows based on $R^2$ values, meanwhile, the same evidence can be found in the comparison of RMSE values as well as SSE values as shown in Table 4-5. These direct outcomes support the hypotheses that the NARX model can provide more accurate milk yield prediction than conventional curve fitting modelling techniques at individual cow level.

Each RMSE value and SSE value of the NARX model’s predictions were lower than those of the Ali and Schaeffer model, which shows that the NARX model provided more accurate forecasts. As shown in Table 4-5, it is clear that the NARX model showed higher forecasting accuracy than the Ali and Schaeffer model for all 39 individual cows. As shown in Figure 4-3, the distribution of $R^2$ values of two test model predictions indicated that the variation in $R^2$ values were between cows rather than between models.
Table 4-1 Summary of ANOVA between treatments.

<table>
<thead>
<tr>
<th></th>
<th>#0</th>
<th>#1</th>
<th>#2</th>
<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>Total</th>
</tr>
</thead>
<tbody>
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<td><strong>NARX</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
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<td>39</td>
<td>39</td>
<td>39</td>
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</tr>
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<td>145.50</td>
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<td>147.03</td>
<td>159.18</td>
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<td>895.93</td>
</tr>
<tr>
<td>Average</td>
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<td>3.73</td>
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<td>3.77</td>
<td>4.08</td>
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</tr>
<tr>
<td>Variance</td>
<td>1.43</td>
<td>0.83</td>
<td>0.81</td>
<td>0.88</td>
<td>1.43</td>
<td>1.30</td>
<td>1.11</td>
</tr>
<tr>
<td><strong>Ali-Schaeffer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
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<td>175.43</td>
<td>173.04</td>
<td>1030.73</td>
</tr>
<tr>
<td>Average</td>
<td>4.38</td>
<td>4.36</td>
<td>4.32</td>
<td>4.44</td>
<td>4.50</td>
<td>4.44</td>
<td>4.40</td>
</tr>
<tr>
<td>Variance</td>
<td>1.65</td>
<td>1.48</td>
<td>1.46</td>
<td>1.65</td>
<td>2.26</td>
<td>2.00</td>
<td>1.72</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>78</td>
<td>78</td>
<td>78</td>
<td>78</td>
<td>78</td>
<td>78</td>
<td>78</td>
</tr>
<tr>
<td>Sum</td>
<td>323.46</td>
<td>315.68</td>
<td>309.25</td>
<td>320.06</td>
<td>334.61</td>
<td>323.60</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>4.15</td>
<td>4.05</td>
<td>3.96</td>
<td>4.10</td>
<td>4.29</td>
<td>4.15</td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>1.58</td>
<td>1.24</td>
<td>1.25</td>
<td>1.36</td>
<td>1.87</td>
<td>1.71</td>
<td></td>
</tr>
</tbody>
</table>

|                |      |      |      |      |      |      |      |
| **ANOVA (P-value)** |    |    |    |    |    |    |      |
| Treatment*      |      |      |      |      |      |      |      |
| NARX            | 0.4438 | 0.2100 | 0.5498 | 0.5444 | 0.8335 |
| Ali-Schaeffer   | 0.9611 | 0.8289 | 0.8393 | 0.7039 | 0.8463 |

Treatment*: #0 standard input, #1 static parity weight, #2 removed the first lactation, #3 removed the first lactation and apply static parity weight, #4 dynamic parity weight, #5 removed the first lactation and apply dynamic parity weight.
4.6.2 Effect of different treatments

Table 4-6 (see Section 4.8) shows RMSE POD values of the 39 test cows for all six treatments (from treatment #0 to treatment #5). The positive or negative POD values in RMSE show how the treatment predictions improved (positive POD) or worsened (negative POD) in the form of decreasing or increasing RMSE values, respectively. Table 4-2 shows the statistical summary of Table 4-6.

Table 4-2-1 shows average RMSE POD values for 18 cows from 2004 - 07, five treatments (#1 - #5) applied to the input data of the NARX model improved 11 to 15 cows’ forecasts (POD > 0) depending on the treatment. The average POD varied from -6.43% (treatment #4, dynamic parity weight) to 13.13% (treatment #2, removed the first lactation) which implies that applying treatment #4 actually increased RMSE values and decreased the model forecasting accuracy on average (18 cows). Applying treatment #2 (removed the
first lactation) decreased RMSE values and improved the model forecasting accuracy on average (18 cows). The five treatments applied to the Ali and Schaeffer model improved between 11 and 13 cows predictions and the average POD varied from -3.74% (treatment #4, dynamic parity weight) to 4.47% (treatment #2, removed the first lactation).

However, for the 21 cow group from 2005 - 08 as shown in Table 4-2-2, neither the NARX model nor the Ali and Schaeffer model display improvements in forecasts (only forecasts for 7 - 9 cows were improved for each treatment of both models), as a consequence, average POD values were all negative for treatments from #1 to #5 applied to both models. The limited data available for this chapter was lacking information related to the cows’ biological conditions (e.g. breed, body weight, cow body condition score) and feed intake. Therefore, there was no definite explanation relating to the discrepancy in results between the cow groups 2004 - 07 and 2005 - 08. One possible reason is that all of the cows in this chapter were situated in pasture-based farms, in close proximity. As climate and weather factors have a strong impact on grazing conditions and the cows’ comfort levels (Hill and Wall, 2015), this may explain variances between the two different groups (2004 - 07 and 2005 - 08). These results highlight the importance of examining the accuracy of milk prediction models and model training strategies across multiple time horizons. Figure 4-4 and 4-5 show distribution of R² values of the NARX model predictions for two groups (2004 - 07 and 2005 - 08), Figure 4-6 and 4-7 shows the distribution of R² values of the Ali and Schaeffer model predictions for two groups (2004 - 07 and 2005 - 08).
Figure 4-4 The distribution of $R^2$ values of the NARX model predictions for group 2004 - 2007.

Figure 4-5 The distribution of $R^2$ values of the NARX model predictions for group 2005 - 2008.

Treatment: #0 standard input, #1 static parity weight, #2 removed the first lactation, #3 removed the first lactation and apply static parity weight, #4 dynamic parity weight, #5 removed the first lactation and apply dynamic parity weight.
Figure 4-6 The distribution of $R^2$ values of the Ali and Schaeffer model predictions for group 2004 - 2007.

![Boxplot of R-squared values for group 2004-2007](image)

Figure 4-7 The distribution of $R^2$ values of the Ali and Schaeffer model predictions for group 2005 - 2008.

![Boxplot of R-squared values for group 2005-2008](image)

Treatment: #0 standard input, #1 static parity weight, #2 removed the first lactation, #3 removed the first lactation and apply static parity weight, #4 dynamic parity weight, #5 removed the first lactation and apply dynamic parity weight.
As shown in Table 4-2-3, the milk yield prediction of 28 cows improved (POD > 0) using at least one treatment. However there was no improvement for the other 11 cows as shown in Table 4-2-4 and the standard inputs were the most effective training inputs for prediction of milk yield in the fourth lactation. From the comparison of Table 4-2-3 and Table 4-2-4, the prediction results varied relative to treatment, however these summary results were based on the average POD values of the group. For all of the 39 test cows in this chapter, forecasts for 28 cows in total received an improvement in forecast accuracy from the application of parity weighting. On further examination, results of these 28 cows demonstrated the maximum possible improvements of applying different treatments in milk yield prediction at the herd level as if a herd were consisted of these 28 cows. The ‘% average’ is the average POD of 28 cows. The ‘number of improved forecasts’ is qualitative and shows the actual number of cows with positive POD values. For example, even though 18 cows’ predictions received improvement from treatment #4 (dynamic parity weight), the average POD of these 28 cows is still negative (-0.97%). Treatment #2 (removed the first lactation) and treatment #3 (removed the first lactation and apply static parity weight) were the two most successful treatments for both the NARX model (POD > 11%) and the Ali and Schaeffer model (POD > 6%). For the 28 cows in Table 4-2-3, treatment #1 (static parity weight: 10.46% and 5.78% forecasts improvement of each model) was more effective than treatment #4 (dynamic parity weight: -0.97% and 0.62% forecasts improvement of each model). Combing dual treatments revealed a further characteristic: after removal of the first lactation, both the application of DPW and SPW increased average POD values: treatment #5 (removed the first lactation and apply dynamic parity weight, equivalent to treatment #2 coupled with treatment #4) performed better than
treatment #4; and treatment #3 (removed the first lactation and apply static parity weight, equivalent to treatment #2 coupled with treatment #1) performed better than treatment #1. This supports the proposed strategy in the Model Inputs section that removing the first lactation record reduced irregular components, and parity weight is an enhancement in removing trends and improving the POD.

Table 4-2-5 shows average RMSE POD values of the tested models using six treatments for 39 cows. Due to the large variation of POD between cows’ forecasts shown in Table 4-3, overall average POD values for each of the five treatments for both tested models were negative values excepted the NRRX model using treatment #1 (static parity weight) and treatment #2 (removed the first lactation). It is clear that removing the first lactation record from the input training set can improve prediction accuracy for the autoregressive model in both quantity of improved cows and overall average POD values. One possible reason for this is that the milk yield of the cows in the first lactation is more irregular than those in subsequent lactations, as well as the peak yield of the first lactation being lower than subsequent lactations. Therefore removing the first lactation record reduced the level of noise and irregular components in the training set.

From the results above, treatment #2 (removed the first lactation) appears to produce superior milk production forecasting in comparison to the original data input methodology. Treatment #1 (static parity weight) was the most simple and the second most successful option. These treatments improved the stationarity of the milking records and showed better prediction performance when applied to the NARX model. This may be due to the NARX model’s ability to process both stationary time series and original (unprocessed data) time series as training inputs (Diaconescu, 2008b). However, the primary focus of
this chapter was on the effect of different treatments on the accuracy of milk production forecasting. For all 39 cows, applying parity weighting improved approximately 50% of milk yield predictions for each individual cow (18 - 23 cows and 19 - 20 cows using each model, respectively). Figure 4-8 and 4-9 show the distribution of $R^2$ values of the NARX model and the Ali and Schaeffer model predictions for 39 test cows using six treatments.
Table 4-2 Statistical summary of RMSE percentage of difference (POD) values.

Positive POD indicates an improvement in prediction.

### 4-2-1 Summary of RMSE POD values for cows from year of 2004 - 2007

<table>
<thead>
<tr>
<th>Treatment*¹</th>
<th>NARX POD*</th>
<th>No. of improved</th>
<th>Ali &amp; Schaeffer POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#0</td>
<td>1</td>
<td>15</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>#1</td>
<td>9.85%</td>
<td>15</td>
<td>3.69%</td>
<td>12</td>
</tr>
<tr>
<td>#2</td>
<td>13.13%</td>
<td>15</td>
<td>4.47%</td>
<td>11</td>
</tr>
<tr>
<td>#3</td>
<td>9.17%</td>
<td>13</td>
<td>3.65%</td>
<td>11</td>
</tr>
<tr>
<td>#4</td>
<td>-6.34%</td>
<td>11</td>
<td>-3.74%</td>
<td>13</td>
</tr>
<tr>
<td>#5</td>
<td>0.21%</td>
<td>13</td>
<td>-2.67%</td>
<td>11</td>
</tr>
</tbody>
</table>

POD*: average POD of prediction for cows in each treatment.

### 4-2-2 Summary of RMSE POD values for cows from year of 2005 - 2008

<table>
<thead>
<tr>
<th>Treatment*¹</th>
<th>NARX POD*</th>
<th>No. of improved</th>
<th>Ali &amp; Schaeffer POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>#1</td>
<td>-6.27%</td>
<td>8</td>
<td>-6.98%</td>
<td>7</td>
</tr>
<tr>
<td>#2</td>
<td>-3.63%</td>
<td>9</td>
<td>-5.00%</td>
<td>7</td>
</tr>
<tr>
<td>#3</td>
<td>-11.23%</td>
<td>9</td>
<td>-11.54%</td>
<td>7</td>
</tr>
<tr>
<td>#4</td>
<td>-10.41%</td>
<td>7</td>
<td>-5.91%</td>
<td>7</td>
</tr>
<tr>
<td>#5</td>
<td>-6.76%</td>
<td>7</td>
<td>-5.24%</td>
<td>7</td>
</tr>
</tbody>
</table>

POD*: average POD of prediction for cows in each treatment.

### 4-2-3 Summary of RMSE POD values for cows with improvement in prediction

<table>
<thead>
<tr>
<th>Treatment*¹</th>
<th>NARX POD*</th>
<th>No. of improved</th>
<th>Ali &amp; Schaeffer POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>#1</td>
<td>10.46%</td>
<td>23</td>
<td>5.78%</td>
<td>19</td>
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<tr>
<td>#2</td>
<td>13.74%</td>
<td>26</td>
<td>6.09%</td>
<td>16</td>
</tr>
<tr>
<td>#3</td>
<td>11.09%</td>
<td>22</td>
<td>6.17%</td>
<td>15</td>
</tr>
<tr>
<td>#4</td>
<td>-0.97%</td>
<td>18</td>
<td>0.62%</td>
<td>20</td>
</tr>
</tbody>
</table>
### 4-2-4 Summary of RMSE POD values for cows without improvement in prediction

<table>
<thead>
<tr>
<th>Treatment*¹</th>
<th>NARX POD*</th>
<th>No. of improved</th>
<th>Ali &amp; Schaeffer POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>#1</td>
<td>-22.48%</td>
<td>0</td>
<td>-21.99%</td>
<td>0</td>
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<tr>
<td>#2</td>
<td>-20.43%</td>
<td>0</td>
<td>-17.74%</td>
<td>0</td>
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<tr>
<td>#3</td>
<td>-34.66%</td>
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<tr>
<td>#4</td>
<td>-27.79%</td>
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<tr>
<td>#5</td>
<td>-24.61%</td>
<td>0</td>
<td>-18.25%</td>
<td>0</td>
</tr>
</tbody>
</table>

POD*: average POD of prediction for cows in each treatment.

### 4-2-5 Summary of RMSE POD values for overall sample

<table>
<thead>
<tr>
<th>Treatment*¹</th>
<th>NARX POD*</th>
<th>No. of improved</th>
<th>Ali &amp; Schaeffer POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>#1</td>
<td>1.17%</td>
<td>23</td>
<td>-2.05%</td>
<td>19</td>
</tr>
<tr>
<td>#2</td>
<td>4.10%</td>
<td>24</td>
<td>-0.63%</td>
<td>18</td>
</tr>
<tr>
<td>#3</td>
<td>-1.82%</td>
<td>22</td>
<td>-4.53%</td>
<td>18</td>
</tr>
<tr>
<td>#4</td>
<td>-8.53%</td>
<td>18</td>
<td>-4.91%</td>
<td>20</td>
</tr>
<tr>
<td>#5</td>
<td>-3.54%</td>
<td>20</td>
<td>-4.06%</td>
<td>18</td>
</tr>
</tbody>
</table>

POD*: average POD of prediction for cows in each treatment.

Treatment*¹: #0 standard input, #1 static parity weight, #2 removed the first lactation, #3 removed the first lactation and apply static parity weight, #4 dynamic parity weight, #5 removed the first lactation and apply dynamic parity weight.
Figure 4-8 The distribution of $R^2$ values of the NARX model predictions for all 39 cows.

Figure 4-9 The distribution of $R^2$ values of the Ali and Schaeffer model predictions for all 39 cows.

Treatment: #0 standard input, #1 static parity weight, #2 removed the first lactation, #3 removed the first lactation and apply static parity weight, #4 dynamic parity weight, #5 removed the first lactation and apply dynamic parity weight.
4.6.3 Comparing parity weight trend and prediction results

Table 4-3 shows the DPW of each cow tested including the DPW of the fourth lactation. The average DPW values for each cow group is shown in Table 4-4 and plotted in Figure 4-10. The cow group 2004 - 07 (the group which responded best to the treatments) displayed an increasing DPW trend from the first lactation (0.78) to the second lactation (0.91) and the third lactation (1.00) along with the smallest decrease in DWP from the third lactation to the fourth lactation (1.00 to 0.95). In comparison to the 2004 - 07 cow group, the 28 cows that displayed prediction improvements had a similar monotonic increase in parity weight from the first lactation (0.78) to the second lactation (0.92) and third lactation (1.00) and a lesser decrease from the third lactation to the fourth lactation (1.00 to 0.96). The worst performing groups (11 unimproved cows group and the 2005 - 08 group) had a large increase in DPW from the first lactation (0.79 and 0.78, respectively) to the second lactation (1.00 and 0.97, respectively) and either small increases or decreases in DPW between the second and third lactation (from 1.00 to 1.00, from 0.97 to 1.00, respectively), and also the largest decreases from the third lactation to the fourth lactation (1.00 to 0.89 for 11 unimproved cows group, 1.00 to 0.94 for cows from the 2005 - 08 group). This DPW trend displays unusual characteristic such as second lactation yields that are higher than the third lactation and fourth lactation yields that are much lower than the third lactation. This is atypical to the conventional DPW trend of Irish dairy cows. In previous cognate studies (Hutchinson et al., 2013; Ruelle et al., 2016), the milk yield ratios for the first, second, third and fourth lactation were (0.76, 0.76), (0.94, 0.94), (1.00, 1.00) and (1.02, 1.00), respectively.
Table 4-3 Dynamic parity weight and the parity weight of the fourth lactation.

<table>
<thead>
<tr>
<th>Cow #</th>
<th>Descriptive Statistics of DMY (4 years)</th>
<th>Parity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Min</td>
</tr>
<tr>
<td>1</td>
<td>22.38</td>
<td>2.40</td>
</tr>
<tr>
<td>2</td>
<td>19.73</td>
<td>0.00</td>
</tr>
<tr>
<td>3</td>
<td>21.49</td>
<td>0.00</td>
</tr>
<tr>
<td>4</td>
<td>20.76</td>
<td>0.10</td>
</tr>
<tr>
<td>5</td>
<td>20.51</td>
<td>0.00</td>
</tr>
<tr>
<td>6</td>
<td>19.50</td>
<td>2.40</td>
</tr>
<tr>
<td>7</td>
<td>24.44</td>
<td>0.20</td>
</tr>
<tr>
<td>8</td>
<td>20.14</td>
<td>0.10</td>
</tr>
<tr>
<td>9</td>
<td>22.33</td>
<td>0.10</td>
</tr>
<tr>
<td>10</td>
<td>22.94</td>
<td>2.40</td>
</tr>
<tr>
<td>11</td>
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<tr>
<td>12</td>
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<td>13</td>
<td>19.27</td>
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<td>14</td>
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<td>15</td>
<td>17.82</td>
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<td>20.99</td>
<td>2.40</td>
</tr>
<tr>
<td>17</td>
<td>20.67</td>
<td>0.10</td>
</tr>
<tr>
<td>18</td>
<td>18.36</td>
<td>0.10</td>
</tr>
<tr>
<td>19</td>
<td>17.90</td>
<td>0.00</td>
</tr>
<tr>
<td>20</td>
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<td>17.90</td>
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</tr>
<tr>
<td>24</td>
<td>19.29</td>
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<td>25</td>
<td>21.50</td>
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<td>26</td>
<td>19.80</td>
<td>0.80</td>
</tr>
<tr>
<td>27</td>
<td>18.95</td>
<td>2.50</td>
</tr>
<tr>
<td>28</td>
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<td>3.00</td>
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<td>29</td>
<td>18.34</td>
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<td>30</td>
<td>18.56</td>
<td>0.00</td>
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<td>31</td>
<td>16.90</td>
<td>1.40</td>
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<td>32</td>
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<td>19.30</td>
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<td>36</td>
<td>17.64</td>
<td>3.10</td>
</tr>
<tr>
<td>37</td>
<td>17.19</td>
<td>0.10</td>
</tr>
<tr>
<td>38</td>
<td>19.95</td>
<td>0.10</td>
</tr>
<tr>
<td>39</td>
<td>17.79</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Notes:

Mean: average or mean value;

Min: smallest value;

Max: maximum value;

Median: median value;

Mode: most frequent value;

Std: standard deviation;

Var: variance.
Table 4-4 Average dynamic parity weight of groups.

<table>
<thead>
<tr>
<th>Group</th>
<th>Number</th>
<th>Parity</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2004 - 07</td>
<td>18</td>
<td>1st</td>
<td>0.78</td>
<td>0.91</td>
<td>1.00</td>
<td>0.95</td>
</tr>
<tr>
<td>2005 - 08</td>
<td>21</td>
<td>2nd</td>
<td>0.78</td>
<td>0.97</td>
<td>1.00</td>
<td>0.94</td>
</tr>
<tr>
<td>Improved*</td>
<td>28</td>
<td>3rd</td>
<td>0.78</td>
<td>0.92</td>
<td>1.00</td>
<td>0.96</td>
</tr>
<tr>
<td>Unimproved+</td>
<td>11</td>
<td>4th</td>
<td>0.79</td>
<td>1.00</td>
<td>1.00</td>
<td>0.89</td>
</tr>
<tr>
<td>Total cows</td>
<td>39</td>
<td></td>
<td>0.78</td>
<td>0.94</td>
<td>1.00</td>
<td>0.94</td>
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Improved*: cows displayed prediction improvements. Unimproved+: cows without prediction improvements.

Figure 4-10 Average parity weight of different statistical groups (group 2004 - 2007, group 2005 - 2008, group improved, group unimproved, group total cows).
The larger the difference between the parity weight of the third lactation and the fourth lactation, the worse the performance of applying parity weight for milk yield prediction. Forecasts for cows with conventional trends in parity weight received larger improvements in forecast accuracy from the application of parity weighting. The target year and validation dataset (the milk yield of the fourth lactation) was simulated to be unknown and assumed to be equal to the yield of the third lactation. Therefore the larger the decrease in milk yield between the fourth and third lactations, the lesser the positive result parity weighting had on the milk production forecasts. This is because the improvement in the stationarity of the time series had less of an impact on prediction accuracy. Figure 4-10 shows the trends in average parity weight in relation to the performance of milk yield prediction in the different cow groups in Table 4-4. Figure 4-11 shows the parity weight in relation to the performance of milk yield prediction for all 39 cows in Table 4-3.
4.7 Conclusion

In this chapter, the NARX model was found to provide better prediction accuracy than the Ali and Schaeffer model for individual cows over a 305-day forecast horizon. Despite varying results between two cow groups for six different parity weight treatments, the NARX model was shown to be more effective than the Ali and Schaeffer model for predicting milk yield at the individual cow level.
The effects of six treatments designed to factor parity information into the model configuration process were tested on the NARX model and the Ali and Schaeffer model. While the milk yield prediction of 61% of the sample cows (24 of 39) achieved a POD improvement with at least one treatment, the results were mixed and varied highly between groups. Applying static parity weight (treatment #1) and removal of the first lactation (treatment #2) were the two most successful treatments for improving milk yield forecasting at the individual cow level over a 305-day lactation. However, what was clearly evident from the result of the parity weighting treatments was that cow parity weighting profiles had a substantial effect on the success rate of the treatments. Milk production predictions for cows that displayed conventional parity weight profiles were much more likely to display POD improvements from the application of parity weighting treatments, while cows that displayed atypical parity weight profiles were much more likely to display POD disimprovements as a result of the same treatments. It was shown the high variance in results was primarily due to the dissimilar parity weight profiles of the two time period groups (2004 - 07, 2005 - 08), where the conventional average parity weight profile of the cows in group 2004 - 07 resulted in an improvement in milk production forecast accuracy for the majority of cows in that respective group. Whereas, the unconventional average parity weight profile of the cows in group 2005 - 08 resulted in a disimprovement in milk production forecast accuracy in the majority of cows in that respective group. These results highlight the importance of examining the accuracy of milk prediction models and model training strategies across multiple time horizons. As the cows in this study were in a pasture based system, these differences may be due to changes in grazing and climatic conditions across different time periods. As discussed in the
Literature Review chapter, there is possibility of predicting milk yields of the earlier three lactation. However due to the nature of both the NARX model and time series forecasting, previous milking records are essential and required as training data. Hence only milk yields of the fourth lactation was predicted for individual cows in this study. Further research using larger cow population sizes over longer time periods is required to investigate the potential of using parity information to enhance the performance of milk prediction models on an individual cow level.
## 4.8 Results tables

Table 4-5 Statistical results of the NARX model and the Ali and Schaeffer model forecasts using six treatments for 39 individual cows.

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Treatment*: #0 standard input, #1 static parity weight, #2 removed the first lactation, #3 removed the first lactation and apply static parity weight, #4 dynamic parity weight, #5 removed the first lactation and apply dynamic parity weight. RMSE unit: kg.

Table 4-6 POD (Percentage of difference) in RMSE of the NARX model and the Ali and Schaeffer model forecasts using six treatments for 39 individual cows.

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143
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<table>
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<th>Cow39</th>
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Treatment*: #0 standard input, #1 static parity weight, #2 removed the first lactation, #3 removed the first lactation and apply static parity weight, #4 dynamic parity weight, #5 removed the first lactation and apply dynamic parity weight.
5 EFFECT OF WEATHER PARAMETERS ON MILK PRODUCTION FORECAST MODELS
5.1 Introduction

In this chapter, the proposed hypothesis was that incorporating weather parameters into existing milk production models may improve model prediction accuracy without the need to employ detailed grass growth models or holistic dairy production models that require more detailed information. The primary objective of this chapter was therefore to investigate the effect of introducing the weather parameters; soil temperature, precipitation and radiation on milk production forecasting accuracy. This was achieved by testing eight input data combinations designed to factor weather information into the model configuration and training process. As discussed in the Literature Review chapter (section 2.5.3), the MLR model has proved successful in predicting the annual average daily milk yield for 13 years individual years (1954 - 1966) using annual average daily cow production records and national weather records in a study based in England and Wales (Smith, 1968). The multiple linear regression (MLR) model and the nonlinear auto-regressive model with exogenous input (NARX) model were selected as the milk production forecasting models.

5.2 Data used in this chapter

The selected models were trained using two categories of data; 1) on-farm data consisting of daily milk yield (DMY) and days in milk (DIM) records both of which are accessible for Irish commercial dairy farms. Empirical data comprising 928,395 daily milking records of pasture based cows were collected from dairy farms (all within close proximity) situated in the south of Ireland over a five year period (2004 - 2008). Each daily milking record
contained date of milking, time of milking, milk yield (kg) and a cow identification number. 2) meteorological data (See Table 5-1) were measured from the nearest Met Éireann weather station (37 km south). For the period 2004 - 2008, meteorological data consisted of daily rainfall (mm), sunshine hours (hour) and soil temperature (degrees Celsius) data. The climate of Ireland can be described as a maritime influenced, mild and temperate climate. Hence Ireland does not suffer from the extremes of temperature, in comparison to many other countries at similar latitude (Met Éireann, 2016). As discussed in the Literature Review, based on the conclusion of previous studies on influence of weather factors on dairy milk production and the correlation of air temperature and soil temperature, the soil temperature was adopted as training input rather than the air temperature.

Table 5-1 Summary of weather data collection (2004 to 2008, 1827 daily records) from Met Éireann weather station (37 km south of Moorepark Teagasc Food Research Centre, Co. Cork).

<table>
<thead>
<tr>
<th>Weather parameter</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Median</th>
<th>Mode</th>
<th>Standard Deviation</th>
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<td>66.3</td>
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<td>0</td>
<td>6.23</td>
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<tr>
<td>Sunshine hours</td>
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<td>0</td>
<td>16.0</td>
<td>3.2</td>
<td>0</td>
<td>3.96</td>
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<tr>
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<td>10.6</td>
<td>8.3</td>
<td>4.69</td>
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</table>

Notes: Rainfall amount (mm) over 24 hour, Sunshine (hours) over 24 hour, Soil temperature (°C) at 10cm depth.
In this chapter, the model simulations and evaluations were set at the individual cow level and sample cows were selected using the MPFOS. The MPFOS was designed to calculate optimal model parameters, conduct statistical analysis and produce milk production forecasts for each chosen model using input data combinations based on individual milk production records and meteorological data stored in the database. Three selection rules were applied to select individual test cows in this chapter. All cows that satisfied the following criteria were selected for analysis; 1) the first lactation occurred in the first model training input year. 2) a minimum of four continuous year-on-year lactation data were available (incomplete lactations were allowed, i.e. less than 305 days). 3) milking records of the fourth lactation were complete. Integrity of milking records in the fourth lactation was vital as these records were used for validation and model performance comparisons. The selection rules were applied to the raw data, which consisted of 779 cows over a span of five years (2004 to 2008). Of these, 307 cows calved in 2004 and 64 of these 307 cows were the in the first lactation. Of these 64 first lactation cows, 18 cows had full datasets for four or more successive lactations and these 18 cows were selected as test group 2004. For the test group that began lactating in 2005, 21 cows were selected using the same methodology described above. In total, 39 cows were selected by the MPFOS and consisted of two groups (2004-07 and 2005-08). As weather conditions vary from year to year, the two groups were also used to test the temporal robustness of the model forecasts. All of the 39 cows selected had four consecutive years of milk production from the first to the fourth lactation, some of which were incomplete lactations (less than 305 days). The DMY of the fourth lactation was chosen for model validation while the first three lactation records were used as model training inputs.
5.3 Model inputs

In this chapter, DMY, DIM and corresponding daily weather meteorological data (rainfall, sunshine hours and soil temperature) were selected as model inputs. This chapter focused on forecasts at the individual cow level as opposed to herd level. The inclusion of the meteorological parameters at this level were chosen to preclude forecast aggregation effects that may occur at herd level (averaging of milk production figures between cows). By operating the models at the individual cow level, the impact of adding meteorological parameters to the milk production prediction accuracy for each cow may be investigated while still allowing averaged values to be calculated. The meteorological data corresponding to each day number was trained in parallel with DIM and DMY.

Multiple combinations of meteorological data were applied and tested along with DIM and DMY as model inputs. The historical milk yield training data were pre-processed using eight treatments designed to factor meteorological data (MD) into the model configuration and training process; #1) standard input (original with DIM and DMY only), Equation 5-1; #2 precipitation, Equation 5-2; #3 sunshine hours, Equation 5-3; #4 soil temperature, Equation 5-4; #5 precipitation and sunshine hours, Equation 5-5; #6 precipitation and soil temperature, Equation 5-6; #7 sunshine hours and soil temperature, Equation 5-7; #8 precipitation, sunshine hours and soil temperature, Equation 5-8. A summary of weather combination input treatments is shown in Table 5-2.
#1 standard input

\[ DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} \]

(Equation 5-1)

#2 precipitation

\[ DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} + MD(\text{precipitation}) \]

(Equation 5-2)

#3 sunshine hours

\[ DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} + MD(\text{sunshine}) \]

(Equation 5-3)

#4 soil temperature

\[ DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} + MD(\text{temperature}) \]

(Equation 5-4)
#5 precipitation and sunshine hours

\[
DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} + MD(\text{precipitation}) + MD(\text{sunshine})
\]

(Equation 5-5)

#6 precipitation and soil temperature

\[
DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} + MD(\text{precipitation}) + MD(\text{temperature})
\]

(Equation 5-6)

#7 sunshine hours and soil temperature

\[
DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} + MD(\text{sunshine}) + MD(\text{temperature})
\]

(Equation 5-7)

#8 precipitation, sunshine hours and soil temperature

\[
DMY_{training} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} = DMY_{original} \begin{pmatrix} L_1 \\ L_2 \\ L_3 \end{pmatrix} + MD(\text{precipitation}) + MD(\text{sunshine}) + MD(\text{temperature})
\]

(Equation 5-8)
Table 5-2 Legend of weather combination in input treatments.

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<th>Sunshine hours</th>
<th>Soil Temperature</th>
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<td>Y</td>
<td>Y</td>
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</table>

5.4 Model configuration

5.4.1 The regression model

The MLR model was chosen in this chapter for two reasons. Firstly, the MLR model has proved to be successful in milk yield forecasting at the herd level (Dongre et al., 2012; Grzesiak et al., 2003; Sharma et al., 2007; Smith, 1968). Secondly, the MLR model can use more input variables than the curve fitting models which can only use DIM and DMY. The study of Smith (1968) has successfully demonstrated that adding rainfall and temperature as additional input variables can improve annual milk yield forecasting accuracy of a MLR model. Hence in this chapter, combing the purpose of utilizing additional weather data and forecasting milk yield for the individual cow, the expression of the MLR model (Equation 5-9) used was revised from that originally developed by Murphy et al. (2014).
\[
Y_t = \varepsilon + \alpha_1 NCM_t + \alpha_2 \text{DIM}_t + \alpha_3 MD_1 + \alpha_4 MD_2 + \ldots + \alpha_M MD_N
\]

(Equation 5-9)

Where \(Y_t\) is the daily milk yield (DMY) and the dependent variable, number of cows milked (NCM), days in milk (DIM) and meteorological data (MD\(_1\) up to MD\(_N\)) are independent variables, \(\alpha_1\), up to \(\alpha_M\) are the regression coefficients and \(\varepsilon\) is the residual error.

5.4.2 The auto-regressive model

In this chapter, Meteorological data was introduced as training inputs as the NARX model has the ability to use multiple inputs. Therefore, the NARX model was trained using individual cow DMY as the predicted time series with the DIM, the NCM and meteorological data (MD\(_1\) up to MD\(_N\)) as corresponding time series. The most accurate NARX configuration for each cow was calculated by the MPFOS including the number of neurons in the hidden layer, the training function and the transfer function in accordance with the methodology used by Murphy et al. (2014). Taped delay lines were used to give the model short-term memory. Multiple day delays were trailed (2, 4 and 6 days) so the model could take into account any existing time lags between the meteorological parameters and milk production.
5.5 Evaluation criteria

The evaluation criteria were chosen and configured from the MPFOS in this chapter, including: Summed Square of Residuals (SSE), Coefficient of determination ($R^2$) and Root Mean Squared Error (RMSE) and the percentage of difference (POD) (Jones, 1997; Murphy et al., 2014; Olori et al., 1999; Sharma and Kasana, 2006).

5.6 Results and discussion

5.6.1 Model comparison

The statistical results of the NARX model and the MLR model forecasts against the validation dataset of 39 individual cows’ DMY are shown in Table 5-6 (see Section 5.8). The statistical summary of Table 5-6 is shown in Table 5-3 (One-way ANOVA between treatments). The training inputs were milk yield records of the first three lactations and records of the fourth lactation were used for evaluation. According to definitions of model quality based on $R^2$ from Olori et al. (1999), the NARX models can be classified as ‘good’ ($R^2$ values greater than 0.70) in 298 of 312 predictions (95.5%, see Table 5-6). In contrast, the MLR model can only be considered ‘good’ in 46 out of 312 cases (14.7%, see Table 5-6). It is clear that the NARX model was more accurate than the MLR model for all 39 cows, based on $R^2$, RMSE and SSE values (see Figure 5-1 and Table 5-7). These direct outcomes support the hypotheses that the NARX model can provide greater accuracy to milk yield than the regression model at the individual cow level. However, a substantial
variation in $R^2$ values between cows can be seen due to atypical curves of the fourth lactations.
Table 5-3 Summary of one-way ANOVA between treatments.

<table>
<thead>
<tr>
<th>Treatment*</th>
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<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>#6</th>
<th>#7</th>
<th>#8</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>NARX</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td>39</td>
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<tr>
<td>Sum</td>
<td>130.04</td>
<td>126.84</td>
<td>124.79</td>
<td>126.50</td>
<td>127.55</td>
<td>126.72</td>
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<tr>
<td>Average</td>
<td>3.33</td>
<td>3.25</td>
<td>3.20</td>
<td>3.24</td>
<td>3.27</td>
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<td>3.27</td>
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<tr>
<td>Variance</td>
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<td>0.63</td>
<td>0.60</td>
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<td>0.61</td>
<td>0.54</td>
<td>0.55</td>
<td>0.57</td>
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<tr>
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<td>1.66</td>
<td>1.54</td>
<td>1.60</td>
<td>1.54</td>
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<td>4.62</td>
<td>4.54</td>
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<td>4.57</td>
<td>4.57</td>
<td>4.54</td>
<td>4.55</td>
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<tr>
<td>Variance</td>
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<td>3.01</td>
<td>2.87</td>
<td>2.86</td>
<td>2.77</td>
<td>2.83</td>
<td>2.71</td>
<td>2.70</td>
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ANOVA (P-value)

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<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>#6</th>
<th>#7</th>
<th>#8</th>
</tr>
</thead>
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<tr>
<td><strong>NARX</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>0.4643</td>
<td>0.6212</td>
<td>0.7297</td>
<td>0.6354</td>
<td>0.6109</td>
<td>0.7126</td>
</tr>
<tr>
<td><strong>MLR</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>0.5605</td>
<td>0.7966</td>
<td>0.7487</td>
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<td>0.7405</td>
<td>0.9147</td>
<td>0.8994</td>
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</table>

Treatment*: #1 standard input, #2 precipitation, #3 sunshine hours, #4 soil temperature, #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, #8 precipitation, sunshine hours and soil temperature.
5.6.2 Effect of different treatments

The RMSE POD values for each of the 39 test cows for all eight treatments (from treatment #1 to treatment #8) is shown in Table 5-7 (see Section 5.8). The positive or negative POD values in RMSE show how the treatment predictions improved (positive POD) or worsened (negative POD) in the form of decreasing or increasing RMSE values, respectively. The statistical summary of Table 5-7 is shown in Table 5-4.

Figure 5-1 Overall $R^2$ values distribution of predictions of test models for 39 cows using seven weather treatments.
Table 5-4 Statistical summary of RMSE percentage of difference (POD) values (NARX and MLR). Positive POD indicates an improvement in prediction.

### 5-4-1 Summary of RMSE POD values for cows from year of 2004-2007

<table>
<thead>
<tr>
<th>Treatment*</th>
<th>POD*</th>
<th>No. of improved</th>
<th>POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>#2</td>
<td>1.5%</td>
<td>11</td>
<td>-0.1%</td>
<td>4</td>
</tr>
<tr>
<td>#3</td>
<td>4.3%</td>
<td>15</td>
<td>2.1%</td>
<td>17</td>
</tr>
<tr>
<td>#4</td>
<td>2.4%</td>
<td>13</td>
<td>2.3%</td>
<td>13</td>
</tr>
<tr>
<td>#5</td>
<td>0.2%</td>
<td>7</td>
<td>2.0%</td>
<td>17</td>
</tr>
<tr>
<td>#6</td>
<td>1.3%</td>
<td>10</td>
<td>2.2%</td>
<td>13</td>
</tr>
<tr>
<td>#7</td>
<td>1.2%</td>
<td>8</td>
<td>3.4%</td>
<td>15</td>
</tr>
<tr>
<td>#8</td>
<td>1.5%</td>
<td>8</td>
<td>3.2%</td>
<td>15</td>
</tr>
</tbody>
</table>

POD*: average POD of prediction for cows in each treatment.

### 5-4-2 Summary of RMSE POD values for cows from year of 2005-2008

<table>
<thead>
<tr>
<th>Treatment*</th>
<th>POD*</th>
<th>No. of improved</th>
<th>POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>#2</td>
<td>2.1%</td>
<td>10</td>
<td>-0.1%</td>
<td>8</td>
</tr>
<tr>
<td>#3</td>
<td>2.7%</td>
<td>15</td>
<td>0.9%</td>
<td>16</td>
</tr>
<tr>
<td>#4</td>
<td>1.5%</td>
<td>12</td>
<td>0.3%</td>
<td>9</td>
</tr>
<tr>
<td>#5</td>
<td>2.0%</td>
<td>14</td>
<td>1.3%</td>
<td>17</td>
</tr>
<tr>
<td>#6</td>
<td>1.6%</td>
<td>13</td>
<td>0.2%</td>
<td>9</td>
</tr>
<tr>
<td>#7</td>
<td>2.1%</td>
<td>10</td>
<td>1.2%</td>
<td>14</td>
</tr>
<tr>
<td>#8</td>
<td>0.7%</td>
<td>8</td>
<td>1.1%</td>
<td>14</td>
</tr>
</tbody>
</table>

POD*: average POD of prediction for cows in each treatment.

### 5-4-3 Summary of RMSE POD values for overall sample

<table>
<thead>
<tr>
<th>Treatment*</th>
<th>POD*</th>
<th>No. of improved</th>
<th>POD*</th>
<th>No. of improved</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>#2</td>
<td>1.8%</td>
<td>21</td>
<td>-0.1%</td>
<td>12</td>
</tr>
<tr>
<td>#3</td>
<td>3.4%</td>
<td>30</td>
<td>1.5%</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>POD</td>
<td>Rainfall</td>
<td>Sunshine</td>
<td>Temperature</td>
</tr>
<tr>
<td>---</td>
<td>------</td>
<td>----------</td>
<td>----------</td>
<td>-------------</td>
</tr>
<tr>
<td>#4</td>
<td>1.9%</td>
<td>25</td>
<td>1.2%</td>
<td>22</td>
</tr>
<tr>
<td>#5</td>
<td>1.2%</td>
<td>21</td>
<td>1.7%</td>
<td>34</td>
</tr>
<tr>
<td>#6</td>
<td>1.5%</td>
<td>23</td>
<td>1.1%</td>
<td>22</td>
</tr>
<tr>
<td>#7</td>
<td>1.7%</td>
<td>18</td>
<td>2.2%</td>
<td>29</td>
</tr>
<tr>
<td>#8</td>
<td>1.1%</td>
<td>16</td>
<td>2.1%</td>
<td>29</td>
</tr>
</tbody>
</table>

POD*: average POD of prediction for cows in each treatment.

Treatment*: #1 standard input, #2 precipitation, #3 sunshine hours, #4 soil temperature, #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #8 sunshine hours and soil temperature, #8 precipitation, sunshine hours and soil temperature.
The average RMSE POD values for 18 cows from the 2004 - 2007 group is shown in Table 5-4-1. Seven treatments (#2 - #8) applied to the input data of the NARX model slightly improved predictions of 7 - 15 cows (POD > 0) depending on the treatment. For the single weather parameter inputs, the average POD varied from 1.5% (treatment #2, precipitation) to 4.3% (treatment #3, sunshine hours) which implied decreased RMSE values and improved model forecasting accuracy on average (18 cows). For the dual weather parameter inputs, the average POD varied from 0.2% (treatment #5, precipitation and sunshine hours) to 1.3% (treatment #6, precipitation and soil temperature) which implied that applying combination of two weather parameters could not provide better model forecasting accuracy than applying single weather parameters for 18 cows from the group 2004 - 07. The input treatments applied on the MLR model improved predictions for 4 - 17 cows and the average POD values varied from -0.1% (treatment #2, precipitation) to 3.4% (treatment #7, sunshine hours and soil temperature).

For the 21 cows from the 2005 - 08 group, a similar pattern was found from the NARX models’ predictions (Table 5-4-2). For the single weather parameter inputs, all three treatments (#2 - #4) slightly improved the model forecasting accuracy (10 - 15 cows) and decreased RMSE values on average (POD > 0). For the dual weather parameter inputs (#5 - #7), three treatments slightly improved model forecasting accuracy (10 - 14 cows). The average POD values were higher, compared with the same treatment in the group 2004 - 07. However, the triple weather parameter input (treatment #8, precipitation, sunshine hours and soil temperature) only improved predictions for 8 cows with a limited positive average POD (0.7%). The input treatments applied to the MLR model improved
predictions for 8 - 17 cows and the average POD were lower than those of same input treatments (#3 - #8) in the group 2004 - 07.

The average RMSE POD values of the tested models using eight treatments for 39 cows is shown in Table 5-4-3. Treatment #3 (sunshine hours) had the highest POD value for the NARX model (3.4%). Treatment #7 (sunshine hours and soil temperature) had the highest POD value the MLR model (2.2%). Treatment #8 (precipitation, sunshine hours and soil temperature) had the second highest POD value for the MLR model (2.1%). For the NARX model, the application of single weather parameter inputs (treatment #2 precipitation, #3 sunshine hours, #4 soil temperature, POD varied from 1.8% - 3.4%) were more effective than dual weather parameter inputs (treatment #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, POD varied from 1.2% - 1.7%) or triple treatment weather parameter inputs (treatment #8 precipitation, sunshine hours and soil temperature, POD = 1.1%).

It is clear that including sunshine hours as a model input can improve prediction accuracy more than applying precipitation for the NARX model. The attempt of combining dual and triple weather parameters (from treatment #5 to treatment #8) showed that although average POD values were increased and RMSE were reduced over treatment 0, POD values were not better than treatment #3 (sunshine hours). This finding was unexpected and suggests that sunshine hours but not soil temperature was the most effective weather parameter, compared to previous studies (Smith, 1968).

Although all seven treatments (#2 - #8) appear to produce superior milk production forecasting in comparison to the original data input methodology (treatment #1) (Table 5-4-3), the improvements were small in most cases and may have been attributable to noise.
in the data sets. The improvements due to the addition of sunshine hours was consistent between the groups but the error reduction was still low.

The average RMSE POD values of different prediction horizons of the NARX model using eight treatments for 39 cows is shown in Table 5-5. Treatment #3 (sunshine hours) delivered the highest POD value in the 10-day and 30-day predictions while treatment #2 (precipitation) delivered the highest POD value in the 305-day prediction.
Table 5-5 Statistical summary of RMSE percentage of difference (POD) values (NARX model). Positive POD indicates an improvement in prediction.

5-5-1 Summary of RMSE POD values for overall sample (18 cows)

<table>
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<th>POD*</th>
<th>No. of improved</th>
<th>POD*</th>
<th>No. of improved</th>
<th>POD*</th>
<th>No. of improved</th>
<th>Average</th>
</tr>
</thead>
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<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2.43%</td>
</tr>
<tr>
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<td>1.5%</td>
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<td>1.4%</td>
<td>12</td>
<td>4.4%</td>
<td>13</td>
<td>2.63%</td>
</tr>
<tr>
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<td>4.3%</td>
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<td>1.5%</td>
<td>10</td>
<td>2.1%</td>
<td>13</td>
<td>0.43%</td>
</tr>
<tr>
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<td>-0.8%</td>
<td>7</td>
<td>-0.3%</td>
<td>9</td>
<td>1.10%</td>
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<td>1.03%</td>
</tr>
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<td>12</td>
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POD*: average POD of prediction for cows in each treatment.

5-5-2 Summary of RMSE POD values for overall sample (21 cows)

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<th>POD*</th>
<th>No. of improved</th>
<th>POD*</th>
<th>No. of improved</th>
<th>Average</th>
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<td>11</td>
<td>1.1%</td>
<td>8</td>
<td>2.77%</td>
</tr>
<tr>
<td>#3</td>
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<td>15</td>
<td>4.3%</td>
<td>16</td>
<td>1.3%</td>
<td>6</td>
<td>2.17%</td>
</tr>
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<td>9</td>
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<td>8</td>
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<td>2.17%</td>
</tr>
<tr>
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<td>3.4%</td>
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<td>1.0%</td>
<td>9</td>
<td>1.43%</td>
</tr>
<tr>
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<td>8</td>
<td>3.1%</td>
<td>15</td>
<td>0.5%</td>
<td>9</td>
<td>1.03%</td>
</tr>
</tbody>
</table>

5-5-3 Summary of RMSE POD values for overall sample (39 cows)

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<th>POD*</th>
<th>No. of improved</th>
<th>POD*</th>
<th>No. of improved</th>
<th>Average</th>
</tr>
</thead>
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<td>1</td>
<td>0</td>
<td>1</td>
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<td>2.03%</td>
</tr>
<tr>
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<td>21</td>
<td>1.7%</td>
<td>23</td>
<td>2.6%</td>
<td>21</td>
<td>2.03%</td>
</tr>
</tbody>
</table>

163
<table>
<thead>
<tr>
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<th>#0 standard input</th>
<th>#1 precipitation</th>
<th>#2 sunshine hours</th>
<th>#3 soil temperature</th>
<th>#4 precipitation and sunshine hours</th>
<th>#5 precipitation and soil temperature</th>
<th>#6 sunshine hours and soil temperature</th>
<th>#7 precipitation, sunshine hours and soil temperature</th>
</tr>
</thead>
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</tr>
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<td>21</td>
<td>1.8%</td>
<td>21</td>
<td>1.77%</td>
<td></td>
</tr>
<tr>
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<td>20</td>
<td>1.0%</td>
<td>17</td>
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<td></td>
</tr>
<tr>
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<td>23</td>
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<td>24</td>
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5.6.3 General discussion

In general, adding weather parameters as training inputs contributed to a small improvement in model forecasting accuracy. The statistical results indicated that sunshine hours was the best weather parameter for all scenarios, consistent with published studies (Hill and Wall, 2015; Roche et al., 2009). However, based on the POD value in this chapter, the improvement was still low. Although soil temperature has been reported to have a major influence on the grass growth all year around (Hurtado-Uria et al., 2013a), it did not have a large impact on milk yield forecasting in this chapter. Smith et al., employed precipitation and soil temperature to aid in the forecast of milk production. However, this chapter was based on averaged national level herd data over 50 years ago and the effect on forecast accuracy from the addition of weather parameters to the model was not quantified. The pasture based management systems during that period were rudimentary and therefore may have been more susceptible to climate conditions. The cows in this study were all on well managed farms that employed state of the art pasture management practices and technologies. Hence, herbage quantity and quality would have been maintained regardless of ambient conditions. Moreover, concentrate supplementation data was not available which may have been employed in periods of very low grass growth or very wet weather when cows could not graze outdoors. A similar issue was addressed in the study of Roche et al (2009) whereby pasture quality was not allowed to vary greatly resulting in weather variables having only a slight effect on milk production in well-managed modern farms. To effectively factor in the influence weather has on milk production, a more holistic milk forecasting model that takes into account the relationship between grazing conditions, feed
intake, farm management and the cows’ physiology (Ruelle et al., 2015) may be more suitable.

5.7 Conclusion

In this chapter, the effects of meteorological factors including precipitation, sunshine hours and soil temperature were tested. Despite varying results between eight different meteorological scenarios, the NARX model was found to provide better prediction accuracy than the MLR model for predicting milk yield at the individual cow level over a 10-day forecast horizon. The statistical results indicate different positive effects of weather factors on milk yield, consistent with published studies (Hill and Wall, 2015; Roche et al., 2009; Smith, 1968). In particular, based on the POD value in this chapter, sunshine hours was the most effective solo weather factor of optimization in short term (10 lactation days) milk yield forecasting at the individual cow level and the best dual weather factors was sunshine hours and precipitation. In addition, applying dual or triple weather factors did not improve performance, compared with using solo weather factor. However, the overall effect of weather factors was small. These unexpected findings may be due to cows from different climate regions have various traits in reaction of environmental factors, such as heat stress previously discussed in the Introduction section. On the other hand, these results could be due to feed being intake limited by Irish pasture based farms which strong influenced by weather conditions (Hurtado-Uria et al., 2013a), compared with those conventional stall based farms, whereas, on a well-managed Irish dairy farm, cows may be fed concentrate supplementation during outdoor grazing periods to avoid affecting by
herbage quantity and quality, and maintain a stable production level. Because of this, fixed grass growth rates were used in previous relative studies (Ruelle et al., 2015; Ruelle et al., 2016). Therefore the synthesis of an accurate grass growth model and a cow energy intake model using more data at cow level (such as supplementary feed, stocking rate and a host of other grazing related conditions data) may improve predictions.
5.8 Results tables

Table 5-6 Statistical results of the NARX model and the MLR model forecasts using eight treatments for 39 individual cows.

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Table 5.7 POD (Percentage of difference) in RMSE of the NARX model and the MLR model forecasts using eight treatments for 39 individual cows.

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<td>-4.8%</td>
<td>8.9%</td>
<td>11.7%</td>
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<th>Cow32</th>
<th>Cow33</th>
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<tr>
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<td>10-d</td>
<td>10-d</td>
<td>10-d</td>
<td>10-d</td>
</tr>
<tr>
<td>MLR</td>
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<td>10-d</td>
<td>10-d</td>
<td>10-d</td>
<td>10-d</td>
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<td>1</td>
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179
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<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>#6</th>
<th>#7</th>
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<td>-6.1%</td>
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<td>8.8%</td>
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</table>

### 2005-2008 Cow39

<table>
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</thead>
<tbody>
<tr>
<td>#1</td>
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<td>1</td>
</tr>
<tr>
<td>#2</td>
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<td>#3</td>
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</tr>
<tr>
<td>#4</td>
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<tr>
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<td>2.6%</td>
</tr>
<tr>
<td>#8</td>
<td>-0.8%</td>
<td>2.7%</td>
</tr>
</tbody>
</table>

**Treatment*: #1 standard input, #2 precipitation, #3 sunshine hours, #4 soil temperature, #5 precipitation and sunshine hours, #6 precipitation and soil temperature, #7 sunshine hours and soil temperature, #8 precipitation, sunshine hours and soil temperature.
6 GLOBAL DISCUSSION
This following chapter presents the synthesis of the research findings and the global discussion in this thesis. As stated in Chapter 1, a problem exists finding the most suitable model for a specific application as well as the analysis of multiple data inputs in an efficient manner for milk production forecasting. Consequently, the milk production forecast model selection configuration and optimization system (MPFOS) was developed and evaluated with two main requirements: Firstly, the MPFOS is required to be capable of evaluating the accuracy of multiple models across multiple categories for varying data inputs. Secondly, the MPFOS also should be able to analyse the effectiveness of introducing additional data combinations to the modelling process.

The first objective was accomplished in Chapter 3. In the experimental section of Chapter 3, the effectiveness of multiple herd milk yield prediction models were compared for an Irish pasture-based dairy herd for different prediction horizons. The Adaptive Stratified Sampling Approach (ASSA) was introduced for filtering and processing experimental data from the raw data stored in the local databases. The experimental sample herd size and scale can be adjusted to fulfil any test requirements. This allowed a research scenario to be created to simulate a 100 cow sample herd consisting of 25 cows, 25 cows, 50 cows in parity one, parity two and parity three or more, respectively. Following this initial test data setup, nine milk prediction modes were selected and categorized into three distinctive types; curve fitting, regression and auto-regressive models. Finally, the MPFOS automatically generated the optimal configuration for each of the nine milk production forecast models and benchmarked their performance over a short (10-day), medium (30-day) and long term (365-day) prediction horizon. The final outputs and statistical results
(SSE, $R^2$, RMSE and RPE) based on the research scenario presented the following significant findings:

- **General results:** The regression and auto-regressive category models produced superior milk production forecasting in comparison to the curve fitting category models under the presupposition that there is a visible difference between the actual herd milk yield and the mean herd yield of the training periods. The curve fitting category models fitted the historical data well however this is the exact challenge that the Irish dairy industry facing to: as discussed in Chapter 1 and Chapter 2, the annual changes (from -4% to 5%) can be seen on the average annual performance level (litres/cow) in Ireland over the period of 2011-2016.

- **Novel findings:** The surface fitting model produced a greater accuracy than the dynamic NARX model for the same prediction horizon (365-day and 30-day). The surface fitting model’s ability to fit a nonlinear function to both DIM and NCM allow it to adapt to changing herd number while traditional method such as the MLR fail to capture this relationship. This finding provides an easy and computationally low cost option for practical milk production yield forecasting.

The above results (further presented in chapter 3) demonstrate the effectiveness of the MPFOS as a model configuration and comparison tool. Following this result, ability of the MPFOS to select the optimal milk production forecast model for a specific application was considered in experimental chapter 4 and chapter 5.
The second objective was accomplished in Chapter 4 and Chapter 5 with the following sub-objectives, respectively: 1) Develop, compare and evaluate pre-processing input treatments designed to factor parity information into the milk prediction model configuration process and compare the effect on milk production prediction accuracy. 2) Conduct an exploratory analysis of adding multiple combinations of meteorological information to the training process of milk production forecast models and analysis the effect of the introduction of this data has on the effectiveness of the milk production models.

In Chapter 4, the prediction accuracy of two milk prediction models (the NARX model and a polynomial curve fitting model) at the individual cow level were compared and tested using six input data pre-processing treatments designed to factor parity information. Input treatments were consisting of different combinations of static parity weight, dynamic parity weight and removal of the first lactation data. Lactation data from 39 individual Irish Holstein-Friesian cows were extracted from raw data in the local database of the MPFOS. Then the MPFOS automatically generated the optimal configuration and predicted yields from the two milk production forecast models for each of the 39 cows. The final outputs and statistical results based on the performance demonstrate following findings:

- General results: The NARX model was found to provide higher prediction accuracy than the polynomial curve fitting model for individual cows using each input treatment. Unlike herd milk yield forecasting, the NARX model showed a more dynamic response to individual cows compared to the rigid curve fitting model due to the milking records of each cow containing many more individual
characteristics. However, the performances of the NARX model among different cows still varied.

- Novel findings: Prediction performance was strongly influenced by the cow’s historical milk production relative to parity and also the prediction year. On average, only part of the treatments delivered an increase in accuracy, such as the removal of the first lactation and applying static parity weight. These were shown to be the two most successful input treatments, but not the dynamic parity weight which comes from each individual cows. Regarding forecasting performance, an obvious pattern can been seen from the average dynamic parity weight of test groups; 1) the larger the difference between the parity weight of the third lactation and the fourth lactation, the worse the performance of applying parity weight for milk yield prediction. This is the essential limitation of time series modelling and forecasting. 2) Like the black box system, model training relies on historical data, therefore, model forecasts are limited by historical data. However, the model will never know the future before it comes, meaning, there is no valid error feedback that may be used for calibration. In this experiment, static parity weights and the removal of the first lactation were anticipated. Static parity weights come from herd historical records while inconsistency between curve of the first lactation and subsequent lactations were reported by other published studies. As a result, the unexpected results were essentially expected as well as expectable, as shown in the results, that historical parity weighting trends have a substantial effect on the success rate of the treatments for both milk production forecast models.
In Chapter 5, the effect of adding meteorological data to the training process of two milk production forecast models (the NARX model and the MLR model) at the individual cow level were analysed and assessed using seven different combinations of precipitation, sunshine hours and soil temperature as additional inputs. Lactation data were the same as used in Chapter 4. The MPFOS outputs the final predictions and statistical results based on the model prediction performance and findings are summarized as follows:

- General results: The introduction of sunshine hours, precipitation and soil temperature data generated a minor improvement the prediction accuracy of individual cow milk prediction for both models. Compared to the MLR model, the predictions of the NARX model benefited much more from additional meteorological data input. This result was consistent with the conclusion of previous study whereby greater forecasting performance may be obtained with shortened prediction horizons and errors feedback. The MLR model did not take into account short-term errors, and as a result, limited the potential increase in prediction accuracy.

- Novel findings: Sunshine hours was found to have the greatest impact on improving forecast accuracy, however the overall improvement was still small. Although soil temperature has been reported to have a major influence on the grass growth in Ireland, it did not have a significant impact on milk yield forecasting within the experimental results. This contrasts with a similar study in the UK in the 1960’s (Smith, 1968) where soil temperature was reported to be an effective parameter in the prediction of milk yield. However, these results complimented the
findings of a cognate study in New Zealand (Roche et al., 2009), the author suggested that the modern grazing management in the dairy farms prevented cows from lacking feed intake. Milk yield may be affected by both quality and quantity of pasture. Due to the importance of feeding cost for running a commercial dairy farm, the weather factors only impact on grass growth and after that, grazing management factors will control the feeding quality and offset the potential impact of pure natural factors in most of dairy farms.

Overall, the performance of MPFOS was demonstrated through evaluating the accuracy of multiple models across multiple categories as well as analysing the effectiveness of introducing additional data combinations to the modelling process. However the limitations of this study was the lack of multiple breeds in the data pool (the Holstein Friesian (HF) breed is the dominant breed (95% of all dairy births) in Ireland). In conclusion, the MPFOS proved to be an effective model configuration and comparison tool regarding the selection of the optimal milk production forecast model for a specific application which simulates milk yield at either the herd level (presented in chapter 3) or the individual cow level (presented in chapter 4 and chapter 5).
This thesis presents a study regarding the accurate prediction of milk production yield at herd level and individual cow level using Irish pasture-based data. Benchmarking has been a challenge in milk yield forecasting due to various reasons, such as each study utilising data encompassing unique conditions. Together with the abolishment of the EU milk quota in 2015, the requirement of milk production forecasting from both the processor and the producer has become more crucial than before. This study proposes an integrated forecasting framework with the concentration on milk production forecasting using heterogeneous data input combinations based on animal, milk production and exogenous (weather variables) records that can easily link to the forecasts on either the herd level or the individual cow level. This study resulted in the development of the Milk Production Forecast Optimisation System (MPFOS), which achieved the purpose of: 1) Comparing the effectiveness of multiple milk yield prediction models for Irish pasture-based dairy cows for different prediction horizons. 2) Evaluating the accuracy of multiple models across multiple categories for varying data inputs and 3) Conducting exploratory analysis
regarding the addition of meteorological information to the training process of forecast models. Finally, from the application perspective, the two primary effects of integrating pre-processing data and additional data were found. Firstly, parity information was observed to have a substantial effect on the forecast model while secondly, meteorological parameters were found to not have a substantial impact on forecast accuracy. This study also resulted in the novel findings by applying the MPFOS which briefly including: 1) The surface model was found to be an easy and computationally low cost option for practical milk production yield forecasting. 2) For prediction of milk yield at the individual cow level, prediction performance was strongly influenced by the cow’s historical milk production relative to parity and also the prediction year. 3) Due to the importance of feeding cost for running a commercial dairy farm in the 21st century (compared to the previous study in the 1060’s), the potential impact of pure natural weather factors are offset by the state of the art grazing management strategy in most of modern dairy farms. Consequently, only sunshine hours was found to have the greatest impact on improving forecast accuracy, however the overall improvement was still small.

The MPFOS was designed to have the ability to perform more experiments for future hypothesis as the architecture was designed to allow both the model library and the database to be extended through a greater number of models and training data. For example, the available experimental data utilised for this research did not allow for the prediction of fat and protein percentages in milk as well as include other biological features and genetic differences as input variables i.e. the body condition score (BCS), growth hormones (BST) and pregnancy effect. There are a number of potential research avenues that could be developed from this study. In relation to animal welfare, it would be useful to
monitor health conditions and disease detection by monitoring individual cow milk yield. Similarly, in relation to decision support, it would be integrated to advanced milking parlours and milking machines as a fundamental data analysis and prediction module.
8 REFERENCES


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Silvestre, A. M., F Petim-Batista, and J Colaço. 2006. “The Accuracy of Seven Mathematical Functions in Modeling Dairy Cattle Lactation Curves Based on Test-


Zhang, F., M. Murphy, R. Sleator, L. Shalloo, and J. Upton. 2014. “Comparative Accuracy

APPENDIX A: MPFOS INTERFACE

Figure A-1 The GUI of MPFOS Presentation Layer displaying the options. The program user may choose for their forecasts and analysis.
Figure A-2 A step by step walkthrough on how to use the MPFOs GUI.

Notes:

Step 1.1: Choose the first year of training data.

Step 1.2: Choose the year of prediction.

Step 1.3: Choose the number of cows from different parities.

Step 1.4: Generate the sample herd based on step 1.1-1.3.

Step 2.1: Choose the input data.

Step 2.2: Choose statistical criteria.

Step 2.3: Choose prediction horizons.

Step 2.4: Choose milk yield forecast models

Step 2.5: Launch the simulation.

Step 3.1: Visual check the simulation results (as shown in Figure A-3).
Figure A-3 The GUI of MPFOS Presentation Layer displaying the graphical output and statistical analysis.
APPENDIX B: CODE

%%%%%%%%%%%%%%%%--ReadMe--%%%%%%%%%%%%%%%%
P1: Model Description
P2: General Function
P3: Instruction
P4: MATLAB Configuration
%%%%%%%%%%%%%%%%--P1: Model Description--%%%%%%%%%%%%%%%%
%% Curve fitting
% model 10: the Average Annual Yield Method
% model 11: Ali & Schaeffer model 1987
% model 12: Ali-B model 2003
% model 13: Kirkpatrick et al. model 1994
% model 14: Green and Silverman model 1994
% model 15: Adediran et al. model 2012
%% Regression
% model 21: MLR (Multiple Linear Regression)
% model 22: SANN (Artificial Neural Networks)
% model 23: Surface fitting
%% Auto-regressive
% model 32: NARX Model
%%%%%%%%%%%%%%%%--P2: General Function--%%%%%%%%%%%%%%%%
%--For each model:
1: Generate prediction milk yield (2009), statistical analysis.
2: Plot the prediction value, actual yield (2009), average annual yield (2004-2008) in one figure.
%--For "main.m"
1: Finally plot all prediction milk yields of each model in one figure.
2: Store all statistical analysis for each model as "resultes_xxxx_xxxx.mat" in "Original_Results" folder.

Option #1: Run as script:

1: Open "main.m" in MATLAB, (2016b is recommended).
2: To run "main.m" script, press "F5" key, or click "Run" button from "EDITOR" menu.
3: Wait until "Command Window" shows "Elapsed time is xxxx.xxxx seconds."
4: Check "Original_Results" folder, there should be "resultes_xxxx_xxxx.mat" for each model.

Option #2: Run as GUI:

1: Double click 'MPFOS_Herd_version.exe' and follow the instructions.

Please make sure open "Parallel" form "HOME" menu.

--> HOME
--> Parallel
--> Parallel Preferences
--> Parallel Computing Toolbox Preferences
--> Parallel Pool
--> "Preferred number of workers in a parallel pool"
   at least "4" or more (depend on the core number of CPU)
--> "Automatically create a parallel pool when parallel keywords are executed"
   Make sure enable this check-box
--> Click "OK" and exit.
Main

clc;
clear;

tic;
load('inputData.mat');
mkdir('.\Original_Results\');

%% Curve fitting
% model 10 : the Average Annual Yield Method
% model 11 : Ali & Schaeffer model 1987
% model 12 : Ali-B model 2003
% model 13 : Kirkpatrick et al. model 1994
% model 14 : Green and Silverman model 1994
% model 15 : Adediran et al. model 2012

Model10();
Model11();
Model12();
Model13();
Model14();
Model15();

%% Regressive
% model 21 : MLR (Multiple Linear Regression)
% model 22 : SANN (Artificial Neural Networks)
% model 23 : 3D

Model21();
Model22();
Model23();

%% Dynamic

% model 32 : NARX Model

Model32();

%% Plot

plot(milkyield09,'Marker','x','LineStyle','none','Color',[0 0.498096 0]);
hold on

Dayof2009 = (1:1:365)';

plot(fitresult_model11, Dayof2009, yData);
hold on

plot(fitresult_model12);
hold on

plot(fitresult_model13);
hold on

plot(fitresult_model14);
hold on

plot(fitresult_model15);
hold on

plot(estiamted_yield_Model21,'Color',[0 0.7 0.9]);
hold on

plot(estiamted_yield_Model22,'Color',[0.5 0.2 0.7]);
hold on

plot(estiamted_yield_Model23,'Color',[0.6 0.7 0.1]);
hold on

plot(estiamted_yield_09_Model32_best,'DisplayName','NARX','Color',[0.9 0.2 0.6]);
hold on

xlim([0,365]);
ylim([0,1500]);

legend('Actual Milk Yield(2009)','Average Annual Yield(06-08)', 'Ali & Schaeffer', 'Ali-B', 'Kirkpatrick et al.', 'Green and Silverman', 'Adediran et al.', 'MLR', 'SANN', '3D', 'NARX', 'Location', 'NorthEast');
xlabel('Day of Year (2009)');
ylabel('Herd Milk Yield (L)');
grid on

toc;

Model_01

% model 10 : the Average Annual Yield Method

mkdir('.\Original_Results\');

herdYieldOneYear = evalin('base', 'herdYieldOneYear');
realYield = evalin('base', 'milkYieldValidate');

% Lengh of X
xlimLength = length(herdYieldOneYear);
ylimLength = 1.2 * max(realYield);

% calculate SSE,Rsquare,RMSE
preditionYield = herdYieldOneYear;

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield-realYield).^2);
gof_Model10{1,1} = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare=1-SSE/SST;
gof_Model10{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((preditionYield - realYield).^2));
gof_Model10{1,3} = RMSE;

% Save workspace to results
save('./Original_Results\resultes_gof_Model10.mat', 'gof_Model10');

% Create a figure for the plots.
figure('Name', 'Average Annual Milk');

YMatrix = [preditionYield realYield];

% Plot fit with data.
h = plot(YMatrix);
legend( h, 'Average Annual Milk', 'Actual Milk Yield', 'Location', 'NorthEast');

set(h(2), 'Marker', 'x', 'LineStyle', 'none', 'Color', [1 0 0]);

% X axis
xlim([1,xlimLength]);

% ylabel('Day of Year');
ylim([0, ylimLength]);

% Label axes
xlabel('Day of Year');
ylabel('Herd Milk Yield (kg)');
grid on

Model_02

% model 11 : Ali & Schaeffer model 1987
% mkdir('./Original_Results');

herdYieldOneYear = evalin('base', 'herdYieldOneYear');
realYield = evalin('base', 'milkYieldValidate');

[xData, yData] = prepareCurveData([], herdYieldOneYear);

% Lengh of X
xlimLength = length(herdYieldOneYear);
ylimLength = 1.2 * max(realYield);

% Set up fittype and options.
ft = fittype('a + b*(7*x/305)+c*((7*x/305).^2)+ d*(log(305)-log(7*x))+e*((log(305)-log(7*x)).^2)+f', 'independent', 'x', 'dependent', 'y');
opts = fitoptions('Method', 'NonlinearLeastSquares');
opts.Algorithm = 'Levenberg-Marquardt';
opts.Display = 'Off';
opts.StartPoint = [0.91361527425611 0.22740688730807 0.463899861487648 0.568146791697448 0.631705789702868 0.291369626872367];

% Fit model to data.
fitresult = fit( xData, yData, ft, opts );

% calculate SSE, Rsquare, RMSE
estiamted_yield_Model11 = fitresult(xData);
preditionYield = estiamted_yield_Model11;

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield-realYield).^2);
gof_Model11{1,1} = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare=1-SSE/SST;
gof_Model11{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((preditionYield - realYield).^2));
gof_Model11{1,3} = RMSE;

% Store gof
fitresult_model11 = [fitresult];

% Save workspace to resultes
save('.\Original_Results\resultes_gof_Model11.mat','gof_Model11','estiamted_yield_Model11','fitresult_model11');

save('.\Original_Results\output_VH_estimated','estiamted_yield_Model11','-append');

% Create a figure for the plots.
figure('Name', 'Ali & Schaeffer');
% Plot fit with data.
subplot( 1, 1, 1 );
actualyyield = [realYield,yData];
h = plot(fitresult,xData,actualyyield);
legend( h, 'Actual Milk Yield', 'Average Annual Yield','Ali & Schaeffer', 'Location', 'NorthEast');
Model_03

% model 12 : Ali-B model 2003
mkdir('.\Original_Results\');
herdYieldOneYear = evalin('base', 'herdYieldOneYear');
realYield = evalin('base', 'milkYieldValidate');

[xData, yData] = prepareCurveData([], herdYieldOneYear);

% Length of X
xlimLength = length(herdYieldOneYear);
ylimLength = 1.2 * max(realYield);

% Set up fittype and options.
ft = fittype('a + c*((7*x/305).^2)+ d*(log(305)-log(7*x))+e*((log(305)-log(7*x)).^2)+f', 'independent', 'x', 'dependent', 'y');
opts = fitoptions('Method', 'NonlinearLeastSquares');
opts.Algorithm = 'Levenberg-Marquardt';
opts.Display = 'Off';
opts.StartPoint = [0.551553456116796 0.954057456667054 0.308932415845111 0.592437685188891 0.520498135821787];

% Fit model to data.
fitresult = fit( xData, yData, ft, opts );

% calculate SSE, Rsquare, RMSE
estimated_yield_Model12 = fitresult(xData);
predictionYield = estimated_yield_Model12;

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((predictionYield-realYield).^2);
gof_Model12{1,1} = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare=1-SSE/SST;
gof_Model12{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((predictionYield - realYield).^2));
gof_Model12{1,3} = RMSE;

% Store gof
fitresult_model12 = [fitresult];

% Save workspace to results
save('.\Original_Results\resultes_gof_Model12','gof_Model12','estiamted_yield_Model12','fitresult_model12');
save('.\Original_Results\output_VH_estimated','estiamted_yield_Model12',-append);

% Create a figure for the plots.
figure('Name', 'Ali-B');
% Plot fit with data.
subplot(1,1,1);
actualYield = [realYield yData];
h = plot(fitreresult,xData,actualYield);
legend(h, 'Actual Milk Yield', 'Average Annual Yield', 'Ali-B', 'Location', 'NorthEast');

set(h(3),'LineWidth',2);
set(h(1),'Marker','x','LineStyle','none','Color',[0 0.498039215803146 0]);

% X axis
xlim([1,xlimLength]);
% ylim([0, 1500]);
ylim([0,ylimLength]);

% Label axes
ylabel('Herd Milk Yield (kg)');
xlabel('Day of Year');
grid on

Model_04

% model 13 : Kirkpatrick et al. model 1994
mkdir('.\Original_Results\');
herdYieldOneYear = evalin('base', 'herdYieldOneYear');
realYield = evalin('base', 'milkYieldValidate');
[xData, yData] = prepareCurveData([], herdYieldOneYear);

% Lengh of X
xlimLength = length(herdYieldOneYear);
ylimLength = 1.2 * max(realYield);

% Set up fittype and options.
ft = fittype( '(1/2)^{(1/2)}*a+(3/2)^{(1/2)}*b*(2*x-310)/300+(5/2)^{(1/2)}*(3*((2*x-310)/300)^2-1)+(7/2)^{(1/2)}*(1/2)*d*(5*((2*x-310)/300)^3-3*((2*x-310)/300))', 'independent', 'x', 'dependent', 'y' );
opts = fitoptions('Method', 'NonlinearLeastSquares');
opts.Display = 'Off';
opts.StartPoint = [0.824332311454505 0.959461900303927 0.490163404796522 0.575234546247615];

% Fit model to data.
fitresult = fit( xData, yData, ft, opts );

%% calculate SSE,Rsquare,RMSE
estiamted_yield_Model13 = fitresult(xData);
preditionYield = estiamted_yield_Model13;

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield-realYield).^2);
gof_Model13{1,1} = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare=1-SSE/SST;
gof_Model13{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((preditionYield-realYield).^2));
gof_Model13{1,3} = RMSE;

% Store gof
fitresult_gof_Model13 = [fitresult];

% Save workspace to resultes
save('./Original_Results\resultes_gof_Model13', 'gof_Model13', 'estiamted_yield_Model13', 'fitresult_gof_Model13');
save('./Original_Results\output_VH_estimated', 'estiamted_yield_Model13', '-append');

% Create a figure for the plots.
figure( 'Name', 'Kirkpatrick et al.' );
% Plot fit with data.
subplot( 1, 1, 1 );
actualyield = [realYield,yData];
h = plot(fitresult,xData,actualyield);
legend( h, 'Actual Milk Yield', 'Average Annual Yield', 'Kirkpatrick et al', 'Location', 'NorthEast' );
set(h(3), 'LineWidth', 2);
```matlab
set(h(1),'Marker','x','LineStyle','none','Color',[0 0.498039215803146 0]);

% X axis
xlim([1,xlimLength]);
ylim([0, 1500]);

% Label axes
xlabel('Day of Year');
ylabel('Herd Milk Yield (kg)');
grid on

Model_05

% model 14 : Green and Silverman model 1994
mkdir('.\Original_Results\');

herdYieldOneYear = evalin('base', 'herdYieldOneYear');
realYield = evalin('base','milkYieldValidate');

[xData, yData] = prepareCurveData([], herdYieldOneYear);

% Length of X
xlimLength = length(herdYieldOneYear);
ylimLength = 1.2 * max(realYield);

% Set up fittype and options.
ft = fittype('smoothingspline');
opts = fitoptions('Method', 'SmoothingSpline');
opts.SmoothingParam = 1.50494187226124e-06;
% Fit model to data.
fitresult = fit(xData, yData, ft, opts);

% calculate SSE,Rsquare,RMSE

estiamted_yield_Model14= fitresult(xData);
preditionYield = estiamted_yield_Model14;

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield-realYield).^2);
gof_Model14{1,1} = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare=1-SSE/SST;
gof_Model14{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((preditionYield - realYield).^2));
```
gof_Model14{1,3} = RMSE;

% Store gof
fitresult_model14 = [fitresult];
% Save workspace to results
save('./Original_Results\resultes_gof_Model14','gof_Model14','estaimted_yield_Model14','fitresult_model14');
save('./Original_Results\output_VH_estimated','estaimted_yield_Model14','-append');

% Create a figure for the plots.
figure('Name', 'Green and Silverman');
% Plot fit with data.
subplot(1, 1, 1);
actualyield = [realYield,yData];
h = plot(fitresult,xData,actualyield);
legend(h, 'Actual Milk Yield', 'Average Annual Yield', 'Green and Silverman', 'Location', 'NorthEast');

set(h(3),'LineWidth',2);
set(h(1),'Marker', 'x', 'LineStyle', 'none', 'Color', [0 0.498039215803146 0]);

% X axis
xlim([1,xlimLength]);
% ylim([0, 1500]);
ylim([0,ylimLength]);

% Label axes
ylabel( 'Herd Milk Yield (kg)' );
xlabel( 'Day of Year' );
grid on

Model_06

% model 15 : Adediran et al. model 2012
%%
mkdir('./Original_Results\');
herdYieldOneYear = evalin('base', 'herdYieldOneYear');
realYield = evalin('base','milkYieldValidate');

[xData, yData] = prepareCurveData( [], herdYieldOneYear);

% Length of X
xlimLength = length(herdYieldOneYear);
ylimLength = 1.2 * max(realYield);

% Set up fittype and options.
ft = fittype('exp(a*((b-log10(x))^2)+c)', 'independent', 'x', 'dependent', 'y');
opts = fitoptions( 'Method', 'NonlinearLeastSquares' );
opts.Display = 'Off';
opts.Lower = [-100 1 1];
opts.Robust = 'LAR';
opts.StartPoint = [0.402829872444909 0.455699833219798 0.7804790476465];

% Fit model to data.
fitresult = fit(xData, yData, ft, opts);

%% calculate SSE, Rsquare, RMSE
estiamted_yield_Model15 = fitresult(xData);
preditionYield = estiamted_yield_Model15;

%SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield-realYield).^2);
gof_Model15{1,1} = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare = 1 - SSE/SST;
gof_Model15{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((preditionYield - realYield).^2));
gof_Model15{1,3} = RMSE;

% Store gof
fitresult_model15 = [fitresult];

% Save workspace to resultes
save('.\Original_Results\resultes_gof_Model15','gof_Model15','estiamted_yield_Model15','fitresult_model15');
save('.\Original_Results\output_VH_estimated','estiamted_yield_Model15','-append');

% Create a figure for the plots.
figure('Name', 'Adediran et al.');
% Plot fit with data.
subplot(1,1,1);
actualYield = [realYield,yData];
h = plot(fitresult,xData,actualYield);
legend(h, 'Actual Milk Yield', 'Average Annual Yield', 'Adediran et al.', 'Location', 'NorthEast');

set(h(3), 'LineWidth', 2);
set(h(1), 'Marker', 'x', 'LineStyle', 'none', 'Color', [0 0.498039215803146 0]);

% X axis
xlim([1,xlimLength]);
% ylim([0, 1500]);
ylim([0,ylimLength]);
% Label axes
ylabel('Herd Milk Yield (kg)');
xlabel('Day of Year');
grid on

Model_07

% model 21 : MLR (Multiple Linear Regression)
% temporarily for name convert
daycow0408 = evalin('base','dayCowTrain');
milkyield0408 = evalin('base','milkYieldTrain');
daycow09 = evalin('base','dayCowValidate');
milkyield09 = evalin('base','milkYieldValidate');

% Lengh of Y
ylimLength = 1.2 * max(milkyield09);

mkdir('.\Original_Results\','Model21');
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
use trigger to decide the horizon array
trigger_table =
[get(handles.day365,'UserData'),get(handles.day120,'UserData'),get(handles.day30,'UserData'),get(handles.day10,'UserData'),get(handles.day1,'UserData')];
ori_refresha = [365;120;30;10;1];
trigger_refresha= [ori_refresha trigger_table];
trigger_refresha(any(trigger_refresha==0,2),:)=[];
refresha=trigger_refresha(:,1);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
loopOfRefresha = length(refresha);

for irefresh=1:1:loopOfRefresha;
    refresh=refresha(irefresh);
estiamted_yield_09_Model21 = [];
predictionResultForEachCombin = cell2mat(cell(365));

    Algo='MLR'
    for i=0:floor(size(daycow09)/refresh) % i is how many time the
        % predicted 2009 year will be refreshed
            % Data arrangement
            % Transpose the Matrix into rows
            % Matrix row names and configuration.
            daycowtr= []; % Empty the data to fill them again the
            milkyieldtr= []; % daycowtr and milkyieldtr are the data
            used to train the model

            % This is how we can do it.
            daycowtr=[daycowtr daycow09(i*refresh:refresh)];
            milkyieldtr=[milkyieldtr milkyield09(i*refresh:refresh)];

            % Train the model
            Algo='MLR'
            model21 = fitlm(daycowtr,milkyieldtr,Algo);

            % Predict
            predictedyield = predict(model21,daycow09(i*refresh:refresh));

            estiamted_yield_09_Model21 = [estiamted_yield_09_Model21 predictedyield];
        end
    predictionResultForEachCombin = [predictionResultForEachCombin estiamted_yield_09_Model21];
end

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daycow09plus=[]; % daycow09plus is a period of the data of 2009 we will add to the data 0108 to be trained
daycow09minus=[]; % daycow09minus is the resized period of 2009 to predict
milkyield09plus=[]; % the same than daycow09plus and daycow09minus
milkyield09minus=[];

if (i>0) % Pick the data which will be added to the 0408 years training
daycow09plus(:,1)=daycow09(1:i*refresh,1);
daycow09plus(:,2)=daycow09(1:i*refresh,2); % The same for the second column
milkyield09plus=milkyield09(1:i*refresh);

% Pick the remaining data of the 2009 year which will be predicted
daycow09minus(:,1)=daycow09(i*refresh+1:end,1);
daycow09minus(:,2)=daycow09(i*refresh+1:end,2);
milkyield09minus=milkyield09(i*refresh+1:end);

% Built the dataset for training
daycowtr=[daycow0408;daycow09plus];
milkyieldtr=[milkyield0408;milkyield09plus];

else % if i=0, the dataset for training are daycow0108, without added period
    daycowtr=[daycow0408];
    milkyieldtr=[milkyield0408];
    milkyield09minus=milkyield09;
    daycow09minus=daycow09;
end

%% Model Predictor

[b,bint,r,rint,stats] = regress(milkyieldtr,daycowtr);

yp1 = daycow09minus *b;

if (length(yp1) > refresh)
estimated_yield_09_Model21 = [estimated_yield_09_Model21 ;
yp1(1:refresh,1)];
elseif (length(yp1) <= refresh)
estimated_yield_09_Model21 = [estimated_yield_09_Model21 ;
yp1(1:end,1)];
end

end

%% goodness of fit

cost_func = 'MSE';
fit_Model21 = goodnessOfFit(estiamted_yield_09_Model21, milkyield09,cost_func);

% calculate SSE, Rsquare, RMSE

preditionYield = estiamted_yield_09_Model21;
realYield = milkyield09;

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield-realYield).^2);
gof_Model21{1,1} = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare=1-SSE/SST;
gof_Model21{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((preditionYield - realYield).^2));
gof_Model21{1,3} = RMSE;

%% % Store gof
estiamted_yield_Model21 = [estiamted_yield_09_Model21];
estiamted_yield_Model21(estiamted_yield_Model21<=0)=0;

b_Model21 = [b];
bint_Model21 = [bint];
r_Model21 = [r];
rint_Model21 = [rint];
stats_Model21 = [stats];
mse_Model21 = [fit_Model21];

%% % Save workspace to resultes
Prediction_Horizon = num2str(refresh);
fileNamePredictionResultForEachHorizon = strcat('estiamted_yield_09_Model21','_','PredictionHorizon','_','Prediction_Horizon);

fileNameGOFResultForEachHorizon = strcat('estiamted_yield_09_Model21','_','PredictionHorizon','_','GOF');

folder = '.\Original_Results\Model21\';

filepath = strcat(folder,fileNamePredictionResultForEachHorizon);
filepath2 = strcat(folder,fileNameGOFResultForEachHorizon);

% eval([fileNamePredictionResultForEachHorizon '=
estiamted_yield_09_Model21'])}
save(filepath,fileNamePredictionResultForEachHorizon);
save(filepath2, 'b_Model21', 'bint_Model21', 'r_Model21', 'rint_Model21', 'stats_Model21', 'mse_Model21', 'gof_Model21', 'estiamted_yield_Model21');

save('./Original_Results\output_VH_estimated', 'estiamted_yield_Model21', '-append');

%%
% Create figure
figure1 = figure;

% Create axes
axes1 = axes('Parent', figure1);

box(axes1, 'on');
hold(axes1, 'all');

YMatrix1 = [estiamted_yield_09_Model21, milkyield09, herdYieldOneYear];

% Create multiple lines using matrix input to plot
plot1 = plot(YMatrix1, 'Parent', axes1, 'LineStyle', 'none');
set(plot1(1), 'LineWidth', 2, 'Color', [1 0 0], 'DisplayName', 'MLR', ...
    'LineStyle', '-');
set(plot1(2), 'Marker', 'x', 'DisplayName', 'Actual Milk Yield');
set(plot1(3), 'Marker', '.', 'Color', [0 0 1], ...
    'DisplayName', 'Average Annual Yield');

% ylim([0,1500]);
xlim([0,365]);
ylim([0,ylimLength]);

% Create title
title('MLR');

% Create xlabel
xlabel('Day of Year');

% Create ylabel
ylabel('Herd Milk Yield(kg)');

% Create legend
legend(axes1, 'show');
end

Model_08

% model 22 : static ANN (Artificial Neural Networks)
daycow0408 = evalin('base', 'dayCowTrain');
milkyield0408 = evalin('base', 'milkYieldTrain');
daycow09 = evalin('base', 'dayCowValidate');
milkyield09 = evalin('base', 'milkYieldValidate');
% Lengh of Y
ylimLength = 1.2 * max(milkyield09);

mkdir('.\Original_Results\','Model22');

%%%%%%%%%%%%%%%%%%%%% use trigger to decide the horizon array
trigger_table = [get(handles.day365,'UserData'),get(handles.day120,'UserData'),get(handles.day30,'UserData'),get(handles.day10,'UserData'),get(handles.day1,'UserData')];
ori_refresha = [365;120;30;10;1];
trigger_refresha= [ori_refresha trigger_table];
trigger_refresha(any(trigger_refresha==0,2),:)=[];
refresha=trigger_refresha(:,1);

loopOfRefresha = length(refresha);

for irefresh=1:1:loopOfRefresha;
    refresh=refresha(irefresh);
    estimated_yield_09_Model22 = [];
    Algo = 'SANN_

    for i=0:floor(size(daycow09)/refresh) % i is how many time the
        % Data arrangement
        % Transpose the Matrix into rows
        % Matrix row names and configuration.
        daycowtr=[];
        % Empty the data to fill them again the
        right way
        milkyieldtr=[];
        % daycowtr and milkyieldtr are the data
        used to train the model
        daycow09plus=[];
        % daycow09plus is a period of the data of
        2009 we will add to the data 0408 to be trained
        daycow09minus=[];
        % daycow09minus is the resized period of
        2009 to predict
        milkyield09plus=[];
        % the same than daycow09plus and
        daycow09minus
        milkyield09minus=[];

        if (i>0)
            % Pick the data which will be added to the 0108 years training
            daycow09plus(:,1)=daycow09(1:i*refresh,1); % The first column of
            daycow09plus(:,2)=daycow09(1:i*refresh,2); % The same for the
            second column
            milkyield09plus=milkyield09(1:i*refresh);
            % Pick the remaining data of the 2009 year which will be
            predicted
            daycow09minus(:,1)=daycow09(i*refresh+1:end,1);
            daycow09minus(:,2)=daycow09(i*refresh+1:end,2);
            milkyield09minus=milkyield09(i*refresh+1:end);
        end
    end
end
% Built the dataset for training
daycowtr=[daycow0408;daycow09plus];
milkyieldtr=[milkyield0408;milkyield09plus];

%         else % if i=0, the dataset for training are daycow0108, without added period
%             daycowtr=[daycow0408];
%             milkyieldtr=[milkyield0408];
%             milkyield09minus=milkyield09;
%             daycow09minus=daycow09;
%         end

%% Model Predictor
inputs = [daycowtr];
targets = [milkyieldtr];

% Create a Fitting Network
hiddenLayerSize = 4;
net = fitnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 90/100;
net.divideParam.valRatio = 10/100;
net.divideParam.testRatio = 0/100;

% For help on training function 'trainlm' type: help trainlm
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainlm'; % Levenberg-Marquardt

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse'; % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,inputs,targets,'useParallel','yes');

% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net, targets, outputs);

% Recalculate Training, Validation and Test Performance
trainTargets = targets .* tr.trainMask{1};
valTargets = targets .* tr.valMask{1};
testTargets = targets .* tr.testMask{1};
trainPerformance = perform(net, trainTargets, outputs);
valPerformance = perform(net, valTargets, outputs);
testPerformance = perform(net, testTargets, outputs);

yp1 = sim(net, [daycow09minus]');
yp1 = yp1';
b = [milkyield09minus]';

if (length(yp1) > refresh)
estimated_yield_09_Model22 = [estimated_yield_09_Model22 ;
    yp1(1:refresh,1)];
elseif (length(yp1) <= refresh)
estimated_yield_09_Model22 = [estimated_yield_09_Model22 ;
    yp1(1:end,1)];
end

% goodness of fit

cost_func = 'MSE';
fit_Model22 = goodnessOfFit(estimated_yield_09_Model22, milkyield09, cost_func);

% calculate SSE, Rsquare, RMSE
preditionYield = estimated_yield_09_Model22;
realYield = milkyield09;

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield - realYield).^2);
gof_Model22{1,1} = SSE;

% Rsquare
SST = sum((realYield - averageOfPrediction).^2);
Rsquare = 1 - SSE/SST;
gof_Model22{1,2} = Rsquare;

% RMSE
RMSE = sqrt(mean((preditionYield - realYield).^2));
gof_Model22{1,3} = RMSE;

% Store gof
estimated_yield_Model22 = [estimated_yield_09_Model22];
tr_Model22 = [tr];
mse_Model22 = [fit_Model22];

% Save workspace to resultses
Prediction_Horizon = num2str(refresh);
fileNamePredictionResultForEachHorizon = strcat('estimated_yield_09_Model22','_','PredictionHorizon','_','Estimatedyield_Model22');
fileNameGOFResultForEachHorizon = strcat('estimated_yield_09_Model22','_','PredictionHorizon','_','GOF');
folder = '.\Original_Results\Model22\';
filepath = strcat(folder,fileNamePredictionResultForEachHorizon);
filepath2 = strcat(folder,fileNameGOFResultForEachHorizon);

% eval([fileNamePredictionResultForEachHorizon ' = ' estimated_yield_09_Model22']);
% save(filepath, fileNamePredictionResultForEachHorizon);
save(filepath2,'tr_Model22','mse_Model22','gof_Model22','estimated_yield_Model22');

save('.\Original_Results\output_VH_estimated','estimated_yield_Model22','-append');

%%
% Create figure
figure1 = figure;

% Create axes
axes1 = axes('Parent',figure1);

box(axes1,'on');
hold(axes1,'all');

YMatrix1 = [estimated_yield_09_Model22,milkyield09,herdYieldOneYear];

% Create multiple lines using matrix input to plot
plot1 = plot(YMatrix1,'Parent',axes1,'LineStyle','none');
set(plot1(1), 'LineWidth',2, 'Color',[1 0 0], 'DisplayName','SANN', ... 'LineStyle','-');
set(plot1(2), 'Marker','x', 'DisplayName','Actual Milk Yield');
set(plot1(3), 'Marker','.','DisplayName','Average Annual Yield');

% ylim([0, 1500]);
xlim([0,365]);
ylim([0,ylimLength]);

% Create title
title('SANN');

% Create xlabel
xlabel('Day of Year');

% Create ylabel
ylabel('Herd Milk Yield (kg)');

% Create legend
Model_09

% model 23 : surface fitting
daycow0408 = evalin('base','dayCowTrain');
milkyield0408 = evalin('base','milkYieldTrain');
daycow09 = evalin('base','dayCowValidate');
milkyield09 = evalin('base','milkYieldValidate');

% Length of Y
ylimLength = 1.2 * max(milkyield09);

mkdir('.\Original_Results\','Model23');

%%%%%%%%%%%%%%%%%%% use trigger to decide the horizon array
trigger_table = [get(handles.day365,'UserData'),get(handles.day120,'UserData'),get(handles.day30,'UserData'),get(handles.day10,'UserData'),get(handles.day1,'UserData')];
ori_refresha = [365;120;30;10;1];
trigger_refresha= [ori_refresha trigger_table];
trigger_refresha(any(trigger_refresha==0,2),:)=[];
refresha=trigger_refresha(:,1);

loopOfRefresha = length(refresha);

for irefresh=1:1:loopOfRefresha;
  refresh=refresha(irefresh);

  estimated_yield_09_Model23 = [];
  Algo='3D_
  for i=0:floor(size(daycow09)/refresh) % i is how many time the predicted 2009 year will be refreshed
    % Data arrangement
    % Transpose the Matrix into rows
    % Matrix row names and configuration.
daycowtr=[]; % Empty the data to fill them again the right way
    milkyieldtr=[]; % daycowtr and milkyieldtr are the data used to train the model
daycow09plus=[]; % daycow09plus is a period of the data of 2009 we will add to the data 0408 to be trained
daycow09minus=[]; % daycow09minus is the resized period of 2009 to predict
    milkyield09plus=[]; % the same than daycow09plus and daycow09minus
    milkyield09minus=[];
    
    if (i>0)
Pick the data which will be added to the 0408 years training
daycow09plus(:,1)=daycow09(1:i*refresh,1); % The first column of
daycow09plus = the first column, row from 1 to i*refresh, of daycow09
daycow09plus(:,2)=daycow09(1:i*refresh,2); % The same for the second column
milkyield09plus=milkyield09(1:i*refresh);
% Pick the remaining data of the 2009 year which will be predicted
daycow09minus(:,1)=daycow09(i*refresh+1:end,1);
daycow09minus(:,2)=daycow09(i*refresh+1:end,2);
milkyield09minus=milkyield09(i*refresh+1:end);
% Built the dataset for training
daycowtr=[daycow0408;daycow09plus];
milkyieldtr=[milkyield0408;milkyield09plus];
% else % if i=0, the dataset for training are daycow0408, without added period
% daycowtr=[daycow0408];
% milkyieldtr=[milkyield0408];
% milkyield09minus=milkyield09;
% daycow09minus=daycow09;
% end

% Fit: '3Dmodel'.
[xInput, yInput, zOutput] = prepareSurfaceData( daycowtr(:,1),
daycowtr(:,2), milkyieldtr);
% Set up fittype and options.
ft = fittype( 'poly33' );
opts = fitoptions( ft );
opts.Lower = [-Inf -Inf -Inf -Inf -Inf -Inf -Inf -Inf -Inf -Inf];
opts.Upper = [Inf Inf Inf Inf Inf Inf Inf Inf Inf Inf];
% Fit model to data.
[fitresult, gof] = fit( [xInput, yInput], zOutput, ft, opts );
% % % % Plot fit with data.
% % % % figure( 'Name', 'Surface Fitting');
% % % % figure2 = figure;
% % % % hold on
% % % % h = plot( fitresult, [xInput, yInput], zOutput );
% % % % legend( h, 'Surface_Fitting', 'Milk Yield vs. DayOfYear, NCM', 'Location', 'NorthEast' );
% % % % xlabel( 'Day Of Year' );
% % % % ylabel( 'NCM' );
% % % % zlabel( 'Milk Yield' );
yp1=fitresult(daycow09minus(:,1),daycow09minus(:,2));
if (length(yp1) > refresh)
estiamted_yield_09_Model23 = [estiamted_yield_09_Model23 ;
    yp1(1:refresh,1)];
elseif (length(yp1) <= refresh)
estiamted_yield_09_Model23 = [estiamted_yield_09_Model23 ;
    yp1(1:end,1)];
end
end
% %             Plot fit with data.
figure( 'Name', 'Surface Fitting' );
h = plot( fitresult, [xInput, yInput], zOutput );
legend( h, 'Surface Fitting', 'Milk Yield vs. DayOfYear, NCM',
'Location', 'NorthEast' );
% Label axes
xlabel( 'Day Of Year' );
ylabel( 'NCM' );
zlabel( 'Milk Yield' );
%% goodness of fit
cost_func = 'MSE';
fit_Model23 = 
goodnessOfFit(estiamted_yield_09_Model23,milkyield09,cost_func);
% calculate SSE,Rsquare,RMSE
preditionYield = estiamted_yield_09_Model23;
realYield = milkyield09;
% SSE
averageOfPrediction = mean(realYield);
SSE = sum((preditionYield-realYield).^2);
gof_Model23{1,1} = SSE;
% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare=1-SSE/SST;
gof_Model23{1,2} = Rsquare;
% RMSE
RMSE = sqrt(mean((preditionYield - realYield).^2));
gof_Model23{1,3} = RMSE;
%% % Store G.O.F
estiamted_yield_Model23 = [estiamted_yield_09_Model23];
mse_Model23 = [fit_Model23];
% Save workspace to resultes
Prediction_Horizon = num2str(refresh);
fileNamePredictionResultForEachHorizon = strcat('estiamted_yield_09_Model23', '_', 'PredictionHorizon', '_', 'PredictionHorizon_09_Model23');
fileNameGOFResultForEachHorizon = strcat('estiamted_yield_09_Model23', '_', 'GOF', 'PredictionHorizon');
folder = './Original_Results_Model23';
filepath = strcat(folder,fileNamePredictionResultForEachHorizon);
filepath2 = strcat(folder,fileNameGOFResultForEachHorizon);
% eval([fileNamePredictionResultForEachHorizon '=
estimated_yield_09_Model23']);
% save(filepath, fileNamePredictionResultForEachHorizon);
save(filepath2,'mse_Model23','gof_Model23', 'estimated_yield_Model23');
save('./Original_Results\output_VH_estimated', 'estimated_yield_Model23', '-append');

%%
% Create figure
figure2 = figure;
% Create axes
axes1 = axes('Parent',figure2);
box(axes1,'on');
hold(axes1,'all');

YMatrix1 = [estimated_yield_Model23,milkyield09,herdYieldOneYear];

% Create multiple lines using matrix input to plot
plot1 = plot(YMatrix1,'Parent',axes1,'LineStyle','none');
set(plot1(1), 'LineWidth', 2, 'Color', [1 0 0], 'DisplayName','Surface Fitting', ...
    'LineStyle', '-');
set(plot1(2), 'Marker','x', 'DisplayName','Actual Milk Yield');
set(plot1(3), 'Marker','.','Color',[0 0 1],... 
    'DisplayName','Average Annual Yield');

% ylim([0, 1500]);
xlim([0,365]);
ylim([0,ylimLength]);

% Create title
title('Surface Fitting');

% Create xlabel
xlabel('Day of Year');

% Create ylabel
ylabel('Herd Milk Yield (kg)');
% Create legend
legend(axes1,'show');
end

Model_10

% model 32 : NARX Model
daycow0408 = evalin('base','dayCowTrain');
milkyield0408 = evalin('base','milkYieldTrain');
daycow09 = evalin('base','dayCowValidate');
milkyield09 = evalin('base','milkYieldValidate');

% Lengh of Y
ylimLength = 1.2 * max(milkyield09);

mkdir('.\Original_Results\','Model32');

%%
%%%%%%%%%%%%%%%%%%% use trigger to decide the horizon array
trigger_table =
[get(handles.day365,'UserData'), get(handles.day120,'UserData'), get(handles.day30,'UserData'), get(handles.day10,'UserData'), get(handles.day1,'UserData')]';
ori_refresha = [365;120;30;10;1];
trigger_refresha= [ori_refresha trigger_table];
trigger_refresha(any(trigger_refresha==0,2),:)=[];
refresha=trigger_refresha(:,1); % moving piecewise horizon

loopOfRefresha = length(refresha);
delayout=1:1:4;
nnarray=[2;4;6]; % neurons in the hidden layer

for delayin=2:2:4
    for irefresh=1:1:loopOfRefresha;
        refresh=refresha(irefresh);

        for inn=1:1:3;
            nn=nnarray(inn);

            for itransfcn=1:4
                if itransfcn==1
                    Transfcn = 'tribas';
                elseif itransfcn==2
                    Transfcn = 'satlin';
                elseif itransfcn==3
                    Transfcn = 'radbas';
                elseif itransfcn==4
                    Transfcn = 'logsig';
                end

                % ALGO BR
                if itransfcn==1 || itransfcn==2 || itransfcn==3 ||
                itransfcn==4
                    predictionResultForEachCombin = cell2mat(cell(365));
                    algo='BR_';

                    for i=0:floor(size(daycow09)/refresh)
                        % Data arrangement
                        % Transpose the Matrix into rows
                        % Matrix row names and configuration.

            end

        end

    end

end
daycowtr=[]; milkyieldtr=[]; daycowpr=[]; milkyieldpr=[];

% transfer original data type to a row cell array
dc0409=[daycow0408;daycow09];
my0409=[milkyield0408;milkyield09];

size0408=size(daycow0408,1);
daycowtr=dc0409(1:size0408+(i*refresh),1:2);
milkyieldtr(:,1)=my0409(1:size0408+(i*refresh),1);

delayin+1:end,1:2);
milkyieldpr(:,1)=my0409(size0408+(i*refresh)-
delayin+1:end,1);

%%

u = [daycowtr]';
y = [milkyieldtr]';

u = con2seq(u);
y = con2seq(y);

%% Configure network settings
d1 = [1:delayin];
d2 = [1:delayout];
narx_net = narxnet(d1,d2,nn);

narx_net.inputs{1}.processFcns =
{ 'removeconstantrows' , 'mapminmax' };

narx_net.inputs{2}.processFcns =
{ 'removeconstantrows' , 'mapminmax' };

% Adynamic error weighting factor can be applied in order to reduce system training errors.
size_milkyieldtr = size(milkyieldtr,1);
ind = 1:size_milkyieldtr;
ew = 1.^(size_milkyieldtr-ind);
figure;plot(new)
new = con2seq(new);

%% Train the network.% the training set will be divided for training.% A minimum target gradient is selected as performance critia.
narx_net.layers{1}.transferFcn=strcat('',Transfcn,'');
narx_net.divideFcn = '';
narx_net.trainParam.min_grad = 1e-10;
[p,Pi,Ai,t,ew1] = preparets(narx_net,u,[],y,new);
% Bayesian regulation backpropagation
net.trainFcn = 'trainbr';
net.performFcn = 'sse';
net.plotFcns =
['plotperform','plottrainstate','plotresponse', ...
'ploterrcorr','plotregression','plotinerrcorr'];
[narx_net,tr] =
trainbr(narx_net,p,t,Pi,Ai,'useParallel','yes');

%% Simulate the network
% simulate the performance of the network over
the time domain
yp = sim(narx_net,p,Pi);
e = cell2mat(yp)-cell2mat(t);

%% Closed Loop Network
narx_net_closed = closeloop(narx_net);

%% % Store gof
tr_p1_Model32 = [tr];

%%
% Chose a time period in which to predict yield
x = con2seq([daycowpr']);
z = con2seq([milkyieldpr']);
yl= z(1:size(daycowpr,1));
u1= x(1:size(milkyieldpr,1));
[p1,Pi1,Ai1,t1] =
preparets(narx_net_closed,u1,{},yl,ewl);
yp1 = narx_net_closed(p1,Pi1,Ai1);

%Determine the Name of the output
nnstr = num2str(nn);
delayinstr = num2str(delayin);
refreshstr = num2str(refresh);
filename =
strcat(algo,Transfcn,'_',refreshstr,'daysR_delay_'.delayinstr,'_nn_'.nnstr);
filenamePredictionResultForEachCombin = filename;
folder = '.\Original_Results\Model32\';

filepath = strcat(folder,filename);
Real=[];
Real=milkyieldpr(delayin+1:end,1);
eachSheet = [cell2mat(yp1')];
sheetadd =
[eachSheet;zeros(length(predictionResultForEachCombin)-
length(eachSheet),1)];
predictionResultForEachCombin = [predictionResultForEachCombin sheetadd];
end

end
eval([filenamePredictionResultForEachCombin '=
predictionResultForEachCombin']);
save(filepath, filenamePredictionResultForEachCombin);
end
end
end
end

%% Calculate SSE, Rsquare, RMSE. Compare and get the best configuration

folder = '.\Original_Results\Model32\';
getfilename=ls('.\Original_Results\Model32\*.mat');
filename = cellstr(getfilename);
realYield = milkyield09;

num_of_files = length(filename);
for i = 1:num_of_files
    onlyname{i} = filename{i}(1:end-4);
sheetsofexcel{i,1} = onlyname{i};
fullname{i} = fullfile(folder, filename{i});
structOfEachCombin = load(fullname{i});

cellOfEachCombin = struct2cell(structOfEachCombin);
sheetsofexcel{i,2} = cellOfEachCombin{1,1};

num_of_coloum = length(sheetsofexcel{i,2}(1,:));
num_of_last_coloum = nnz(sheetsofexcel{i,2}(:,end));
num_of_coloum = (365 - num_of_last_coloum) / (num_of_coloum - 1);

prediction_results_of_year_p1 = sheetsofexcel{i,2}(1:num_of_coloum,1:end-1);
prediction_results_of_year_p1 = reshape(prediction_results_of_year_p1,[],1);
prediction_results_of_year_p2 = sheetsofexcel{i,2}(1:num_of_last_coloum,end);
prediction_results_of_year = [prediction_results_of_year_p1; prediction_results_of_year_p2];

sheetsofexcel(i,3) = prediction_results_of_year;

% calculate SSE, Rsquare, RMSE
predictionYield = sheetsofexcel(i,3);

% SSE
averageOfPrediction = mean(realYield);
SSE = sum((predictionYield-realYield).^2);
sheetsofexcel(i,5) = SSE;

% Rsquare
SST = sum((realYield-averageOfPrediction).^2);
Rsquare = 1 - SSE/SST;
sheetsofexcel(i,6) = Rsquare;

% RMSE
RMSE = sqrt(mean((predictionYield - realYield).^2));
sheetsofexcel(i,4) = RMSE;
results_and_statistical_analysis_of_Model32 = sheetsofexcel;
end

% Lowest RMSE
[lowestRMSEvalue, row_of_lowest_RMSE] = 
    min(cell2mat(results_and_statistical_analysis_of_Model32(:,4)));
lowestRMSE = results_and_statistical_analysis_of_Model32(row_of_lowest_RMSE,1);
results_and_statistical_analysis_of_Model32(i+1,1) = 'the lowest RMSE is: ';
results_and_statistical_analysis_of_Model32(i+1,2) = lowestRMSE;
results_and_statistical_analysis_of_Model32(i+1,3) = lowestRMSEvalue;

% Lowest SSE
[lowestSSEvalue, row_of_lowest_SSE] = 
    min(cell2mat(results_and_statistical_analysis_of_Model32(:,5)));
lowestSSE = results_and_statistical_analysis_of_Model32(row_of_lowest_SSE,1);
results_and_statistical_analysis_of_Model32(i+2,1) = 'the lowest SSE is: ';
results_and_statistical_analysis_of_Model32(i+2,2) = lowestSSE;
results_and_statistical_analysis_of_Model32(i+2,3) = lowestSSEvalue;

% Best Rsquare
[lowestRsquarevalue, row_of_lowest_Rsquare] = 
    max(cell2mat(results_and_statistical_analysis_of_Model32(:,6)));
lowestRsquare = results_and_statistical_analysis_of_Model32(row_of_lowest_Rsquare,1);
results_and_statistical_analysis_of_Model32{i+3,1} = 'the Best Rsquare is : ';
results_and_statistical_analysis_of_Model32{i+3,2} = lowestRsquare;
results_and_statistical_analysis_of_Model32{i+3,3} = lowestRsquarevalue;
estimated_yield_Model32_best = 
results_and_statistical_analysis_of_Model32{row_of_lowest_RMSE,3};
save('.', 'Original_Results\resultses_prediction_Model32.mat','results_and_statistical_analysis_of_Model32','estimated_yield_Model32_best');
save('.', 'Original_Results\output_VH_estimated','estimated_yield_Model32_best', '-append');

%%
% Create figure
figure1 = figure;

% Create axes
axes1 = axes('Parent', figure1);
box(axes1, 'on');
hold(axes1, 'all');

YMatrix1 = [estimated_yield_Model32_best, milkyield09, herdYieldOneYear];

% Create multiple lines using matrix input to plot
plot1 = plot(YMatrix1, 'Parent', axes1, 'LineStyle', 'none');
set(plot1(1), 'LineWidth', 2, 'Color', [1 0 0], 'DisplayName', 'NARX', ...
LineStyle', '-');
set(plot1(2), 'Marker', 'x', 'DisplayName', 'Actual Milk Yield');
set(plot1(3), 'Marker', '.', 'Color', [0 0 1], ...
DisplayName', 'Average Annual Yield');

% ylim([0, 1500]);
xlim([0, 365]);
ylim([0, ylimLength]);

% Create title
title('NARX');

% Create xlabel
xlabel('Day of Year');

% Create ylabel
ylabel('Herd Milk Yield (kg)');

% Create legend
legend(axes1, 'show');
function varargout = MPFOS_Herd_version(varargin)

% MPFOS_HERD_VERSION MATLAB code for MPFOS_Herd_version.fig
% MPFOS_HERD_VERSION, by itself, creates a new MPFOS_HERD_VERSION or raises
% the existing singleton*. 
% H = MPFOS_HERD_VERSION returns the handle to a new
% MPFOS_HERD_VERSION or the handle to
% the existing singleton*. 
% MPFOS_HERD_VERSION('CALLBACK',hObject,eventData,handles,...) calls
% the local function named CALLBACK in MPFOS_HERD_VERSION.M with the given
% input arguments.
% MPFOS_HERD_VERSION('Property','Value',...) creates a new
% MPFOS_HERD_VERSION or raises the
% existing singleton*. Starting from the left, property value pairs
% are applied to the GUI before MPFOS_Herd_version_OpeningFcn gets
called. An
% unrecognized property name or invalid value makes property
% application stop. All inputs are passed to MPFOS_Herd_version_OpeningFcn via
% varargin.
% *See GUI Options on GUIDE's Tools menu. Choose "GUI allows only
% one
% instance to run (singleton)".
% See also: GUIDE, GUIDATA, GUICHANDLES

% Edit the above text to modify the response to help MPFOS_Herd_version

% Last Modified by GUIDE v2.5 29-Sep-2016 21:48:12

% Begin initialization code - DO NOT EDIT

gui_Singleton = 1;
gui_State = struct('gui_Name', mfilename, ... 'gui_Singleton', gui_Singleton, ... 'gui_OpeningFcn', @MPFOS_Herd_version_OpeningFcn, ... 'gui_OutputFcn', @MPFOS_Herd_version_OutputFcn, ... 'gui_LayoutFcn', [], ... 'gui_Callback', []);

if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else

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gui_mainfcn(gui_State, varargin{:});
end
% End initialization code - DO NOT EDIT

% --- Executes just before MPFOS_Herd_version is made visible.
function MPFOS_Herd_version_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% varargin   command line arguments to MPFOS_Herd_version (see VARARGIN)

% Choose default command line output for MPFOS_Herd_version
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes MPFOS_Herd_version wait for user response (see UIRESUME)
% uiwait(handles.figure1);

% --- Outputs from this function are returned to the command line.
function varargout = MPFOS_Herd_version_OutputFcn(hObject, eventdata, handles)
% varargout  cell array for returning output args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;

% --- Executes on button press in radiobutton1.
function radiobutton1_Callback(hObject, eventdata, handles)
% hObject    handle to radiobutton1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of radiobutton1

% --- Executes on button press in radiobutton2.
function radiobutton2_Callback(hObject, eventdata, handles)
% hObject    handle to radiobutton2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of radiobutton2

% --- Executes on selection change in trainingStart.
function trainingStart_Callback(hObject, eventdata, handles)
% hObject    handle to trainingStart (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
index_selected = get(hObject, 'Value');
list = get(hObject, 'String');
trainingStartYear = list{index_selected};
handles.item = trainingStartYear;
assignin ('base', 'trainingStartYear', handles.item);

% Hints: contents = cellstr(get(hObject, 'String')) returns trainingStart contents as cell array
%        contents{get(hObject, 'Value')} returns selected item from trainingStart

% --- Executes during object creation, after setting all properties.
function trainingStart_CreateFcn(hObject, eventdata, handles)
    % hObject    handle to trainingStart (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    empty - handles not created until after all CreateFcns called
    % Hint: listbox controls usually have a white background on Windows.
    %       See ISPC and COMPUTER.
    if ispc && isequal(get(hObject, 'BackgroundColor'), get(0, 'defaultUicontrolBackgroundColor'))
        set(hObject, 'BackgroundColor', 'white');
    end

% --- Executes on selection change in targetYear.
function targetYear_Callback(hObject, eventdata, handles)
    % hObject    handle to targetYear (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    index_selected = get(hObject, 'Value');
    list = get(hObject, 'String');
    targetEndYear = list{index_selected};
    handles.item = targetEndYear;
    assignin ('base', 'targetEndYear', targetEndYear);

    % Hints: contents = cellstr(get(hObject, 'String')) returns targetYear contents as cell array
    %        contents{get(hObject, 'Value')} returns selected item from targetYear

    % --- Executes during object creation, after setting all properties.
    function targetYear_CreateFcn(hObject, eventdata, handles)
        % hObject    handle to targetYear (see GCBO)
        % eventdata  reserved - to be defined in a future version of MATLAB
        % handles    empty - handles not created until after all CreateFcns called
        % Hint: listbox controls usually have a white background on Windows.
        %       See ISPC and COMPUTER.
        if ispc && isequal(get(hObject, 'BackgroundColor'), get(0, 'defaultUicontrolBackgroundColor'))
            set(hObject, 'BackgroundColor', 'white');
        end
% --- Executes on selection change in parity01.
function parity01_Callback(hObject, eventdata, handles)
% hObject    handle to parity01 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Determine the selected data set.
str = get(hObject, 'String');
val = get(hObject, 'Value');
% Set current data to the selected data set.
switch str(val)
    case '0'
        % User selects cow number 0.
        handles.current_data = 0;
    case '5'
        % User selects cow number 5.
        handles.current_data = 5;
    case '10'
        % User selects cow number 10.
        handles.current_data = 10;
    case '15'
        % User selects cow number 15.
        handles.current_data = 15;
    case '25'
        % User selects cow number 25.
        handles.current_data = 25;
    case '50'
        % User selects cow number 50.
        handles.current_data = 50;
    case '75'
        % User selects cow number 75.
        handles.current_data = 75;
    case '100'
        % User selects cow number 100.
        handles.current_data = 100;
    case '150'
        % User selects cow number 150.
        handles.current_data = 150;
    case '200'
        % User selects cow number 200.
        handles.current_data = 200;
end
% Save the handles structure.
set(handles.parity01, 'UserData', handles.current_data);

% Hints: contents = cellstr(get(hObject,'String')) returns parity01
% contents as cell array
% contents(get(hObject,'Value')) returns selected item from parity01

% --- Executes during object creation, after setting all properties.
function parity01_CreateFcn(hObject, eventdata, handles)
% hObject    handle to parity01 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty handles not created until after all CreateFcns called

% Hint: popupmenu controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject, 'BackgroundColor', 'white');
end
% --- Executes on button press in checkbox1.
function checkbox1_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox1

% --- Executes on button press in checkbox2.
function checkbox2_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox2

% --- Executes on button press in checkbox3.
function checkbox3_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox3 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox3

% --- Executes on button press in checkbox4.
function checkbox4_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox4 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox4

% --- Executes on button press in checkbox5.
function checkbox5_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox5 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox5

% --- Executes on button press in checkbox6.
function checkbox6_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox6 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of checkbox6

% --- Executes on button press in checkbox7.
function checkbox7_Callback(hObject, eventdata, handles)
% hObject    handle to checkbox7 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% Hint: get(hObject,'Value') returns toggle state of checkbox7

% --- Executes on selection change in parity02.
function parity02_Callback(hObject, eventdata, handles)
    % hObject    handle to parity02 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Determine the selected data set.
    str = get(hObject, 'String');
    val = get(hObject, 'Value');
    % Set current data to the selected data set.
    switch str{val};
        case '0'
            % User selects cow number 0.
            handles.current_data = 0;
        case '5'
            % User selects cow number 5.
            handles.current_data = 5;
        case '10'
            % User selects cow number 10.
            handles.current_data = 10;
        case '15'
            % User selects cow number 15.
            handles.current_data = 15;
        case '25'
            % User selects cow number 25.
            handles.current_data = 25;
        case '50'
            % User selects cow number 50.
            handles.current_data = 50;
        case '75'
            % User selects cow number 75.
            handles.current_data = 75;
        case '100'
            % User selects cow number 100.
            handles.current_data = 100;
        case '150'
            % User selects cow number 150.
            handles.current_data = 150;
        case '200'
            % User selects cow number 200.
            handles.current_data = 200;
    end
    % Save the handles structure.
    set(handles.parity02,'UserData',handles.current_data);

    % Hints: contents = cellstr(get(hObject,'String')) returns parity02
    % contents as cell array
    % contents{get(hObject,'Value')} returns selected item from
    % parity02

% --- Executes during object creation, after setting all properties.
function parity02_CreateFcn(hObject, eventdata, handles)
    % hObject    handle to parity02 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    empty - handles not created until after all CreateFcns
    % called

    % Hint: popupmenu controls usually have a white background on Windows.
    % See ISPC and COMPUTER.
    if ispc && isequal(get(hObject,'BackgroundColor'),
        get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end
end

% --- Executes on selection change in parity03.
function parity03_Callback(hObject, eventdata, handles)
% hObject    handle to parity03 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Determine the selected data set.
str = get(hObject, 'String');
val = get(hObject, 'Value');
% Set current data to the selected data set.
switch str(val);
    case '0' % User selects cow number 0.
        handles.current_data = 0;
    case '5' % User selects cow number 5.
        handles.current_data = 5;
    case '10' % User selects cow number 10.
        handles.current_data = 10;
    case '15' % User selects cow number 15.
        handles.current_data = 15;
    case '25' % User selects cow number 25.
        handles.current_data = 25;
    case '50' % User selects cow number 50.
        handles.current_data = 50;
    case '75' % User selects cow number 75.
        handles.current_data = 75;
    case '100' % User selects cow number 100.
        handles.current_data = 100;
    case '150' % User selects cow number 150.
        handles.current_data = 150;
    case '200' % User selects cow number 200.
        handles.current_data = 200;
end
% Save the handles structure.
set(handles.parity03, 'UserData', handles.current_data);

% Hints: contents = cellstr(get(hObject, 'String')) returns parity03 contents as cell array.
% contents(get(hObject, 'Value')) returns selected item from parity03

% --- Executes during object creation, after setting all properties.
function parity03_CreateFcn(hObject, eventdata, handles)
% hObject    handle to parity03 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty handles not created until after all CreateFcns called
% Hint: popupmenu controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject, 'BackgroundColor'), get(0, 'defaultUicontrolBackgroundColor'))
    set(hObject, 'BackgroundColor', 'white');
end

end
% --- Executes on button press in Polynomial.
function Polynomial_Callback(hObject, eventdata, handles)
% hObject    handle to Polynomial (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
model11_trigger = get(handles.Polynomial, 'Value');
set(handles.Polynomial,'UserData',model11_trigger);
% Hint: get(hObject,'Value') returns toggle state of Polynomial

% --- Executes on button press in Adaptive_Polynomial.
function Adaptive_Polynomial_Callback(hObject, eventdata, handles)
% hObject    handle to Adaptive_Polynomial (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
model12_trigger = get(handles.Adaptive_Polynomial, 'Value');
set(handles.Adaptive_Polynomial,'UserData',model12_trigger);
% Hint: get(hObject,'Value') returns toggle state of Adaptive_Polynomial

% --- Executes on button press in Legendre_Polynomial.
function Legendre_Polynomial_Callback(hObject, eventdata, handles)
% hObject    handle to Legendre_Polynomial (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
model13_trigger = get(handles.Legendre_Polynomial, 'Value');
set(handles.Legendre_Polynomial,'UserData',model13_trigger);
% Hint: get(hObject,'Value') returns toggle state of Legendre_Polynomial

% --- Executes on button press in Cubic_Splines.
function Cubic_Splines_Callback(hObject, eventdata, handles)
% hObject    handle to Cubic_Splines (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
model14_trigger = get(handles.Cubic_Splines, 'Value');
set(handles.Cubic_Splines,'UserData',model14_trigger);
% Hint: get(hObject,'Value') returns toggle state of Cubic_Splines

% --- Executes on button press in NARX.
function NARX_Callback(hObject, eventdata, handles)
% hObject    handle to NARX (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
model32_trigger = get(handles.NARX, 'Value');
set(handles.NARX,'UserData',model32_trigger);
% Hint: get(hObject,'Value') returns toggle state of NARX

% --- Executes on button press in Log_quadratic.
function Log_quadratic_Callback(hObject, eventdata, handles)
% hObject    handle to Log_quadratic (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
model15_trigger = get(handles.Log_quadratic, 'Value');
set(handles.Log_quadratic,'UserData',model15_trigger);
% Hint: get(hObject,'Value') returns toggle state of Log_quadratic

% --- Executes on button press in MLR.
function MLR_Callback(hObject, eventdata, handles)
    % hObject    handle to MLR (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    model21_trigger = get(handles.MLR, 'Value');
    set(handles.MLR, 'UserData', model21_trigger);
    % Hint: get(hObject,'Value') returns toggle state of MLR

% --- Executes on button press in SANN.
function SANN_Callback(hObject, eventdata, handles)
    % hObject    handle to SANN (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    model22_trigger = get(handles.SANN, 'Value');
    set(handles.SANN, 'UserData', model22_trigger);
    % Hint: get(hObject,'Value') returns toggle state of SANN

% --- Executes on button press in Surface_Fitting.
function Surface_Fitting_Callback(hObject, eventdata, handles)
    % hObject    handle to Surface_Fitting (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    model23_trigger = get(handles.Surface_Fitting, 'Value');
    set(handles.Surface_Fitting, 'UserData', model23_trigger);
    % Hint: get(hObject,'Value') returns toggle state of Surface_Fitting

% --- Executes on button press in day365.
function day365_Callback(hObject, eventdata, handles)
    % hObject    handle to day365 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    day365_trigger = get(handles.day365, 'Value');
    set(handles.day365, 'UserData', day365_trigger);
    % Hint: get(hObject,'Value') returns toggle state of day365

% --- Executes on button press in day120.
function day120_Callback(hObject, eventdata, handles)
    % hObject    handle to day120 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    day120_trigger = get(handles.day120, 'Value');
    set(handles.day120, 'UserData', day120_trigger);
    % Hint: get(hObject,'Value') returns toggle state of day120

% --- Executes on button press in day30.
function day30_Callback(hObject, eventdata, handles)
    % hObject    handle to day30 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    day30_trigger = get(handles.day30, 'Value');
    set(handles.day30, 'UserData', day30_trigger);
    % Hint: get(hObject,'Value') returns toggle state of day30

% --- Executes on button press in Calculate.
function Calculate_Callback(hObject, eventdata, handles)
main_f

% --- Executes on button press in randomlySelect.
function [vh_indiCowDailyYieldofGroup_start_end] =
randomlySelect_Callback(hObject, eventdata, handles)

parity01cowsNO = get(handles.parity01, 'UserData');
parity02cowsNO = get(handles.parity02, 'UserData');
parity03cowsNO = get(handles.parity03, 'UserData');

vh_indiCowDailyYieldofGroup =
generate_random_combination_of_Virtual_Herd_f(parity01cowsNO, parity02cowsNO, parity03cowsNO);

time = load('MPFOS_herd_preprocess.mat');

% load start year and end year, transfer to date format
trainingStartYear = evalin('base', 'trainingStartYear');
targetEndYear = evalin('base', 'targetEndYear');
trainingStartYear = strcat(trainingStartYear, '-01-01');
targetEndYear = strcat(targetEndYear, '-12-31');

% reorganize milk yield by date
vh_indiCowDailyYieldofGroup_start_end =
herd_Yield_NCM_by_Group_Date(vh_indiCowDailyYieldofGroup, trainingStartYear, targetEndYear);
assignin
('base', 'vh_indiCowDailyYieldofGroup_start_end', vh_indiCowDailyYieldofGroup_start_end);

% --- Executes on button press in Save_and_View.
function Save_and_View_Callback(hObject, eventdata, handles)

load output_VH_estimated;
milkYieldValidate = evalin('base', 'milkYieldValidate');
herdYieldOneYear = evalin('base', 'herdYieldOneYear');

% load results
load output_VH_estimated;
%plot results
plotDayOfYear = (1:1:365);

plot (plotDayOfYear, milkYieldValidate, 'DisplayName', 'Actual Milk Yield', 'Marker', 'x', 'LineStyle', 'none', 'Color', [0 0.498096 0]);
hold on

plot (herdYieldOneYear, 'DisplayName', 'Average Annual Yield Input', 'Marker', '+', 'LineStyle', 'none', 'Color', [0 0.498096 0.9]);
hold on

if (get(handles.Polynomial, 'UserData') == 1)
    plot (estimated_yield_Model11, 'DisplayName', 'Polynomial');
    hold on
end

if (get(handles.Adaptive_Polynomial, 'UserData') == 1)
    plot (estimated_yield_Model12, 'DisplayName', 'Adaptive Polynomial');
    hold on
end

if (get(handles.Legendre_Polynomial, 'UserData') == 1)
    plot (estimated_yield_Model13, 'DisplayName', 'Legendre Polynomial');
    hold on
end

if (get(handles.Cubic_Splines, 'UserData') == 1)
    plot (estimated_yield_Model14, 'DisplayName', 'Cubic Splines');
    hold on
end

if (get(handles.Log_quadratic, 'UserData') == 1)
    plot (estimated_yield_Model15, 'DisplayName', 'Log quadratic');
    hold on
end

if (get(handles.MLR, 'UserData') == 1)
    plot (estimated_yield_Model21, 'DisplayName', 'MLR', 'Color', [0 0.7 0.9]);
    hold on
end

if (get(handles.SANN, 'UserData') == 1)
    plot (estimated_yield_Model22, 'DisplayName', 'SANN', 'Color', [0.5 0.2 0.7]);
    hold on
end

if (get(handles.Surface_Fitting, 'UserData') == 1)
    plot (estimated_yield_Model23, 'DisplayName', 'Surface Fitting', 'Color', [0.6 0.7 0.1]);
    hold on
end

if (get(handles.NARX, 'UserData') == 1)
plot(estimated_yield_Model32_best,'DisplayName','NARX','Color',[0.9 0.2 0.6]);
end
hold on
xlim([0,365]);
ylimLength = 1.2 * max(milkYieldValidate);
ylim([0,ylimLength]);

legend( 'Location', 'bestoutside' );
xlabel( 'Day of Year' );
ylabel( 'Herd Milk Yield (kg)' );
grid on
hold off

% --- Executes on button press in day10.
function day10_Callback(hObject, eventdata, handles)
% hObject    handle to day10 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
day10_trigger = get(handles.day10,'Value');
set(handles.day10,'UserData',day10_trigger);
% Hint: get(hObject,'Value') returns toggle state of day10

% --- Executes on slider movement.
function slider1_Callback(hObject, eventdata, handles)
% hObject    handle to slider1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'Value') returns position of slider
%        get(hObject,'Min') and get(hObject,'Max') to determine range of slider

% --- Executes during object creation, after setting all properties.
function slider1_CreateFcn(hObject, eventdata, handles)
% hObject    handle to slider1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: slider controls usually have a light gray background.
if isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor',[.9 .9 .9]);
end

% --- Executes on button press in loadPreprocessedData.
function loadPreprocessedData_Callback(hObject, eventdata, handles)
% hObject    handle to loadPreprocessedData (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
load MPFOS_herd_preprocess;
assignin ('base','indiCowDailyYieldofGroup01',indiCowDailyYieldofGroup01);
assignin ('base','indiCowDailyYieldofGroup02',indiCowDailyYieldofGroup02);
assignin ('base', 'indiCowDailyYieldofGroup03', indiCowDailyYieldofGroup03);

% --- Executes on button press in Generate_training_inputs.
function Generate_training_inputs_Callback(hObject, eventdata, handles)
% hObject    handle to Generate_training_inputs (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
trainingStartYear = evalin('base', 'trainingStartYear');
targetEndYear = evalin('base', 'targetEndYear');
vh_indiCowDailyYieldofGroup_start_end = evalin('base', 'vh_indiCowDailyYieldofGroup_start_end');
% oneYearYieldAverage = 
oneYearYieldAverage_for_group_vh_f(vh_indiCowDailyYieldofGroup_start_end, trainingStartYear, targetEndYear);
[oneYearYieldAverage, dayCowTrain, milkYieldTrain, dayCowValidate, milkYieldValidate] = 
trainingInputs_for_group_vh_f(vh_indiCowDailyYieldofGroup_start_end, trainingStartYear, targetEndYear);

% normally use the following
assignin ('base', 'herdYieldOneYear', oneYearYieldAverage);
assignin ('base', 'dayCowTrain', dayCowTrain);
assignin ('base', 'milkYieldTrain', milkYieldTrain);
assignin ('base', 'dayCowValidate', dayCowValidate);
assignin ('base', 'milkYieldValidate', milkYieldValidate);

% for old namespaces only
% assignin ('base', 'herdYieldOneYear', oneYearYieldAverage);
% assignin ('base', 'daycow0408', dayCowTrain);
% assignin ('base', 'milkyield0408', milkYieldTrain);
% assignin ('base', 'daycow09', dayCowValidate);
% assignin ('base', 'milkyield09', milkYieldValidate);

% --- Executes on button press in Average_of_Training.
function Average_of_Training_Callback(hObject, eventdata, handles)
% hObject    handle to Average_of_Training (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
model10_trigger = get(handles.Average_of_Training, 'Value');
set(handles.Average_of_Training, 'UserData', model10_trigger);
% Hint: get(hObject,'Value') returns toggle state of Average_of_Training

% --- Executes on button press in day1.
function day1_Callback(hObject, eventdata, handles)
% hObject    handle to day1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
day1_trigger = get(handles.day1, 'Value');
set(handles.day1, 'UserData', day1_trigger);
% Hint: get(hObject,'Value') returns toggle state of day1

% --- Executes during object creation, after setting all properties.
function axes1_CreateFcn(hObject, eventdata, handles)
% hObject    handle to axes1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% handles empty - handles not created until after all CreateFcns called
% Hint: place code in OpeningFcn to populate axes1

GUI_P2

function varargout = MPFOS_herd_version_show_results(varargin)
% MPFOS_HERD_VERSION_SHOW_RESULTS MATLAB code for MPFOS_herd_version_show_results.fig
% MPFOS_HERD_VERSION_SHOW_RESULTS, by itself, creates a new MPFOS_HERD_VERSION_SHOW_RESULTS or raises the existing singleton.
% H = MPFOS_HERD_VERSION_SHOW_RESULTS returns the handle to a new MPFOS_HERD_VERSION_SHOW_RESULTS or the handle to the existing singleton.
% MPFOS_HERD_VERSION_SHOW_RESULTS('CALLBACK',hObject,eventData,handles,...) calls the local function named CALLBACK in MPFOS_HERD_VERSION_SHOW_RESULTS.M with the given input arguments.
% MPFOS_HERD_VERSION_SHOW_RESULTS('Property','Value',...) creates a new MPFOS_HERD_VERSION_SHOW_RESULTS or raises the existing singleton. Starting from the left, property value pairs are applied to the GUI before MPFOS_herd_version_show_results_OpeningFcn gets called. An unrecognized property name or invalid value makes property application stop. All inputs are passed to MPFOS_herd_version_show_results_OpeningFcn via varargin.
% *See GUI Options on GUIDE's Tools menu. Choose "GUI allows only one instance to run (singleton)".
% See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to help MPFOS_herd_version_show_results

% Last Modified by GUIDE v2.5 29-Sep-2016 21:15:33

% Begin initialization code - DO NOT EDIT
gui_Singleton = 1;
gui_State = struct('gui_Name', mfilename, ...
    'gui_Singleton', gui_Singleton, ...
    'gui_OpeningFcn', @MPFOS_herd_version_show_results_OpeningFcn, ...
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end

% End initialization code - DO NOT EDIT

% --- Executes just before MPFOS_herd_version_show_results is made visible.
function MPFOS_herd_version_show_results_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% varargin   command line arguments to MPFOS_herd_version_show_results (see VARARGIN)

%*************************************************
axes(handles.axes4);

milkYieldValidate = evalin('base','milkYieldValidate');
herdYieldOneYear = evalin('base','herdYieldOneYear');

% load results
load output_VH_estimated;
% estiamted_yield_Model11 = evalin('base','estiamted_yield_Model11');
% estiamted_yield_Model12 = evalin('base','estiamted_yield_Model12');
% estiamted_yield_Model13 = evalin('base','estiamted_yield_Model13');
% estiamted_yield_Model14 = evalin('base','estiamted_yield_Model14');
% estiamted_yield_Model15 = evalin('base','estiamted_yield_Model15');
% estiamted_yield_Model21 = evalin('base','estiamted_yield_Model21');
% estiamted_yield_Model22 = evalin('base','estiamted_yield_Model22');
% estiamted_yield_Model23 = evalin('base','estiamted_yield_Model23');
% estiamted_yield_09_Model32_best = evalin('base','estiamted_yield_09_Model32_best');

% plot results
plotDayOfYear = (1:1:365)';
plot(plotDayOfYear,milkYieldValidate,'DisplayName','Actual Milk Yield','Marker','x','LineStyle','none','Color',[0 0.498096 0]);
hold on
plot(herdYieldOneYear,'DisplayName','Average Annual Yield Input','Marker','.','LineStyle','none','Color',[0 0.498096 0.9]);
hold on

plot(estimated_yield_Model11,'DisplayName','Polynomial'); hold on
plot(estimated_yield_Model12,'DisplayName','Adaptive Polynomial'); hold on
plot(estimated_yield_Model13,'DisplayName','Legendre Polynomial'); hold on
plot(estimated_yield_Model14,'DisplayName','Cubic Splines'); hold on
plot(estimated_yield_Model15,'DisplayName','Log quadratic'); hold on
plot(estimated_yield_Model21,'DisplayName','MLR','Color',[0 0.7 0.9]); hold on
plot(estimated_yield_Model22,'DisplayName','SANN','Color',[0.5 0.2 0.7]); hold on
plot(estimated_yield_Model23,'DisplayName','Surface Fitting','Color',[0.6 0.7 0.1]); hold on
plot(estimated_yield_Model32_best,'DisplayName','NARX','Color',[0.9 0.2 0.6]); hold on
xlim([0,365]); ylimLength = 1.2 * max(milkYieldValidate); ylim([0,ylimLength]);

legend( 'Location', 'NorthEast' );
xlabel( 'Day of Year' );
ylabel( 'Herd Milk Yield (kg)' );
grid on

% if (get(handles.Polynomial,'UserData') == 1)
%     plot(estimated_yield_Model11,'DisplayName','Polynomial'); hold on
% end

% if (get(handles.Adaptive_Polynomial,'UserData') == 1)
%     plot(estimated_yield_Model12,'DisplayName','Adaptive Polynomial'); hold on
% end

% if (get(handles.Legendre_Polynomial,'UserData') == 1)
%     plot(estimated_yield_Model13,'DisplayName','Legendre Polynomial'); hold on
% end

% if (get(handles.Cubic_Splines,'UserData') == 1)
%     plot(estimated_yield_Model14,'DisplayName','Cubic Splines');
if (get(handles.Log_quadratic,'UserData') == 1)
%     plot(estiamted_yield_Model15,'DisplayName','Log quadratic');
%     hold on
% end
%
if (get(handles.MLR,'UserData') == 1)
%     plot(estiamted_yield_Model21,'DisplayName','MLR','Color',[0 0.7 0.9]);
%     hold on
% end
%
if (get(handles.SANN,'UserData') == 1)
%     plot(estiamted_yield_Model22,'DisplayName','SANN','Color',[0.5 0.2 0.7]);
%     hold on
% end
%
if (get(handles.Surface_Fitting,'UserData') == 1)
%     plot(estiamted_yield_Model23,'DisplayName','Surface Fitting','Color',[0.6 0.7 0.1]);
%     hold on
% end
%
if (get(handles.NARX,'UserData') == 1)
%     plot(estiamted_yield_Model32_best,'DisplayName','NARX','Color',[0.9 0.2 0.6]);
% end
%
% Choose default command line output for MPFOS_herd_version_show_results
varargout{1} = handles.output;
%
% Executes on button press in pushbutton1.
function varargout = MPFOS_herd_version_show_results_OutputFcn(hObject, eventdata, handles)
% varargout  cell array for returning output args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;

% --- Executes on button press in pushbutton1.
function pushbutton1_Callback(hObject, eventdata, handles)
    % hObject    handle to pushbutton1 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % --- Executes on button press in radiobutton9.
    function radiobutton9_Callback(hObject, eventdata, handles)
    % hObject    handle to radiobutton9 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hint: get(hObject,'Value') returns toggle state of radiobutton9

    % --- Executes on button press in radiobutton10.
    function radiobutton10_Callback(hObject, eventdata, handles)
    % hObject    handle to radiobutton10 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hint: get(hObject,'Value') returns toggle state of radiobutton10

    % --- Executes on button press in radiobutton11.
    function radiobutton11_Callback(hObject, eventdata, handles)
    % hObject    handle to radiobutton11 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hint: get(hObject,'Value') returns toggle state of radiobutton11

    % --- Executes on button press in radiobutton12.
    function radiobutton12_Callback(hObject, eventdata, handles)
    % hObject    handle to radiobutton12 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hint: get(hObject,'Value') returns toggle state of radiobutton12

    % --- Executes on button press in pushbutton2.
    function pushbutton2_Callback(hObject, eventdata, handles)
    % hObject    handle to pushbutton2 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % --- Executes on button press in radiobutton13.
    function radiobutton13_Callback(hObject, eventdata, handles)
    % hObject    handle to radiobutton13 (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hint: get(hObject,'Value') returns toggle state of radiobutton13

    % --- Executes on button press in Polynomial.
    function Polynomial_Callback(hObject, eventdata, handles)
% hObject    handle to Polynomial (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model11_trigger = get(handles.Polynomial, 'Value');
set(handles.Polynomial,'UserData',model11_trigger);
% Hint: get(hObject,'Value') returns toggle state of Polynomial

% --- Executes on button press in Adaptive_Polynomial.
function Adaptive_Polynomial_Callback(hObject, eventdata, handles)
% hObject    handle to Adaptive_Polynomial (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model12_trigger = get(handles.Adaptive_Polynomial, 'Value');
set(handles.Adaptive_Polynomial,'UserData',model12_trigger);
% Hint: get(hObject,'Value') returns toggle state of Adaptive_Polynomial

% --- Executes on button press in Legendre_Polynomial.
function Legendre_Polynomial_Callback(hObject, eventdata, handles)
% hObject    handle to Legendre_Polynomial (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model13_trigger = get(handles.Legendre_Polynomial, 'Value');
set(handles.Legendre_Polynomial,'UserData',model13_trigger);
% Hint: get(hObject,'Value') returns toggle state of Legendre_Polynomial

% --- Executes on button press in Cubic_Splines.
function Cubic_Splines_Callback(hObject, eventdata, handles)
% hObject    handle to Cubic_Splines (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model14_trigger = get(handles.Cubic_Splines, 'Value');
set(handles.Cubic_Splines,'UserData',model14_trigger);
% Hint: get(hObject,'Value') returns toggle state of Cubic_Splines

% --- Executes on button press in NARX.
function NARX_Callback(hObject, eventdata, handles)
% hObject    handle to NARX (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model132_trigger = get(handles.NARX, 'Value');
set(handles.NARX,'UserData',model132_trigger);
% Hint: get(hObject,'Value') returns toggle state of NARX

% --- Executes on button press in Log_quadratic.
function Log_quadratic_Callback(hObject, eventdata, handles)
% hObject    handle to Log_quadratic (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model115_trigger = get(handles.Log_quadratic, 'Value');
set(handles.Log_quadratic,'UserData',model115_trigger);
% Hint: get(hObject,'Value') returns toggle state of Log_quadratic

% --- Executes on button press in MLR.
function MLR_Callback(hObject, eventdata, handles)
% hObject    handle to MLR (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model21_trigger = get(handles.MLR, 'Value')
set(handles.MLR,'UserData',model21_trigger);
% Hint: get(hObject,'Value') returns toggle state of MLR

% --- Executes on button press in SANN.
function SANN_Callback(hObject, eventdata, handles)
% hObject handle to SANN (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model22_trigger = get(handles.SANN, 'Value');
set(handles.SANN,'UserData',model22_trigger);
% Hint: get(hObject,'Value') returns toggle state of SANN

% --- Executes on button press in Surface_Fitting.
function Surface_Fitting_Callback(hObject, eventdata, handles)
% hObject handle to Surface_Fitting (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)
model23_trigger = get(handles.Surface_Fitting, 'Value');
set(handles.Surface_Fitting,'UserData',model23_trigger);
% Hint: get(hObject,'Value') returns toggle state of Surface_Fitting

% --- Executes on button press in Average_of_Training.
function Average_of_Training_Callback(hObject, eventdata, handles)
% hObject handle to Average_of_Training (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

% Hint: get(hObject,'Value') returns toggle state of Average_of_Training