Advances in Manufacturing Technology XXX

The urgent need to keep pace with the accelerating globalization of manufacturing in the 21st century has produced rapid advancements in manufacturing technology, research and expertise.

This book presents the proceedings of the 14th International Conference on Manufacturing Research (ICMR 2016), entitled Advances in Manufacturing Technology XXX. The conference also incorporated the 31st National Conference on Manufacturing Research, and was held at Loughborough University, Loughborough, UK, in September 2016. The ICMR conference is renowned as a friendly and inclusive environment which brings together a broad community of researchers who share the common goal of developing and managing the technologies and operations key to sustaining the success of manufacturing businesses.

The proceedings is divided into 14 sections, including: Manufacturing Processes; Additive Manufacturing; Manufacturing Materials; Advanced Manufacturing Technology; Product Design and Development, as well as many other aspects of manufacturing management and innovation. It contains 92 papers, which represents an acceptance rate of 75%.

With its comprehensive overview of current developments, this book will be of interest to all those involved in manufacturing today.

ISBN 978-1-61499-667-5 (print)
ISBN 978-1-61499-668-2 (online)
ISSN 2352-751X (print)
ISSN 2352-7528 (online)

9 781614 996675

IOS Press

3

Advances in Manufacturing Technology XXX

Y.M. Goh and K. Case (Eds.)

IOS Press

Advances in Transdisciplinary Engineering series

volume 3

Advances in Manufacturing Technology XXX

Proceedings of the 14th International Conference on Manufacturing Research, incorporating the 31st National Conference on Manufacturing Research, September 6 – 8, 2016, Loughborough University, UK

EDITED BY
Yee Mey Goh
Keith Case

IOS Press

Advances in Transdisciplinary Engineering

Advances in Transdisciplinary Engineering (ATDE) is a peer-reviewed book series covering the developments in the key application areas in product quality, production efficiency and overall customer satisfaction.

ATDE will focus on theoretical, experimental and case history-based research, and its application in engineering practice. The series will include proceedings and edited volumes of interest to researchers in academia, as well as professional engineers working in industry.

Volume 3

Recently published in this series

Vol. 2. R. Curran, N. Wognum, M. Borsato, J. Stjepandić and W.J.C. Verhagen (Eds.), Transdisciplinary Lifecycle Analysis of Systems – Proceedings of the 22nd ISPE Inc. International Conference on Concurrent Engineering, July 20–23, 2015

Vol. 1. J. Cha, S.-Y. Chou, J. Stjepandić, R. Curran and W. Xu (Eds.), Moving Integrated Product Development to Service Clouds in the Global Economy – Proceedings of the 21st ISPE Inc. International Conference on Concurrent Engineering, September 8–11, 2014

ISSN 2352-751X (print)
ISSN 2352-7528 (online)

Advances in Manufacturing Technology XXX

Proceedings of the 14th International Conference on Manufacturing Research

Incorporating the 31st National Conference on Manufacturing Research

September 6–8, 2016
Loughborough University, UK

Edited by

Yee Mey Goh
Loughborough University, UK

and

Keith Case
Loughborough University, UK

IOS Press

Amsterdam • Berlin • Washington, DC

Dr Pedro Ferreira, Loughborough University
Dr Yee Mey Goh, Loughborough University
Dr Ian Graham, Loughborough University
Dr David Hutt, Loughborough University
Dr Laura Justham, Loughborough University
Dr Peter Kinnell, Loughborough University
Dr Niels Lohse, Loughborough University
Dr Irfan Manarvi, Prince Sultan University, KSA
Dr Radmehr Monfared, Loughborough University
Dr Mahmoud Shafik, University of Derby
Professor Yi Qin, Strathclyde University
Josip Stjepandic, PROSTEP AG
Professor Andrew Thomas, Cardiff Metropolitan University
Dr Zahid Usman, Coventry University
Dr Elliot Woolley, Loughborough University

Contents

Preface and Acknowledgements v
Yee Mey Goh and Keith Case

Organising Committee ix

Part 1. Keynote

The Hidden Information and Its Potential in Manufacturing Data (abstract) 3
Tom Neat and Felix Ng

Part 2. Manufacturing Processes

Toolpath Geometry and High Speed Machine Axis Motion 7
L. Chanda and R.J. Cripps

Numerical Modelling and Simulation of Temperature Distribution in End Milling 13
Sunday Joshua Ojolo, Ibukunoluwa Aina and Gbeminiyi Musibau Sobamowo

Investigating the Sensitivities of Tool Wear When Applied to Monitoring Various Technologies for Micro Milling and Drilling 19
James M. Griffin and Hala Abdelaziz

Vibro-Impact Machining – An Application in Surface Grinding 25
Andre D.L. Batako, Heisum Ewad, Grzegorz Bechcinski and Witold Pawlowski

Structural Transformations of Polymers Using Laser Irradiation 31
Jimsher N. Aneli, Nana V. Bakradze, Teimuraz N. Dumbadze and Andre D.L. Batako

Finite Element Analysis of Single Point Incremental Forming 37
Spyridon Kotsis and Jonathan Corney

Injection Moulding – Properties Customisation by Varying Process Conditions 43
Tino Meyer, Paul Sherratt, Andy Harland, Barry Haworth, Chris Holmes and Tim Lucas

Simulation of Material Removal in Mould Polishing for Polymer Optic Replication 49
Rui Almeida, Rainer Börret, Wolfgang Rimkus, David K. Harrison and Anjali De Silva

Fabrication of Micro Components with MSZ Material Using Electrical-Field Activated Powder Sintering Technology 55
Hasan Hijji, Yi Qin, Kunlan Huang, Song Yang, Muhammad Bin Zulkipli and Jie Zhao

Forming Alumina (Al_2O_3) by Micro-FAST 61
Hasan Hijji, Yi Qin, Kunlan Huang, Muhammad Bin Zulkipli, Song Yang and Jie Zhao

A Methodology for Assessing the Feasibility of Producing Components by Flow Forming 67
Daniele Marini, David Cunningham and Jonathan R. Corney

Texturing of Tool Insert Using Femtosecond Laser 73
Ashfaq Khan, Aftab Khan, Kamran Shah, Izhar Ul Haq, Mushtaq Khan, Syed Husain Imran, Mohammad A. Sheikh and Lin Li

Part 3. Additive Manufacturing

Challenges of Redesigning a Planetary Transmission to Be Made by Additive Manufacturing 81
Adrian Cubillo and Suresh Perinpanayagam

Investigating Relationships Between Laser Metal Deposition Deployment Conditions and Material Microstructural Evolution 87
Mike Wilson, Grant Payne, Abdul Ahmad, Stephen Fitzpatrick, William Ion and Paul Xirouchakis

Remanufacturing H13 Steel Moulds and Dies Using Laser Metal Deposition 93
Grant Payne, Abdul Ahmad, Stephen Fitzpatrick, Paul Xirouchakis, William Ion and Michael Wilson

Additive and Hybrid Manufacturing Processes 99
Mark Elvy and Dean Carran

Advancement in Additive Manufacturing & Numerical Modelling Considerations of Direct Energy Deposition Process 104
Quanren Zeng, Zhenhai Xu, Yankang Tian and Yi Qin

Part 4. Manufacturing Materials

The Effects of Composite Microstructure on Normalized Maximum Principal Stress Under Transverse Tension and Shear of a Unidirectional Carbon Fibre Reinforced Composite 113
Rui Cai and Jesper Christensen

Factors Influencing Structural Properties of Low Silicon Bainite Cast Irons 119
Nugzar Khidasheli, Gocha Beradze, Nana Bakradze, Teimuraz Dumbadze and Andre D.L. Batako

Investigation of Machining Parameters for Different Microstructures of AISI P20 in Wire-Cut EDM 125
Sadaf Zahoor, Adeel Shehzad, Muhammad Qaiser Saleem, Muhammad Ayyaz, M. Ehsan and Ali Maqsood

Nanoscale Elastic Recovery of Silicon While Cutting at Different Temperatures: An MD Simulation-Based Study 131
Saeed Zare Chavoshi and Xichun Luo

A Study of Linear Heat Transfer Gradients on 3D Printed Specimens 137
Robert Benham and Fayyaz Rehman

Analysis and Impacts of Chips Formation on Hole Quality During Fibre-Reinforced Plastic Composites Machining 143
Sikiru Oluwarotimi Ismail, Hom Nath Dhakal, Ivan Popov and Johnny Beaugrand

Wear Behaviour of Laser Cladded Ni-Based WC Composite Coating for Inconel Hot Extrusion: Practical Challenges and Effectiveness 149
Lynne McIntosh, Javad Falsafi, Stephen Fitzpatrick and Paul L. Blackwell

Effect of Powder Metallurgy Parameters on the Performance of EDM Tool Electrodes 155
Amoljit Singh Gill and Sanjeev Kumar

A Novel Adaptation of the T-Peel Bimetal Bond Test Based on the Thin Film Bonding Theory Using Cold Roll Bonded AlSn/Steel Bimetal Laminates 161
Laurie Da Silva, Mahmoud El-Sharif, Colin Chisholm and Stuart Laidlaw

Part 5. Advanced Manufacturing Technology

A Path Planning Algorithm for a Materials Handling Gantry Robot and Its Validation by Virtual Commissioning 169
Ruth Fleisch, Robert Schöch, Thorsten Prante and Reinhard Pfefferkorn

Integrating Optimisation with Simulation for Flexible Manufacturing System 175
Boyang Song, Windo Hutabarat, Ashutosh Tiwari and Shane Enticott

Automatic Generation of a Detailed Outfitting Planning and Determining the Effect of Multi-Skilled Mounting Teams 181
Christopher Rose and Jenny Coenen

Development of PID Controller for Vibratory Milling 187
Wael Naji Alharbi, Andre Batako and Barry Gomm

An Application of Autoregressive Hidden Markov Models for Identifying Machine Operations 193
Dimitrios Pantazis, Adrian Ayastuy Rodriguez, Paul P. Conway and Andrew A. West

Improving Data Accuracy in Simulation of Flexible Manufacturing Systems 199
Justyna Rybicka, Ashutosh Tiwari and Shane Enticott

AFRC's Image Processing Platform: A High Speed User-Friendly Architecture for Real Time Object Detection in Forging Processes 205
Danial Kahani and Remi Zante

A Multi Degree of Freedom Actuation System for Robot and Machine Vision Industrial Applications 211
Mfortaw Elvis Ashu, Mahmoud Shafik and Ilias Oraifige

Part 6. Human Aspects of Manufacturing

Deployment of Assisted Living Technology Using Intelligent Body Sensors Platform for Elderly People Health Monitoring 219
Riyad Elsaadi and Mahmoud Shafik

Motivation and Learning in Manufacturing Industries 225
Shafizal Mat, Keith Case, Shahrol Mohamaddan and Yee Mey Goh

Cognitive Aspects Affecting Human Performance in Manual Assembly 231
Anna Brolin, Keith Case and Peter Thorvald

Ergonomic Risk Assessment – A Case Study of a Garment Manufacturing Industry 237
Amjad Hussain, Iqra Javed, Keith Case, Ashfaq Ahmad and Nadeem Safdar

Distributed Cognition in Manufacturing: Collaborative Assembly Work 243
Rebecca Andreasson, Jessica Lindblom and Peter Thorvald

Agile Assembly Planning for Multi-Variant Production Based on 3D PDF 249
Felix Kahl, Stefan Rulhoff, Josip Stjepandić and Klaus Thatenhorst

The Impacts of Ageing on Manufacturing Sectors 255
Renuga Nagarajan and Patrícia Ramos

Part 7. Product Design and Development

Design Optimisation of Passive Humidification Device for Intensive Care Medical Applications 263
Mahmoud Shafik and Anne Lechevretel

Evaluation of 3D Renewable Micro Power Station for Smart Grid Applications 269
Moglo Komlanvi, Mahmoud Shafik and Mfortaw Elvis Ashu

Design & Development of a Bicycle Cleat Adapter 275
Fayyaz Rehman and Santiago Díaz Montalvo

3D Alignment for Interactive Evolutionary Design 281
Theodora Retzepi, Ian J. Graham and Yee Mey Goh

Design and Manufacturing of a Miniature Insulin Administration Device for Non Compliant Diabetic Patients of Kingdom of Saudi Arabia (KSA) 287
Irfan Anjum Manarvi and Nader Maher Kamel Matta

Identifying Sequence Maps or Locus to Represent the Genetic Structure or Genome Standard of Styling DNA in Automotive Design 293
Shahriman Zainal Abidin, Azlan Othman, Zafruddin Shamsuddin, Zaidi Samsudin, Halim Hassan and Wan Asri Wan Mohamed

Design and Manufacturing of a Fire Protection Suit Through Reverse Engineering 299
Irfan Anjum Manarvi and Haris Rehman

An Intelligent Anti-Collision System for Electric Vehicles Applications 305
Ikenna Chinazaekpere Ijeh and Mahmoud Shafik

A Case Study Analysis of the Application of Design for Manufacture Principles by Industrial Design Students 311
Russell Marshall and Tom Page

Part 8. Digital Manufacturing (Industrie 4.0)

Industrie 4.0 Implementations in the Automotive Industry 319
Diana Segura-Velandia, Aaron Neal, Paul Goodall, Paul Conway and Andrew West

Component Detection with an On-Board UHF RFID Reader for Industrie 4.0 Capable Returnable Transit Items 325
Aaron Neal, Diana Segura-Velandia, Paul Conway and Andrew West

Factory Automation and Information Technology Convergence in Complex Manufacturing 331
Ip-Shing Fan and Leon Oswin

Optimising Mixed Model Assembly Lines for Mass Customisation: A Multi Agent Systems Approach 337
Olatunde Banjo, David Stewart and Maria Fasli

A Data Management System for Identifying the Traceability of Returnable Transit Items Using Radio Frequency Identification Portals 343
Paul Goodall, Aaron Neal, Diana Segura-Velandia, Paul Conway and Andrew West

Product Lifecycle Management Enabled by Industry 4.0 Technology 349
Filipe Ferreira, José Faria, Américo Azevedo and Ana Luisa Marques

Part 9. Sustainable Manufacturing

Development of a Simulation-Based Approach to Smart Management of Energy Consumption in Buildings and Their Implementation 357
A.N.R. Pour and K. Cheng

A Decision Support Tool for Improving Value Chain Resilience to Critical Materials in Manufacturing 363
Liam Gardner and James Colwill

Lean & Green, How to Encourage Industries to Establish Pro-Environmental Behaviour 369
Elzbieta Pawlik, Dagmara Gutowska, Remigiusz Horbal, Zofia Maśluszczak, Robert Miehe, Ivan Bogdanov and Ralph Schneider

A Manufacturing Approach to Reducing Consumer Food Waste 375
Aicha Jellil, Elliot Woolley, Guillermo Garcia-Garcia and Shahin Rahimifard

Societal Benefit Assessment: An Integrated Tool to Support Sustainable Toy Design and Manufacture 381
Kei Lok Felix Shin and James Colwill

Sustainable Process Planning for Customized Production Optimization 387
Sheng Wang, Xin Lu and Weidong Li

An Examination of Application Scale for Material Flow Assessment in Manufacturing Systems 393
Oliver Gould and James Colwill

Part 10. Information and Knowledge Management

An Investigation into the Management of Design for Manufacturing Knowledge in an Aerospace Company 401
Mohammed El Souri, James Gao, Oladele Owodunni, Clive Simmonds and Nick Martin

Networked Engineering Notebooks for Smart Manufacturing 407
Peter Denno, Charles Dickerson and Jennifer Harding

Investigation into the Design and Development of Knowledge-Based Innovation Processes in Manufacturing Companies 413
Lakhvir Singh, Reza Ziarati, Martin Ziarati, Richard Gatward and Feng Chen

Intelligent Semantic Query for Manufacturing Supply Chain 419
Salman Saeidlou, Mozafar Saadat and Ebrahim Amini Sharifi

Part 11. Organisation Management

Organizational Learning Capability: An Empirical Assessment of Innovative Supply Chain Development 427
Andrew Thomas, Peter Dorrington, Filipa Costa and Gareth Loudon

Manufacturing Supply Chain Demand Study – Profiling UK Manufacturing Performance 433
Andrew Thomas, Hefin Rowlands, Peter Dorrington, Filipa Costa, Mark Francis and Ron Fisher

An Investigation into Re-Shoring Decision: Case Study Approach 439
Hamid Moradlou and Chris Backhouse

Conceptual Understanding, Design and Management of Supply Chain in 21st Century – A Review 445
Sameh M. Saad and Adewale A. Ogunsanwo

A Review of Resilience Within the UK Food Manufacturing Sector 451
James Colwill, Stella Despoudi and Ran Bhamra

Responsiveness Optimisation in the Fractal Supply Network 457
Sameh M. Saad and Ramin Bahadori

Part 12. Cost Engineering and Forecasting

Process Selection Using Variation and Cost Relations 465
Vincent McKenna, Yan Jin, Adrian Murphy, Michael Morgan, Caroline McClory, Colm Higgins and Rory Collins

Cost Modelling for Aircraft in a Multi-Disciplinary Design Context 471
Davide Di Pasquale, David Gore, Mark Savill, Timoleon Kipouros and Carren Holden

Management of Promotional Activity Supported by Forecasts Based on Assorted Information 477
Cátia Ribeiro, José Manuel Oliveira and Patrícia Ramos

Sales Forecasting in Retail Industry Based on Dynamic Regression Models 483
José Manuel Pinho, José Manuel Oliveira and Patrícia Ramos

Evaluating the Forecasting Accuracy of Pure Time Series Models on Retail Data 489
Patrícia Ramos, José Manuel Oliveira and Rui Rebelo

Part 13. Lean and Quality Management

Development of Lean Six-Sigma Conceptual Implementation Model for Manufacturing Organisations 497
Sameh M. Saad and Mohamed Khamkham

Do Inspections Really Help? 503
Moshe Eben Chaime

The Quality Journey of Greek SMEs 508
G. Sainis, G. Haritos, Th. Kriemadis and M. Fowler

Creating Industrially Relevant Environments for Teaching Lean Manufacturing at Karlstad University 514
Lasse Jacobsson, Anders Wickberg and Leo De Vin

Part 14. Decision Support and Optimisation

Critical Success Factors for In-House Production, Partial Production or Outsourcing in Garment Industry 523
C.S. Libânio, Fernando Gonçalves Amaral and Sérgio Almeida Migowski

Fuzzy Analytic Hierarchy Process for the Selection of Maintenance Policies Within Petroleum Industry 529
Abdel M. Mohamed and Sameh M. Saad

Application of a Multivariate Process Control Technique for Set-Up Dominated Low Volume Operations 535
Steven Cox, Scott Anderson, Neil Gray, Oliver Vogt and Apostolos Kotsialos

Standardization of Smart Manufacturing Change Management 541
Nils Macke, Stefan Rulhoff and Josip Stjepandić

An Analytical Hierarchy Process Based Evaluation of Global Facility Location Methodologies 547
Hafiz Muhammad Khurram Ali, Khalid Akhtar and Mirza Jahanzaib

Influencing Factors for Implementing Automation in Manufacturing Businesses – A Literature Review 553
Simon Micheler, Yee Mey Goh and Niels Lohse

Part 15. Manufacturing Business Innovation

Productisation Business Model in Non-OEM Aero-Engine MRO Service Providers 561
Arie Wibowo, Benny Tjahjono and Tetsuo Tomiyama

Operational Acceptance Testing of Manufacturing Process Innovation Initiatives 567
Alireza Javahernia and Funlade T. Sunmola

Selecting Innovation Deployment Risk Response Strategies via Simulation Optimisation 573
Funlade T. Sunmola and Alireza Javahernia

Subject Index 579

Author Index 583

Part 1

Keynote

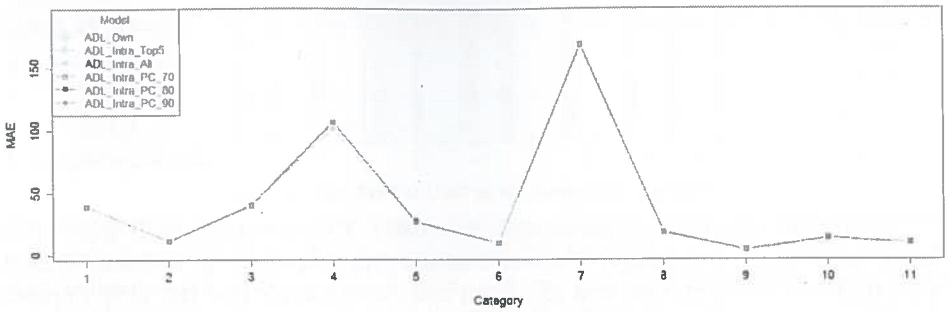

Figure 2. MAE of all models by category.

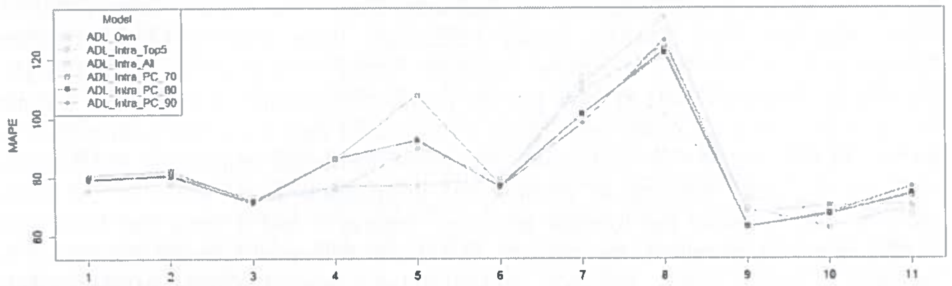

Figure 3. MAPE of all models by category.

Acknowledgements

Project "TEC4Growth - Pervasive Intelligence, Enhancers and Proofs of Concept with Industrial Impact/NORTE-01-0145-FEDER-000020" is financed by the North Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, and through the European Regional Development Fund (ERDF).

References

[1] D. Mourtzis, M. Doukas and F. Psarommatis, Design and operation of manufacturing networks for mass customisation, *CIRP Annals - Manufacturing Technology* **62**(1) (2013), 467-470.

[2] D. Mourtzis, M. Doukas and F. Psarommatis, A multi-criteria evaluation of centralized and decentralized production networks in a highly customer-driven environment, *CIRP Annals - Manufacturing Technology* **61** (1) (2012), 427-430.

[3] A.J. Dietrich, S. Kirn and V. Sugumaran, A service-oriented architecture for mass customization – a shoe industry case study, *IEEE Transactions on Engineering Management* **54**(1) (2007), 190-204.

[4] T. Huang, R. Fildes and D. Soopramanien, The value of competitive information in forecasting FMCG retail product sales and the variable selection problem, *European Journal of Operational Research* **237**(2) (2014), 738-748.

[5] P. Ramos, N. Santos and R. Rebelo, Performance of state space and ARIMA models for consumer retail sales forecasting, *Robotics and Computer-Integrated Manufacturing* **34** (2015), 151-163.

[6] S. Ma, R. Fildes and T. Huang, Demand forecasting with high dimensional data: The case of SKU retail sales forecasting with intra- and inter-category promotional information, *European Journal of Operational Research* **249(1)** (2016), 245-257.

Advances in Manufacturing Technology XXX
Y.M. Goh and K. Case (Eds.)
IOS Press, 2016

doi:10.3233/978-1-61499-668-2-483

Sales Forecasting in Retail Industry Based on Dynamic Regression Models

José Manuel PINHO[a], José Manuel OLIVEIRA[a,b] and Patrícia RAMOS[b,c,1]
[a] *Faculty of Economics, University of Porto, 4200-464 Porto, PORTUGAL.*
[b] *INESC Technology and Science, Campus da FEUP, 4200-465 Porto, PORTUGAL.*
[c] *School of Accounting and Administration of Porto, Polytechnic Institute of Porto, 4465-004 S. Mamede de Infesta PORTUGAL.*

Abstract. Sales forecasts gained more importance in the retail industry with the increasing of promotional activity, not only because of the considerable portion of products under promotion but also due to the existence of promotional activities, which boost product sales and make forecasts more difficult to obtain. This study is performed with real data from a Portuguese consumer goods retail company, from January 2012 until April 2015. To achieve the purpose of the study, dynamic regression is used based on information of the focal product and its competitors, with seasonality modelled using Fourier terms. The selection of variables to be included in the model is done based on the lowest value of AIC in the train period. The forecasts are obtained for a test period of 30 weeks. The forecasting models overall performance is analyzed for the full period and for the periods with and without promotions. The results show that our proposed dynamic regression models with price and promotional information of the focal product generate substantially more accurate forecasts than pure time series models for all periods studied.

Keywords. Retailing, machine learning, forecasting, time series, promotions, dynamic regression.

1. Introduction

The effectiveness of sales forecasting is gaining increasingly importance in the retail sector. With retailers continuously trying to minimize stock and increase customer satisfaction it helps to reduce inventory investment costs and to improve logistics operations. A bad sales forecast may cause losses to the retailer, either by rupture or by excess of stock. Recent studies [1] indicate that in the case of rupture of stock of a product consumers decide to change to another store, not purchasing a replacement product, as initially thought. The promotional activity has increased sharply in recent years leading usually to a considerable increase of sales in the periods in which products are under promotional actions [2]. The efficacy of simple forecast methods, often used in the retail sector, is reduced when applied to periods when there are promotions [3]. The aim of this work is to incorporate promotions on econometric models to improve sales forecasting, especially in periods of promotional campaigns, and measure the impact of promotions on sales. This analysis is of particular importance because in recent literature models that integrate the promotional activity of

[1] Corresponding Author. pramos@inesctec.pt

food retail companies are relatively scarce [4-6]. We applied this approach to sales data from a Portuguese retailer trying to analyze which models perform better in this promotional context. The rest of the paper is organized as follows. Section 2 presents the case study and relevant descriptive statistics of data. Section 3 identifies the methodology used in the work. The results are presented and analyzed on Section 4. Finally, Section 5 points the main conclusions of this work.

2. Data

This study used information from daily sales of a single store of a Portuguese retailer, from January 2012 until April 2015. The option for a single store is due to the purpose of analyzing the influence of competing products (available in the store) on each product. This store had 24316 products of the following areas: groceries (6217), beverages (1995), not specialized products (3682), specialized products (6302), personal products (3606), and cleaning products (2514). From these products, a sample of 968 products that had sales on every weeks (173 weeks) was selected. The sample was further reduced to 15 categories representing the six areas mentioned above totaling 100 SKUs (Stock Keeping Unit). Table 1 presents some descriptive statistics of these 15 categories (ordered by the average percentage of promotion weeks). The lift was calculated as the percentage increase of the average weekly sales on weeks with promotions when compared with the average weekly sales on weeks without promotions. The sales time series of different products have different types of behavior including seasonality (left side of Figure 1) and negative (right side of Figure 1) and positive trends. Note that in Figure 1 the product price is represented by a red line, the sales by a black line and promotions in sales are marked with a blue ball.

Table 1. Descriptive statistics of the sample.

	Category	Nº of SKUs	Promo weeks (%)	Lift (%)		Category	Nº of SKUs	Promo weeks (%)	Lift (%)
1	Pork fresh meat	11	24.43	163	9	Cereals	12	6.21	461
2	Cola	8	16.11	182	10	Ice-creams	13	5.56	303
3	Beer	10	12.43	271	11	Toilet paper	5	5.2	158
4	Sugar	2	10.12	200	12	Wash all	6	5.01	269
5	Cooking oil	5	8.78	453	13	UHT milk	5	4.74	166
6	Tuna	5	7.17	450	14	Rice	8	3.97	249
7	Deodorant	4	6.94	368	15	Laundry detergent	2	1.44	163
8	Olive oil	4	6.65	648					

3. Methodology

This section presents the models used in the sales forecasting. We used a more advanced approach based on dynamic regression, which was compared with a pure time series forecasting model, in this case ARIMA (Autoregressive Integrated Moving Average), where the only information used was the sales history of the focal product. The ARIMA model (1.ARIMA) is given by

$$(1-\varphi_1 B-\cdots-\varphi_p B^p)(1-\Phi_1 B^s-\cdots-\Phi_p B^s)(1-B)^d(1-B^s)^D Y_t = c+(1-\theta_1 B-\cdots-\theta_q B^q)(1-\Theta_1 B^s-\cdots-\Theta_q B^s)\varepsilon_t, \quad (1)$$

where $(1-B)^d(1-B^s)^D Y_t$ represents a stationary series after being differentiated d and seasonally differentiated D times, $\varphi_1,\dots,\varphi_p$ and $\Phi_1,\dots,\Phi_p$ are respectively the nonseasonal and seasonal autoregressive parameters, $\theta_1,\dots,\theta_q$ and $\Theta_1,\dots,\Theta_q$ are respectively the nonseasonal and seasonal moving average parameters and ε_t is the error term assumed iid$(0,\sigma^2)$. In order to incorporate more than one seasonal pattern, which is common in the retail sector, an evolution of the ARIMA model was considered (3.ARIMA Fourier)

$$Y_t = \beta_0 + \sum_{j=1}^{k}\left[\alpha j \sin\left(\frac{2\pi jt}{Freq}\right) + \beta\text{j} \cos\left(\frac{2\pi jt}{Freq}\right)\right] + n_t, \quad (2)$$

where the sin and cos terms, usual known as the Fourier terms, incorporate seasonality and n_t the ARIMA structure. The first two dynamic regression models (1 and 2) only use variables of the own product to explain its sales (5.OWN). Those variables are the price, the number of week days with promotion, calendar events and the last week of the month. Lags of two time instants were also considered for the first two co-variables

$$Y_t = \beta_0 + \beta_1 Price_t + \beta_2 Price_{t-1} + \beta_3 Price_{t-2} + \beta_4 PromotionDays_t + \beta_5 PromotionDays_{t-1} + \beta_6 PromotionDays_{t-2} + \beta_7 4^{th}week_t + \beta_8 CalendarEvents_t + n_t. \quad (3)$$

An evolution of these models also incorporates co-variables from competitive products from the same category (6.OWN intra). These variables are selected through Principle Component Analysis (PCA) done over the price, the number of week days with promotion and the lags of two time instants of these two variables, from the competitive products. This model is given by

$$Y_t = \beta_0 + \beta_1 x_t + \cdots + \beta_f PCA(Price_{m,t}) + \beta_g PCA(PromotionDays_{m,t}) + n_t. \quad (4)$$

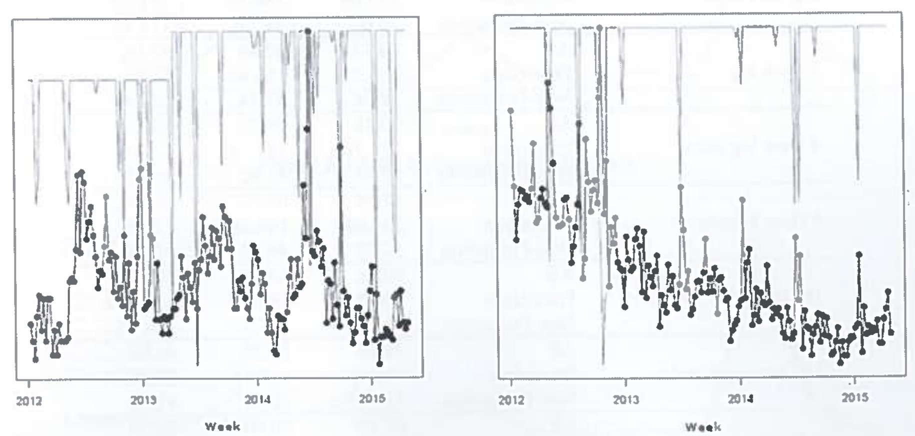

Figure 1. Weekly sales, price and promotions of two products.

For these last two dynamic regression models (3 and 4), the equivalent ones obtained by incorporating the Fourier terms were also considered (9.Own Fourier and 10.Own intra Fourier). For all the previous six models, we also consider the equivalent ones resulting from applying the logarithm to the sales and price, identified in the model name by the *log* tag (2.ARIMA log, 4.ARIMA Fourier log, 7.Own log, 8.Own log intra, 11.Own log Fourier and 12.Own log intra Fourier). In order to compare the several forecasting models three error measures were used namely the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) [7].

4. Results and discussion

This section analyzes the results obtained using the twelve models presented in Section 3. For the models performance evaluation a test period of 30 weeks was considered and one-step forecasts with fixed origin were obtained. Table 2 shows the results of the error measures obtained by all models splitted into three periods: the full period and the periods with and without promotion. Bold values show the best result for each period.

Table 2. Models overall performance for the full period and for the periods with and without promotion.

Model	Period	RMSE	MAE	MAPE
1.ARIMA	All	111.60	79.43	102.70
	Promotion	223.44	196.63	74.34
	Non-Promotion	78.78	60.46	112.96
2.ARIMA log	All	110.88	71.39	68.11
	Promotion	245.79	219.12	62.61
	Non-Promotion	65.73	46.75	71.43
3.ARIMA Fourier	All	107.90	79.72	79.86
	Promotion	218.42	193.11	67.47
	Non-Promotion	73.94	63.84	85.92
4.ARIMA Fourier log	All	106.24	72.05	50.92
	Promotion	232.80	205.18	58.58
	Non-Promotion	63.57	53.05	51.52
5.OWN	All	81.82	57.24	83.10
	Promotion	151.48	127.80	144.53
	Non-Promotion	63.95	48.97	75.02
6.OWN intra	All	91.69	65.89	118.29
	Promotion	165.04	140.19	151.40
	Non-Promotion	70.60	54.17	115.22
7.Own log	All	**70.73**	**47.56**	57.16
	Promotion	136.01	113.44	57.88
	Non-Promotion	**49.06**	**37.34**	52.24
8.Own log intra	All	90.38	58.71	58.02
	Promotion	174.28	143.11	77.77
	Non-Promotion	57.25	43.92	55.01
9.Own Fourier	All	82.56	60.29	68.51
	Promotion	**132.80**	**109.65**	120.51
	Non-Promotion	60.79	49.13	61.68
10.Own intra Fourier	All	90.16	65.16	108.42
	Promotion	400.24	380.67	1617.30
	Non-Promotion	71.79	55.75	104.85
11.Own log Fourier	All	94.94	66.25	**45.90**
	Promotion	140.13	118.55	**55.30**
	Non-Promotion	51.904	38.82	**41.67**
12.Own log intra Fourier	All	91.49	60.00	60.50
	Promotion	368.56	344.24	1343.54
	Non-Promotion	58.79	42.88	58.06

These are the average errors for the 100 sample products. For the three periods considered the model with the best performance is always a dynamic regression model, which indicates that additional information besides the sales of the product itself can

improve the forecast accuracy. However, the competitive information from the products of the same category of the focal product provided by the PCA (the intra models) does not improve the forecasting performance in any case, regardless of the error measure considered. In which concerns the RMSE and the MAE values the 7.Own log model forecasts are the most accurate for the full period and for the period without promotion. This indicates that the price and promotional information about the focal product is always important to improve the forecast accuracy of the model even for periods without promotion. Also concerning the RMSE and the MAE values the 9.Own Fourier model forecasts are the most accurate for the period with promotion which points that Fourier terms can be successfully used to model seasonality in dynamic regression. When considering the MAPE value the 11.Own log Fourier model forecasts are the most accurate for all the periods studied which reinforces the importance of the logarithm transformation applied to sales and price and the Fourier terms to additionally model multiple seasonality. It can also be observed that the RMSE and MAE values are always higher for the period with promotion which shows that sales with promotional actions at the product level in a particular store are difficult to forecast. The differences to periods without promotion is even higher in the pure models (1.ARIMA, 2.ARIMA log, 3.ARIMA Fourier, 4.ARIMA Fourier log) which indicates that the additional information besides the sales of the focal product always improve the forecast accuracy. Figures 2, 3 and 4 show respectively RMSE, MAE and MAPE by category for each model for the full test period. It is clear from Figure 4 that all models have similar performance for categories with fewer promotions (11-15). However for categories with more promotions and higher lifts the dynamic regression models have much better performance than pure ones.

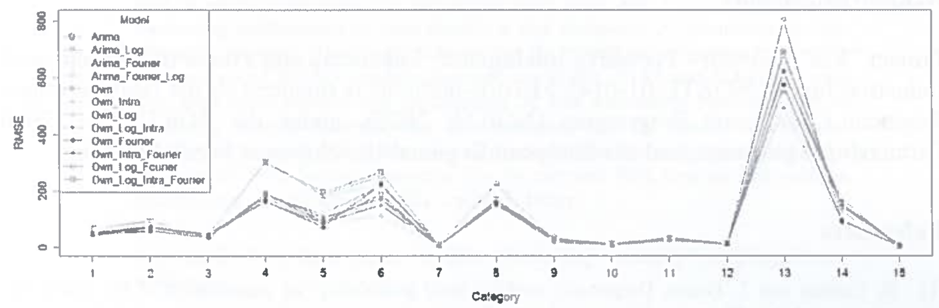

Figure 2. RMSE by category for all models.

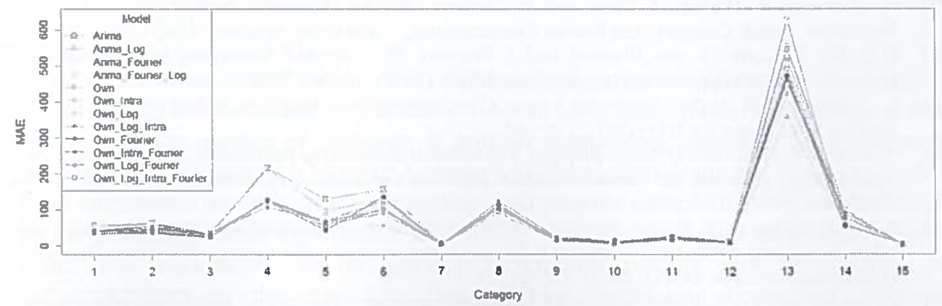

Figure 3. MAE by category for all models.

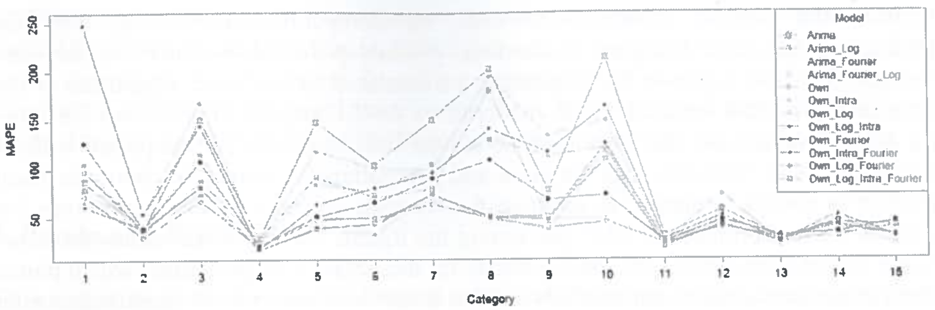

Figure 4. MAPE by category for all models.

5. Conclusions

Sales forecasting is a major challenge in retail industry particularly in the context of continuous promotional activity. In this work dynamic regression models based on price and promotional information of the focal product and its competitors, and Fourier terms to accommodate multiple seasonality, are used for sales forecasting. The forecasting models overall performance is analyzed for the full test period and for the periods with and without promotions. The results show that the dynamic regression models generate substantially more accurate forecasts than pure time series models for all periods studied.

Acknowledgements

Project "TEC4Growth - Pervasive Intelligence, Enhancers and Proofs of Concept with Industrial Impact/NORTE-01-0145-FEDER-000020" is financed by the North Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, and the European Regional Development Fund (ERDF).

References

[1] D. Corsten and T. Gruen, Desperately seeking shelf availability: an examination of the extent, the causes, and the efforts to address retail out-of-stocks, *International Journal of Retail & Distribution Management* **31(12)** (2003), 605-617.

[2] K. Ailawadi, B. Harlam, J. Cesar and D. Trounce, Retailer Promotion Profitability: The Role of Promotion, Brand, Category, and Market Characteristics, *J. Marketing Research* **43(4)** (2006), 518-535.

[3] Ö.G Ali, S. Sayin, T. van Woensel and J. Fransoo, SKU demand forecasting in the presence of promotions, *Expert Systems with Applications* **36(10)** (2009), 12340-12348.

[4] L. Aburto and R. Weber, Improved supply chain management based on hybrid demand forecasts, *Applied Soft Computing* **7(1)** (2007), 136-144.

[5] T. Huang, R. Fildes and D. Soopramanien, The value of competitive information in forecasting FMCG retail product sales and the variable selection problem, *European J. Operational Res.* **237(2)** (2014), 738-748.

[6] S. Ma, R. Fildes and T. Huang, Demand forecasting with high dimensional data: the case of SKU retail sales forecasting with intra- and inter-category promotional information, *European Journal of Operational Research* **249(1)** (2014), 245-257.

[7] A. Davydenko and R. Fildes, Measuring forecasting accuracy: The case of judgmental adjustments to SKU-level demand forecasts, *International Journal of Forecasting* **29(3)** (2013), 510-522.

Advances in Manufacturing Technology XXX
Y.M. Goh and K. Case (Eds.)
IOS Press, 2016

doi:10.3233/978-1-61499-668-2-489

Evaluating the Forecasting Accuracy of Pure Time Series Models on Retail Data

Patrícia RAMOS[a,b,1], José Manuel OLIVEIRA[a,c] and Rui REBELO[a]
[a] *INESC Technology and Science, Campus da FEUP, 4200-465 Porto, PORTUGAL.*
[b] *School of Accounting and Administration of Porto, Polytechnic Institute of Porto, 4465-004 S. Mamede de Infesta, PORTUGAL.*
[c] *Faculty of Economics, University of Porto, 4200-464 Porto, PORTUGAL.*

Abstract. Forecasting future sales is one of the most important issues that is beyond all strategic and planning decisions in effective operations of retail supply chains. For profitable retail businesses, accurate sales forecasting is crucial in organizing and planning purchasing, production, transportation and labor force. Retail sales series belong to a special type of time series that typically contain strong trend and seasonal patterns, presenting challenges in developing effective forecasting models. This paper compares the forecasting performance of state space models and ARIMA models. The forecasting performance is demonstrated through a case study of retail sales of five different categories of women footwear: Boots, Booties, Flats, Sandals and Shoes. An approach based on cross-validation is used to identify automatically appropriate state space and ARIMA models. The forecasting performance of these models is also compared by examining the out-of-sample forecasts. The results indicate that the overall out-of-sample forecasting performance of ARIMA models evaluated via RMSE, MAE and MAPE is better than state space models. The performance of both forecasting methodologies in producing forecast intervals was also evaluated and the results indicate that ARIMA produces slightly better coverage probabilities than state space models for the nominal 95% forecast intervals. For the nominal 80% forecast intervals the performance of state space models is slightly better.

Keywords. Pure time series models; forecasting accuracy; retailing; cross-validation

1. Introduction

Time series often exhibit strong trend and seasonal variations presenting challenges in developing effective forecasting models. How to effectively model time series in order to improve the quality of forecasts is still an outstanding question. State space and Autoregressive Integrated Moving Average (ARIMA) models are the two most widely-used approaches to time series forecasting, and provide complementary methodologies to the problem. While exponential smoothing methods are based on a description of trend and seasonality in the data [1], ARIMA models aim to describe the autocorrelations in the data [2]. The ARIMA forecasting framework originally developed by Box *et al.* [3] involves an iterative three-stage process of model selection, parameter estimation and model checking. A statistical framework for exponential

[1] Corresponding Author. pramos@inesctec.pt