University of Maribor

UNIVERSITY OF THE WEST *of* SCOTLAND
UWS

10TH International Conference on Sustainable Energy and Environmental Protection:

Power Distribution

(June 27TH - 30TH, 2017, Bled, Slovenia)

(Conference Proceedings)

Editors:
Emeritus Prof. dr. Jurij Krope
Prof. dr. Abdul Ghani Olabi
Prof. dr. Darko Goričanec
Prof. dr. Stanislav Božičnik

University of Maribor Press

University of Maribor Press

University of Maribor Press

10TH International Conference on Sustainable Energy and Environmental Protection

Power Distribution

(June 27TH – 30TH, 2017, Bled, Slovenia)

(Conference Proceedings)

Editors:
Emeritus Prof. dr. Jurij Krope
Prof. dr. Abdul Ghani Olabi
Prof. dr. Darko Goričanec
Prof. dr. Stanislav Božičnik

June 2017

Title: 10^{TH} International Conference on Sustainable Energy and Environmental Protection (June 27^{TH} – 30^{TH}, 2017, Bled, Slovenia) (Conference Proceedings)

Subtitle: Power Distribution

Editors: Emeritus Prof. Jurij Krope, Ph.D. (University of Maribor, Slovenia),
Prof. Abdul Ghani Olabi, Ph.D. (University of the West of Scotland, UK),
Asso. Prof. Darko Goričanec, Ph.D. (University of Maribor, Slovenia),
Asso. Prof. Stanislav Božičnik (University of Maribor, Slovenia).

Review: Prof. Željko Knez, Ph.D. (University of Maribor, Slovenia),
Prof. Niko Samec, Ph.D. (University of Maribor, Slovenia).

Tehnical editors : Jan Perša (University of Maribor Press),
Armin Turanović (University of Maribor Press).

Design and layout: University of Maribor Press

Conference: 10^{TH} International Conference on Sustainable Energy and Environmental Protection

Honorary Committee: Abdul Ghani Olabi, Ph.D. (Honorary President, University of the West of Scotland, United Kingdom), Igor Tičar, Ph.D (Rector of the University of Maribor, Slovenia), Niko Samec Ph.D. (Pro-rector of University of Maribor, Slovenia), Zdravko Kravanja, Ph-D. (Dean of the Faculty of Chemistry and Chemical Engineering, University of Maribor, Slovenia).

Organising Committee: Jurij Krope, Ph.D. (University of Maribor, Slovenia), Darko Goričanec, Ph.D. (University of Maribor, Slovenia), Stane Božičnik, Ph.D. (University of Maribor, Slovenia), Peter Trop, Ph.D. (University of Maribor, Slovenia), Danijela Urbancl, Ph.D. (University of Maribor, Slovenia), Sonja Roj (University of Maribor, Slovenia), Željko Knez, Ph.D. (University of Maribor, Slovenia), Bojan Štumberger, Ph.D. (University of Maribor, Slovenia), Franci Čuš, Ph.D. (University of Maribor, Slovenia), Miloš Bogataj, Ph.D. (University of Maribor, Slovenia), Janez Žlak, Ph.D (Mine Trbovlje Hrastnik, Slovenia), LL. M. Tina Žagar (Ministry of Economic Development and Technology), Igor Ivanovski, MSc. (IVD Maribor, Slovenia), Nuša Hojnik, Ph.D. (Health Center Maribor).

Programme Committee: Prof. Abdul Ghani Olabi (UK), Emeritus Prof. Jurij Krope (Slovenia), Prof. Henrik Lund (Denmark), Prof. Brian Norton (Ireland), Prof. Noam Lior (USA), Prof. Zdravko Kravanja (Slovenia), Prof. Jirí Jaromír Klemeš (Hungary), Prof. Stane Božičnik (Slovenia), Prof. Bojan Štumberger (Slovenia), Prof. Soteris Kalogirou (Cyprus), Prof. Stefano Cordiner (Italy), Prof. Jinyue Yan (Sweden), Prof. Umberto Desideri (Italy), Prof. M.S.J. Hashmi (Ireland), Prof. Michele Dassisti (Italy), Prof. Michele Gambino (Italy), Prof. S. Orhan Akansu (Turkey), Dr. David Timoney (Ireland), Prof. David Kennedy (Ireland), Prof. Bekir Sami Yilbas (Saudi Arabia), Dr. Brid Quilty (Ireland), Prof. B. AbuHijleh (UAE), Prof. Vincenc Butala (Slovenia), Prof. Jim McGovern (Ireland), Prof. Socrates Kaplanis (Greece), Dr. Hussam Jouhara (UK), Prof. Igor Tičar (Slovenia), Prof. Darko Goričanec (Slovenia), Dr. Joseph Stokes (Ireland), Prof. Antonio Valero (Spain), Prof. Aristide F. Massardo (Italy), Prof. Ashwani Gupta (USA), Dr. Aoife Foley (UK), Dr. Athanasios Megartis (UK), Prof. Francesco Di Maria (Italy), Prof. George Tsatsaronis (Germany), Prof. Luis M. Serra (Spain), Prof. Savvas Tassou (UK), Prof. Luigi Alloca (Italy), Prof. Faek Diko (Germany), Dr. F. Al-Mansour (Slovenia), Dr. Artur Grunwald (Germany), Dr. Peter Trop (Slovenia), Prof. Philippe Knauth (France), Prof. Paul Borza (Romania), Prof. Roy Douglas (UK), Prof. Dieter Meissner (Austria), Dr. Danijela Urbancl (Slovenia), Prof. Daniel Favrat (Switzerland), Prof. Erik Dahlquist (Sweden), Prof. Eric Leonhardt (USA), Prof. GianLuca Rospi (Italy), Prof. Giuseppe Casalino (Italy), Prof. J. Dawson (USA), Dr. Josè Simoes (Portugal), Prof. Kadir Aydin (Turkey), Dr. Khaled Benyounis (Ireland), Prof. Laszlo Garbai (Hungary), Prof. Mariano Martin (Spain), Prof. Masahiro Ishida (Japan), Prof. Michael Seal (USA), Prof. Marco Spinedi (Italy), Prof. Michio Kitano (Japan), Prof. Milovan Jotanović (BiH), Prof. Nafiz Kahraman (Turkey), Prof. Na Zhang (China), Prof. Naotake Fujita (Japan), Prof. Niko Samec (Slovenia), Prof. Oleksandr Zaporozhets (Ukraine), Prof. Osama Al-Hawaj (Kuwait), Prof. Petar Varbanov (Hungary), Prof. Peter Goethals (Belgium), Prof. Qi Zhang (China), Prof. Rik Baert (The Netherlands), Prof. Rolf Ritz (USA), Dr. Stephen Glover (UK), Prof. Signe Kjelstrup (Norway), Dr. Sumsun Naher (UK), Prof. Sven Andersson (Sweden), Dr. Salah Ibrahim (UK), Prof. Sebahattin Unalan (Turkey), Prof. Sabah Abdul-Wahab Sulaiman (Oman), Prof. Somrat Kerdsuwan (Thailand), Prof. T. Hikmet Karakoç (Turkey), Prof. Tahir Yavuz (Turkey), Prof. Hon Loong Lam (Thailand), LL.M. Tina Žagar (Slovenia), Prof. A.M.Hamoda (Qatar), Prof. Gu Hongchen (China), Prof. Haşmet Turkoglu (Turkey), Dr. Hussam Achour (Ireland), Dr. James Carton (Ireland), Dr. Eivind Johannes (Norway), Prof. Elvis Ahmetović (BiH), Prof.

First published in 2017 by
University of Maribor Press
Slomškov trg 15, 2000 Maribor, Slovenia
tel. +386 2 250 42 42, fax +386 2 252 32 45
http://press.um.si, zalozba@um.si

Co-published by
University of Maribor, Faculty of Chemistry and Chemical Engineering
Smetanova ulica 17,2000 Maribor, Slovenia
tel. +386 (0)2 22 94 400, faks + 386 (0)2 25 27 774
http://www.fkkt.um.si, fkkt@um.si

Published: 5. July 2017

CIP - Kataložni zapis o publikaciji
Univerzitetna knjižnica Maribor

621.31:502.131.1(082)(0.034.2)

INTERNATIONAL Conference on Sustainable Energy and Environmental Protection (10 ; 2017 ; Bled)
Power distribution [Elektronski vir] : (Conference proceedings) / 10th International Conference on Sustainable Energy and Environmental Protection, (June 27th-30th, 2017, Bled, Slovenia) ; [organised by] University of Maribor [and] University of the West of Scotland ; editors Jurij Krope ... [et al.]. - El. zbornik. - Maribor : University of Maribor Press, 2017

Način dostopa (URL): http://press.um.si/index.php/ump/catalog/book/251

ISBN 978-961-286-060-8 (pdf)

doi: 10.18690/978-961-286-060-8
1. Gl. stv. nasl. 2. Krope, Jurij 3. Univerza (Maribor)
COBISS.SI-ID 92432641

ISBN 978-961-286-060-8

DOI: https://doi.org/10.18690/978-961-286-060-8

Price: Free copy

For publisher: Prof. Igor Tičar, Ph.D., rector (University of Maribor)

https://doi.org/10.18690/978-961-286-060-8 ISBN 978-961-286-060-8

Preface

The 10th International Conference on Sustainable Energy and environmental Protection – SEEP 2017 was organised on June 27th – 30th 2017 in Bled, Slovenia, by:

- Faculty of Chemistry and Chemical Engineering, University of Maribor, Slovenia,
- University of the West of Scotland, School of Engineering and

The aim of SEEP2017 is to bring together the researches within the field of sustainable energy and environmental protection from all over the world.

The contributed papers are grouped in 18 sessions in order to provide access to readers out of 300 contributions prepared by authors from 52 countries.

We thank the distinguished plenary and keynote speakers and chairs who have kindly consented to participate at this conference. We are also grateful to all the authors for their papers and to all committee members.

We believe that scientific results and professional debates shall not only be an incentive for development, but also for making new friendships and possible future scientific development projects.

General chair
Emeritus Prof. dr. Jurij Krope
Jurij Krope

Plenary Talk on The Relation between Renewable Energy and Circular Economy

ABDUL GHANI OLABI - BIBLIOGRAPHY

Prof Olabi is director and founding member of the Institute of Engineering and Energy Technologies (www.uws.ac.uk\ieet) at the University of the West of Scotland. He received his M.Eng and Ph.D. from Dublin City University, since 1984 he worked at SSRC, HIAST, CNR, CRF, DCU and UWS. Prof Olabi has supervised postgraduate research students (10 M.Eng and 30PhD) to successful completion. Prof Olabi has edited 12 proceedings, and has published more than 135 papers in peer-reviewed international journals and about 135 papers in international conferences, in addition to 30 book chapters. In the last 12 months Prof Olabi has patented 2 innovative projects. Prof Olabi is the founder of the International Conference on Sustainable Energy and Environmental Protection SEEP, www.seepconference.co.uk

He is the Subject Editor of the Elsevier Energy Journal https://www.journals.elsevier.com/energy/editorial-board/abdul-ghani-olabi, also Subject editor of the Reference Module in Materials Science and Materials Engineering http://scitechconnect.elsevier.com/reference-module-material-science/ and board member of a few other journals. Prof Olabi has coordinated different National, EU and International Projects. He has produced different reports to the Irish Gov. regarding: Hydrogen and Fuel Cells and Solar Energy.

CORRESPONDENCE ADDRESS: Abdul Ghani Olabi, Ph.D., Professor, University of the West of Scotland, School of Engineering and Computing, D163a, McLachlan Building, Paisley, United Kingdom, e-mail: Abdul.Olabi@uws.ac.uk.

https://doi.org/10.18690/978-961-286-060-8 ISBN 978-961-286-060-8

Available at: http://press.um.si.

10TH International Conference on Sustainable Energy and
Environmental Protection (June 27TH – 30TH, 2017, Bled,
Slovenia), Power Distribution
J. Krope, A.Ghani Olabi, D. Goričanec & S. Božičnik

Plenary Talk on Energy Footprints Reduction and Virtual Footprints Interactions

Jiří Jaromír Klemeš & Petar Sabev Varbanov

Increasing efforts and resources have been devoted to research during environmental studies, including the assessment of various harmful impacts from industrial, civic, business, transportation and other economy activities. Environmental impacts are usually quantified through Life Cycle Assessment (LCA). In recent years, footprints have emerged as efficient and useful indicators to use within LCA. The footprint assessment techniques has provided a set of tools enabling the evaluation of Greenhouse Gas (GHG) – including CO_2, emissions and the corresponding effective flows on the world scale. From all such indicators, the energy footprint represents the area of forest that would be required to absorb the GHG emissions resulting from the energy consumption required for a certain activity, excluding the proportion absorbed by the oceans, and the area occupied by hydroelectric dams and reservoirs for hydropower.

An overview of the virtual GHG flow trends in the international trade, associating the GHG and water footprints with the consumption of goods and services is performed. Several important indications have been obtained: (a) There are significant GHG gaps between producer's and consumer's emissions – US and EU have high absolute net imports GHG budget. (b) China is an exporting country and increasingly carries a load of GHG emission and virtual water export associated with consumption in the relevant importing countries. (c) International trade can reduce global environmental pressure by redirecting import to products produced with lower intensity of GHG emissions and lower water footprints, or producing them domestically.

To develop self-sufficient regions based on more efficient processes by combining neighbouring countries can be a promising development. A future direction should be focused on two main areas: (1) To provide the self-sufficient regions based on more efficient processes by combining production of surrounding countries. (2) To develop the shared mechanism and market share of virtual carbon between trading partners regionally and internationally.

Correspondence Address: Jiří Jaromír Klemeš, DSc, Professor, Brno University of Technology - VUT Brno, Faculty of Mechanical Engineering, NETME Centre, Sustainable Process Integration Laboratory – SPIL, Technická 2896/2, 616 69 Brno, Czech Republic, e-mail: klemes@fme.vutbr.cz. Petar Sabev Varbanov, Ph.D., Associate Professor, Brno University of Technology - VUT Brno, Faculty of Mechanical Engineering, NETME Centre, Sustainable Process Integration Laboratory – SPIL, Technická 2896/2, 616 69 Brno, Czech Republic, e-mail: varbanov@fme.vutbr.cz.

https://doi.org/10.18690/978-961-286-060-8 ISBN 978-961-286-060-8

JIŘÍ JAROMÍR KLEMEŠ - BIBLIOGRAPHY

Head of “Sustainable Process Integration Laboratory – SPIL”, NETME Centre, Faculty of Mechanical Engineering, Brno University of Technology - VUT Brno, Czech Republic and Emeritus Professor at “Centre for Process Systems Engineering and Sustainability”, Pázmány Péter Catholic University, Budapest, Hungary.

Previously the Project Director, Senior Project Officer and Hon Reader at Department of Process Integration at UMIST, The University of Manchester and University of Edinburgh, UK. Founder and a long term Head of the Centre for Process Integration and Intensification – CPI2, University of Pannonia, Veszprém, Hungary. Awarded by the EC with Marie Curies Chair of Excellence (EXC). Track record of managing and coordinating 91 major EC, NATO and UK Know-How projects. Research funding attracted over 21 M€.

Co-Editor-in-Chief of Journal of Cleaner Production (IF=4.959). The founder and President for 20 y of PRES (Process Integration for Energy Saving and Pollution Reduction) conferences. Chairperson of CAPE Working Party of EFCE, a member of WP on Process Intensification and of the EFCE Sustainability platform.

He authored nearly 400 papers, h-index 40. A number of books published by McGraw-Hill; Woodhead; Elsevier; Ashgate Publishing Cambridge; Springer; WILEY-VCH; Taylor & Francis).

Several times Distinguished Visiting Professor for Universiti Teknologi Malaysia, Xi’an Jiaotong University; South China University of Technology, Guangzhou; Tianjin University in China; University of Maribor, Slovenia; University Technology Petronas, Malaysia; Brno University of Technology and the Russian Mendeleev University of Chemical Technology, Moscow. Doctor Honoris Causa of Kharkiv National University “Kharkiv Polytechnic Institute” in Ukraine, the University of Maribor in Slovenia, University POLITEHNICA Bucharest, Romania. “Honorary Doctor of Engineering Universiti Teknologi Malaysia”, “Honorary Membership of Czech Society of Chemical Engineering", "European Federation of Chemical Engineering (EFCE) Life-Time Achievements Award" and "Pro Universitaire Pannonica" Gold Medal.

CORRESPONDENCE ADDRESS: Jiří Jaromír Klemeš, DSc, Professor, Brno University of Technology - VUT Brno, Faculty of Mechanical Engineering, NETME Centre, Sustainable Process Integration Laboratory – SPIL, Technická 2896/2, 616 69 Brno, Czech Republic, e-mail: klemes@fme.vutbr.cz.

https://doi.org/10.18690/978-961-286-060-8 ISBN 978-961-286-060-8

10th International Conference on Sustainable Energy and Environmental Protection (June 27th – 30th, 2017, Bled, Slovenia), Power Distribution
J. Krope, A.Ghani Olabi, D. Goričanec & S. Božičnik

Plenary Talk on Renewable energy sources for environmental protection

Hakan Serhad Soyhan

Development in energy sector, technological advancements, production and consumption amounts in the countries and environmental awareness give shape to industry of energy. When the dependency is taken into account in terms of natural resources and energy, there are many risks for countries having no fossil energy sources. Renewable and clean sources of energy and optimal use of these resources minimize environmental impacts, produce minimum secondary wastes and are sustainable based on current and future economic and social societal needs. Sun is one of the main energy sources in recent years. Light and heat of sun are used in many ways to renewable energy. Other commonly used are biomass and wind energy. To be able to use these sources efficiently national energy and natural resources policies should be evaluated together with the global developments and they should be compatible with technological improvements. Strategic plans with regard to energy are needed more intensively and they must be in the qualification of a road map, taking into account the developments related to natural resources and energy, its specific needs and defining the sources owned by countries. In this presentation, the role of supply security was evaluated in term of energy policies. In this talk, new technologies in renewable energy production will be shown and the importance of supply security in strategic energy plan will be explained.

Correspondence Address: Hakan Serhad Soyhan, Ph.D., Professor, Sakarya University, Engineering Faculty, Esentepe Campus, M7 Building, 54187 - Esentepe /Sakarya, Turkey, e-mail: hsoyhan@sakarya.edu.tr.

https://doi.org/10.18690/978-961-286-060-8 ISBN 978-961-286-060-8

Available at: http://press.um.si.

HAKAN SERHAD SOYHAN - BIBLIOGRAPHY

Professor at Sakarya University, Engineering Faculty. 50 % fot teaching and the rest for reasearch activities.

Teaching, courses taught:

Graduate courses:

- Combustion technology;
- Modelling techniques;

Undergraduate courses:

- Combustion techniques;
- Internal combustion engines;
- Fire safety.

Tehnical skills and competences professional societies:

- 25 jurnal papers in SCI Index. 23 conference papers;
- Editor at FCE journal. Co-editor at J of Sakarya University;
- Head of Local Energy Research Society (YETA);
- Member od American Society of Mechanical engineers (ASME);
- Member of Turkish Society of Mechanical Engineers (TSME).

CORRESPONDENCE ADDRESS: Hakan Serhad Soyhan, Ph.D., Professor, Sakarya University, Engineering Faculty, Esentepe Campus, M7 Building, 54187 - Esentepe /Sakarya, Turkey, e-mail: hsoyhan@sakarya.edu.tr.

https://doi.org/10.18690/978-961-286-060-8 ISBN 978-961-286-060-8

Table of Contents

CONFERENCE PROCEEDINGS

10TH INTERNATIONAL CONFERENCE ON SUSTAINABLE ENERGY AND ENVIRONMENTAL PROTECTION (JUNE 27TH – 30TH, 2017, BLED, SLOVENIA), POWER DISTRIBUTION
J. Krope, A.Ghani Olabi, D. Goričanec & S. Božičnik

Smart Grid Power System Condition Monitoring Using Gas Nano-Sensor

HATTAB GUESMI

Abstract Stability and reliability of a grid power system in many respects depend on the condition of power transformers, whose failures and damage may cause the outage of a power system. The traditional power grid in many countries suffers from high maintenance costs and scalability issues along with the huge expense of building new power stations, and lack of efficient system monitoring that could increase the overall performance by acting proactively in preventing potential failures. Recently, wireless sensor networks (WSNs) have been recognized as a promising technology to achieve seamless, energy efficient, reliable, and low-cost remote monitoring and control in smart grid power system applications. The real-time information gathered from these sensors can be analyzed to diagnose problems early and serve as a basis for taking remedial action. The paper presents an online diagnostic system based on smart nano-sensors based on ZnO thin film which can record the temperature and measure the concentration of some dissolved gases in transformer oil. Different faults if they are occurring inside the transformer can be predicted from the sensed data using dissolved gas analysis (DGA) method. ZnO thin film was the most appropriate sensor exhibits good sensitivity, stability and linearity for hydrocarbon gases dissolved in power transformers oil.

Keywords: • WSN • DGA • gas sensor • condition monitoring • smart grid •

CORRESPONDENCE ADDRESS: Hattab Guesmi, Ph.D., Monastir University, Monastir Faculty of Science, Laboratory of electronic and microelectronic, Avenue de l'Environment - Monastir – 5000, Tunisia, e-mail: hattab.guesmi@fsm.rnu.tn.

https://doi.org/10.18690/978-961-286-060-8.1 ISBN 978-961-286-060-8

1 Introduction

The advances in wireless communication and highly integrated electronics devises have allowed the conception of low cost, low-power, and multifunctional sensors. The development of wireless sensor networks is a result of the deployment of these devices. A next-generation electric power system, called the smart grid, has been proposed as an evolutionary system for power generation, transmission, and distribution. In these systems, the required information can be provided to electric utilities by wireless sensor systems to enable them to achieve high system efficiency [1]. These unique features make WSN a promising platform to implement an online power transformer fault diagnosis systems. The gas nano-sensor uses thin film ZnO to capture the five dissolved gases in the oil for diagnosing major faults occurring inside the transformer. To determine the condition of the transformer it is required to capture samples continously using gas nano-sensor wireless network. Then DGA methods are applied to determine the condition of the power transformer. The condition of these equipment have to be known, in order to avoid any possible outage and to choose the appropriate maintenance should be done to minimize the risk of failures, so a fault is avoided before it makes a catastrophic failure. In traditional maintenance experts take sample from transformers periodically and grid system is turned-off to verify the transformers condition [1, 2]. An important predictive maintenances is required for power transformer health assessment has conduct to the online condition monitoring systems using smart nano-sensors. The dissolved gases in the transformer oil are extracted, separated, identified and quantitatively determined [2, 3]. The principle advantage of DGA method is to detect an incipient fault before it leads. In a tradition manner this method was performed out with acquiring an oil sample from the equipment, then taking it to the laboratory to determine the results of fault diagnosis process. Samples must be taken at separated intervals decided by the operator. Until now, the main method to analyse the captured gases are carried in laboratories. However, given results varies from one laboratory to another and from one sample to another due to the dynamic behaviour of the captured gases which needs continuously monitoring. The present work develop a smart nano-sensor for online condition monitoring power transformers to overcome these short comings. The proposed nano-sensor based on gas sensors is fabricated by nanotechnology. The semiconductor metal oxide sensor sensitivity varies due to the resistance. The nano-sensor based on ZnO present a high selectivity for hydrocarbons gases (hydrogen, methane, ethane, acetylene and carbon monoxide) at many sensing work temperature. Despite, samples captured from transformer present many dissolved gases that will be controlled by nano-sensors. The main hydrocarbon gases sensed are hydrogen, methane, ethane, acetylene and ethylene [4, 5, 6]. This work propose and develop a wireless sensor network using a gas nano-sensor fabricated by nanotechnology for online condition monitoring of smart grids.

2 Fault diagnosis methods based on DGA

The well-used techniques for fault diagnosis in power transformer is the dissolved gas analysis (DGA) method. The DGA method tests, analyses and interprets the acquired gas concentration from transformer which are used to conclude the fault situation with periodically samples. Hydrocarbon oils are used as insulating fluids in power transformers because hydrocarbon oils have high dielectric strength, chemical stability and heat transfer properties. The insulating fluid used in power transformer decompose under the stress caused by thermal and electrical over load [7]. This decomposition generates dissolved gases in transformer oil. C_2H_2, C_2H_4, CH_4, H_2 and C_2H_6 are the most gases generated and dissolved in oil of the transformer. The detection of an incipient fault on the power transformers based on DGA method starts with the increase of the generated gas rates that exceed the normal quantities. IEC Publication 60599 gives a list of faults that can be detected by DGA method. Generally, the dissolved gases used for fault diagnosis by DGA are H_2, CH_4, C_2H_2, C_2H_6, and C_2H_4 [8, 9]. DGA methods uses the ratios of these dissolved gases for faults detection. There are many ratio analysis methods used, but we have studied only the gas key, Doernenburg ratios method and Rogers ratios method. These methods are applied to detect the incipient faults in power transformer [10, 11]. The type of faults in the power transformer studied in this work are: Partial discharge (PD), Low energy discharge (D1), High energy discharge (D2), Low temperature thermal $T < 300$ °C (T1), Medium temperature thermal $300 < T < 700$ ºC (T2) and High temperature thermal $T > 700$ ºC (T3).

3 WSN for condition monitoring of power transformer

3.1 Thin film ZnO for power transformer gas sensing

Many nano-sensors have been appeared in the recent years fabricated with many technologies such as metal oxide semiconductor, polymer and carbon nanotubes. These sensors are used to sense gases dissolved in transformer oil. Metal oxide semiconductor is the most advantage sensing technology, which gives sensors that have many advantages such as low cost, high sensitivity, simple fabrication process and long service life. Sensors fabricated with metal oxide semiconductor method are well used to capture dissolved gases through the redox reactions between the dissolved gases and the sensor surface [12, 13].

Thin film ZnO is one among all nano-sensors fabricated with metal oxide semiconductors which have relative high sensitivity so, it is well used in many domains. However, thin film ZnO has a high sensitivity due to its high working temperature. Its working temperature range varies from 25°C to 500°C [14]. Figure 1 shows the relationship between gas concentration and sensitivity for the sensor. It presents that the sensor exhibits a good selectivity and sensitivity to the transformer oil dissolved gases.

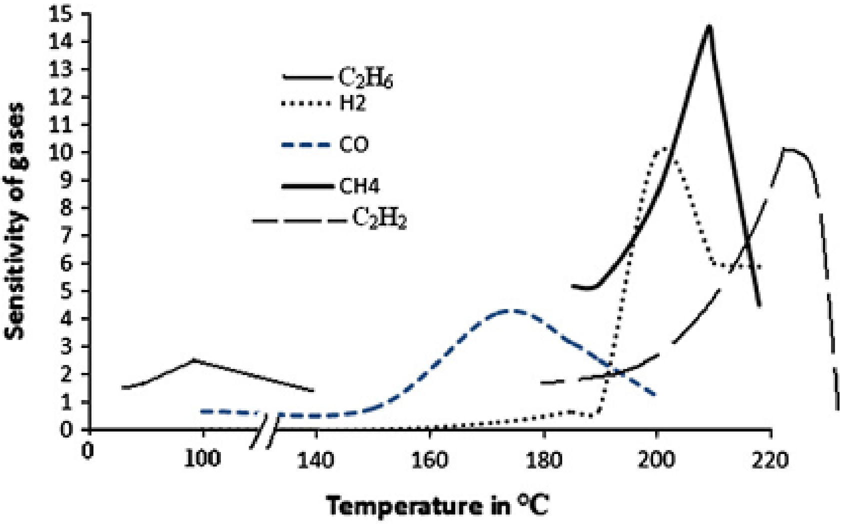


Figure. 1. sensor sensitivity variation with respect to temperature for dissolved gases[14]

The rates of gas evolution depend to the volume of oil in the system. The gases are measured in terms of concentration in parts per million (ppm) and the gases generated by a fault depend on the volume of oil. A moderate accumulation of generated dissolved gases during an interval can indicate an incipient fault, at the same time a rapid accumulation of generated gases can indicate an active fault. Regarding to the properties of the thin film ZnO, that show a high selectivity for methane, hydrogen, ethane, acetylene and ethylene at different sensing temperature but they also present fairly significant cross-sensitivities [15, 16]. Despite, transformer oil contains some dissolved gases that can be captured by thin film ZnO, the main dissolved gases studied in this work are : methane, hydrogen, acetylene, ethane and ethylene.

3.2 The proposed smart sensor for power transformer condition monitoring

The fault diagnosis process for power transformer is implemented in the smart sensor to be installed at the transformer side. The proposed methodology of online fault detection based on DGA method uses a nano-sensor to measure the key gas concentrations (ppm) dissolved in the power transformer oil. The measured concentrations are acquired through a connected Data Acquisition Card then, the signal is conditioned to the wright form. Subsequently, the acquired signal is converted from analogue to digital at the converter block (ADC). The digital data is fed to the smart processor that is in charge to verify the acquired signal and to apply the fault detection process then to send the fault to the monitoring centre via WSN. Fault detection scheme is presented in figure 2. When the concentration of each key gas is correctly received from the converter block, then the ratio of CH_4/H_2, C_2H_2/CH_4, C_2H_6/C_2H_2, C_2H_4/C_2H_6, and C_2H_2/C_2H_4 are calculated and stored in a FIFO. Then DGA method is applied to determine the incipient fault. finally, the radio is switched on to send the data to the monitoring centre, then the radio is switched off if the data is sent with no error to the monitoring center and to the remote user via WSN network [17].

The smart sensor architecture is composed of three basic components : sensor unit, processor unit, power source unit, and a network interface unit. They may also have application dependent additional components such as a location finding system. The sensor unit is in charge of acquiring data from the power transformer, it is made up of two subunits: nano-sensors and ADC converter. Sensors sense the concentrations of each key gas. The acquired signals by the nano-sensors are converted to digital signals with the ADC subunit, and then passed into the processor unit. The processor unit manages the procedures that make the sensor node collaborate with the other nodes to carry out the assigned sensing gases which is usually involve with a small memory. However, in our proposed architecture the processor unit manages the communication procedure and the fault detection procedure, so it is also associated with a fault detection unit. The fault detection unit is composed of :

- One memory RAM (128 Kbytes) is used to store the measured data, the calculated increase rate for each key gas and the thresholds related to typical value of a healthy transformer and DGA methods.
- Concentration converter algorithm used to convert the sensed electrical signal to ppm concentration of each key gas based on the cross-sensitivity of the thin film SnO_2 nano-sensor.
- The DGA processor implements the DGA algorithm used for fault detection such as Rogers ratio method, or Doernenmberg ratio method.
- The delay to the next data acquisition algorithm determine the delay for the next data acquisition based on the comparison of sensed data and the stored threshold data and the increasing rate of each gas concentration.

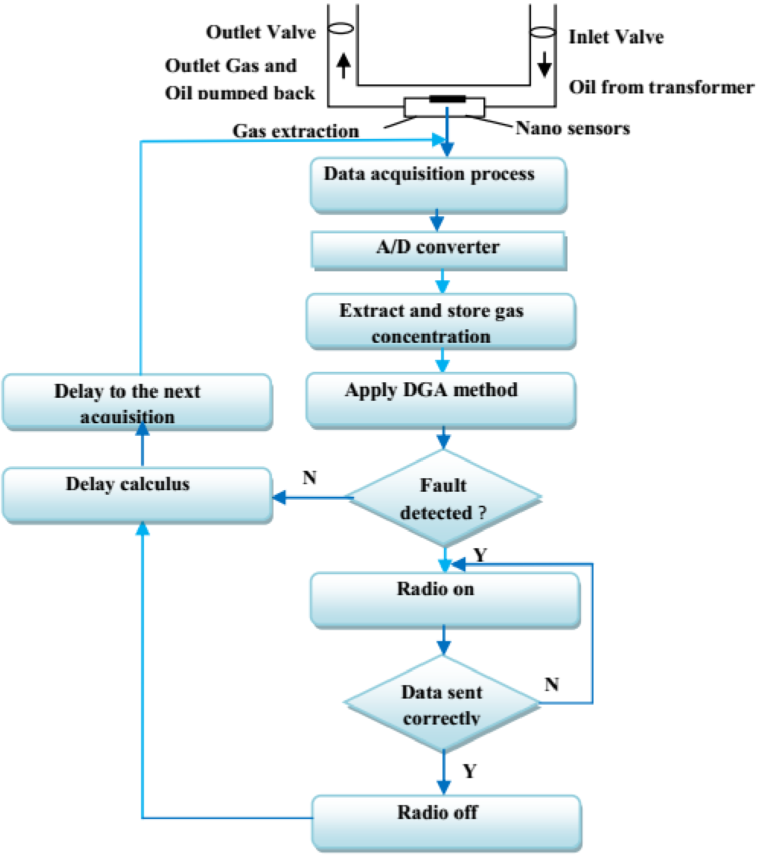


Figure. 2. Sensor fault detection scheme

The fault detection unit automatically makes the transformer condition diagnosis based on the output of the DGA algorithm. The network interface executes procedures that interconnect the nano-sensor node to the network. the power source unit carried the alimentation to the sensor node which is considered as the most important components. Power source units may be supported by a power scavenging unit such as solar cells. Smart sensor architecture composed also with other units which are application dependent. Many sensor nodes use the location finding system because when they execute network routing techniques and sensing tasks they require to know the location of other nodes with high accuracy [18].

4 Implementation of the WSN architecture

The proposed wireless system based on smart sensor follows a sensor fusion approach for condition monitoring and provides early warning of impending problems. It provides a low-cost alternative, and their key performance objectives are [19, 20]:

- Detect faults in power transformer with a probability of 75%.
- Produce false alarm no more than 0.1%.
- Have high accuracy (> 99%) of correctly identifying the nature and severity of the fault.

Our proposed solution is a smart WSN system for online and continuous real-time condition monitoring of power transformer which is shown in figure 3. The proposed system employs multiple gas nano-sensors and a temperature sensor mounted on a common wireless sensor platform with the capability of installation inside the transformer. Every smart sensor attached to the transformer continuously collects and performs data at a sampling rate equals one sample every day. When the concentration of the hydrocarbon gases passed the threshold the sampling rate is changed based on the increase of each gas concentration. The same time is used to carry correctly the gathered data from the smart sensor node and to send the results to the monitoring center in the form of packets. When all packets are sent out and the sampling time is arrived, the smart sensor node starts to collect data again. Each packet consists of the sensor node ID and the packet number ID followed by the processing data. In the data area, 114 byte is used for the fault nature and one additional byte is used to mark the Cyclic Redundancy Check.

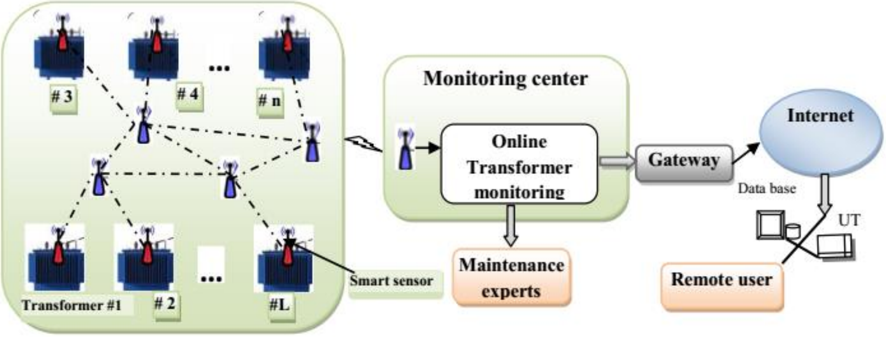


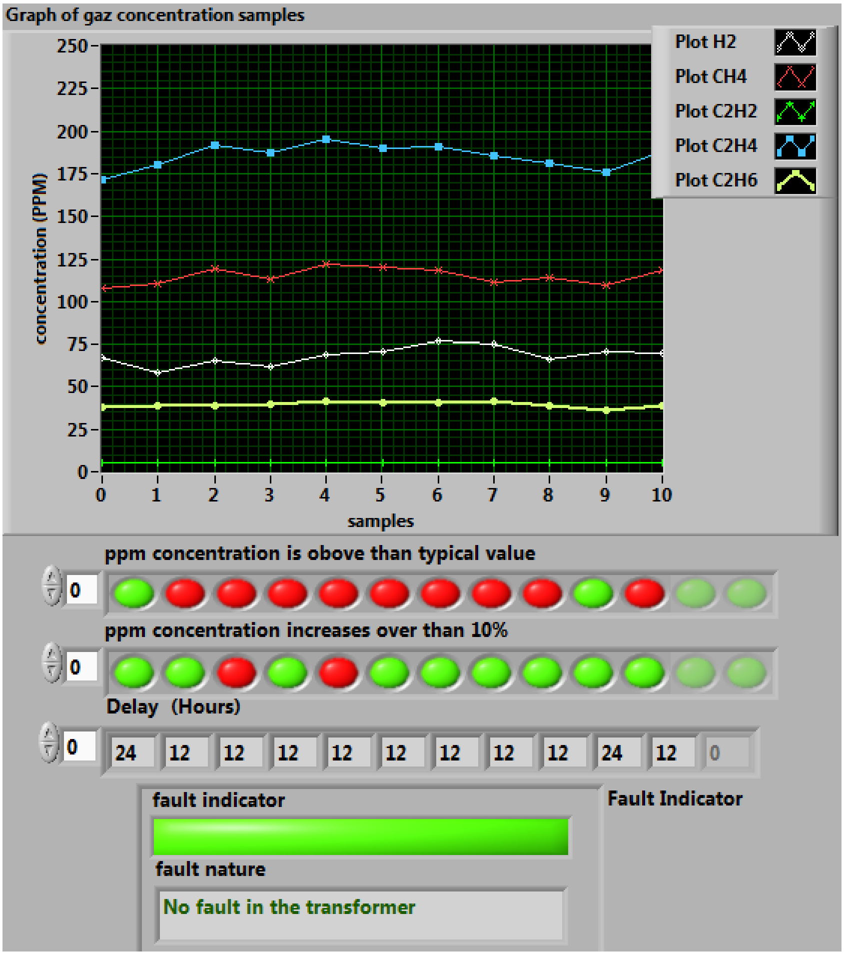
Figure. 3. Online framework for overall scheme of transformer fault diagnosis system.

5 Experimental results and discussions

The proposed system is fully implemented in a single FPGA, in order to maintain low cost of the architecture and to comply with the processing speed requirements. All the system was fully developed using Lab View description. Nano-sensor platform is developed to capture the key gas concentration based on thin film ZnO and to apply DGA method for fault diagnosis, then to send the fault nature to the monitoring center. The input applied to our model is the electric signal received from each nano-sensor. The smart nano-sensor platform outputs are waveform graph which present the evolution of the key gas concentration samples, and the fault nature. After training the architecture simulations results are presented in figure 4 and 5. Figure 4 shows that there is no fault for the transformer however, the key gas concentrations is above the typical value for a healthy transformer and the delay to the next acquisition is equal to 12 hours. Figure 5 shows a healthy transformer where the key gas concentration rate increases then 10%

which fix the delay to the next acquisition to 12 hours, also the key gas concentration exceed the typical value at the seventh sample.

The simulation results indicate that the developed preprocessing approach can significantly improve the fault diagnosis system for power transformer fault diagnosis. The other advantage is that the model is practically applicable and will be utilized for an automated power transformer diagnosis for smart grids. Finally, to improve the fault detection accuracy we can implement an intelligent classification method at the smart sensor platform.



ppm concentration is above than typical value

0 🟢 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🟢 🔴 ○ ○

ppm concentration increases over than 10%

0 🟢 🟢 🔴 🟢 🔴 🟢 🟢 🟢 🟢 🟢 🟢 ○ ○

Delay (Hours)

0 24 12 12 12 12 12 12 12 12 24 12 0

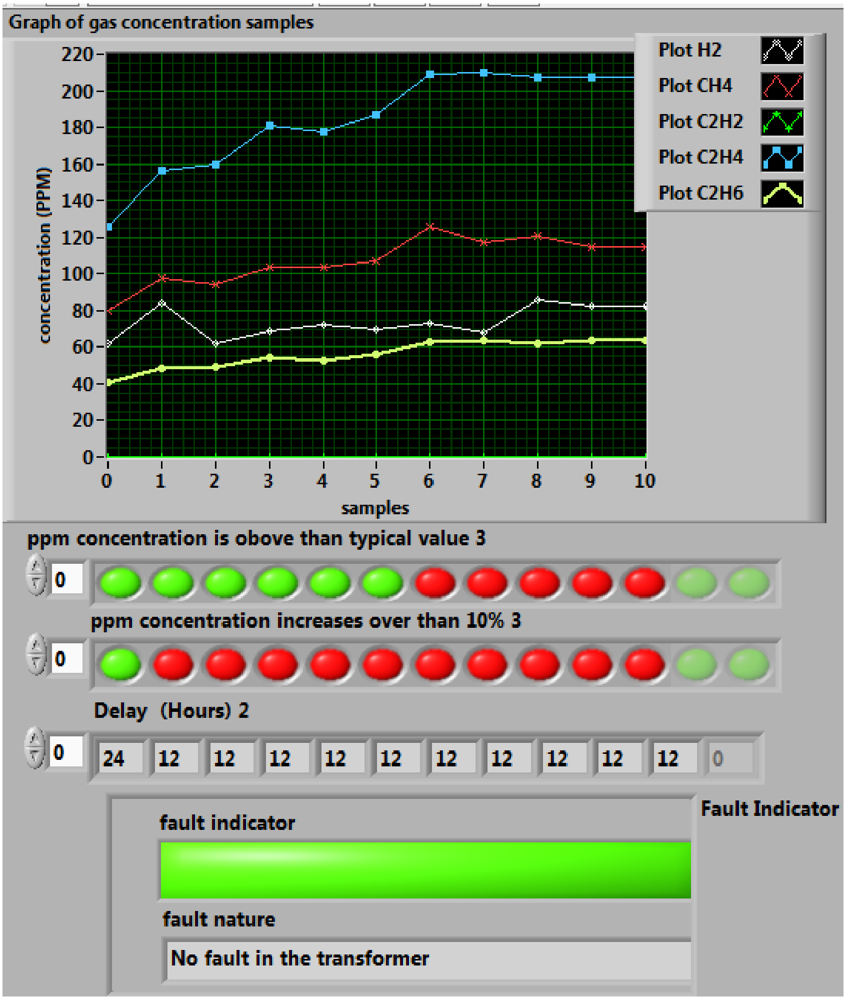
fault indicator 🟩

Fault Indicator

fault nature

No fault in the transformer

Figure 4: Historical evolution of sensed gas concentration for a tested transformer.



ppm concentration is above than typical value 3
0
ppm concentration increases over than 10% 3
0
Delay (Hours) 2
0
24 12 12 12 12 12 12 12 12 12 12 0
Fault Indicator
fault indicator
fault nature
No fault in the transformer

Figure 5: Historical evolution of sensed gas concentration for a second tested transformer.

6 Conclusions

The fault diagnosis of power transformer are estimated based on only gas concentration data using DGA methods. In this paper, The gas sensors fabricated by nanotechnology are developed for dissolved gas sensing in power transformers to detect and warn incipient fault when it occurs. From the study performed, we conclude that the thin film ZnO is the most suitable gas sensors will be used to sense the dissolved gases in power transformer because it has a high and linear sensitivity for hydrocarbon gases. The proposed method has a large potential in practice for smart grids. The fault diagnosis based on DGA approach using nano-sensors provides a very useful and accurate maintenance tool to solve problems in power transformer faults detection. The power transformer fault diagnosis using DGA methods has good reliability and requires few samples and training time, also it is very suitable for fault diagnosis of transformer.

Acknowledgments

The author would like to acknowledge the financial support for this work from the Deanship of Scientific Research (DSR), Jazan University, Saudi Arabia, under grant no 4251.

References

[1] A-P. Sakis Meliopoulos, G. Cokkinides, R. Huang, E. Farantatos, S. Choi, Y. Lee, X. Yu, Smart Grid Technologies for Autonomous Operation and Control, IEEE Transactions on smart grid, vol. 2, no. 1, (2011)
[2] S-W. Fei, Y. Sun, Forecasting dissolved gases content in power transformer oil based on support vector machine with genetic algorithm, Electric Power Systems Research 78 (2008) 507–514.
[3] W. H. Tang, J. Y. Goulermas, Q. H.Wu, Z. J. Richardson, and J. Fitch, A Probabilistic Classifier for Transformer Dissolved Gas Analysis With a Particle Swarm Optimizer, IEEE Transactions on Power Delivery 23 (April (2)) (2008) 751–759.
[4] M. Nafar, T. Niknam, A. Gheisari, Using correlation coefficients for locating partial discharge in power transformer, Electrical Power and Energy Systems 33 (2011) 493–499.
[5] V. Miranda, A. R-G Castro, Improving the IEC Table for Transformer Failure Diagnosis With Knowledge Extraction From Neural Networks, IEEE Transactions on Power Delivery 20 (October (4)) (2005) 2509–2516.
[6] C-H. Lin, C-H. Wub, P-Z. Huang, Grey clustering analysis for incipient fault diagnosis in oil-immersed transformers, Expert Systems with Applications 36 (2009) 1371–1379.
[7] Benounis M, Aka-Ngnui T, Jaffrezic N, Dusta JP, NIR and optical fiber sensor for gas detection produced by transformer oil degradation, Sens Actuators A, 141 (2008), 76-83.
[8] N Yadaiah, N Ravi, Internal fault detection techniques for power transformers, Applied Soft Computing 11 (2011) 5259–5269.
[9] S-W Fei,Y Sun, Forecasting dissolved gases content in power transformer oil based on support vector machine with genetic algorithm, Electric Power Systems Research 78 (2008) 507–514.
[10] H-C Sun, Y-C Huang, C-M Huang, A Review of Dissolved Gas Analysis in Power Transformers, Energy Procedia 14 (2012) 1220 – 1225.
[11] J. Haema, R. Phadungthin, Power Transformer Condition Evaluation by the Analysis of DGA methods, Power and Energy Engineering Conference (APPEEC), 2012 Asia-Pacific.
[12] Gong H, Hu JO, Wang JH,Ong CH, Zhu Fr, Nano-crystalline Cu dopped ZnO thin film gas sensor for CO, sens and Actuators B:chem 2006;115(1):247-251.
[13] Gruber D, Kraus F, Muller J, “A novel gas sensor design based on CH4/H2/H2O plasma etched ZnO thin films”, sens Actuators B 2003; 92: 81-90.
[14] A. Chatterjee, P. Bhattacharjee, N-K. Roy, P. Kumbhakar, Usage of nanotechnology based gas sensor for health assessment and maintenance of transformers by DGA method, Electrical Power and Energy Systems 45 (2013) 137–141.
[15] Q. Zhou, W. Chen, S. Peng, X. Su, Nano-tin oxide gas sensor detetction characteristic for hydrocarbon gases dissolved in transformer oil, Int. conf. on High voltage engineering and application, Shanghai, Sep(2012) 17-20.
[16] X-L. Cheng, H. Zhao, L-H. Huo, S. Gao, J-G. Zhao, ZnO nanoparticulate thin film: preparation, characterization and gas-sensing property, Sensors and Actuators B 102 (2004) 248–252.

[17] P. Jarventausta, S. Repo, A. Rautiainen, J. Partanen, Smart grid power system control in distributed generation environment, Annual Reviews in Control 34 (2010) 277–286.
[18] V-C. Güngör, D. Sahin, T. Kocak, S. Ergüt, C. Buccella, C. Cecati, G-P. Hancke, Smart Grid Technologies: Communication Technologies and Standards, IEEE Transactions on industrial informatics, vol. 7, no. 4, november 2011.
[19] A. Flammini, P Ferrari, D. Marioli, E. Sisinni, A. Taroni, “Wired and wireless sensor networks for industrial applications”, Microelectronics Journal, 40 (2009) 1322–1336.
[20] J. Yick, B. Mukherjee, D. Ghosal, “Wireless sensor network survey”, Computer Networks, 52 (2008) 2292–2330.

10TH INTERNATIONAL CONFERENCE ON SUSTAINABLE ENERGY AND ENVIRONMENTAL PROTECTION (JUNE 27TH – 30TH, 2017, BLED, SLOVENIA), POWER DISTRIBUTION
J. Krope, A.Ghani Olabi, D. Goričanec & S. Božičnik

Optimal Day-Ahead Reconfiguration Strategy for Active Distribution Systems with Renewable Distributed Generation

HAYTHAM M. A. AHMED & MAGDY M. A. SALAMA

Abstract This paper proposes a network reconfiguration algorithm for active distribution systems (DSs). The proposed algorithm determines the optimal day-ahead reconfiguration schedule considering the forecasted data for load demands and renewable distributed generators (DGs). The objective of the proposed algorithm is to minimize the day-ahead energy losses of the DS. Due to the presence of the binary variables that represent the reconfiguration decisions, as well as the nonlinear power balance equations, the algorithm is formulated as a mixed-integer nonlinear problem. The algorithm also takes into account the maximum number of switching operations for each controlled switch as well as for each hour in the day-ahead. The proposed algorithm was employed to find the optimal day-ahead reconfiguration schedule for a medium-voltage DS that included different types of renewable DGs. The results obtained from the algorithm were compared to the base-case solution in order to evaluate the benefits provided by the proposed algorithm.

Keywords: • Active distribution system • renewable distributed generation • system reconfiguration • mixed-integer optimization • day-ahead operational planning •

CORRESPONDENCE ADDRESS: Haytham M. A. Ahmed, Ph.D. Candidate, University of Waterloo, Department of Electrical and Computer Engineering, 200 University Ave. W, Waterloo, ON, Canada, email: h2abdelr@uwaterloo.ca. Magdy M. A. Salama, Professor, University of Waterloo, Department of Electrical and Computer Engineering, 200 University Ave. W, Waterloo, ON, Canada, email: msalama @uwaterloo.ca.

https://doi.org/10.18690/978-961-286-060-8.2 ISBN 978-961-286-060-8

1 Introduction

The increased environmental concerns as well as the depletion of fossil fuel resources have motivated all nations to increase electric power production from renewable distributed generators (DGs), such as photovoltaic (PV) panels and wind DGs [1], [2]. Integrating these technologies into the distribution systems (DSs) creates the notion of smart active DSs. Although the renewable DGs provide economical and environmental benefits, they will pose more complexity in the operation of active DSs due to their intermittent nature.

Remotely controlled switches are used in active DSs for reconfiguration management. The network reconfiguration is the process by which the open/closed status of the sectionalized (or tie) switches are controlled to achieve optimal operation schedule for smart DSs. Several studies have discussed the DS reconfiguration techniques. For example, the authors of [3] have proposed an operational planning strategy for smart active DSs. The objective of the strategy is to minimize the day-ahead operation costs considering the hourly reconfiguration capability of the DS network. In two further studies [4], [5], the authors have proposed reconfiguration algorithms for distribution networks. The studies revealed that the use of the reconfiguration strategy has provided several benefits, including reduction in the DS power losses as well as improvement in the DS voltage profile. In order to achieve maximum power loss reduction for DSs, the authors of [6] and [7] have proposed a simultaneous reconfiguration and DG allocation algorithms to minimize the DS power losses and to improve the voltage profile. In [8] and [9], optimal reconfiguration strategies have been proposed to minimize the power losses in the distribution networks. The authors of [10] have introduced a concurrent approach to the network reconfiguration and DG allocation for balanced and unbalanced DSs. The approach uses a genetic algorithm (GA) and aims to improve the power losses, voltage profile, voltage unbalance, and current unbalance of the DS. In another study [11], a mixed-integer conic programming algorithm for DS reconfiguration in the presence of DGs was proposed to minimize the active power losses of the DS. The work reported in [12] introduced an optimal power flow strategy for DS reconfiguration. The strategy takes into consideration the capability of controlling different DS components, such as DGs, capacitor banks, and transformer taps, in order to determine the optimal operating conditions for DSs. However, the methods presented in [4]–[12] have not studied the day-ahead reconfiguration schedule for DSs, and so they have not taken the maximum limit of daily switching operations into account. In addition, these methods do not incorporate the renewable-based DGs and their variations in the operation of DSs.

This paper introduces a day-ahead network reconfiguration strategy for DSs with renewable DGs. The accurate day-ahead forecasted data for load demands and renewable DGs are assumed to be available. The objective of the proposed algorithm is to determine the optimal day-ahead reconfiguration schedule that minimizes the day-ahead energy losses of the DS. The proposed algorithm was successfully employed to find the day-ahead operation schedule for a case study of a medium-voltage DS that included PV panels and wind DGs. The benefits provided by the algorithm were verified through a comparison between the algorithm's solution and the base-case results.

The remainder of the paper is organized as follows: Section 2 presents the formulation of the reconfiguration algorithm. Section 3 presents the test system used for evaluating the effectiveness of the proposed reconfiguration algorithm. Section 4 summarizes the conclusions of the paper.

2 Formulation of the reconfiguration algorithm

The main goal of the proposed algorithm is to find the optimal day-ahead reconfiguration schedule that minimizes the DS energy losses. The network configuration is described by the connection matrix U ($N \times N$). The elements of U represent the binary decision variables of the reconfiguration algorithm. The element U_{nm} is equal to 0 if the line connecting buses n and m is open, and equal to 1 if the line connecting buses n and m is closed. The proposed reconfiguration algorithm is a mixed-integer nonlinear optimization problem, which is solved using the MATLAB GA. The formulation of the proposed reconfiguration algorithm is described in the following subsections.

2.1 The Objective Function

The objective function is to minimize the day-ahead energy losses, as follows:

$$\min F = \sum_{t=1}^{T} (P_{TG,t} - P_{TD,t})\ \Delta t \tag{1}$$

where

$$P_{TG,t} = \sum_{i=1}^{I_{ac}} P^{ac}_{G_i,t} + \sum_{j=1}^{J_{dc}} P^{dc}_{G_j,t} \quad , \quad \forall t \in T \tag{2}$$

$$P_{TD,t} = \sum_{n=1}^{N} (P^{ac}_{L_n,t} + P^{dc}_{L_n,t}) \quad , \quad \forall t \in T \tag{3}$$

2.2 The Constraints

The constraints of the optimization problem can be classified as follows:

1) Network Topology Constraints:

These constraints are divided into a) the integer constraint (4) for the binary variables of the connection matrix *U*, and b) the radiality constraints (5)-(6) that are used to guarantee the radial operation of the DS.

$$\begin{cases} U_{nm} \in \{0,1\} & if \quad U_{nm} \in NS \\ U_{nm} = 1 & if \quad U_{nm} \in NS_C \\ U_{nm} = 0 & otherwise \end{cases} \quad , \quad \forall\, n, m \in N \tag{4}$$

$$\sum_{n=1}^{N} \sum_{\substack{m=1 \\ m>n}}^{N} U_{nm} \;=\; N-1 \tag{5}$$

$$\sum_{n=1}^{N} U_{nm} \;\geq\; 1 \;\; , \;\; \forall n \in N \tag{6}$$

2) Switching Constraints:

The switching constraints (7)-(8) are used to guarantee that the switching actions will not violate the maximum allowable limits. The constraint (7) is used to limit the number of daily switching actions for each controlled switch, while the constraint (8) is used to limit the number of switching actions per hour.

$$\sum_{t=1}^{T} \left| \psi_{s,t} - \psi_{s,t-1} \right| \;\leq\; N_{SW,s}^{\max} \quad , \quad \forall s \in NS \tag{7}$$

$$\sum_{s=1}^{NS} \left| \psi_{s,t} - \psi_{s,t-1} \right| \;\leq\; N_{SW,t}^{\max} \quad , \quad \forall t \in T \tag{8}$$

$$\sum_{\substack{m=1 \\ m\neq n}}^{N} U_{nm} \left(V_n^2 G_{nm} - V_n V_m (G_{nm} \cos\theta_{nm} + B_{nm} \sin\theta_{nm}) \right)$$

$$= \left(P_{G_n}^{ac} - P_{L_n}^{ac} + \eta_{i-n} P_{G_n}^{dc} - \eta_{r-n}^{-1} P_{L_n}^{dc} \right) \; , \forall n \in N \tag{9}$$

$$\sum_{\substack{m=1\\ m\neq n}}^{N} U_{nm}\left(-V_n^2 B_{nm} - V_n V_m (G_{nm}\sin\theta_{nm} - B_{nm}\cos\theta_{nm})\right)$$

$$=\left(Q_{G_n}^{ac} - Q_{L_n}^{ac}\right)\ ,\forall n\in N \qquad (10)$$

4) Network Security Constraints:

The network security constraints include the limits for voltage magnitudes, voltage angles, and line capacities. These constraints are given by

$$V_n^{\min} \le V_n \le V_n^{\max} \qquad (11)$$

$$\theta_n^{\min} \le \theta_n \le \theta_n^{\max} \qquad (12)$$

$$\sqrt{P_{nm}^2 + Q_{nm}^2} \le S_{nm}^{\max} \qquad (13)$$

5) Generator Constraints:

The active and reactive power limits for the system generators are expressed as follows:

$$P_{G_i}^{ac-\min} \le P_{G_i}^{ac} \le P_{G_i}^{ac-\max}\quad ,\quad \forall i\in I_{ac} \qquad (14)$$

$$P_{G_j}^{dc-\min} \le P_{G_j}^{dc} \le P_{G_j}^{dc-\max}\quad ,\quad \forall j\in J_{dc} \qquad (15)$$

$$Q_{G_i}^{ac-\min} \le Q_{G_i}^{ac} \le Q_{G_i}^{ac-\max}\quad ,\quad \forall i\in I_{ac} \qquad (16)$$

3 Case study

This section presents the case study that was used for evaluating the effectiveness of the proposed reconfiguration algorithm.

3.1 Description of the Test System

The modified IEEE 33-bus DS shown in Figure 1 was used for the case study. The network impedances are shown in Table 1. The data given for the system loads and energy resources are listed in Table 2 and Table 3, respectively. The base values used for this distribution system are S_{base} = 10 MVA and V_{base} = 12.66 kV. The efficiency of each PV inverter is given as 95 %. The DS under study includes 37 sections; each can be open or closed. The maximum number of switching actions per hour is given as six, while the maximum number of daily switching actions for each controlled switch is given as four [3].

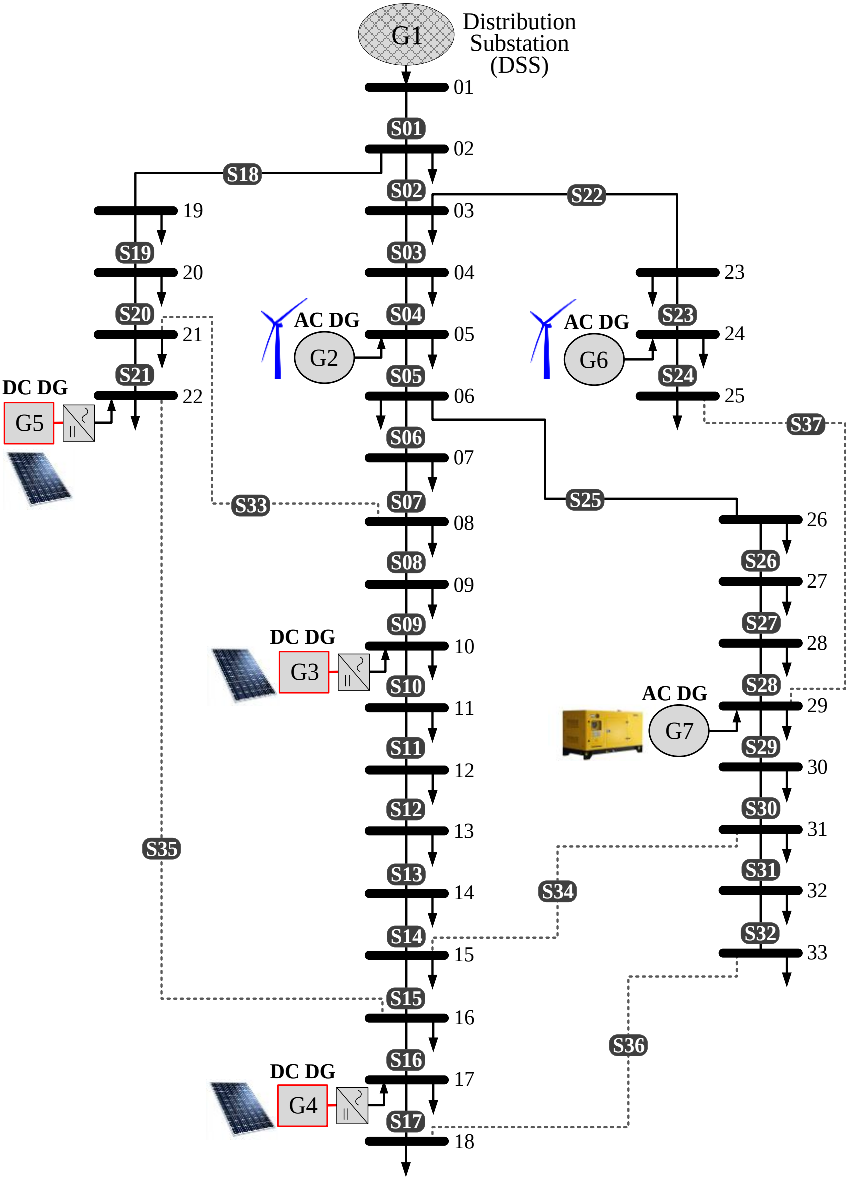


Figure 1. Modified IEEE 33-Bus DS.

Table 1. Impedances of the 33-Bus DS

R [*] **(Ω)**	***X*** [*] **(Ω)**		**Section No.**
0.0922	0.0470		S20
0.4930	0.2511		S21
0.3660	0.1864		S22
0.3811	0.1941		S23
0.8190	0.7070		S24
0.1872	0.6188		S25
0.7114	0.2351		S26
1.0300	0.7400		S27
1.0440	0.7400		S28
0.1966	0.0650		S29
0.3744	0.1238		S30
1.4680	1.1550		S31
0.5416	0.7129		S32
0.5910	0.5260		S33[**]
0.7463	0.5450		S34[**]
1.2890	1.7210		S35[**]
0.7320	0.5740		S36[**]
0.1640	0.1565		S37[**]
1.5042	1.3554		

[*] *R* and *X* are the resistance and reactance of each section.
[**] Tie lines (i.e., normally open sections).

Table 2. Load Data for the 33-Bus DS

Bus No.	P_L^{ac} (kW)	Q_L^{ac} (kVAr)	**Bus No.**	P_L^{ac} (kW)	Q_L^{ac} (kVAr)
02	100	60	18	90	40
03	90	40	19	90	40
04	120	80	20	90	40
05	60	30	21	90	40
06	60	20	22	90	40
07	200	100	23	90	50
08	200	100	24	420	200
09	60	20	25	420	200
10	60	20	26	60	25
11	45	30	27	60	25
12	60	35	28	60	20
13	60	35	29	120	70
14	120	80	30	200	600
15	60	10	31	150	70
16	60	20	32	210	100
17	60	20	33	60	40

Table 3. Data for the Energy Resources

DG No.	**Resource Type**	$P_G^{\max}$ (MW)	$P_G^{\min}$ (MW)	$Q_G^{\max}$ (MVAr)	$Q_G^{\min}$ (MVAr)
G1	DSS, AC	10.0	1.0	5.00	0.50
G2	Wind DG, AC	0.50	-	-	-
G3	PV DG, DC	0.25	-	-	-
G4	PV DG, DC	0.25	-	-	-
G5	PV DG, DC	0.25	-	-	-
G6	Wind DG, AC	0.50	-	-	-
G7	Diesel DG, AC	0.50	0.05	0.25	0.05

3.2 Forecasted Day-ahead Data for the Stochastic Variables in the System

The day-ahead variations of the system's stochastic variables (load demands, PV DGs, and wind DGs) are shown in Table 4 and Figure 2 [13]. These variations are percentages of the maximum value of each variable.

3.3 Simulation Results

Table 5 shows a comparison between the results obtained from the proposed algorithm and those obtained from the base-case system. The open switches in the base-case are

S33, S34, S35, S36, and S37. The value of the day-ahead energy losses was found to be 1636.276 kWh for the base-case system and was reduced to 1215.699 kWh when the proposed reconfiguration algorithm was employed. The comparison therefore revealed that the proposed algorithm successfully achieved a significant reduction of 420.577 kWh (i.e., 25.7 %) in the day-ahead energy losses, for the DS under study.

Table 4. Forecasted Day-Ahead Data

Hour	**Load Demand**	**PV DG Output Power**	**Wind DG Output Power**
1	64.00	0.00	94.92
2	60.00	0.00	97.97
3	58.00	0.00	100.00
4	56.00	0.00	96.45
5	56.00	0.00	93.91
6	58.00	0.71	91.88
7	64.00	10.03	89.85
8	76.00	29.28	84.77
9	87.00	54.24	75.13
10	95.00	73.86	67.01
11	99.00	89.22	59.90
12	100.00	100.00	55.84
13	99.00	99.69	60.91
14	100.00	99.10	66.50
15	100.00	90.39	71.07
16	97.00	71.25	76.14
17	96.00	53.82	65.48
18	96.00	26.27	64.97
19	93.00	9.80	70.05
20	92.00	2.07	72.59
21	92.00	0.00	71.07
22	93.00	0.00	72.59
23	87.00	0.00	78.68
24	72.00	0.00	82.23

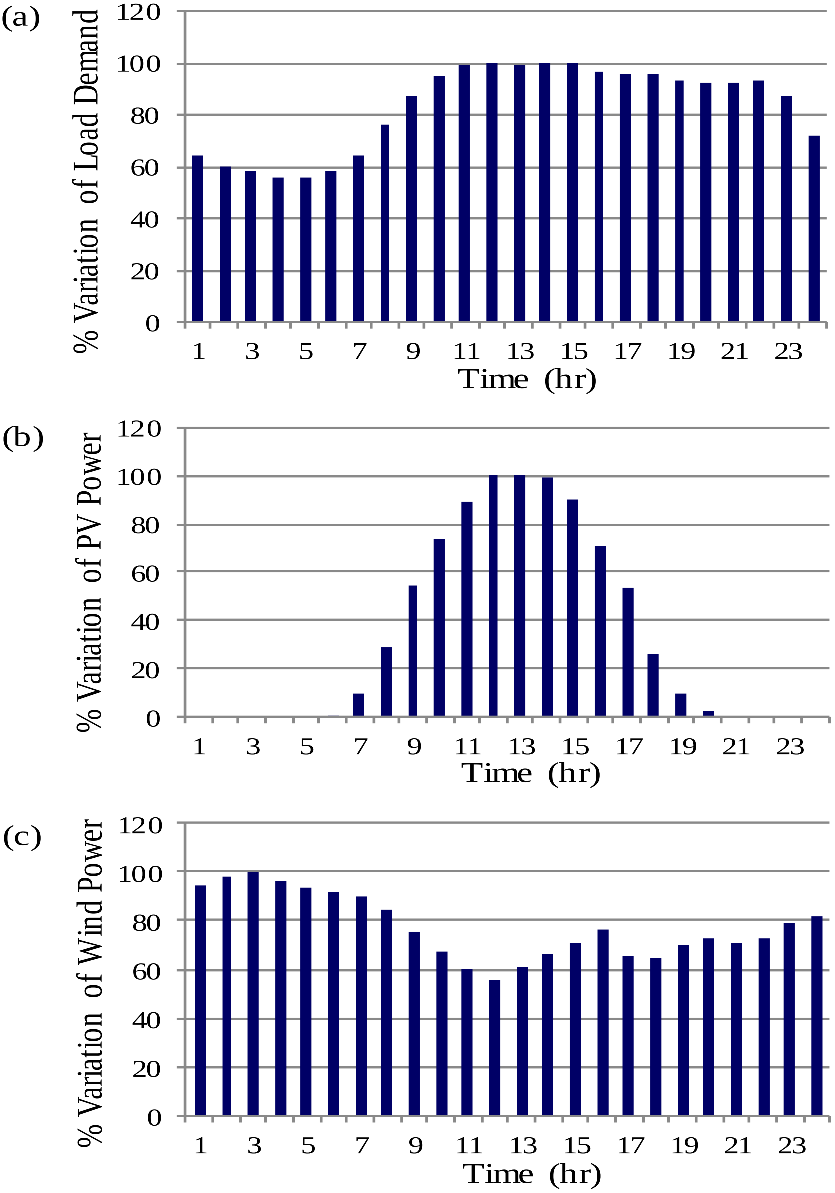


Figure 2. Forecasted Day-Ahead Variations for a) Load Demand, b) PV-DG Output Power, and c) Wind-DG Output Power.

Table 5. Simulation Results

Hour	**The Base Case**	**The Proposed Algorithm**	
	Power Losses (kW)	**Open Switches**	**Power Losses (kW)**
1	27.237	12, 33, 34, 36, 37	19.695
2	26.082	12, 33, 34, 36, 37	18.795
3	25.993	12, 28, 33, 34, 36	16.934
4	24.946	12, 28, 33, 34, 36	16.124
5	24.424	12, 28, 33, 34, 36	15.899
6	24.724	12, 28, 33, 34, 36	16.556
7	29.773	12, 28, 33, 34, 36	21.908
8	48.598	12, 28, 33, 34, 36	37.538
9	72.322	13, 28, 31, 33, 34	56.673
10	92.267	13, 28, 31, 33, 34	71.994
11	104.387	13, 28, 31, 33, 34	81.795
12	109.030	13, 28, 31, 33, 34	86.127
13	105.737	13, 28, 31, 33, 34	83.787
14	106.626	13, 28, 31, 33, 34	84.212
15	104.388	13, 28, 31, 33, 34	81.722
16	94.378	13, 28, 31, 33, 34	73.008
17	92.625	13, 28, 31, 33, 34	70.134
18	91.376	13, 28, 31, 33, 34	66.373
19	82.825	13, 28, 31, 33, 34	58.961
20	79.900	13, 28, 31, 33, 34	56.214
21	80.265	13, 28, 32, 33, 34	54.084
22	82.338	13, 28, 32, 33, 34	55.409
23	67.258	13, 28, 32, 33, 34	45.271
24	38.777	13, 28, 32, 33, 34	26.486
Total Losses	**1636.276 kWh**		**1215.699 kWh**

4 Conclusion

This paper presents a reconfiguration algorithm for DSs with renewable DGs. The proposed algorithm determines the optimal day-ahead reconfiguration schedule that minimizes the DS energy losses. The algorithm takes into consideration the maximum number of switching operations for each controlled switch in the network as well as for each hour in the day-ahead. The proposed algorithm was tested on a case study of a medium-voltage DS with different types of DGs, including PV panels and wind DGs. In order to assess the effectiveness of the proposed algorithm, the solution obtained from the algorithm was compared to the base-case solution. The comparison between the two solutions demonstrated that the proposed algorithm successfully achieved a significant reduction in the DS energy losses, which reveals the efficacy of the proposed algorithm.

Nomenclature

B_{nm}	Susceptance of the line connecting buses *n* and *m*, p.u.
G_{nm}	Conductance of the line connecting buses *n* and *m*, p.u.
I_{ac}	Number of AC generators in the system.
J_{dc}	Number of DC generators in the system.
$N_{SW,t}^{\max}$	Maximum number of switching actions at time *t*.
$N_{SW,s}^{\max}$	Maximum number of daily switching actions for switch *s*.
N	Number of buses in the network.
$P_{TG,t}$	Total active power generated at time *t*.
$P_{TD,t}$	Total active power demand at time *t*.
P_{nm}	Active power transmitted from bus *n* to bus *m*.
$P_{G_n}^{dc}$	Output power of the DC DG at bus *n*.
$P_{G_n}^{ac}$	Active power of the AC DG at bus *n*.
$P_{L_n}^{dc}$	Power demand of the DC load at bus *n*.
$P_{L_n}^{ac}$	Active power demand of the AC load at bus *n*.
Q_{nm}	Reactive power transmitted from bus *n* to bus *m*.
$Q_{G_n}^{ac}$	Reactive power of the AC generator at bus *n*.
$Q_{L_n}^{ac}$	Reactive power demand of the AC load at bus *n*.
S_{nm}	Apparent power transmitted from bus *n* to bus *m*.
NS	Set of the network sections that have the flexibility to be either open or closed.
NS_C	Set of the network sections that are permanently closed.
T	Set of the day-ahead time intervals.
Δt	Duration of each time interval, $\Delta t = 1$ h.
U_{nm}	Binary element of the line *nm* in the connection matrix *U*.
V_n	Voltage magnitude at bus *n*, in kV or p.u.
θ_n	Voltage angle at bus *n*, in rad or degrees.
θ_{nm}	Voltage angle difference ($\theta_{nm} = \theta_n - \theta_m$).

η_{i-n}	Efficiency of an inverter at bus *n*, as a %.
η_{r-n}	Efficiency of a rectifier at bus *n*, as a %.
$\psi_{s,t}$	Status of the switch *s* at time *t*. It is equal to 0 if switch *s* is open, and equal to 1 if switch *s* is closed.
$\blacklozenge^{\max}$	Maximum limit of the variable $\blacklozenge$.
$\blacklozenge^{\min}$	Minimum limit of the variable $\blacklozenge$.

References

[1] European Photovoltaic Industry Association (EPIA). Global market outlook for photovoltaics 2014-2018. [Online]. Available: http://www.epia.org/news/publications/global-market-outlook-for-photovoltaics-2014-2018.

[2] Ontario Power Authority. (2016, Feb.). Fit program. [Online]. Available: http://fit.powerauthority.on.ca/fit-program.

[3] S. Golshannavaz, S. Afsharnia, and F. Aminifar, “Smart distribution grid: Optimal day-ahead scheduling with reconfigurable topology,” *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2402–2411, Sept. 2014.

[4] C.-T. Su and C.-S. Lee, “Network reconfiguration of distribution systems using improved mixed-integer hybrid differential evolution,” *IEEE Transactions on Power Delivery*, vol. 18, no. 3, pp. 1022–1027, July 2003.

[5] T. T. Nguyen and A. V. Truong, “Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm,” *International Journal of Electrical Power & Energy Systems*, vol. 68, pp. 233 – 242, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/ pii/S0142061514008023.

[6] R. Rajaram, K. S. Kumar, and N. Rajasekar, “Power system reconfiguration in a radial distribution network for reducing losses and to improve voltage profile using modified plant growth simulation algorithm with distributed generation (dg),” *Energy Reports*, vol. 1, pp. 116 – 122, 2015. [Online]. Available: http://www.sciencedirect.com/ science/article/pii/S2352484715000165.

[7] S. Jena and S. Chauhan, “Solving distribution feeder reconfiguration and concurrent DG installation problems for power loss minimization by multi swarm cooperative PSO algorithm,” *IEEE/PES Transmission and Distribution Conference and Exposition*, pp. 1–9, May 2016.

[8] S. Naveen, K. S. Kumar, and K. Rajalakshmi, “Distribution system reconfiguration for loss minimization using modified bacterial foraging optimization algorithm,” *International Journal of Electrical Power & Energy Systems*, vol. 69, pp. 90 – 97, 2015. [Online]. Available: http://www.sciencedirect.com/science/article /pii/S0142061515000150.

[9] Jaswanti and T. Thakur, “Minimum loss configuration of power distribution system,” *International Conference on Power Electronic, Drives and Energy Systems*, pp. 1–6, Dec. 2006.

[10] S. A. Taher and M. H. Karimi, "Optimal reconfiguration and DG allocation in balanced and unbalanced distribution systems ," *Ain Shams Engineering Journal*, vol. 5, no. 3, pp. 735 – 749, 2014. [Online]. Available: http://www.sciencedirect.com/ science/article/pii/S2090447914000380.

[11] R. A. Jabr, R. Singh, and B. C. Pal, "Minimum loss network reconfiguration using mixed-integer convex programming," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 1106–1115, May 2012.

[12] H. M. Khodr, J. Martinez-Crespo, M. A. Matos, and J. Pereira, "Distribution systems reconfiguration based on OPF using Benders decomposition," *IEEE Transactions on Power Delivery*, vol. 24, no. 4, pp. 2166–2176, Oct. 2009.

[13] H. M. A. Ahmed, A. B. Eltantawy, and M. M. A. Salama, "A planning approach for the network configuration of AC-DC hybrid distribution systems," *IEEE Transactions on Smart Grid*, vol. PP, no. 99, pp. 1–1, 2016.

10TH INTERNATIONAL CONFERENCE ON SUSTAINABLE ENERGY AND ENVIRONMENTAL PROTECTION (JUNE 27TH – 30TH, 2017, BLED, SLOVENIA), POWER DISTRIBUTION
J. Krope, A.Ghani Olabi, D. Goričanec & S. Božičnik

Spatial Prediction of Renewable Energy Resources for Reinforcing and Expanding Power Grids

BEOMJUN PARK & JIN HUR

Abstract Due to intermittency of wind and solar generating resources, it is very hard to manage renewable energy resources in system operation and planning. In order to incorporate higher wind and solar power penetrations into power systems maintaining a secure and economic power system operation, the accurate estimation of wind and solar power outputs is needed. As wind and solar farm outputs depend on natural resources that vary over space and time, spatial analysis is also needed. Predictions about suitability for locating new wind and solar generating resources can be performed by optimal spatial modelling. In this paper, we propose a new spatial prediction of renewable energy resources for reinforcing and expanding power grids. Capacity factors of renewable energy resources for long-term power grid planning are estimated by optimal spatial modelling based on Kriging. The proposed method is verified by empirical data from industrial wind and solar farms in South Korea.

Keywords: • spatial modelling • kriging technique • ordinary kriging (OK) • spatial prediction • outputs prediction •

CORRESPONDENCE ADDRESS: BeomJun Park, Graduate student, Sangmyung University, Department of Electrical Engineering, 20, Hongjimun 2-gil, Jongno-gu, Seoul, Republic of Korea, e-mail: 201737010.sangmyung.kr. Jin Hur, Ph.D., Assistant Professor, Sangmyung University, Department of Electrical Engineering, 20, Hongjimun 2-gil, Jongno-gu, Seoul, Republic of Korea, e-mail: jinhur@smu.ac.kr.

https://doi.org/10.18690/978-961-286-060-8.3 ISBN 978-961-286-060-8

1 Introduction

As global economic recession is persistent and oil prices are increased, the concern of variable energy has grown rapidly over the past decades. The expansion of variable generating resources has experienced an important boost in recent. In case of wind power generation, total accumulated wind power capacity reached 319 GW in 2013. The worldwide total of wind power capacity was 432.9 GW in 2015 [1]. And wind power capacity is expected to increase consistently, to the point where wind power will generate 4,337 TWh in 2035. In case of solar power generation, it is expected to provide 11% of the global electricity consumption in 2050 [2]. High penetration of renewable energy into grids are challenging to balance due to variable generation weather dependent energy resources. For this reason, wind and solar power prediction which is a technique to determine the quantity of outputs is becoming a salient point of research. Prediction of variable generation are proven methods for reducing the need for scheduling of ancillary generation and mitigating resource uncertainty. Therefore, it is essential for considering the variability, reducing the uncertainty and penetrating variable energy resources into power system. Especially, when we construct new variable generation, we need to predict outputs of variable generation for reinforcing and expanding power grids. Many approaches to predict variable energy have been proposed to increase reliability of prediction values. Most of approaches to predict variable energy are based on time series such as Auto Regression Moving Average (ARMA) / Auto Regression Integrated Moving Average (ARIMA)[3-4]. However, wind and solar farm outputs depend on natural resources that vary over space and time, spatial analysis and modelling is also needed. Time series prediction requires existing data which to predict outputs of unknown variable energy resources, and cannot be applied to predict in new areas without current measured data. However, spatial modelling prediction [5] does not require existing data and can be applied to predict variable generating resources in new areas. Therefore, we propose ordinary kriging (OK), a popular spatial model system, to predict variable energy resources. OK is an advanced prediction model where the estimation is not biased and error variance is minimized by linearly combining two or more variables. We used empirical data from wind and solar farms in Korea to predict variable generating resources at area of interest in a number of regions.

2 Capacity prediction of variable emergy

In this chapter, we explain database (DB) and spatial modelling, and provides the prediction results.

2.1 DB modelling for predicting capacity factor of variable generating resources

Before predicting the capacity factor, we model the DB of variable generating resources capacity and locational data for 2014–2015 from Korea.

1)Existing variable generating resources

To apply spatial modelling, we constructed a DB of the current variable generating resource hourly capacity and locational data for 2014–2015 in Korea, summarized in Table 1, and Fig. 1.

Table 1. Wind and solar farms in Korea, 2014–2015

Type	Year	The number of farm
Solar farm	2014	40
	2015	69
Wind farm	2014	39
	2015	48

2) New area locational data

After constructing DB about existing variable generating resource's hourly capacity factor and locational data, we make additional DB about new area's locational data for predict capacity factor of new areas which are primary points for integrating renewable energy resources. The locational data of new areas are represented in Table 2.

Table 2. Location details for new areas of renewable energy resources

Area	Zone	Latitude(°)	longitude(°)
Capital	A s/s	37.2248	126.7263
Middle	B s/s	36.7420	126.2875
Jeju Island	C s/s	33.4010	126.2720
South-west	D s/s	35.4545	126.4470
	E s/s	35.2813	126.4875
South-East	F s/s	36.5362	129.0768
	G s/s	36.4412	129.8348
	H s/s	36.7089	129.4336
East	I s/s	37.3682	128.6848
	J s/s	37.1954	128.8701
	K s/s	37.2333	129.0400
	L s/s	37.6772	128.6720
	M s/s	37.7174	128.6759
	N s/s	37.4946	128.1751

The locational data of existing wind, solar farm and new area are represented in Figure 1.

Figure 1. Location details for existing wind and solar farms, and new areas in Korea 2014–2015

As shown in Figure 1, The locational data of existing wind, solar farm are represented by turbines and PV panels. And the locational data of new area are represented by red circles. In this paper, we predict capacity factor at red circles by using the spatial correlation between existing wind and solar farm's capacity factor and locational data.

2.2 Spatial modelling

Time series models are commonly used to predict outputs of variable generation resources. However, time series prediction requires a mathematical model to describe the sequence, which must be developed from previous known values [6]. Thus, time series prediction requires known past data train patterns and provide forecast values.

However, wind and solar farm outputs depend on natural resources that vary over space and time, and we must consider spatial characteristics. Spatial modelling analyzes data which has spatial correlations, and has the advantage that it does not require past data to predict outcomes for new areas.

Therefore, we propose spatial modelling to predict variable generating resources. We first need to define the sample spaces of variables of interest. Then collect data for these sample spaces and analyze the spatial correlations between areas. Where correlations between resource and spatial data exist, we can predict outcomes for new areas using geostatistics. Most representative method of spatial modelling is kriging which is based on the probability theory. This method predicts values which are expectation at the point of interest by combining nearby measured values. In this paper, the proposed method is verified by empirical data from industrial wind and solar farms in South Korea.

1) Variograms

The variogram is a basic geostatistics tool, and represents spatial correlations between data which are keeping a certain distance. From it one infers the model form that is applicable to the kriging. The equation of variogram can be expressed as:

$$2\gamma(d) = E\left|\left(z(x+d) - z(x)\right)^2\right| \tag{1}$$

In the equation (1), x is the interested point and d is a separation distance. The variogram is a expectation which is gained by calculating values at point x and point x+d. z is actual value at the point of exist. Generally, we can get small variogram values when the distance is close. The semi variogram is a value that is half of variogram. It is used to calculate real variogram for convenience in calculation. The semi variogram is represented as:

$$\gamma(d) = \frac{E\left|\left(z(x+d)-z(x)\right)^2\right|}{2} \tag{2}$$

To adapt the kriging method, we analyze spatial correlation between measured data using the experimental variogram. After calculating experimental variogram, we find the theoretical variogram and accomplish modelling. For adapting the theoretical variogram, we must define parameters those are called sill, nugget and range. The sill is the value at which the model first flattens out, this parameter give us information about point of loss of spatial correlation. The nugget is the distance at which the model first flattens out, that means the value at sill. And the nugget is the value which means uncertainty of data at which the semi variogram intercepts the y-value. After defining the parameters, we adapt the variogram model which is the most suitable.

There are several different possible variogram models, including linear, spherical, exponential, and Gaussian, as shown in Fig. 2.

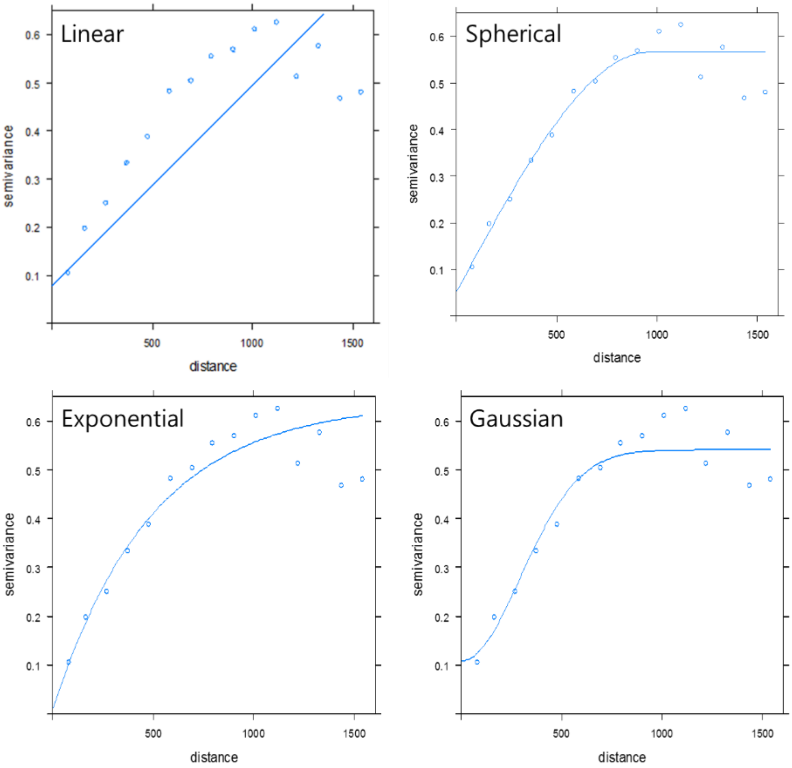


Figure 2. Possible variogram models

Linear models are simple and easy to use, but are difficult to contain data deviation. Spherical models are represented by tertiary polynomials, and commonly used. Exponential models have the advantage that with increasing *d*, the predicted values converge to sill. Gaussian models are used when the data has high correlations over small distributed distances.

2)Ordinary Kriging

Kriging [7] is a spatial modeling technique that predicts characteristic values of points of interest using already known spatial data. The basic kriging model can be expressed as:

$$z^* = \sum_{k=1}^{n} \lambda_k z_k \tag{3}$$

where z^* is the expectation and z_k is actual value at the point of exist, λ_k is the applied weight, and *k* is the number of data points used in the prediction.

There are many kriging models [8], but five types are typically used, as shown in Table 3.

Table 3. Typical kriging methods

Method	Description
Simple Kriging (SK)	Calculate the estimated value by linearizing combination of known values and minimizing variance
Block Kriging (BK)	Create a single kriging equation for the desired point and predict values
Co Kriging (CK)	Two or more variables are combined to predict the value at the specific point
Universal Kriging (UK)	Compute the weight of kriging without removing the average which is given specific tendency of the space
Ordinary Kriging (OK)	The equation of estimate is not biased and error deviations are minimized

Ordinary kriging is a technique that improves the disadvantages of simple kriging[9]. because the estimate is not biased and error deviations are minimized [10]. To preventing bias, the sum of deviations is defined as 1. Thus, we use OK to predict capacity for renewable energy resources in new areas. In this paper, we use ordinary kriging for predicting capacity factors of renewable energy resources.

3 Case studies : renewable energy resources in Korea

The capacity represents the efficiency of renewable energy. Accurate estimation of wind and solar capacity is essential to incorporate higher wind and solar power penetration into power systems while maintaining secure and economic operation. Therefore, we propose to predict wind and solar farm capacity using spatial modelling.

1) Prediction of Wind Farm's Capacity Factor

We used measured capacities from 2014–2015 and location data to predict wind farm capacities for new zones in each area, and the largest predicted capacity for each month was selected as the representative value for the corresponding area. Predicted values are shown in Table 4, and representative (maximum) capacities are shown in Fig. 3.

Table 4. Predicted values of wind farm

Capital	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	22.07	13.72	22.42	13.81	20.02	9.56
	2015	25.56	20.09	23.87	17.53	16.35	9.95
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	12.44	13.24	8.99	15.71	20.79	31.67
	2015	14.18	13.11	10.63	21.46	19.94	14.77
Middle	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	29.79	14.45	28.17	12.24	25.71	11.55
	2015	32.12	32.13	28.17	24.44	20.49	7.57
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	16.65	17.67	11.56	17.07	23.92	37.64
	2015	20.81	15.06	15.02	24.23	23.94	17.35
East	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	45.82	18.56	43.69	23.10	41.64	13.94
	2015	43.38	23.38	45.74	38.33	32.83	15.23
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	33.73	25.18	14.29	28.88	33.01	48.25
	2015	32.02	22.13	14.37	38.70	24.06	45.88
South-West	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	28.09	21.42	29.45	16.52	23.57	10.64
	2015	38.85	36.52	28.75	23.81	22.20	17.04
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	15.23	16.93	12.02	19.06	25.94	40.51
	2015	20.85	14.91	13.98	25.41	24.52	32.68
South-East	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	40.60	25.05	33.15	25.71	32.82	15.65
	2015	37.81	40.59	36.78	32.14	26.47	13.52
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	22.33	22.18	15.61	29.47	28.58	46.07
	2015	26.92	16.19	16.57	28.70	26.23	41.53
Jeju Island	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	33.27	36.18	34.29	22.72	19.28	11.86
	2015	40.06	33.68	26.37	22.02	16.19	13.50
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	14.52	20.36	15.61	27.68	23.85	40.38
	2015	19.43	13.53	15.75	21.64	22.73	30.60

After performing prediction, we select maximum capacity factors at each region. Then selected wind power capacity factors are becoming representative values. This is represented in Figure 3.

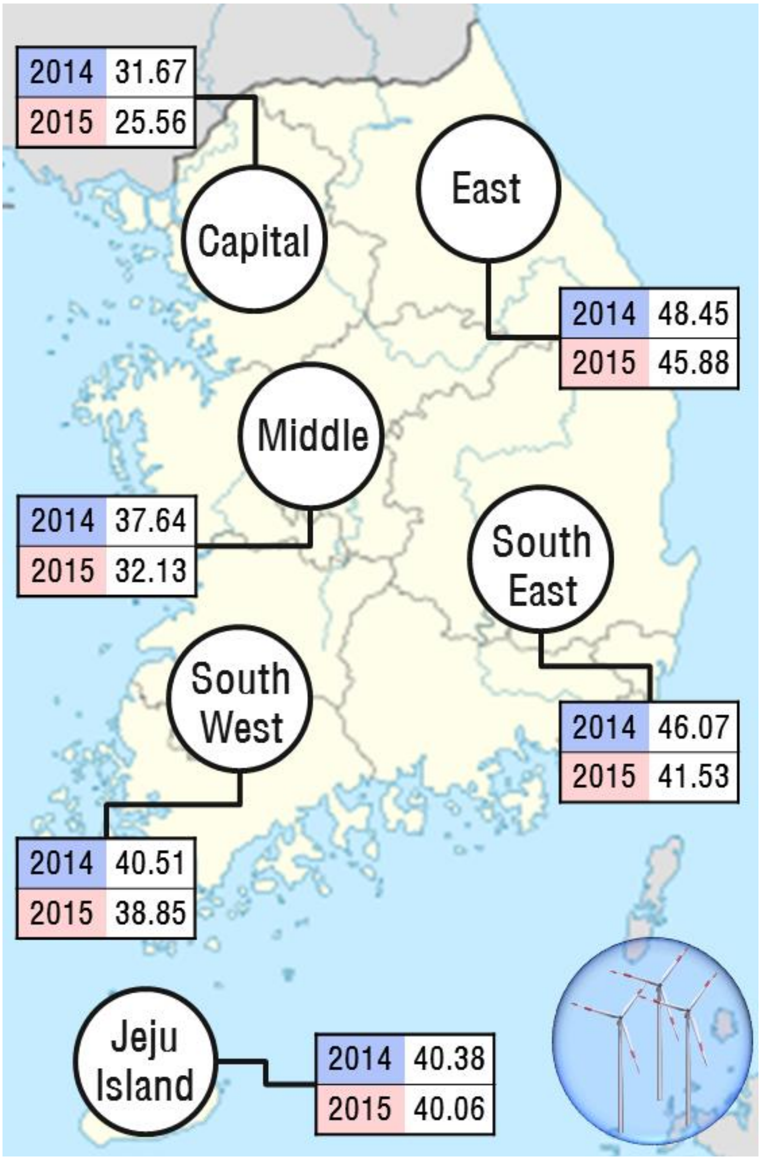


Figure 3. Predicted values of wind farm

These values can provide the information which are represented values when we installed wind turbines at each region. By using these data, we can plan reinforcing and expanding power grid pursuant to spread of supply of wind power generator. The predicted values allow better planning to expand the power grid using wind power generators.

2) Prediction of Solar Farm's Capacity Factor

We predicted solar farm capacity using measured capacity for 2014–2015 and location data. The prediction method for solar farm capacity for each zone was the same as for wind power generation. Predicted results are shown in Table 5, and representative (maximum) capacities are shown in Fig. 4.

Table 5. Predicted values of solar farm

Capital	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	28.42	29.17	33.05	33.71	34.46	28.36
	2015	32.53	30.36	38.53	31.68	36.97	30.63
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	25.02	21.70	29.57	34.03	26.43	21.29
	2015	27.11	31.25	33.69	35.57	19.00	27.62
Middle	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	28.21	29.12	33.47	33.31	35.45	31.75
	2015	30.00	30.26	40.53	32.26	37.14	32.40
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	26.96	23.15	32.20	35.24	25.32	20.85
	2015	27.32	31.68	34.92	34.23	16.37	23.56
East	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	27.54	32.05	32.74	35.37	39.77	29.89
	2015	25.13	31.40	40.65	31.97	39.06	34.27
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	29.57	24.81	31.20	32.83	27.49	27.02
	2015	27.35	31.13	34.76	34.50	16.67	22.89
South-West	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	30.47	27.85	33.05	33.13	36.53	29.14
	2015	26.08	28.17	37.15	29.35	34.34	26.89
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	24.10	22.35	30.54	34.50	26.13	21.33
	2015	25.49	29.01	32.05	33.69	15.73	20.15
South-East	Month	Jan	Feb	Mar	Apr	May	Jun
	2014	27.72	28.77	30.15	31.73	36.93	27.81
	2015	26.72	30.87	35.94	27.66	34.65	27.91
	Month	Jul	Aug	Sep	Oct	Nov	Dec
	2014	27.77	22.17	30.13	33.96	26.66	25.99
	2015	25.26	28.82	30.24	33.64	17.77	23.70

The same as wind power, we select maximum capacity factors of solar farm at each region. This is represented in Figure 4.

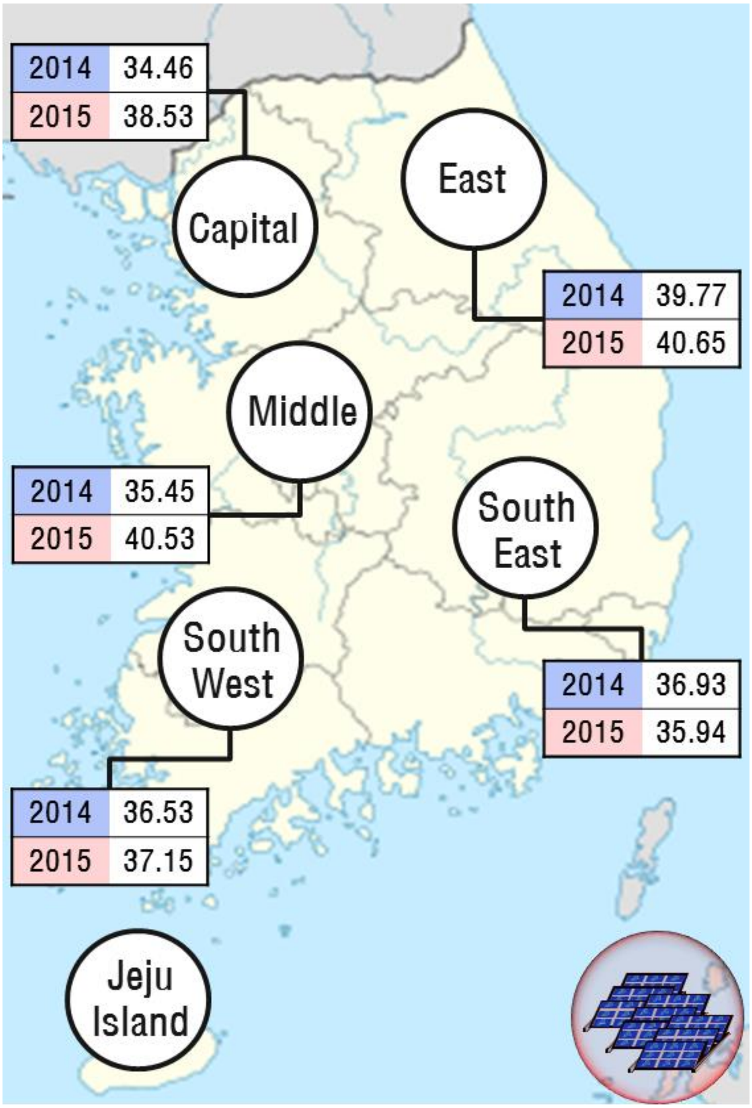


Figure 4. Predicted values of solar farm

These predicted capacities provide representative for installed PV power generators at each region, allowing better planning to expand the power grid using PV generators.

3 Conclusion

With increasing penetration of renewable energy resources into power grids, prediction of renewable energy capacity is becoming an important issue for grid integration. We can establish reasonable augmentation plans for electrical facilities and operate power system safety by accurately predicting output capacity.

Since wind and solar farm outputs depend on natural resources that vary over space and time, spatial analysis is required. Prediction of location suitability for new wind and solar generation can be provided by optimal spatial modelling.

We predicted renewable energy resource capacity using ordinary kriging spatial modelling, providing useful inputs for long-term power grid planning. This will allow higher wind and solar power penetration into power systems, while maintaining secure and economic power generation. We can also develop forward plans to reinforce and expand the power grid utilizing renewable energy resources

Acknowledgements

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (No. 20161210200560).

References

[1] "Renewable 2015 Global Status Report", Renewable Energy Policy Network for the 21th century, 2015.
[2] "World Energy Outlook 2015", International Energy Agency, 2015.
[3] Almoataz Youssef Abdelaziz1, "Short Term Wind Power Forecasting Using Autoregressive Integrated Moving Average Approach", Journal of Energy and Power Engineering 7, 2013.
[4] V. Prema, K. Uma Rao, "Development of statistical time series models for solar power prediction", Renewable Energy 83 100-109, 2015.
[5] Andreas Lichtenstern, "Kriging methods in spatial statistics, Technische Universitat Munchen Department of Mathematics, 2013.
[6] Wu Xiaodan, Liu Wenying, "Short-term wind power prediction based on time series analysis model", Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering, 2013.
[7] Stein, Michael L. *Interpolation of spatial data: some theory for kriging*. Springer Science & Business Media, 2012.
[8] Cressie, Noel, "The origins of kriging. " Mathematical geology 22.3 (1990): 239-252.
[9] Kiš, Ivana Mesić. "Comparison of Ordinary and Universal Kriging interpolation techniques on a depth variable (a case of linear spatial trend), case study of the Šandrovac Field." *Rudarsko-geološko-naftni zbornik* 31.2 (2016): 41-58.
[10] Oliver, Margaret A., Richard Webster, "Kriging: a method of interpolation for geographical information systems.", International Journal of Geographical Information System 4.3, 1990.

[11] M. Cellura, G. Cirrincione, A. Marvuglia, and A. Miraoui, “Wind speed spatial estimation for energy planning in sicily: Introduction and statistical analysis,” Int. J. of Renewable Energy, vol. 33, no. 6, pp. 1237–1250, 2008.

[12] M. Cellura and G. Cirrincione and A. Marvuglia and A. Miraoui, “Wind speed spatial estimation for energy planning in sicily: A neural kriging application,” Int. J. of Renewable Energy, vol. 33, no. 6, pp. 1251–1266, 2008.

[13] R. Olea, “A six-step practical approach to semivariogram modeling,” Int. J. of Stochastic Environmental Research and Risk Assessment, vol. 20, pp. 307–318, 2006.

[14] R. Webster and M. Oliver, Geostatistics Environmental Scientists. West Sussex, England: John Wiley and Sons Ltd, 2000.

[15] N. Hofstra and M. New, “Spatial variability in correlation decay distance and influence on angular-distance weighting interpolation of daily precipitation over europe,” Int. J. of Climatology, vol. 29, no. 12, pp. 1872–1880, 2009.

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana

METTLER TOLEDO

PRINSIS

energetika ljubljana