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Communications in Computer and Information Science 516

Intelligence in the Era of Big Data

4th International Conference on Soft Computing, Intelligent Systems and Information Technology, ICSIIT 2015
Bali, Indonesia, March 11–14, 2015, Proceedings

Springer

Communications in Computer and Information Science 516

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ISSN 1865-0929 ISSN 1865-0937 (electronic)
Communications in Computer and Information Science
ISBN 978-3-662-46741-1 ISBN 978-3-662-46742-8 (eBook)
DOI 10.1007/978-3-662-46742-8

Library of Congress Control Number: 2015934823

Springer Heidelberg New York Dordrecht London

Printed on acid-free paper

Springer-Verlag GmbH Berlin Heidelberg is part of Springer Science+Business Media
(www.springer.com)

Preface

This proceedings volume contains papers presented at the fourth International Conference on Soft Computing, Intelligent System and Information Technology (the 4th ICSIIT) held in Bali, Indonesia, during March 11–14, 2015. The main theme of this international conference is "Intelligence in the Era of Big Data," and it was organized and hosted by Informatics Engineering Department, Petra Christian University, Surabaya, Indonesia.

The Program Committee received 92 submissions for the conference from across Indonesia and around the world. After peer-review process by at least two reviewers per paper, 53 papers were accepted and included in the proceedings. The papers were divided into 14 groups: fuzzy logic and control system, genetic algorithm and heuristic approaches, artificial intelligence and machine learning, similarity-based models, classification and clustering techniques, intelligent data processing, feature extraction, image recognition, visualization technique, intelligent network, cloud and parallel computing, strategic planning, intelligent applications, and intelligent systems for enterprise government and society.

We would like to thank all Program Committee members for their effort in providing high-quality reviews in a timely manner. We thank all the authors of submitted papers and the authors of selected papers for their collaboration in preparation of the final copy.

Compared to the previous ICSIIT conferences, the number of participants at the 4th ICSIIT 2015 is not only higher, but also the research papers presented at the conference are improved both in quantity and quality. On behalf of the Organizing Committee, once again, we would like to thank all the participants of this conference, who contributed enormously to the success of the conference.

We hope all of you enjoy reading this volume and that you will find it inspiring and stimulating for your research and future work.

February 2015

Rolly Intan
Chi-Hung Chi
Henry N. Palit
Leo W. Santoso

Organization

The International Conference on Soft Computing, Intelligent System and Information Technology (ICSIIT) 2015 (http://icsiit.petra.ac.id) took place in Bali, Indonesia, during March 11–14, 2015, hosted by Informatics Department, Petra Christian University.

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Keynote and Invited Papers

Data Mining Model for Road Accident Prediction in Developing Countries

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Abstract. Human loss due to road traffic accident (RTA) in developing countries is a big challenge. It becomes more serious in those developing countries where road conditions are not good and due to several reasons government is not able to maintain roads on regular basis. Additionally, increasing number of vehicles, inefficient driving and environmental conditions are also some of the factors which are responsible for RTA. In this work we present architecture of a data mining model. The proposed model is applied on real data set of RTAs from a developing country. The analysis of data gives several useful results, which can be used for future planning to reduce RTAs in developing countries. This paper also presents that how data mining model is better than other models.

Keywords: Data mining, road accident, vehicles, clusters, traffic road.

Behaviour Informatics: Capturing Value Creation in the Era of Big Data

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Abstract. Under the era of Big Data, people have been exploring ways of realizing value from data that are at their fingertips. However, it is found that while collecting data is not difficult, value creation is often a big challenge. This makes the approach of "collecting data first before knowing what to do with them" questionable. In this presentation, we discuss the current challenges of big data analytics and suggest how behaviour analytics on trajectory data can help to realize value creation from Big Data.

1 Background and Challenges

As we move to the fourth paradigm of computing – data intensive scientific discovery, numerous research efforts have been spent in building huge big data repositories. Together with data mining and machine learning research, it is hoped that better and more intelligent decisions can be made in real time.

This movement is accelerated by the advance in at least three areas. The first one is social network, where people share their views and opinions in public. The second one is cloud computing, which is an on-demand infrastructure that facilitates sharing of data, collaboration among multiple parties, and support for on-demand computational and storage infrastructure services at low cost. The third one is the internet-of-things. With the maturity of sensor technologies, trajectory movement of entities (including human and things) can now be monitored in real time at low cost. However, gaining access to big data is only the starting point. There are still open issues that need to be addressed in the value creation process when dealing with big data.

One result of the big data mega trend is the building of huge data repositories around the world. In Australia, the government has been pushing for sharing bureau data through spatial information platforms. It is true that data are collected and can be made available to users, but how to make sense out of these data practically and economically is still a mystery to be explored. Without value creation, the high maintenance cost of these repositories cannot be justified, and the motivation for data providers to update their data inside will also disappear.

In the past few years, sensors and sensing techniques have been advancing rapidly for real time data collection with good enough accuracy. Cost of deploying these technologies is also becoming low enough to make real-time data tracking of human, animals, and even insects (e.g. honey bees) possible. However, without efficient and effective ways to integrate and transform these trajectory data and their context information into manageable knowledge, these data are actually burdens instead of potentials to their owners.

It is true that there have been numerous research efforts in data mining and machine learning. However, most of them are focused on theoretical algorithmic study, and much less emphasis is put in the incorporation of semantic domain knowledge (in particular, the semantic definition of interdependence among various data sources) into the data mining and pattern discovery processes, and in the use of the behaviour interior dimensions such as loyalty and purchase power of customers to support self service analytics.

Related to the analytics platform, internet-of-things, service and cloud computing techniques are quite mature, and lots of machine learning algorithms are also widely available in both commercial (e.g. MatLib) and open source ("Project R") packages. However, how to put them together in a single service platform and how to compose them together automatically (this is called the vertical service composition) to provide "intelligence-as-a-service" for a given domain are still open for exploration.

2 Real Time Trajectory Data and Its Challenges in Value Creation

In the era of big data, one new important data source for analytics and value creation is the real-time behaviour trajectory data streams of entities (e.g. human) as well as their context dynamics (e.g. environmental such as air quality) that are captured through internet-of-things and sensors (in particular body sensors such as those from Android wears and location position sensors). Its value creation process is both complex and challenging because these data are in general heterogeneous and inter-dependent on each other. Furthermore, the potential number of data sources, each describing one measurement view of the behaviour dynamics of an entity/event, is in theory, infinite.

Traditional data mining and machine learning approaches from computer science often try to explore co-occurrence patterns and inter-relationship among trajectory data. However, this is usually done without making full use of the interdependence defined by their implicit semantic meaning and domain knowledge. Heterogeneity of data adds another level of complication because quantification measures such as distance are not uniformly and consistently defined across different data types. On the other hand, although domain experts have full knowledge on the semantics of data, they are often not as knowledgeable as computer scientists when dealing with the real time computation on trajectory data streams. This result in the first challenge, how to use data mining / machine learning techniques and domain knowledge together to effectively define and discover the inter-relationships among different trajectory data sources and to perform effective behaviour analysis.

As trajectory-driven behaviour analytics is gaining its recognition in different business and industry sectors, the expectation of decision makers also goes beyond what traditional analytics that mainly focus on statistical summaries and association/patterns discovery of transactional/measurable behaviour exterior dimensions often provide. Ultimately, what decision makers want is the deep insight about the behaviour interior knowledge dimensions of entities, by incorporating domain knowledge into the knowledge discovery processes. As an example, the owner of an online shop wants to know not only the "bestselling products of the week", but also the "loyalty", "purchase power", "experience", and "satisfaction" of customers. This results in the second challenge, how to quantify behaviour interior dimensions from exterior transactional (or physically measured) trajectory data and to discover their inter-relationships and relative importance for effective and efficient behaviour analysis.

3 Research Topics in Behaviour Analytics

To achieve this goal, the following is a list of sample research topics for behaviour analytics:

- Effective and efficient deployment of high resolution location tracking network (using Blue-Tooth LE, WiFi-RFIDs, UWB, and Electromagnetic Field) for entities in both indoor and outdoor environment. This forms the basis for behaviour trajectory data tracking and capturing.
- Semantic enrichment of behaviour trajectory data of entities through aggregation of raw trajectory data with their contextual data dynamics, followed by domain knowledge-driven transformation to form behaviour interior dimensions knowledge. This is the data aggregation, integration, and transformation aspects of behaviour analytics; it incorporates domain knowledge into the behaviour trajectory data to create behaviour interior dimensions knowledge as well as to define the interdependence relationship among them.
- Discovery of interdependence relationship among trajectory-driven behaviour data (exterior) and knowledge streams (interior) using data mining techniques. This addresses the interdependence relationships of trajectory data and knowledge streams from the run-time dynamics aspect.
- Coupling interdependence relationships of behaviour trajectory data and knowledge streams into data mining and pattern discovery processes for deep behaviour understanding and prediction. This gives a much better understanding on why things occur; it also gives potentials for future behaviour prediction.
- Design and implementation of a behaviour analytics service system that serves as a publishing, management and operation platform for: (i) software services, (ii) raw trajectory data services, (iii) semantically annotated behaviour trajectory data services (both individuals and collective), (iv) behaviour knowledge services (both individuals and collective), and (v) infrastructure services. Tools to facilitate composition and orchestration of all these services with QoS assurance using public cloud infrastructure such as Amazon EC2 should be developed. Also, automatic matching of behaviour trajectory data/knowledge services with machine learning/data mining algorithms based on their features should also be supported on this platform.

On the Relation of Probability, Fuzziness, Rough and Evidence Theory

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Abstract. Since the appearance of the first paper on fuzzy sets proposed by Zadeh in 1965, the relationship between probability and fuzziness in the representation of uncertainty has been discussed among many people. The question is whether probability theory itself is sufficient to deal with uncertainty. In this paper the relationship between probability and fuzziness is analyzed by the process of perception to simply understand the relationship between them. It is clear that probability and fuzziness work in different areas of uncertainty. Here, fuzzy event in the presence of probability theory provides *probability of fuzzy event* in which fuzzy event could be regarded as a generalization of crisp event. Moreover, in rough set theory, a rough event is proposed representing two approximate events, namely lower approximate event and upper approximate event. Similarly, in the presence of probability theory, rough event can be extended to be *probability of rough event*. Finally, the paper shows and discusses relation among lower-upper approximate probability (probability of rough events), belief-plausibility measures (evidence theory), classical probability measures, probability of generalized fuzzy-rough events and probability of fuzzy events.

Keywords: Probability, Rough Sets, Fuzzy Sets, Evidence Theory.

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A Simulation Model for Strategic Planning In Asset Management of Electricity Distribution Network

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Abstract. Asset management of electricity distribution network is required in order to improve the network reliability so as to reduce electricity energy distribution losses. Due to strategic asset management requires long-term predictions; it would require a simulation model. Simulation of asset management is an approach to predict the consequences of long-term financing on maintenance and renewal strategies in electrical energy distribution networks. In this research, the simulation method used is System Dynamics based on consideration that this method enables us to consider internal and external influenced factors. To obtain the model parameter, we utilized PLN Pamekasan for the case study. The results showed the reduction of low voltage network assets condition on average in the range 6% per year, the average decline in the transformer condition is approximately 6.6% per year, and the average decline in the condition of medium voltage network assets is approximately 4.4% per year. In general, the average technical losses average of 1,359,981.60 KWH / month or about 16,319,779.24 KWH / year.

1 Introduction

1.1 Background

Electricity energy losses are losses incurred in the transfer of electricity energy through the distribution network. These losses increase along the channel of distribution and depend on the amount of transferred power. Some of the factors that influence the distribution losses are: network configuration, utilization, load profile, as well as power factor [1]. Asset management is required in order to improve the network reliability as well as to reduce the losses of electricity distribution.

There are four strategies in asset management as seen in Fig.1 [2]. Corrective Maintenance treatment is carried out when the network is impaired, while the Time Base Maintenance is maintenance and inspections that are conducted periodically at certain times. Furthermore, Condition Based Maintenance is a

R. Intan et al. (Eds.): ICSIIT 2015, CCIS 516, pp. 481–492, 2015.
DOI: 10.1007/978-3-662-46742-8_44

condition in which the asset is continuously monitored and conducted in accordance with the purposes of treatment. Finally, Reliability Centered Maintenance is asset maintenance that will be conducted based on priorities by considering the assets conditions and risks.

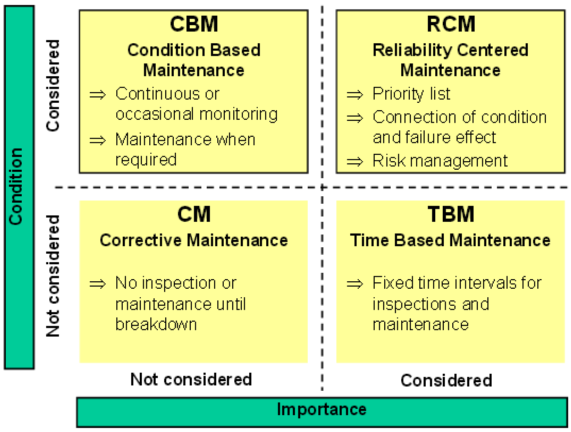

Fig 1. Network Maintenance Strategy Classification [2]

In this research, we used "Reliability Centered Maintenance" strategy which is very suitable to be applied in the area of Madura - Indonesia (Pamekasan) so that the network asset management can be performed based on priorities of the loss distribution of electrical energy which are prevalent in low voltage network (LVN). The purpose of this research is to develop a system dynamics model that can analyze the condition of the electricity distribution assets in deciding the effective and efficient asset maintenance policy.

1.2 Problem Solving Approach

In electricity energy distribution, asset management can be defined as a systematic process of the operation, maintenance, and improvement of distribution network reliability by combining the practices of "reengineering" and economic analysis [3].

In general, distribution network assets can be grouped into two parts, namely primary asset and secondary assets. The primary assets include air ducts, power transformer, high voltage, medium and low voltage cables. The secondary assets include power system protection relays, power meters, and control infrastructure. Due to strategic asset management requires long-term predictions; it would require a simulation model for asset management. Simulation asset is an approach to predict the consequences of long-term financing strategy in network maintenance and renewal of the electrical energy [4].

In this research, we utilized system dynamics framework to learn about the dynamic behavior of a distribution system, where such behavior is a direct result of a causal relationship between the internal and external elements of the system. The effects of causal relationships that are based on assumptions and decision rules then be formalized by using mathematical equations. System Dynamics focuses on the interrelationships into account non-linear with changing process that occurs throughout the time horizon, thus allowing the user to model very complex system [5]. With the System Dynamics framework, enable us to develop scenario and assessment for asset management strategic planning.

2. Method

System dynamics is a method to analyze and design a policy. Some steps is required to develop the model [6]: (a) problem definition which determine the significant variables; (b) model formulation which describe the relationship between components; (c) data collection; (d) model development; (e) model verification; (f) model validation used mean comparison and variance comparison [7]; (g) scenario development to improve the system performance (h) model interpretation; and (i) implementation.

3. RESULTS

3.1 System Dynamic Model Development

Asset management planning is a strategic framework for asset management. It also shows how the company will serve the needs of the country's power sector that is efficient, reliable, and quality services. Impairment of assets conditions can substantially increase the overall maintenance cost, raises issues other risk management, and have a negative impact on the environment, the overall state economic and increase operating costs [8].

Asset management program support the objectives and performance targets. Network performance targets to be a reference for asset planning and regular maintenance in the next year. It is also a reference to the actions required; whether the asset should be replaced or just need the maintenance. In the end, the target is expected to improve customer satisfaction, as shown in Fig. 2. Network performance can be affected by several factors, including temperature, humidity, weather, geographic, and the usage [9].

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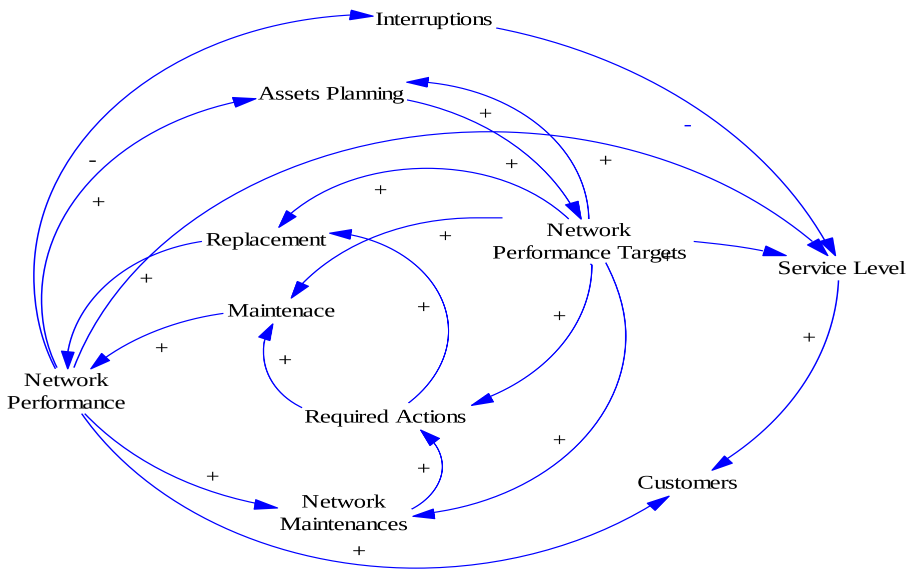

Fig 2. The link between performance targets, maintenance, and service levels

The other factors are the lives of assets that have been set by the manufacturer also affect network performance. When the assets is getting closer to the limit of the age, the higher the frequency of damage to assets, as shown in Fig. 3.

Indications disorders are categorized into two types: the transmission and distribution. In distribution, the two indicators are often used of SAIDI and SAIFI. And in terms of transmission, two things became calculation that System Outage Duration (SOD) and System Outage Frequency (SOF) as shown in Fig. 4.

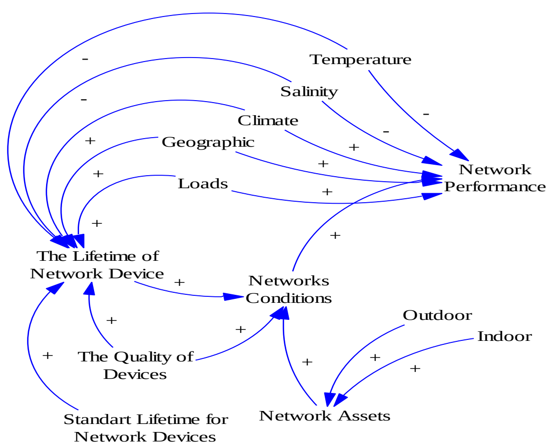

Fig 3. The causal relationship of asset lifetime

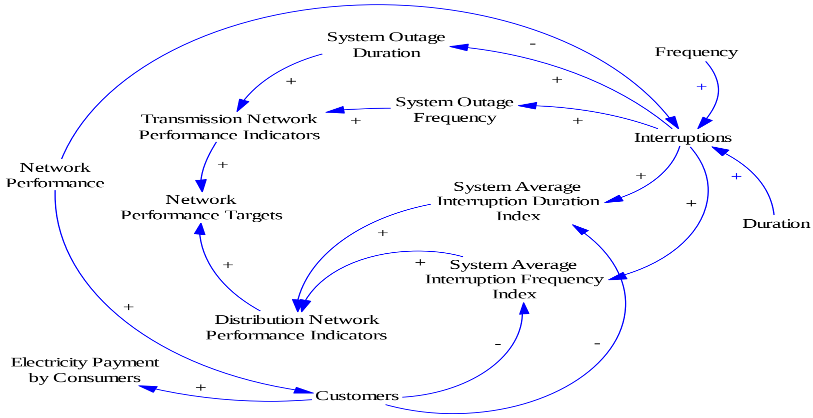

Fig. 4. The linkage of network performance indicators [8]

From the several significant variables above, caustics diagram can be developed as shown in Fig. 5.

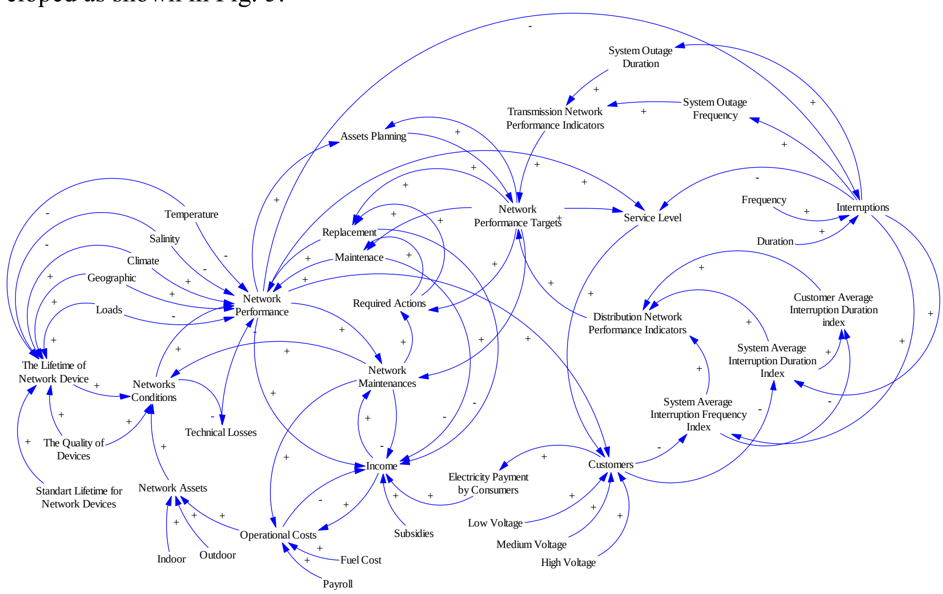

Fig. 5. Asset management distribution network caustic diagram

From Fig. 5, it can be seen that the asset management plan is determined by the network performance network performance targets. Network performance is affected by network conditions, asset maintenance, asset renewal, as well as external factors such as temperature, salinity, climate, geographical conditions, as well as network load. The target network performance is affected by the performance of the transmission network, the performance of the distribution network, as well as asset management planning. Service level is influenced by the frequency and duration of the disturbance (interruption), the performance of

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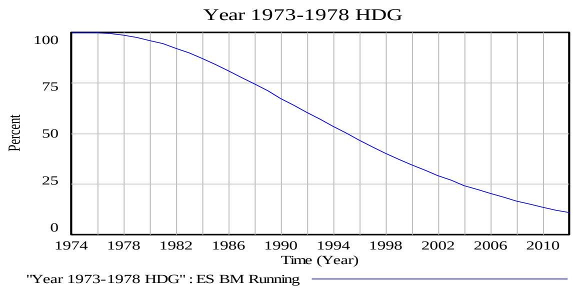
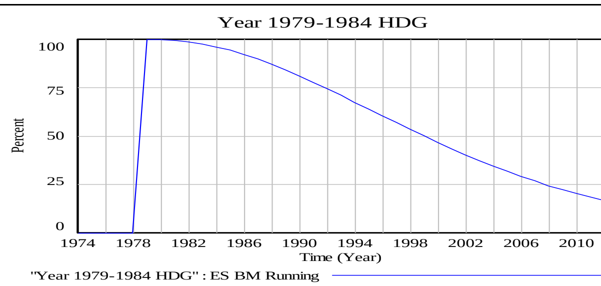
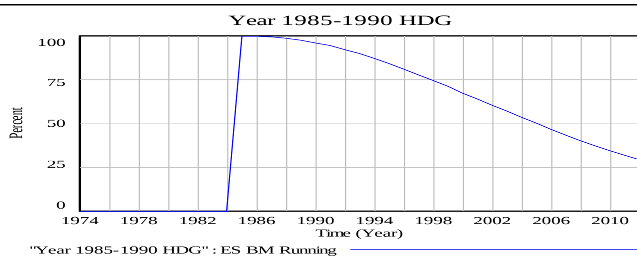
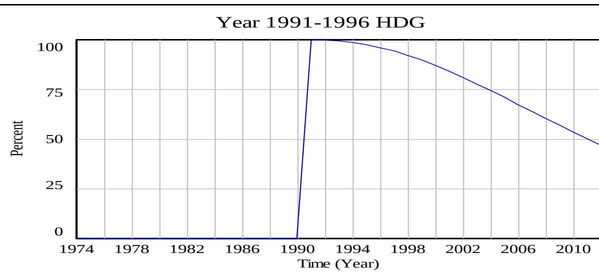
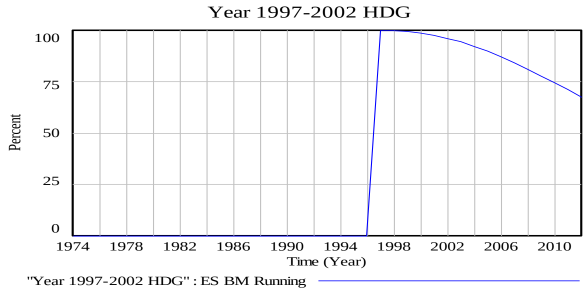
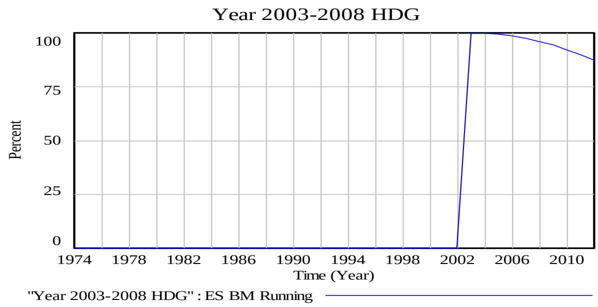
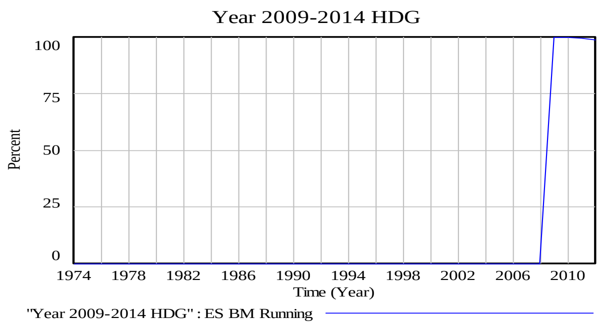
the network (network performance), as well as performance targets network to improve service levels.

3.2. Low Voltage Network Assets

From the simulation results can be seen that the low voltage network assets can be grouped into seven periods of the installation as shown in Table 1.

Table 1. Low voltage network asset condition by installation period

Year	Quantity	Low Voltage Network Asset Condition
1973-1978	3	
1979-1984	28	
1985-1990	387	
1991-1996	39.749	

Year	Quantity	Low Voltage Network Asset Condition
1997-2002	7.616	
2003-2008	21.750	
2009-2014	26.475	

From Table 1, it can be seen that the condition of the low voltage network assets installed in the period 1973 to 1990, has been under acceptable condition (<50%), so it is necessary to reform the asset. Overall, the average assets condition in the low voltage network by considering the assets installation can be seen in Fig. 6.

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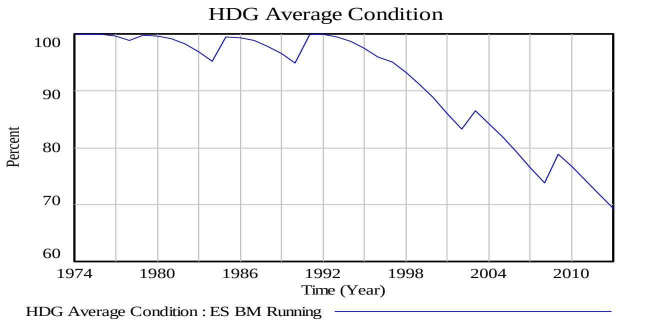

Fig. 6. The Average Assets Condition in the Low Voltage Network by Considering the Assets Installation

3.3. Transformer Assets

Based on data from PLN UPJ Pamekasan, transformers assets can be grouped into three installation periods as shown in Table 2. From Table 2, it can be seen that the condition of the asset transformers installed in the period 1979 to 1980, has been under acceptable condition (<50%), so it is necessary to reform the transformer assets. Overall, the condition of transformers on average assets by considering te installation of the assets can be seen in Fig. 7. From Fig. 7 it can be seen that the general condition of the asset transformers, already under acceptable condition, as a percentage of the bulk transformers which 72.95% had need of renewal (for the period 1979-1980).

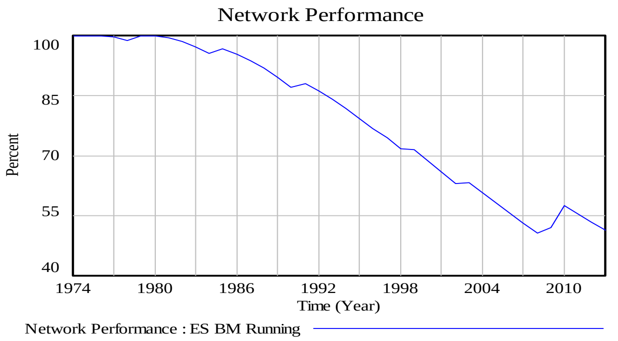

Fig. 7. Network Performance

3.4. Network Performance

The results of variable network performance can be seen in Fig. 8. While the results of variable performance losses as a result of the performance losses can be seen in Fig. 8.

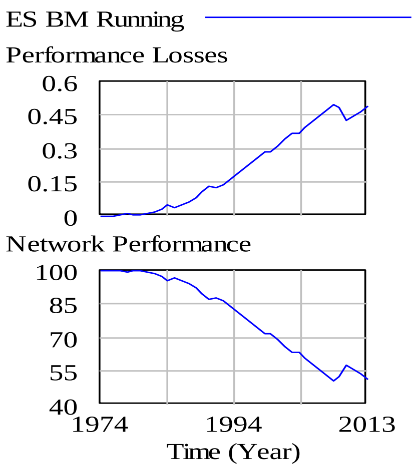

Fig. 8. Performance losses as an effect of network performance

3.5. Medium Voltage Assets

The results of the simulation shows that the average decline in the medium voltage network assets is approximately 4.4% per year as shown in Fig. 9. Conditions of medium voltage network assets installed in 1975-1990, under acceptable condition (50%), and in need of reform.

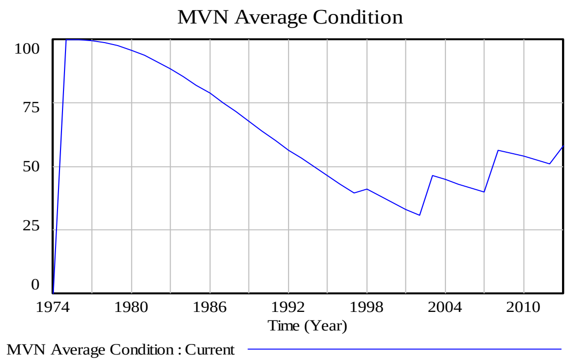

Fig. 9. Medium voltage assets

3.6. SAIDI and SAIFI

From Fig. 10 and Fig. 11, it can be seen that in the period 2003-2013, the average SAIDI = 7.4 hours / year, while the average SAIFI = 3.4 times / customers. SAIDI can be formulated as follows:

*SAIDI = (Duration Interruption * Number of Customer Impaired) / Total Customer* (1)

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DOI: 10.1007/978-3-662-46742-8_44

While SAIFI is the ratio of total customers who experienced outages on the number of subscribers that can be formulated as follows:

$$SAIFI = Number\ of\ Customer\ Impaired\ /\ Total\ Customer \quad (2)$$

The equation (1) and (2) are used to analyze data in the period 2003-2013.

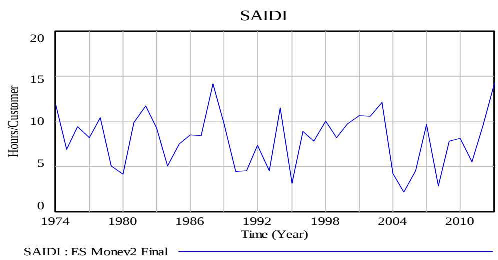

Fig. 10. SAIDI in UPJ Pamekasan

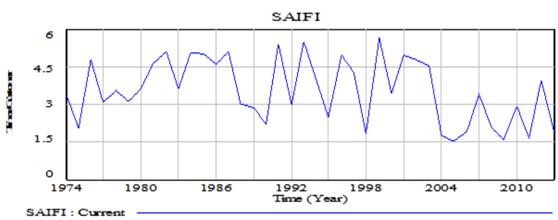

Fig. 11. SAIFI in UPJ Pamekasan

3.7. Technical Losses

The simulation results of monthly technical losses can be seen in Fig. 12.

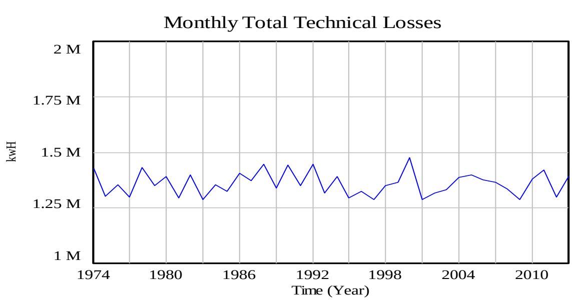

Fig. 12. Monthly technical losses

From Fig. 12, it is seen that the average technical losses in UPJ Pamekasan average of 1,359,981.60 KWH / month or about 16,319,779.24 KWH / year. Meanwhile, the comparison between data and simulation model of technical losses is given in Fig. 13.

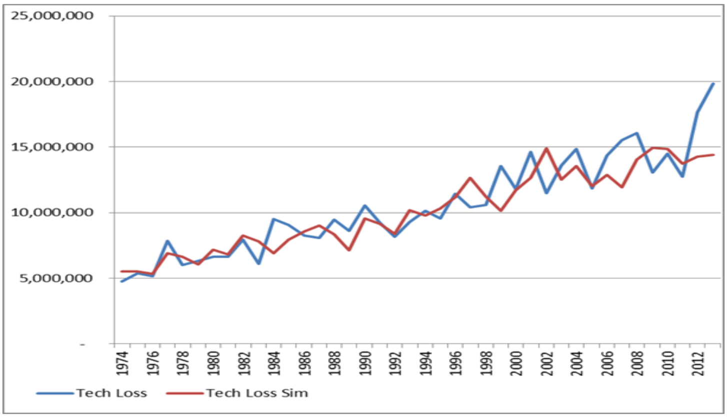

Fig 13. The comparison between data and simulation model of technical losses

As we can see from Fig. 13, the Error variance is less than 30% (Error variance = 17.31%), which means the model is valid.

5 CONCLUSION

From the research that has been done, it can be concluded some important things such as following:

1. The original contribution in this paper is providing framework for developing model of assets management that accommodate the internal and internal factors that affect the assets condition, as well as link up the assets condition to SAIDI and SAIFI
2. Caustic diagram is required as a basic framework to develop a model.
3. The flow diagram illustrates the relationship between variables expressed in the form of symbols such as the level, rate, and auxiliary, so it can be used to develop a mathematical model.
4. In general, the asset condition is determined by the asset treatment (maintenance) and a decrease in assets (deteriorate), which can be influenced by internal factors such as the standard lifetime and external factors such as geographical conditions, the temperature, the quality of network components, network load, climate, and salinity.
5. Asset condition will decrease over time. It is caused by a decrease in asset condition (deteriorate) has greater effect, when compared with assets treatment (maintenance).
6. Decrease in low voltage network assets conditions, on average, in the range of 6% per year.
7. The average of decrease in medium voltage networks asset condition is in the range of 4.4% per year.
8. The average decrease in transformers the condition of, is approximately 6.6% per year.

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9. Condition of the low voltage network is affected by the amount of total assets installed within a certain time and condition of the assets.
10. Conditions of transformer asset are affected by the total number of transformers installed in the certain period and conditions of the transformers.
11. The distribution network performance is affected by the overall condition of the property. Network performance will have an impact on the performance losses.
12. In the period 2003-2013, average SAIDI - average = 7.4 hours / year, while the average SAIFI in the year 1975 to 2013 = 3.4 times / customer.
13. The losses of electricity distribution network can occur in medium voltage networks, low voltage, house connections, and transformer losses.
14. The average technical losses in UPJ Pamekasan average of 1,359,981.60 KWH / month or approximately 16,319,779.24 KWH / year.

Acknowledgments.

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