Pattern-based monte carlo simulation for AMR electricty load analysis

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***Abstract*—This paper proposes customer behavior analysis for pattern analysis of AMR electricity customer.**

In this paper univaraite models for short-term load forecasting based on customer's pattern behavior analysis and probabilistic monte carlo simulation are proposed. The proposed method were compared with that of other models based on ARIMA, exponential smoothing and neural networks. Application examples confirm valuable properties of the proposed approaches and their high accuracy.

***Index Terms*—Autometic meter reading, confidence interval**

I. Introduction

Here is introduction. In a revolutionary change in enegy section transform the traditional unidirectional electricty grid replaced by bidirectional or smart grid (SG). As a results of increasing in number of Intelligent Electronic Devices (IEDs) in the power system, especailly metering field. Consequently, there are repidly jump in enormous data volume in power system for storage, mining, sharing and visualization [1]. The advance meter read (AMR) with 15-min read intervals has also been develop to replacve the traditional managtic once a month reading meters. The AMR reads 96 data per day and carries out 2880 data per month, which means that 2880 times customer data are fed to utility. In addition, other states variables also transported.

In previous work, there is observation that the forecasting accuracy highly depend on hourly load patterns incorporate with other variables [2]. In addition, it can also help in long term applications i.e., model customer behavior under various incentive and pricing structures, planning processes [4].

Monte Carlo simulation is a computerized mathematical technique that allows people to account for risk in quantitative analysis and decision making. The technique is used by professionals in such widely disparate fields as finance, project management, energy, manufacturing, engineering, research and development, insurance, oil gas, transportation, and the environment.

Monte Carlo simulation furnishes the decision-maker with a range of possible outcomes and the probabilities they will occur for any choice of action.. It shows the extreme possibilitiesthe outcomes of going for broke and for the most conservative decisionalong with all possible consequences for middle-of-the-road decisions.

The technique was first used by scientists working on the atom bomb; it was named for Monte Carlo, the Monaco resort town renowned for its casinos. Since its introduction in World War II, Monte Carlo simulation has been used to model a variety of physical and conceptual systems.

II. Literature reviews

Here is Literature reviews.

The big data has brought numberous tengible benefits to utilities and electricity uesers, which can be systemically concluded as follows: *accident*

- *Increasing System Stability Reliability* here is examples (find new ref.)
- *Increasin Asset Utilization Efficiency* here is examplesshere is examples
- *Better Customer Experience Satisfaction* here is examples

There is several benefits of deploying AMR at homes and office. The mass rollout enables easier billing, fraud detection, forewarning of blackouts, smart real-time pricing schemes, demand response and efficient energy utilization. However, to acheive aboved benefits, there need advanced data analytics, especailly customer behavior analysis, which is the main motivation of this study.

In addition, the customer pattern also was clustered using Markov model with CFSFDP [5] In previous works, electrical customer consumption's pattern is formulated using various approach. Gaussian mixture model (GMM) is proposed to formaulate individual AMR-based electricity comsumption pattern [3].

The contribution of this work is ...

III. Problem Formulation

Here is Problem formulation. The overall methodology is shown in Figure1

A. Data collection

where the data comes from: PEA total number of AMR customer: duration: 2 years???

PEA, AIT, NEU

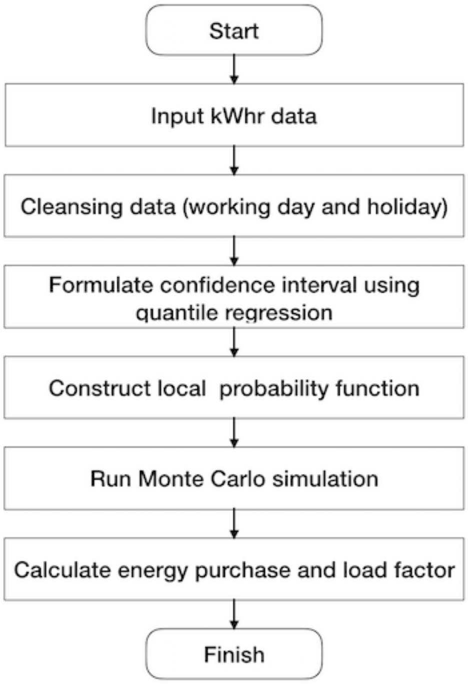

Fig. 1. Conceptual methodology

B. Pattern formulation using confidence intervals for quantiles calculation

C. Probability distribution constuction

D. Monte carlo simulation

E. Find cost and load factor

IV. Result and discussion

Here is results. See in I, II

V. Conclusion

Here is Conclusion.

The major contribution of this work is to propose new simulation univariate monte carlo simulation models based on pattern of customer behavior analysis.

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References

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TABLE I
Energy cost per day

AMR-ID	Raw data Mean	Raw data SD	Proposed approach (20 samples) mean	Proposed approach (20 samples) sd
21652			77,237	8,749
136898			155,553	9,814
137091			33,058	4,064
137138			33,287	4,428
42432			234,394	13,161
66543			10,216	972
21654			6,211	1,485
42421			64,839	2,910
42423			4,206	1,627
43958			67,014	5,795
137110			10,046	658
21655			3,201	577
42431			10,343	1,339
44834			60,980	2,693
56452			210,350	8,138
56457			34,282	1,600
56458			25,900	880
124642			61,568	2,779
124647			55,025	2,078
124649			240,474	8,326
124656			55,453	1,961
124683			12,682	887
185767			19,449	1,496
56448			49,236	2,403
136900			82,306	2,424
137094			236,504	14,334
164978			8,819	1,015
189318			146,082	2,761
193781			59,507	6,183
44318			29,833	2,093
124687			3,275	205
21689			61,861	3,784
44831			55,889	2,733
56459			9,709	1,210
124678			54,263	4,025

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TABLE II
LF PER DAY

AMR-ID	Raw data		Proposed approach (20 samples)	
	Mean	SD	mean	sd
21652			0.436	0.065
136898			0.410	0.033
137091			0.241	0.045
137138			0.302	0.049
42432			0.425	0.045
66543			0.289	0.042
21654			0.161	0.036
42421			0.380	0.033
42423			0.058	0.025
43958			0.701	0.056
137110			0.392	0.086
21655			0.157	0.047
42431			0.300	0.046
44834			0.501	0.046
56452			0.545	0.053
56457			0.493	0.052
56458			0.565	0.055
124642			0.529	0.050
124647			0.440	0.055
124649			0.546	0.048
124656			0.461	0.052
124683			0.388	0.065
185767			0.391	0.058
56448			0.462	0.042
136900			0.642	0.053
137094			0.306	0.027
164978			0.268	0.065
189318			0.570	0.046
193781			0.358	0.079
44318			0.451	0.051
124687			0.510	0.129
21689			0.216	0.013
44831			0.489	0.059
56459			0.232	0.060
124678			0.380	0.028