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]. The behavior of applicace in resident customer helps to forecast shorterm load [6].

In this article, we propose to generate behavior pattern for AMR customer consumption using confidence interval and Monte Carlo simulation. In particular, we make the following contributions:

- We show how to extrat a feature of customer consumption behavior by confidence interval with quantile values in order to reduce mumber of data.
- We formulate probabilistic function of individual customer behavior from extracted features.
- We deploy Monte Carlo simulation technique to simulate power consumption using individual probabilistic customer behavior.

PEA, AIT, NEU

II. Literature reviews

Here is Literature reviews.

The AMR data and individual major applicance usage learning are used to predict short-term residential load using Long short-term memory (LSTM) technique [6].

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

- *Increasing System Stability Reliability:* Wide area mornitoring require numberous of measurement units, especailly phase measurement units (PMUs) to ensure that the operator can manage system stability. In coorporate with AMR or Smart meter could help in this situation[cite ????].
- *Increasing Asset Utilization Efficiency:* With low accuray of GIS input data, the distribution network topology need to be verified, especially the under ground feeder which are difficult to check [8]. The big data proces could help to develop modeling of secondary size of transformer as well as energy theft [7].
- *Better Customer Experience Satisfaction:* Demand response program is an effective way to manage power balance during high congestion period as well as high tariff. The customer who engaging though demand response program could reduce their energy bill or earn incentives [cite ???].

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].

So far, there is less number of article study on electricity customer behavior. The contribution of this work is ...

III. Problem Formulation

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

A. Pattern formulation using confidence intervals for quantiles calculation

In this paper 15 minutes based kilowatt data are collected from AMR system. These data are accumulate into 30-minutes based kiloWatt-hour.

$$X = \{X^1, X^2, X^3, ..., X^n\} \tag{1}$$

$$X^n = \{X_1^n, X_2^n, X_3^n, ..., X_d^n, ..., X_{366}^n\} \tag{2}$$

$$X_d^n = \{X_{d,1}^n, X_{d,2}^n, X_{d,3}^n, ..., X_{d,t}^n, ..., X_{d,48}^n\} \tag{3}$$

where X is set of customer, X^n is set of daily consumtion of custome n, X_d^n is set of 30 minutes based power consumption (kWhr) of customer n on day d. $x_{d,t}^n$ is power consumption of customer n on day d at time t. The equation (1)-(3) are cleansing into equation (4). X^{n*} is set of power consumption at individual time step. X_t^{n*} is set of power consumption at time t of customer n.

$$X^{n*} = \{X_1^{n*}, X_2^{n*}, X_3^{n*}, ..., X_t^{n*}, ..., X_{48}^{n*}\} \tag{4}$$

The X^{n*} is cleansing raw data prepared to feature extraction process. As memntion above, this paper proposed confidential interval at quantile value as extracted feature. The extracted feature processes are shown in equation (5)- (6).

$$Y^n = \{Y_1^n, Y_2^n, Y_3^n, ..., Y_t^n, ..., Y_{48}^n\} \tag{5}$$

$$Y_t^n = \{Y_{t,0}^n, Y_{t,0.05}^n, Y_{t,0.1}^n, ..., Y_{t,q}^n, ..., Y_{t,1}^n\} \tag{6}$$

Where Y^n is representing set of extract feature of customer n at individual time period, Y_t^n is set of extracted feature of customer n at time period t which content 20 step of quantile value, q, (0 to 1 at 0.05 step size). $Y_{t,q}^n$ is formulated using equation (7).

$$Y_{t,q}^n = \int_{q-1}^{q} F_{X^{n*}}(q)dq \tag{7}$$

Where $F_{X^{n*}}$ is commulative distribution function of power consumption of customer n at time t. So, $Y_{t,q}^n$ is expected power consumption of customer n at time period t, and quantile q.

Hence, we can extract customer behavior feature as well as reduce number of process data in next step.

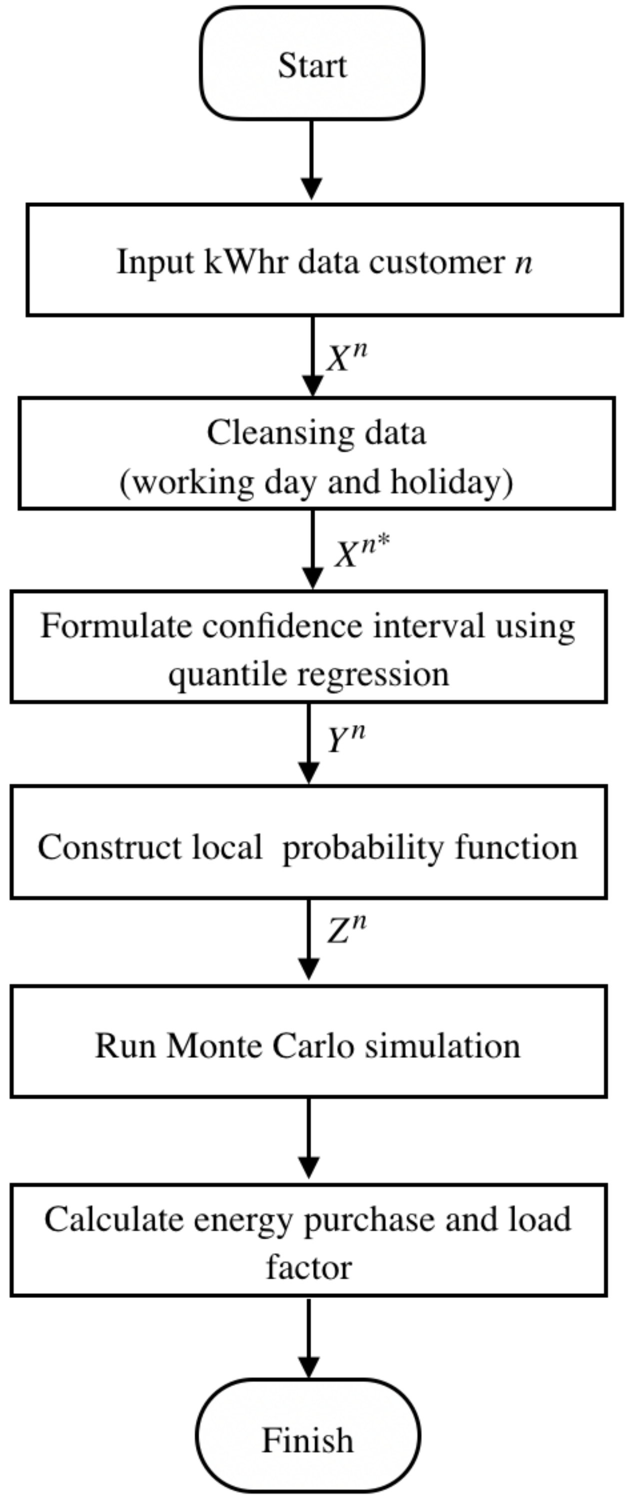

Fig. 1. Conceptual methodology

B. Continuous Probability Distribution constuction

$$Z^n = \{Z_0^n, Z_1^n, Z_3^n, ..., Z_t^n, ..., Z_{48}^n\} \tag{8}$$

$$Z_t^n = \{z_{0,50}^n, z_{50,100}^n, z_{100,150}^n, ..., z_{a,b}^n, ..., z_{19500,2000}^n\} \tag{9}$$

where Z^n is set of continous probability distribution function of power consumption of customer n. Z_t^n is set of continous probability distribution function of power consumption of customer n at time t with difference consumption range (from 0 to 20,000 kiloWatt-hour with 50 kiloWatt-hour step size). $z_{a,b}^n$ is probability of power consumption between lower a and upper b kiloWatt-hour of customer n which is be formulation by equation (10).

$$z_{a,b}^n = \mathrm{P}[a \leq Y_t^n \leq b] = \int_a^b Y_t^n dY_t^n \tag{10}$$

where a and b is lower and upper kilowatt-hour in range $[a, b]$.

C. Monte carlo simulation

From Z^n, monte carlo simulation generate electricity consumption as

$$P^n = \{P_1^n, P_2^n, P_3^n, ..., P_i^n, ..., P_m^n\} \tag{11}$$

$$P_i^n = \{P_{i,1}^n, P_{i,2}^n, P_{i,3}^n, ..., P_{i,t}^n, ..., P_{i,48}^n\} \tag{12}$$

where m is number of samples. $P_{i,t}^n$ is generated electricity consumption of customer n at time t at sample i.

D. Find cost and load factor

$$C_i^n = \sum_{t=1}^{48} P_{i,t}^n \times a_t \tag{13}$$

where C_i^n is cost of energy purchasing of customer n at sample i, a_t is electricity tariff at time t.

$$\mathrm{LF}_i^n = \frac{\mathrm{average}(P_i^n)}{\max(P_i^n)} \tag{14}$$

where LF_i^n is load factor of customer n at sample i.

IV. Test Cases and Results

In this study, AMR data is collected from PEA. This dataset comprehensively records the quarter hourly kilowatt reading of 35 commercial and industrial customers. We accomulate the kilowatt reading into kilowatt hour for every 30 minutes. The AMR customer names are change to alias for information security.

In feature extraction processes, total number of 70,272 raw data for each individual customer (2 years of collections) can be reduce to 1,920 data points (960 point for each working day and holiday).

The result of MC simulation with numbers of samples (20 samples) are consider as witness in this study Here is results. See in I, II

TABLE I
Energy cost per day

AMR-ID	Raw data Mean	SD	Proposed approach (20 samples) mean	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

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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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

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