

Pattern-based monte carlo simulation for AMR electricity load analysis

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

In this paper univariate 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—Automatic meter reading, confidence interval

I. INTRODUCTION

Here is introduction. In a revolutionary change in energy section transform the traditional unidirectional electricity grid replaced by bidirectional or smart grid (SG). As a results of increasing in number of Intelligent Electronic Devices (IEDs) in the power system, especially metering field. Consequently, there are rapidly 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 replace the traditional magnetic 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 appliance in resident customer helps to forecast short-term 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 extract a feature of customer consumption behavior by confidence interval with quantile values in order to reduce number 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.

II. LITERATURE REVIEWS

Here is Literature reviews.

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

The big data has brought numerous tangible benefits to utilities and electricity users, which can be systemically concluded as follows:

- *Increasing System Stability Reliability*: Wide area monitoring require numerous of measurement units, especially phase measurement units (PMUs) to ensure that the operator can manage system stability. In cooperate with AMR or Smart meter could help in this situation[cite ???].
- *Increasing Asset Utilization Efficiency*: With low accuracy 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 process 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 achieve above benefits, there need advanced data analytics, especially 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

formulate individual AMR-based electricity consumption 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.

$$X = \{X^1, X^2, X^3, \dots, X^n\} \quad (1)$$

$$X^n = \{X_1^n, X_2^n, X_3^n, \dots, X_d^n, \dots, X_{366}^n\} \quad (2)$$

$$X_d^n = \{X_{d,1}^n, X_{d,2}^n, X_{d,3}^n, \dots, X_{d,t}^n, \dots, X_{d,48}^n\} \quad (3)$$

where X is set of customer, X^n is set of daily consumption 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 .

$$X^{n*} = \{X_1^{n*}, X_2^{n*}, X_3^{n*}, \dots, X_t^{n*}, \dots, X_{48}^{n*}\} \quad (4)$$

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).

$$Y^n = \{Y_1^n, Y_2^n, Y_3^n, \dots, Y_t^n, \dots, Y_{48}^n\} \quad (5)$$

$$Y_t^n = \{Y_{t,0}^n, Y_{t,0.05}^n, Y_{t,0.1}^n, \dots, Y_{t,q}^n, \dots, Y_{t,1}^n\} \quad (6)$$

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).

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

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.

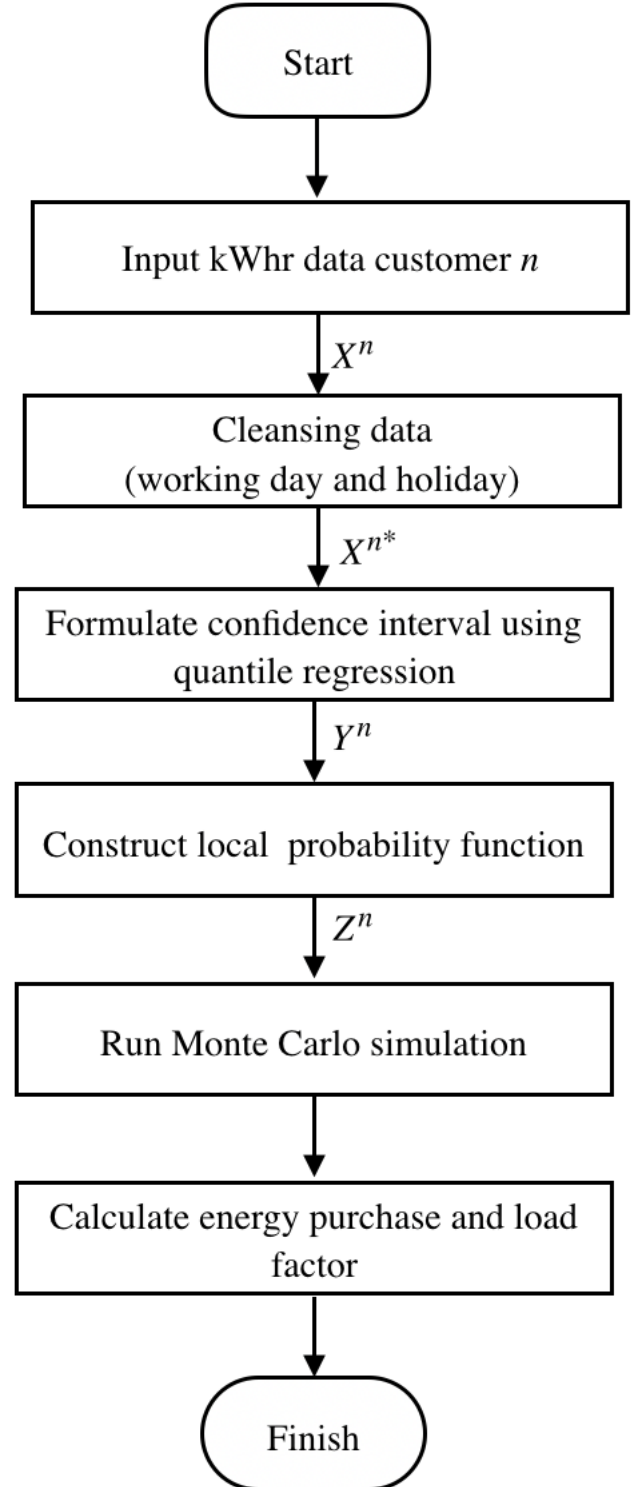


Fig. 1. Conceptual methodology

B. Continuous Probability Distribution construction

$$Z^n = \{Z_0^n, Z_1^n, Z_3^n, \dots, Z_t^n, \dots, Z_{48}^n\} \quad (8)$$

$$Z_t^n = \{z_{0,50}^n, z_{50,100}^n, z_{100,150}^n, \dots, z_{a,b}^n, \dots, z_{19500,2000}^n\} \quad (9)$$

where Z^n is set of continuous probability distribution function of power consumption of customer n . Z_t^n is set of continuous 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).

$$z_{a,b}^n = P[a \leq Y_t^n \leq b] = \int_a^b Y_t^n dY_t^n \quad (10)$$

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

C. Monte carlo simulation

D. Find cost and load factor

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 accumulate 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).

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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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

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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