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Analyzing & Modelling Energy Consumption Logs

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Abstract

Fossil fuel being the dominant source of energy in the world contributes about 80 per cent (91,000 TWh) of the total primary energy supply. Electricity generation has 64 per cent (9,400 TWh). UNDP highlights that large-scale hydropower and combustion of different types of biomass currently provide the bulk of the energy supplied from renewable energy sources. The new renewables - wind turbines, solar cells and solar collectors - are now diffusing at a quite rapid rate. Nigerian population is increasing exponentially hence more energy is consumed. As one aspect of the energy consumption, building energy consumption accounts for a considerable proportion Therefore, it is necessary to analyze energy consumption in other to model consumption patterns. From these strategies an efficient algorithm for autonomous system can be designed to promote building energy utilization rate. Artificial neural networks (ANN) methodology is adopted. ACme (AC meter) would be used to collect data. ACme are wireless power meters that provide data readings as frequently as every ten seconds. By collecting power measurements from numerous meters over several months, large quantity of data was generated. To this end an automated statistical analysis software shall be used. The said analysis tools would ensure success in checking the status of the data collection system. ACme meters would report data in real-time to the database, and this enabled analysis tools to automatically check which, if any, nodes had failed to report data recently.

Keywords: Renewable energy; Artificial neural network; Pattern recognition; Fossil fuel; Consumption

Introduction

Fossil fuel being the dominant source of energy in the world contributes about 80 per cent (91,000 TWh) of the total primary energy supply. Electricity generation has 64 per cent (9,400 TWh). UNDP highlights that large-scale hydropower and combustion of different types of biomass currently provide the bulk of the energy supplied from renewable energy sources. The new renewables - wind turbines, solar cells and solar collectors - are now diffusing at a quite rapid rate. Nigerian population is increasing exponentially hence more energy is consumed. As one aspect of the energy consumption, building energy consumption accounts for a considerable proportion Therefore, it is necessary to analyze energy consumption in other to model consumption patterns. From these strategies an efficient algorithm for autonomous system can be designed to promote building energy utilization rate. Artificial neural networks (ANN) methodology is adopted. ACme (AC meter) would be used to collect data. ACme are wireless power meters that provide data readings as frequently as every ten seconds. By collecting power measurements from numerous meters over several months, large quantity of data was generated. To this end an automated statistical analysis software shall be used. The said analysis tools would ensure success in checking the status of the data collection system. ACme meters would report data in real-time to the database, and this enabled analysis tools to automatically check which, if any, nodes had failed to report data recently.

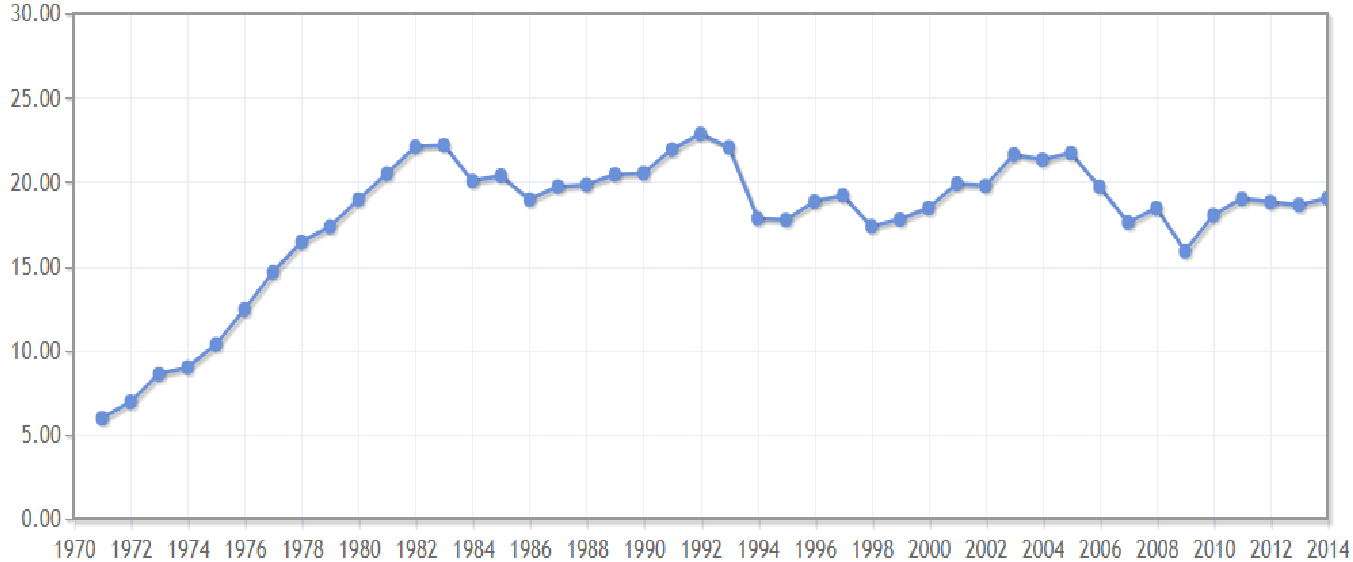

Figure 1. Nigerian fossil fuel Consumption [4]

[19] provides the Nigerian statistics for energy consumptions as depicted in figure 2 below.

Total final energy consumption **4987287**	Energy savings of primary energy **826371**	Thermal efficiency in power supply **40.02** %
Transmission and distribution losses **11.7** %	Energy intensity of industrial sector **2.96**	Energy intensity of agricultural sector **0.00086**
Energy intensity of service sector **0.3303**	Energy intensity of transportation sector **25.47**	Energy intensity of residential sector **112**
Divisia Decomposition Analysis - Energy Intensity component Index **0.8429**	Divisia Decomposition Analysis - Activity component Index **2.14**	Divisia Decomposition Analysis - Energy Intensity component rate of improvement **0.3707** %
Divisia Decomposition Analysis - Activity component rate of improvement **3.03** %	Divisia Decomposition Analysis - Structure component rate of improvement **1.35** %	Traditional biomass consumption (% in TFEC) **77.11** %
		Marine energy consumption (% in TFEC) **0** %
Modern biomass consumption (% in TFEC) **8.99** %	Hydro energy consumption (% in TFEC) **0.3698** %	Liquid biofuels consumption (% in TFEC) **0** %
Wind energy consumption (% in TFEC) **0** %	Solar energy consumption (% in TFEC) **0** %	Geothermal energy consumption (% in TFEC) **0** %
Waste energy consumption (% in TFEC) **0** %	Biogas consumption (% in TFEC) **0** %	Access to Non-Solid Fuel **24.85** %

Figure 2. Nigerian statistics for energy consumption [19]

Today a great deal of efforts is made for the development of renewable energies. Photovoltaic solar energy, wind energy, biomass, bio-fuels etc. are examples of this development. In the field of electrical energy output, photovoltaic solar energy and wind energy are increasingly used. Sophisticated techniques for an accurate estimation of the available energy potential and an effective control of systems operation [5]. Artificial Intelligence (AI) techniques i.e. neural network, pattern recognition and machine learning are increasingly used in various area. They aid in studying complex systems without any knowledge of the exact relations governing their operation. Once data is trained, they can be able to handle noisy and incomplete data, perform tasks as complex as prediction, optimization, modeling, identification, forecasting and control.

Due to exponential increase in Nigerian population as shown in figure 3, more and more energy is consumed. As one aspect of the energy consumption, building energy consumption accounts for a considerable proportion. For example, in China, statistical data shows that building energy consumption accounted for 28% of the total energy consumption in 2011, and that it will reach 35% by 2020 [6]; in the United States, building energy consumption is close to 39% of the total energy consumption [7]. Therefore, it is necessary to analyze energy consumption in other to model consumption patterns. From these strategies an efficient algorithm for autonomous system can be designed to promote building energy utilization rate. Building energy consumption prediction can help managers to make better decisions so as to reasonably control all kinds of equipment. Hence, this is an efficient and helpful way to reduce the consumption of building energy and to improve the energy utilization rate.

Population of Nigeria (2018 and historical)

Year	Population	Yearly % Change	Yearly Change	Migrants (net)	Median Age	Fertility Rate	Density (P/Km^2)	Urban Pop %	Urban Population	Country's Share of World Pop	World Population	Nigeria Global Rank
2018	**195,875,237**	2.61 %	4,988,926	-60,000	17.9	5.67	215	51.0 %	99,967,871	2.57 %	7,632,819,325	7
2017	**190,886,311**	2.63 %	4,896,671	-60,000	17.9	5.67	210	50.2 %	95,764,092	2.53 %	7,550,262,101	7
2016	**185,989,640**	2.65 %	4,807,896	-60,000	17.9	5.67	204	49.3 %	91,668,667	2.49 %	7,466,964,280	7
2015	**181,181,744**	2.70 %	4,520,697	-60,000	17.9	5.74	199	48.4 %	87,680,500	2.45 %	7,383,008,820	7
2010	**158,578,261**	2.68 %	3,927,757	-60,000	17.9	5.91	174	43.8 %	69,440,943	2.28 %	6,958,169,159	7
2005	**138,939,478**	2.58 %	3,317,494	-34,000	18.0	6.05	153	39.3 %	54,541,496	2.12 %	6,542,159,383	9
2000	**122,352,009**	2.52 %	2,868,109	-19,005	17.9	6.17	134	35.0 %	42,810,252	1.99 %	6,145,006,989	10
1995	**108,011,465**	2.54 %	2,548,295	-19,154	17.7	6.37	119	32.3 %	34,918,670	1.88 %	5,751,474,416	10
1990	**95,269,988**	2.64 %	2,331,338	-18,281	17.4	6.60	105	29.8 %	28,379,229	1.79 %	5,330,943,460	10
1985	**83,613,300**	2.62 %	2,030,515	-134,328	17.5	6.76	92	25.7 %	21,508,164	1.72 %	4,873,781,796	10
1980	**73,460,724**	3.00 %	2,017,430	170,930	18.0	6.76	81	22.0 %	16,191,472	1.65 %	4,458,411,534	11
1975	**63,373,572**	2.51 %	1,478,434	-7,705	18.3	6.61	70	19.8 %	12,573,568	1.55 %	4,079,087,198	11
1970	**55,981,400**	2.23 %	1,170,837	-8,669	18.7	6.35	61	17.8 %	9,969,016	1.51 %	3,700,577,650	11
1965	**50,127,214**	2.12 %	997,880	674	19.1	6.35	55	16.6 %	8,315,202	1.50 %	3,339,592,688	13
1960	**45,137,812**	1.90 %	810,450	541	19.1	6.35	50	15.4 %	6,967,110	1.49 %	3,033,212,527	13
1955	**41,085,563**	1.65 %	645,164	674	19.1	6.35	45	11.1 %	4,541,081	1.48 %	2,772,242,535	13

Figure 3. Nigerian population form 1955 – 2018 [8]

The objective of this study is to resolve sustainability issues and reliance on conventional energy by adopting a three-pronged approach that involves (a) analyzing energy consumption logs using machine learning techniques, (b) using pattern recognition to predict and model consumption patterns and (c) designing efficient algorithms for autonomous modulating systems.

This study shall use existing knowledge to create new knowledge by finding innovative ways to utilize natural resources surrounding us. This can be achieved by exploiting the field of artificial intelligence to predict and model energy consumption. From the result, an effective algorithm shall be designed in order to reduce reliance on conventional energy. This knowledge can further be disseminated through journal publications.

Related Work

[12] expressed that "a great number of prediction approaches have been proposed in the past several decades for building energy consumption prediction. The majority of the case studies depend on the historical energy consumption time series data to construct the prediction models". Building energy consumption and prediction generally fall into two categories i.e. statistical methods and artificial intelligence methods. Statistical approaches exploit the historical data to construct probabilistic models in order to estimate and analyze the future energy consumption [9]. Principal component analysis (PCA) were employed to select the significant consumption prediction of inputs for the energy [10]. Linear regression was applied to estimate electricity consumption in an institutional building, and moreover, fuzzy modeling and artificial neural networks were chosen as two comparative approaches to evaluate the performance of the linear regression method. [20] utilized the autoregressive model with extra inputs (ARX) to estimate the parameters of building components. In addition, [21] developed an autoregressive integrated moving average (ARIMA) model to implement online building energy consumption prediction. [22] used the ARIMA with external inputs (ARIMAX) model hence applied to predict the power demand of the buildings. [23] articulated that regression-based method—conditional demand analysis (CDA) was used for predicting the building energy consumption.

From aforementioned, methods used by artificial intelligence obtained more accurate prediction and consumption results in most real-world applications and have been widely applied to the prediction of energy consumption. [15] applied cluster wise regression, a novel technique that integrates clustering and regression simultaneously was proposed for forecasting building energy consumption. [24] applied data mining techniques to electricity-related time series forecasting. [25] employed a support vector machine (SVM) was utilized to predict the energy consumption of low-energy buildings with a relevant data selection method. Artificial neural networks (ANNs) play an important role in the forecasting of building energy consumption, and different kinds of ANNs have been given for this application. Thus, a short-term predictive ANN model for electricity demand was developed for the bioclimatic building. The Levenberg–Marquardt and Output-Weight-Optimization (OWO)-Newton algorithm-based ANN was utilized to forecast the residential building energy consumption. A study by [11] however, presented an ANN combined with a fuzzy inference system to predict the building energy consumption. Two adaptive ANNs with accumulative training and sliding window training were proposed for real-time online building energy prediction. ANN trained by the extreme learning machine (ELM) was proposed to estimate the building energy consumption and was compared with the genetic algorithm (GA)-based ANN [11].

Although the statistical methods and the existing artificial intelligence methods can give satisfactory results, it is still a challenging task to obtain accurate prediction results because of random characteristics that can be affected by the weather, the working hours, the human distribution and the equipment in the buildings. On the other hand, the deep learning techniques that have emerged in recent years provide us with a powerful tool to achieve better modeling and prediction performance. The deep learning algorithm uses deep architectures or multiple-layer architectures adopting the layer wise pre-training method for parameter optimization to obtain great feature learning ability [12]. The inherent features of data extracted from the lowest level to the highest level of the deep learning model are more representative than for the traditional shallow neural network. Hence, the deep architectures have greatly improved performance for the modeling, classification and visualization problems, and they have found lots of applications.

Methodology

Artificial neural networks (ANN) are computational techniques modeled on the learning processes of the human cognitive system and the neurological functions of the brain [13]. Recently, there has been considerable interest in the development of artificial neural networks for solving a wide range of problems from different fields. Neural networks are distributed information processing systems composed of many simple computational elements interacting across weighted connections [14]. [26] were inspired in their study by the architecture of the human brain, neural networks exhibit certain features such as the ability to learn complex patterns of information and generalize the learned information. Neural networks are simply parameterized non-linear functions that can be fitted to data for prediction purposes [15].

There are several categories of artificial neural networks based on supervised and unsupervised learning methods and feed-forward and feedback recall architectures. A back propagation neural network (BPNN) exploits supervised learning method and feed-forward architecture. The most frequently utilized neural network techniques for prediction and classification is BPNN. Neural networks main application is their resilient in approximating a wide range of functional relationships between inputs and output. [22] methods demonstrate that sufficiently complex neural networks are able to approximate arbitrary functions arbitrarily well. Among the most motivating properties of neural networks methodology is their ability to work and forecast even on the basis of incomplete, noisy, and fuzzy data.

Artificial neural network does not need a prior hypothesis and do not impose any functional form between inputs and output. This is the reason why neural networks are quite practical to use. Especially, in the cases where knowledge of the functional form relating inputs and output is lacking, or when a prior assumption about such a relationship should be avoided. The success of the artificial neural network models be contingent on properly selected parameters such as the neurons (number of nodes) and layers, learning algorithm, the nonlinear function used in the nodes, initial weights of the inputs and layers, and the number of epochs that the model is iterated. The sample data in ANN methodology is often divided into two main sub-samples which referred as *training* and *test sets*. In the training process, ANN studies the relationship between input and output criteria, whereas in the testing process; test set are used to evaluate the performance of the model.

ACme (AC meter) would be used to collect data. ACme are wireless power meters that provide data readings as frequently as every ten seconds. [17] demonstrate that ACme is accurate to about 0.5% of the reading. ACme would wirelessly transmit the data back to an open platform that can be improved and adapted for any given project [16]. Thus, ACme meter involves three tiers: ACme node as shown in figure 4. Figure 5 however display installed ACme in which it provides a metering interface to a single AC outlet, a network fabric that consents the meter data to be communicated over an Internet Protocol (IP) network, and application software that collects the power and energy data, stores it in a database, and provides various data processing functions.

Figure 4. ACme node [17]

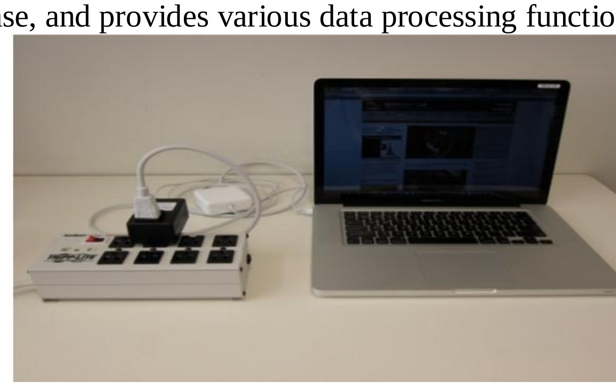

Figure 5. ACme node & metering interface [17]

Figure 6 summarized the architecture used in residential buildings. The same architecture can be used by commercial building as well except the TED meter is not present and multiple edge routers are used for greater floor-area coverage.

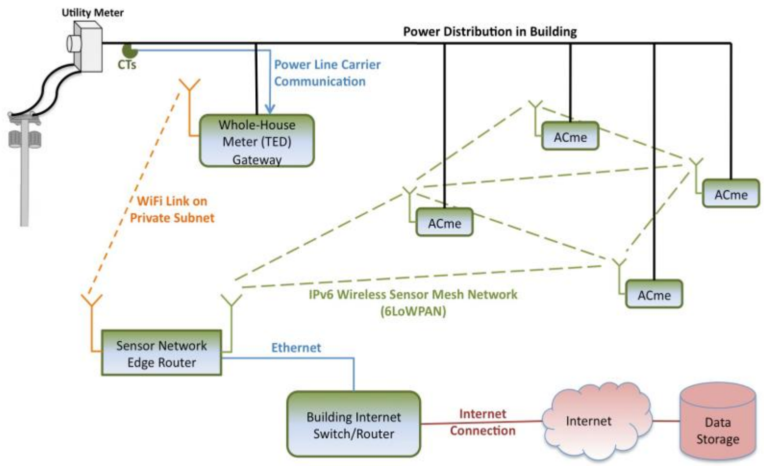

Figure 6. ACme Residential Metering [17]

The ACme wireless power meters to be used in this study consumed 0.4W per meter. The meter had a significantly smaller form factor and capable of handling 15A currents for extended periods of time. Figure 6 shows the typical configuration when the ACme is connected to devices for metering, respectively [17]. Each device runs the TinyOS operating system and uses the open-standard 6LoWPAN network protocol to provide IPv6 (a dynamic, scalable routing protocol) network connectivity [17]. To provide scalability to hundreds of ACmes, the Ethernet networking consists of a number of load-balancing routers [17]. The benefit of automated data collection is the ability to detect and correct meter faults during the data collection period rather than after data collection completed. Finally, the ACmes are smaller than traditional meters making them less obtrusive to the occupants].

Result & Discussion

By collecting power measurements from numerous meters over several months shall generates a large quantity of data. To this end an automated statistical analysis software shall be used. By exploiting open-source tools like Python and MySQL, development time would significantly be reduced. The said analysis tools would ensure success in checking the status of the data collection system. ACme meters would report data in real-time to the database, and this enabled analysis tools to automatically check which, if any, nodes had failed to report data recently. To prevent any failure and/or identify if there is any failed node, the researcher would receive a daily email report on the health of the data collection system. Additionally, the researcher would also identify which specific meters require attention, or should the meter need to be reset. The ability to receive a daily report on the number of meters reporting data would aid in accurate analysis.

Below we present our findings from the inventory and metering data we collected thus far in the study. Figure 7 below presents a preliminary study of office building. It shows devices distribution based on a full inventory in official building. The building contains a variety of devices to a tune of 127 different types.

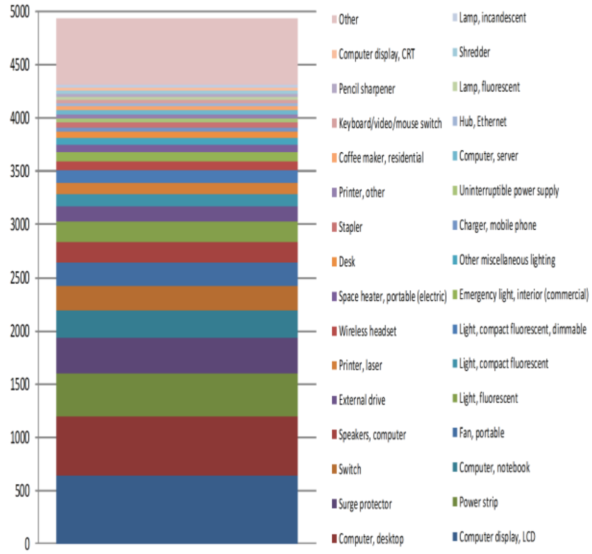

Figure 7. Sample distribution of office building

A motivating aspect is the use inventory and metering data to compare the count and energy use between devices. The study would present the count of top five energy users and all other devices, scaled with their respective energy usage in annual energy terms, for the official building. Energy consumption estimates for the entire building are projected from the ACme metered sample of devices using sample probability weights. A device that use most energy compared to their count in the building was the computers, while other devices depicts the opposite. For the reason that the building is mostly used as office space, displays, imaging, lighting, and networking are the next largest energy users. The energy consumption breakdown presents that information technology equipment is the largest target for energy efficiency improvements.

Some computers were left on almost the entire time whereas some were not used during the week of prelim study. Therefore, effective means of improving energy efficiency for devices that are not routinely turned off is increasing device sleep time. Computers that are left on for hours per day differ in energy usage by almost ten times. Thus, improving the on-state efficiency of devices will also be an effective means of reducing energy consumption. These findings are shown for computers, but they apply to other devices in the building as well.

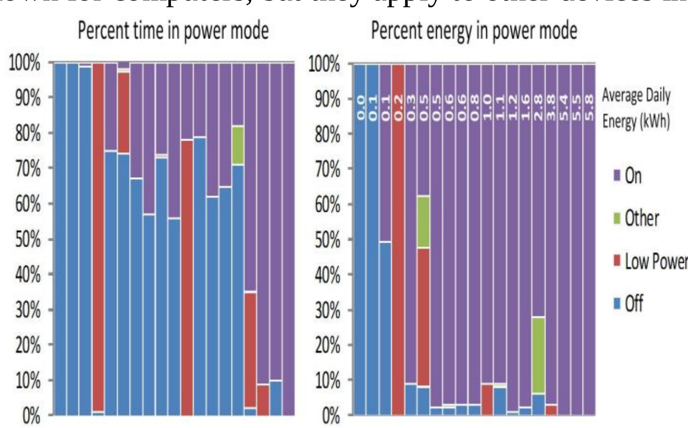

Figure 8. Time percentage and energy consumption in power modes for 19 computers metered for week in office building. Each column represents a distinct computer, sorted from left to right by increasing energy use. Device ordering is the same in both charts

The average energy consumption in everyday for computers in office building with a one-minute sampling period. The average consumption is presented by light traces of the individual computers. From the findings, it shows that there is a great deal of variation from device to device and significant usage during off-hours, but the average load shape reflects the most common building occupancy periods.

Conclusions and Future Works

The range of plug-in devices has made it tough for policy makers to apply uniform standards to reduce their energy consumption due to unlike appliances in traditional end uses. To develop an effective approach to reduce energy consumption, large-scale data collection is needed to understand the areas of improvement available. The development of ACme system meters with wireless mesh-networking technology has made large-scale data collection possible in a cost-effective way. The relatively high measurement accuracy and sampling frequency permit new types of analysis, such as accurate power-mode identification and approximate device-type identification.

Even though, the metering done was preliminary, data gathered so far has provided valuable insight about the inventory, usage patterns, and device correlations for office buildings. Furthermore, the data gathered has provided the data collection strategies and meter specifications needed to improve understanding of energy consumption. For example, from the collected data, its understood that a sampling frequency of no longer than one minute is needed in order to capture the rapid change in power mode in some devices, and a prolonged metering period is needed to understand device usage pattern and seasonal variation. Due to the variety of models for some device types such as computers, a large sample is needed for more accurate results. ACme meters are developed using an open platform, the mesh network and respective meters are highly adaptable to meet the research needs.

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