Optimal Operation of Residential EVs using DNN and Clustering based Energy Forecast

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***Abstract*— In this paper, we present a scheduling scheme for household Electric vehicles based on deep neural network based demand forecast. A novel clustering based Short Term Load Forecasting (STLF) using deep neural network (DNN) is presented in this paper to forecast the household and EV demand. The forecasting is performed on electricity demand profiles for 200 households from the Midwest region of the United States. Tensor-flow based deep learning platform was used to develop deep learning structure. The households are clustered according to demand profiles and the grouped consumers are used as the forecasting parameters. The scheduling model uses the forecasted household and EV demand values to develop a linear programming based optimization model to minimize the electricity cost for consumers. Household and cluster constraints are considered in the optimization model to limit the sudden surge in power demand during low-price time periods.**

Keywords—Electrical Vehicle Scheduling, Optimization, Deep Neural Network, Clustering, Residential Load Forecasting.

I. Introduction

The increased conservation efforts to reduce the pollution caused by fuel powered vehicles and increasing penetration of renewable energy sources have created a considerable interest in consumers to shift towards EVs (Electric Vehicles). In the future, EVs are expected to dominate the transportation industry [1]. The power industry is trying to accommodate this increased EV demand without substantial investment in the electrical grid infrastructure. The increasing number of charging stations in residential areas are creating several challenges for the electrical distribution system. A system needs to be introduced to reduce the peak surge in energy demand from connected EVs [2], [3].

The impact on the distribution system from the increased penetration of EVs are discussed in [4]. The effects on electricity generation adequacy, transformer aging and distribution power quality are presented in this work. The paper also proposes mitigation techniques such as Time-Of-Use (TOU) pricing schemes and smart charging algorithms to mitigate the effects of connected EVs. A coordinated framework to charge EV fleet was presented by M. Usman et al. [5]. The paper proposed a control scheme to maintain the grid capacity while satisfying the needs of the EV fleet.

Load forecasting remains an important research issue in operation and planning of electrical power and energy systems. Electrical load forecasting using big data has been an important research topic because of its commercial value [6]. Traditional machine learning based short-term load forecasting (STLF) shows its effectiveness on forecasting loads, especially for solving non-linear feature fitting of loads, where Artificial Neural Network (ANN) and Support Vector Regression (SVR) are the most common machine learning methods for constructing forecasting models [7], [8].

There are many challenges to mine accurate patterns in the load forecasting. For example, electricity load signals are highly unpredictable due to their nonlinear and non-stationary characteristics, which are affected by seasonal, temperature, humidity, renewable energy generation, and demand response participation [8]. Moreover, while developing forecasting methods, it is difficult to process big volumes of data provided by smart meters, and detect the domination factors that are most related to the electricity load [9].

II. Methodology for DNN Forecast

Deep learning techniques such as RNN has shown its high performance on solving STLF by treating STLF as a time series forecasting problem [10], [11]. However, in this study, a novel method of combining DNN and clustering techniques for forecasting loads on an electricity big data is proposed. There are two phases in the procedure of creating the proposed method. In phase 1, raw data is preprocessed by removing noises and numerical processing. And then related factor analysis on the clean data is performed for feature extraction and selection. Millions of load samples consist of the chosen features and target electricity loads to form a big data set. On the data set, we utilized the clustering technique to partition the set into subsets. Furthermore, these subsets are divided into training sets and testing sets. On the training sets, the method is constructed based on DNN models. In phase 2, the method is adopted to forecast loads for 10 minutes interval on these testing sets. The framework of the presented method is shown in Figure 1. K-Means algorithm is utilized to divide the dataset into small clusters. Then, these clusters are segmented into training set with the DNN Based Model. In 2nd phase we use the method to forecast loads on each testing subset so as to conduct results on each testing subset. Load values are generated by these prediction results from the DNN models, which is shown in figure 2.

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III. DNN BASED DAY-AHEAD ENERGY FORECAST

It is significant to forecast household daily consumption in order to design and size suitable renewable energy systems and battery storage [12]. In this work, we did a Short-Term Load Forecasting (STLF) of household equipment. DNN was used to forecast one day ahead household energy consumption. Despite the household electric power consumption unpredictability, we were able to forecast the household electric demand with improved accuracy.

A. *Designing Deep Neural Networks*

Selecting an appropriate design is the first step of DNN-based forecasting system. In the current studies, the network architecture was built based on multilayer perceptron (MLP), full-connected, which is a feed-forward type of neural network, and the training task was performed through a backpropagation learning algorithm [13]. The backpropagation learning algorithms, most commonly used in feed-forward DNN, are based on steepest-descent methods that perform stochastic gradient descent on the error surface. Backpropagation is typically applied to multiple layers of neurons and works by calculating the overall error rate of an artificial neural network. The output layer is then analyzed to see the contribution of each of the neurons to that error. The neurons weights and threshold values are then adjusted, according to how much each neuron contributed to the error, to minimize the error in the next iteration.

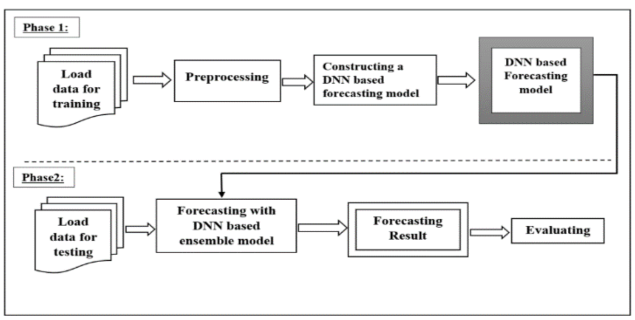

Fig. 1. Framework of constructing the model

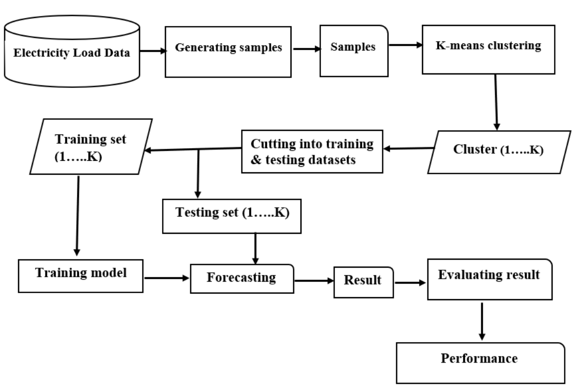

Fig. 2. Flows of constructing the DNN based method with K-Means algorithm

B. *Clustering and k-means cluster analysis:*

Clustering is the grouping of load profiles into a number of clusters such that profiles within the same cluster are similar to each other [14]. At the same time, load profiles that are assigned to different clusters are as dissimilar as possible. Clustering implies that the number of output clusters is less than or equal to the number of input load profiles. Applications of clustering include classification, pattern recognition, and clustering based estimation. Large numbers of cluster analysis methods have been developed. In this work we used K-mean model to conduct the Data clustering. For K-means, the number of clusters K is a hyper-parameter that cannot be learned directly. Therefore, we employed trial and error method to search the optimal value of K.

Table 1. Household k-Means Clustering

Cluster	No of households	No of EVs
Cluster 1	7	22
Cluster 2	28	111
Cluster 3	9	20
Cluster 4	27	54
Cluster 5	99	141

III. IMPLEMENTATION OF DEEP NEURAL NETWORKS (DNN) FOR RESIDENTIAL LOAD FORECASTING

In our work we have used keras on top of tensorflow to implement deep neural network. Keras is a high-level neural networks written in python and it is capable of running on top of either Theano or tensor flow [15], [16]. Recently, Tensorflow is the most leading library used in developing of deep learning models. However, Tensorflow is not simple to use. On the contrary, keras is a high level API built on tensorflow and can also be used on top of theano too. It is more user friendly and simple to use as compared to tensorflow [17].

Table 2. Deep learning Tensor-flow parameter

Parameters	Values
Total number of samples	52560
Training samples	52416
Validation samples	1440
epochs	100
Learning rate	0.001
Mini batch size	100
Activation function	Linear
Number of hidden layer	3

IV. EXPERIMENTAL RESULTS AND ANALYSIS :

A. *Data Set:*

We collected data from national renewable energy laboratory (NREL). This file includes electricity demand profiles for 200 households randomly selected among the ones available in the 2009 RECS data set for the Midwest region of the United States. The profiles have been generated using the modeling proposed by Muratori et al. [2], [3], that produces realistic patterns of residential power consumption, validated using metered data, with a resolution of 10 minutes.

Households vary in size and number of occupants and the profiles represent total electricity use, in watts.

B. Evaluation Metrics:

Mean absolute percentage error (MAPE), root-mean-square error (RMSE), normalized mean absolute error (NMAE), and normalized root-mean-square error (NRMSE) are the commonly used evaluation metrics to measure performance of models. We choose MAPE to measure the accuracy of our model.

The MAPE is a measure of prediction accuracy in statistics. It defines accuracy as a percentage and is defined by the following equation.

$$MAPE = \frac{\sum_{t=1}^{t=N} |y' - y| / y}{N} * 100\% \qquad (1)$$

C. Results:

MAPE value of different individual house and for clusters is presented. We get better MAPE value with clustering than without clustering based forecasting. The MAPE evaluation for different scenario is given below-

Table 3: Individual household MAPE evaluation (cluster 1)

Individual Household	MAPE (%)
Household_30	0.9246
Household_39	2.2683
Household_63	5.0400
Household_82	1.7297
Household_90	1.4886
Household_92	0.6877
Household_174	1.7513

Table 4: Individual household MAPE evaluation (cluster 2)

Individual Household	MAPE (%)	Individual Household	MAPE(%)
Household_2	1.0888	Household_87	4.9994
Household_3	2.5945	Household_89	1.8492
Household_11	4.2287	Household_94	1.9623
Household_13	1.7995	Household_103	1.2306
Household_15	6.3944	Household_112	5.5128
Household_17	2.5094	Household_113	5.6158
Household_24	1.3055	Household_114	7.7941
Household_25	5.8439	Household_119	4.4184
Household_27	0.9761	Household_129	3.1815
Household_29	0.4838	Household_131	4.1239
Household_32	3.5507	Household_133	1.2859
Household_33	1.6708	Household_138	1.7034
Household_44	1.1075	Household_145	8.3453
Household_46	1.2260	Household_148	1.3259
Household_48	2.6987	Household_78	8.3917
Household_49	4.8470	Household_138	2.3726
Household_58	1.1161	Household_145	1.8319
Household_65	1.4677	Household_148	2.4454
Household_67	2.1196	Household_151	6.3813
Household_77	2.3199	Household_159	1.8449
Household_160	6.8975	Household_167	6.1170
Household_166	2.6473		

Table 5: Individual household MAPE evaluation (cluster 3)

Individual Household	MAPE(%)
Household_62	0.4276
household_72	1.5132
Household_76	0.5266
Household_110	2.8294
Household_134	1.5547
Household_144	1.1238
Household_199	4.4991

Table 6: Individual household MAPE evaluation (cluster 4)

Individual Household	MAPE(%)	Individual Household	MAPE(%)
Household5	4.4534	Household139	2.8080
Household12	2.8008	Household143	2.4922
Household50	0.8774	Household146	3.1442
Household55	0.7716	Household149	2.5568
Household57	0.4225	Household154	0.6155
Household61	1.3923	Household155	1.2220
Household66	0.8672	Household158	3.1765
Household81	3.8605	Household179	2.8790
Household83	3.5200	Household186	4.9979
Household84	0.8664	Household192	1.0872
Household93	1.8596	Household198	3.6919
Household96	7.4798	Household118	2.0880
Household116	1.2890	Household123	3.7901

Table 7: clustered household MAPE evaluation with DNN

Cluster	Number of neuron	Linear activation	ReLU Activation	ELU Activation
Cluster1	50	1.3415	0.7209	0.6143
	100	0.9598	1.5437	1.3940
	150	0.9279	0.6540	1.9098
	200	1.0064	1.1308	0.7539
Cluster2	50	0.1183	1.6351	1.0436
	100	0.4671	0.8255	0.7207
	150	0.9824	1.6707	1.0111
	200	1.1018	0.6628	1.4814
Cluster3	50	1.0660	1.3335	1.9121
	100	0.9628	2.0996	2.0720
	150	0.7191	1.6229	0.5662
	200	1.3347	0.6880	1.170
Cluster4	50	1.7349	0.8861	1.310
	100	1.942	0.534	1.687
	150	1.863	1.115	1.615
	200	1.3078	1.216	0.963

V. Scheduling Model

The future power grid system needs to accommodate the increased energy consumption from EVs without a surge in demand during peak hours. The scheduling model needs to consider the user comfort, household energy consumption, EV demand, energy price etc. while reducing the electricity cost of total EVs in the system [18]. The cost reduction model will bring in more customers into committing their EVs to the scheduling scheme based on TOU price.

A. System Modeling

The objective of the proposed model is to minimize the total electricity cost for EV charging in a residential location.

$$\text{Min} \sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij} C_j \tag{3}$$

Here, M stands for the number of connected EVs in the system and N represents the time-slots in the varying energy price. P_{ij} represents the energy scheduled for the i[th] EV in time-period j and C_j represents the energy cost in time period j. The EV is scheduled in the model subjected to several user-defined and power system constraints [18]–[20].

(1) Demand Constraint

The constraint makes sure that the forecasted demand for each individual EVs are met while scheduling for the time-period.

$$\sum_{j=1}^{N} P_{ij} = EV_j \tag{4}$$

EV_j represents the forecasted demand for the EVs in the system. The sum of all the energy scheduled in N time periods should meet the forecasted demand.

(2) Consumer Preferred Time

Preferred time duration for charging EVs will vary with the customer. The model allows the residential consumer to specify his preferred time of charging for the EV. The energy scheduling model will only be allocated within the user-specified time-period.

$$P_{ij} \geq 0 \text{ if } T_{ij} = 1 \text{ else } 0 \tag{5}$$

T_{ij} represents the user preference for the i[th] EV at time j. The program accepts the user preference as a set of ones and zeros for the next 24 hours.

(3) Consumer Preferred Charger

The model provides an option for customers to provide a preferred charging port. The energy allocation will be done based on the user specified charging port. The customers have the option to specify L1 or L2 charging ports for their EVs.

(4) EV Charger Rating

This constraint makes sure that no more than the specified charger capacity is not allocated in each time-period. If more than the rated charger capacity is allocated by the optimization model, the charger points will not be able to support that power level.

$$P_{ij} \leq \text{Charger Rating}$$

The charger rating will be 1.92KW (L1) or 6.6KW (L2) depending on the user preference for which charger to use for each individual EV.

(5) SOC

The user can also provide the percentage of demand to be met for the next day. If the user does not plan to make longer trips with their EVs, a reduced charging percentage can be given to reduce the cost.

$$\sum_{j=1}^{N} P_{ij} \geq (FSOC_j) * EV_j \tag{6}$$

FSOC represents the user specified percentage of charge for each individual EV.

(6) EVs Connected to the Household

All the households considered in this dataset have connected EVs, with ownership varying from one to six vehicles. The scheduling of all connected EVs in a household at the same time can cause sudden surge in demand and can create power stability issues. The constraint throttles the scheduled EV energy in each hour from a single household to a maximum of 25% of the total demand for the household.

$$\sum_{i=1}^{E_h}\sum_{j=1}^{N} P_{ij} \leq K_h H \tag{7}$$

For each household in the system, E_h represents the number connected EVs , H the corresponding household demand and K_h represents the percentage of household demand allowed in each hour.

(7) Households in a cluster

In each cluster, the number of households vary from 7 to 99 and a have considerable set of EVs connected to them. If all the EVs in a cluster are turned on at the same time, it can create transmission and generation issues for the power companies. This constraint limits the total scheduled energy for all the EVs in the cluster in each hour to a maximum of 20% of the total household demand in the cluster.

$$\sum_{i=1}^{E_c}\sum_{j=1}^{N} P_{ij} \leq K_c \sum_{h=1}^{H_c} H_j \tag{8}$$

For each cluster, H_c represents the number of houses in the cluster, E_c represents the connected EVs for all the households in the cluster and K_c represents the percentage of total demand allowed in each hour.

B. Dataset

The model considers a set of 200 households having a set of 348 EVs connected to them. All the residential customers considered in the set own EVs, with the number varying from one to six. Clustering techniques were used to group the households based on their energy consumption pattern. Here, we considered a 5-cluster system obtained by means of k-means clustering. The households in each cluster vary from 7 to 99. The day-ahead scheduling for the EVs are based on the forecasted demand of EVs and household energy consumption. A DNN based forecasting was used to predict the energy consumption of EVs and households based on a year-long dataset with 10-minute resolution.

The energy price for a 24- hour duration was considered for this optimization model. The day-ahead energy price from the MISO (Midcontinent Independent System Operator) on 31st December 2016 was used for the model [21]. MISO is an RTO providing open-access transmission service and monitoring the high-voltage transmission system in the Midwest United States. Figure 1, shows the variation in the energy price for the different hours of the day.

Table 8. MISO day-ahead energy price.

Time-period	Energy Price	Time-period	Energy Price
0	0.01322	12	0.01978
1	0.01064	13	0.02021
2	0.00925	14	0.02156
3	0.00821	15	0.02116
4	0.009	16	0.02175
5	0.00883	17	0.02883
6	0.00912	18	0.03114
7	0.01288	19	0.02453
8	0.01514	20	0.02133
9	0.01669	21	0.01933
10	0.01927	22	0.01885
11	0.01976	23	0.01456

Customers have an option of L1 and L2 charging points, L1 charging points have a rating of 1.92 KW and L2 have a rating of 6.6 KW. Consumers prefer to use L2 charging points because of the increased speed of charging. L1 can charge a depleted EV battery in 20 hours or more from a standard 110V outlet while L2 can do the same in 4 to 6 hours from a 220V outlet. Consumers usually keep their EVs for charging at night and may not necessarily need the speed of a L2 charger but it can be used to deliver short burst of power [22]. The households in the clusters are assumed to have access to both the L1 and L2 charging points and the optimization is performed considering the user preference for the charging port.

The proposed scheduling model also provides an option for households to provide their preferred timing for individual EVs. The users have the choice of selecting any hours in a 24- hour duration to charge their EVs. Some customers may not always takeout their EVs for long distances and does not require a full charge on their vehicles. The model supports the option to give the EVs a reduced amount of charge for the next-day according to the customer's needs.

The different parameters used for the scheduling model are listed in the table 9.

Table 9. Optimization model parameters

Sl. No	Model Parameters
1	Forecasted EV demand
2	Forecasted household demand
3	Schedule time (1 hour)
4	Day-Ahead energy price
5	Consumer preferred charging time
6	Consumer preferred charger type (L1 or L2)
7	Final State of Charge (SOC)
8	EVs in each household
9	Households in each cluster

C. *Optimization*

A Mathematical Programming Language (AMPL) was used in this research to model the linear programming based scheduling model. AMPL is an algebraic modeling language to solve large scale optimization and scheduling problems. It was developed at Bell Laboratories by Robert Fourer, David Gay, and Brian Kernighan. The software supports several open-source and commercial solvers. The AMPL coding syntax is similar to mathematical notation of optimization problems, which helps developers to program their model.

VI. Results and Discussion

The first part of this paper investigated the MAPE accuracies with deep learning platform for residential load forecasting with DNN, clustering based DNN forecasting with different activation function. The best accuracy was obtained for cluster 2 with linear activation function of fifty neurons.

The forecasted results were used in the second part to develop a scheduling scheme for EVs in the region to minimize cost and prevent the aggregated charging during low price hours.

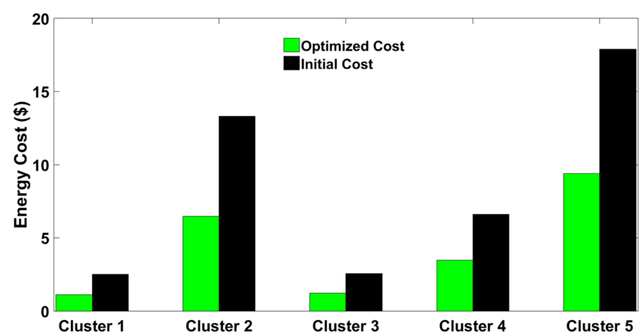

Figure 3. Cluster cost analysis.

The total energy cost of the connected EVs in each individual cluster is represented in figure 3. There is a significant reduction in energy cost for all clusters in the region. The energy cost almost reduces by half for the clusters by properly scheduling the connected EVs. The individual household energy costs for their EVs are shown in figure 4, 5 and 6. All the households in each cluster have savings in cost from the scheduling process.

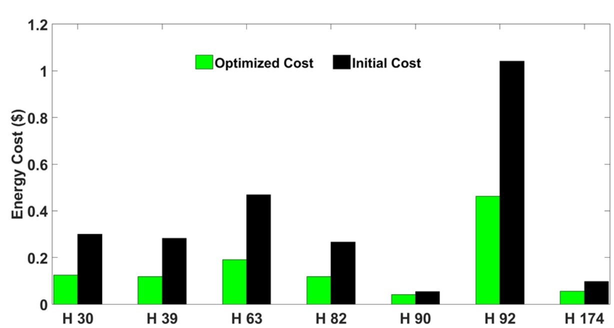

Figure 4. Household cost analysis in cluster 1.

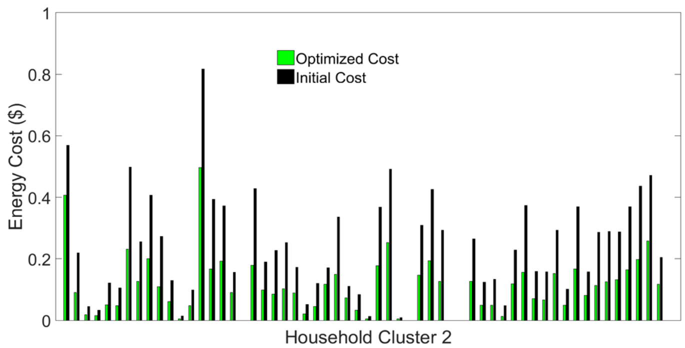

Figure 5. Household cost analysis in cluster 2.

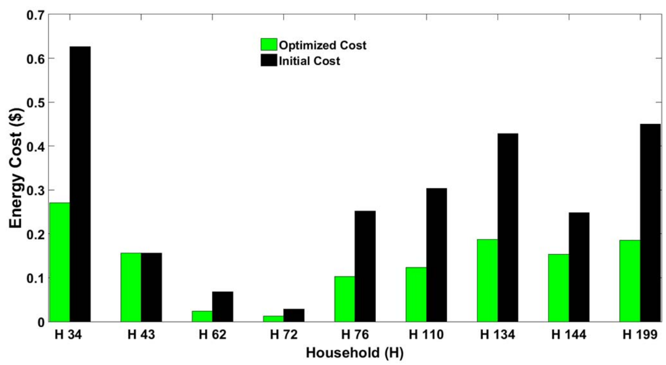

Figure 6. Household cost analysis in cluster 3.

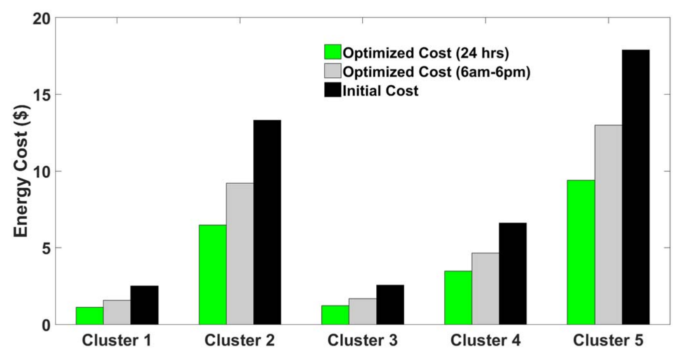

Figure 7. Household cost analysis in cluster.

The model can perform the EV schedule based on user preference. The figure 7 shows the cluster wise cost when a user preferred timing of 6am-6pm is provided. The model can achieve a cost saving even with the user providing a preferred time of use. The model schedules EVs during off-peak hours (low-energy price) to shift the load from peak hours while lowering energy cost of consumers.

VII. Conclusion

In this paper, a novel method to schedule the electric vehicle charging was proposed using concepts from DNN and K-means clustering. K-Means algorithm was employed to segment the data set into subsets for constructing models faster and more efficiently. The model was evaluated on a large real-world residential data set. The forecasting results obtained from clustering the input parameters and without clustering are presented and the result shows that the clustering based forecasting is more accurate than without clustering. The scheduled EVs will help to reduce the energy cost along with reduced power surge from households and residential regions.

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