Improved modelling of electric loads for enabling demand response by applying physical and data-driven models

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Improved Modelling of Electric Loads for Enabling Demand Response by Applying Physical and Data-Driven Models

Project RESPONSE

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***Abstract*—Accurate load and response forecasts are a critical enabler for high demand response penetrations and optimization of responses and market actions. Project RESPONSE studies and develops methods to improve the forecasts. Its objectives are to improve 1) load and response forecast and optimization models based on both data- driven and physical modelling, and their hybrid models, 2) utilization of various data sources such as smart metering data, weather data, measurements from substations etc., and 3) performance criteria of load forecasting. The project applies, develops, compares, and integrates various modelling approaches including partly physical models, machine learning, modern load profiling, autoregressive models, and Kalman-filtering. It also applies non-linear constrained optimization to load responses. This paper gives an overview of the project and the results achieved so far.**

Keywords— forecasting, machine learning, physically based models, hybrid models, active demand, optimization

I. INTRODUCTION

There is very little energy storage in power systems so accurate balancing generation and consumption is critical for the operation. Accurate forecasting of the power balance improves efficiency and reduces costs and environmental impacts. Power system load forecasting is a very much studied and published area. See [1], [2], [3] and [4], for example.

The research plan of project RESPONSE identified the following research needs and opportunities as compared to previous research: 1) The traditional load modelling either does not include any control response models or the response models are static or nearly static. For example, they do not take into account the fact that the responses and their dynamics depend very much on the variations of the ambient temperature and time of occurrence (i.e. time of the day, weekday/weekend, season of the year). 2) In future smart grids, the modelling needs are very diverse and response models are needed both for aggregated responses of customer groups and for individual customers. Electricity markets and system level power balance control benefit from customer group models, whereas low voltage network control and customer energy management need also models of individual customers. 3) New data are now available. In Finland, almost all customers have had smart hourly interval metering for several years. The access to other relevant data is also opening. Together they enable further development and update of new data-driven models and schemes for load and response forecasting. 4) The analysis of the influence of weather forecasting errors, performance criteria and confidence intervals on load and response forecasting was often omitted or inadequate and should be evaluated more extensively.

Research hypotheses of the project are the following. 1) Hybrid models can combine the benefits of the different load modelling approaches, thus providing models that

(a) forecast relatively accurately in different situations including also those that have not been experienced before,

(b) adapt to changes in the load behavior, especially to those that can be expected

(c) are reasonably easy and fast to maintain and update.

2) Models that combine all relevant available information can forecast more accurate than black box models that are based purely on measurement data or models that are purely

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physically based. This paper explains the results achieved so far and how they support the hypotheses.

II. OBJECTIVES OF THE PROJECT

The project RESPONSE aims at 1) developing forecasting and optimisation models for loads and distributed energy resources based on data driven, physically based and hybrid approaches. To support that it also analyses and develops 2) forecasting performance criteria and 3) utilisation of various data sources for the forecasting. See Fig. 1.

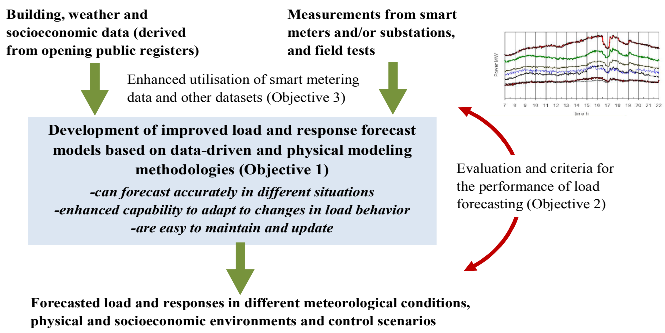

Figure 1. The project objectives.

III. EXTENSIVE FIELD TEST DATA

Measurement data from a representative number of active demand customers are necessary for modelling the aggregated responses. The measurement periods need to span at least two years, because the temperature dependence of the loads is strong and nonlinear. The customer groups studied have electrical heating. But even in the colder climate zones there is also a significant amount of cooling load which means that the temperature response changes its direction in the warm summer days. In addition, the saturation of the heating and cooling create strong nonlinearities in the aggregated load behavior. Saturation also affects strongly on the active demand (AD) responses. Consequently, rather long measurement time series is necessary. At least one year for identification and one year for verification are in principle necessary for a proper study. In addition, especially the machine learning methods require some months of independent data for tuning the structure and parameters in a way that adequately controls overfitting.

The project has hourly interval data from over 15 000 customers of whom about 9000 were subject to AD. Power measurements at 3-minute from distribution substations cover about 15 000 AD customers and many more non-active customers. The analysis of the results shows that the amount of customers is adequate for the study, and increasing the number of the customers does not anymore increase substantially relevant information of the customer groups studied. The data are from several power distribution areas that cover different climate zones. Typically, we have at least one-year data for identification and another year for verification. In some cases, we have somewhat shorter time periods. These are long enough for testing the methods, but not adequate for a proper comparison and evaluation. Fig. 2 shows the distribution areas and test periods of the research data.

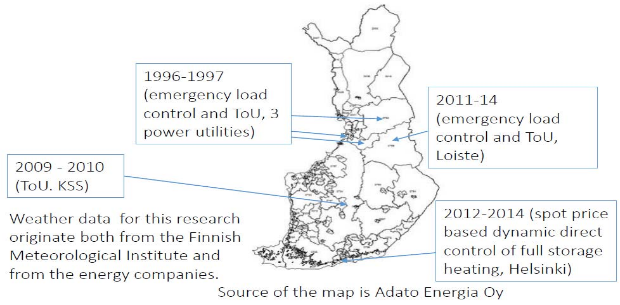

Figure 2. The project uses data from several distribution areas, field tests and decades in Finland.

IV. FORECASTING IN THE PRESENCE OF ACTIVE DEMAND

As the penetration of variable generation increases, the need for balancing power increases. Balancing using only or mainly the big power plants increases costs and emissions thus eventually cancelling the benefits from renewable generation. A solution is to increase the use of demand side flexibility or AD for balancing. Ignoring the explicit presence of active demand in the load models leads to unsatisfactory forecasts according to [4] and [5].

One of the main barriers for high AD penetration is that the energy industry uses such mainstream forecasting methods that completely fail in the presence of AD. The other major barriers, such as market structures and grid regulation, seem also solvable, but are outside the scope of this research. The project RESPONSE has already developed hybrid methods that provide accurate forecasts for aggregated loads also in the presence of AD.

A. Hybrid forecasting methods

Control responses and load saturation are forecast using a physically based model structure. The residual is forecast with a machine learning model designed and tuned to learn also the time dynamics of the system. The load forecast is the sum of these component forecasts. See Fig. 3. As the machine learning method we compared a support vector machine (SVM) and a Multi Layer Perceptron (MLP) neural network. We optimized the structures of the machine learning methods using a genetic algorithm and a sensitivity function.

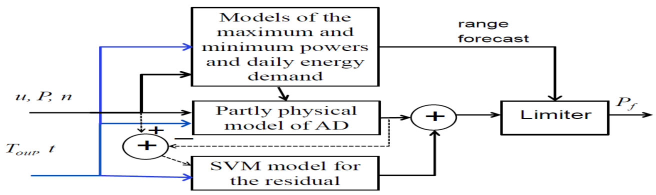

Figure 3. The main structure of the hybrid model applied [6].

P is the measured power, P_f the power forecast, u is the control signal and n is the number of houses. T_{out} is a combination of the measured and forecast temperatures as available at the time of forecasting the power. Time t is also an input signal. Each controlled group has its own control signal u and model. We explain in [5] and [6] successful application of the approach to short term forecasting of hourly interval powers of active demand customer groups.

B. Result with hybrid forecasting

The hybrid method has so far always been superior to its component methods even, when load control has been applied very seldom. In emergency load control tests, there were 13 months of identification data, and 14 months of verification data. Table I shows some selected results from [6]. It compares the forecasting performance for the verification period.

In this case, the response model was identified from 1996–1997 test data and then adapted the 2011–2012 identification data. It was necessary to use the model from the old field tests together with building codes (dimensioning requirements) as a starting point, because the new response identification test did not, during the control actions, include cold enough temperatures for the identification of the load saturation.

TABLE I. AN EXAMPLE WHERE A HYBRID MODEL PERFORMED BEST IN THE VERIFICATION IN 2013-2014.

Method	Normalized Root Mean Square Error (RMSE)			
	Group 1	**Group 2**	**Group 3**	**Group 4**
SVM alone	0.1457	0.1756	0.6850	0.6866
MLP alone	0.1283	0.1651	0.8904	0.9622
SVM with response model	0.1122	0.1143	0.1718	0.1639
MLP with response model	0.1047	0.1431	0.1640	0.1820

In Table I the results of the pure machine learning methods for groups 3 and 4 show clearly poor performance. Analysis revealed that the reason for this poor performance of machine learning was the loss of relevant information when grouping the identification data. Splitting the identification groups according to the site annual mean consumption improved the performance with the groups 3 and 4 substantially. With the response model this problem does not appear, because for the response model, it was necessary to identify the size dependence separately, and we applied this dependence function to the total forecast. There were only two load control events per group in the whole 14-month verification period, and the load control events were short. When the performance evaluation focused on the load control moments, the hybrid methods were very accurate and the pure machine learning methods failed completely; see Fig 4.

V. SMART METERING DATA BASED LOAD PROFILING AND CHANGE DETECTION

The development of hybrid methods for forecasting loads in the presence of AD was discussed above. The project RESPONSE studies and develops also other smart metering data based methods and uses of load modelling. It develops smart metering based load profiles to support state estimation of the electricity distribution system [7]. In our initial study [8], the smart meter based load profiles showed roughly equal performance with two other short-term load forecasting methods that were a neural network, and a Kalman-filter based predictor with input nonlinearities and a physically based main

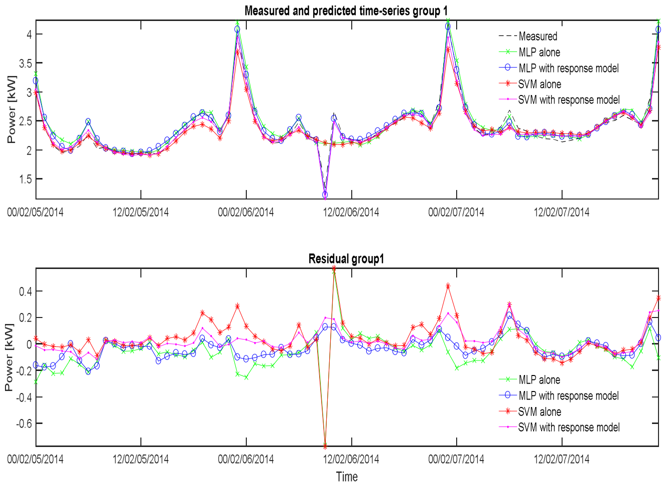

Figure 4. Only the hybrid methods forecast accurately at the AD events [6].

structure. These three methods had the best performance in the study. Each of the three forecasting method had its relative strengths and weaknesses. The smart meter based load profiles were computationally light to use and could flexibly model both individual customers and groups of aggregated customers. Both the load profiles and the neural networks require relatively long identification periods, preferably several years, in order to reach their best accuracy. The long identification period is a disadvantage, especially, if a customer behavior changes. For this reason, we studied customer change detection from smart meter data.

Earlier in [9] fuzzy memberships were used to determine, if the weekly load profile of a customer has changed or not. In this project, we aimed for a mathematically more sound method. Cumulative sum (CUSUM) method and Pearson (PE) divergence methods were tested and the PE method was found more promising [10]. In order to detect changes in customer behavior, the consumption was compared in two consecutive years and the load profile shape similarities were analyzed. One way to measure the similarity of data sets is to compare the underlying probability distributions. To calculate the dissimilarity one must know or estimate the probability densities. Density estimation is a hard problem, and therefore it is convenient to estimate the density-ratio directly without the need for individual densities. In this study, the relative unconstrained least-squares information fitting (RuLSIF) method presented in [11] was used for density estimation. The Pearson divergence was chosen, because it leads to a squared loss function that has an analytical solution. It is therefore more efficient and robust than estimating e.g. Kullback-Leibler divergence, which leads to a nonlinear log-loss function that needs to be solved iteratively [12].

The results show that the PE divergence method is able to detect changes much faster than the CUSUM method. Fig. 5 shows an example. The installation of electric sauna stove to a typically row house is simulated. It increases consumption mostly on Saturday evenings, which makes it difficult to detect the change. The dashed horizontal line in Fig. 5. is the

95th percentile of PE scores calculated from the previous year data. The significance of the change can be evaluated by counting the number of (consecutive) days the score is above this percentile line. The robustness of the PE divergence method was tested by adding random noise to the measurement data. Even with 5 % added noise, when the sauna stove installation was hardly visible to a human eye in the hourly measurements, the change was clearly visible in the PE score chart.

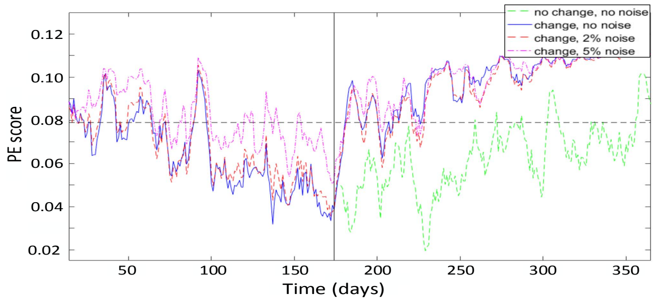

Figure 5. Change detection with PE divergence. Vertical line marks the sauna stove installation day [10].

VI. Electrical Energy Storages in Households' Energy Management in Finland

In Finland, household customers can choose a spot market-based electricity contract, where every hour has its own price. This gives customers incentive to shift consumption to the time of cheaper electricity price. In addition, if the customers have own electricity production, e.g. solar panels, they want to maximize the self-consumption of the produced electricity and minimize the amount of excess electricity sold to the grid. Both these goals, consumption shifting and maximization of self-consumption, can be achieved with a smart electrical energy storage system. In project RESPONSE, an intelligent battery energy management algorithm is developed and its operation is simulated in households with different consumption profiles, solar system sizes and battery capacities. This section presents a summary of this work. A more detailed description is in [13].

A. Control algorithm and the simulation model

The developed energy management algorithm consists of two parts. The first part is called hourly control and it optimizes on an hourly level when and how much the battery is charged and discharged. The second part is called continuous control and it implements—within the hour—the hourly charging and discharging targets given by the hourly control. The hourly control aims to minimize the total electricity costs of the customer. For this, the hourly control calculates how much energy should be charged or discharged during the hours in the near future. This is a complex task, because sometimes it is more profitable to keep the battery charged for the future than discharge it during the first profitable hour.

Since the hourly control deals with future hours, load and production forecasts are needed. The load forecasts are based on each customer's consumption history and outdoor temperature measurements and forecasts [14]. For solar power forecasting, we use the solar radiation model available in [15].

The length of the optimization horizon is one important research question. The hourly control benefits from a long optimization horizon but the accuracy of the forecasts declines if they are made far into the future. In this study, we experimentally determined that the most suitable length for the optimization horizon is 18 hours. The optimization horizon is sliding and the hourly control gives target value for continuous control at the beginning of every hour. Even though the actual consumption and production are not the same as the forecast values, the continuous control tries to implement the given targets as well as possible.

The battery model used in simulations is based on the properties of lithium iron phosphate (LiFePO4) batteries with a graphite negative electrode. This alternative is suitable for energy storage use because of its long cyclic and calendar lifetime and its good safety features [16]. The efficiency of the energy storage is modelled assuming that the internal efficiency of the battery depends on the current and the converters and inverters have constant efficiencies.

B. Initial data

Hourly smart meter measurements from several single-family houses of different type were used as inputs in the simulations. All the houses were located in central Finland and measurements were available for several years. For testing the operation of the continuous control, and to study the intra-hour changes in consumption, the electricity consumption of one house was measured with six-second intervals.

Solar power production was modelled based on the radiation measurements taken from the roof of one building in Tampere University of Technology campus area. The calculated production was then scaled to correspond solar systems of different size.

C. Simulation results

When the charging and discharging of the battery is optimized, the customer's load profile changes in desired direction. As an example, Fig. 6 shows how the daily load profile of one single-family house changes. The behavior of the load was simulated assuming that the house has a 1 kWp solar panel array and a 10 kWh battery. For reference, also the load without the battery is shown. Fig. 6 shows that with storage, all the produced energy is used within the house and consumption during expensive hours in the morning and evening is shifted to early morning and afternoon.

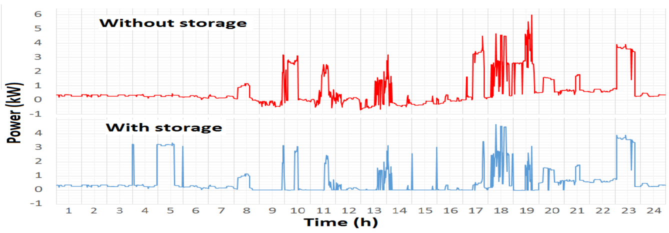

Figure 6. Electricity consumption of one single-family house for one day with the energy storage and without the energy storage [13].

The financial benefits from shifting the consumption to cheaper hours depend on the volatility of the spot prices, the load profile, and the size of the energy storage. The benefits from the increased self-consumption depend mainly on the volumetric price of the distribution tariff. As an example, we simulated a typical customer with electric heating and different battery energy storage (BES) and solar system sizes. The annual consumption of the chosen customer was 18.3 MWh. The simulations utilized day-a-head spot market area prices for Finland and a distribution tariff with a volumetric price of 6 c/kWh. The savings with intelligently controlled energy storages are shown in Fig. 7.

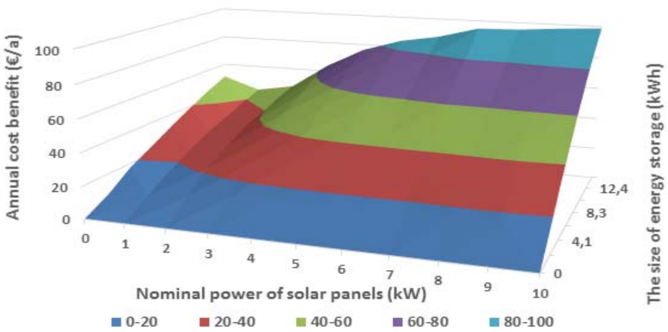

Figure 7. The annual cost benefit of energy storage as a function of energy storage and solar system size [13].

Currently the prices of energy storage systems are so high that the investment payback period is longer than the expected lifetime of the storage system. However, the prices of Li-ion batteries have been decreasing in recent years and the price decline is expected to continue in the future. Also, since the annual cost benefit is greatly affected by the volatility of spot prices [13], the energy storages became more profitable if the volatility increases in the future. In addition, the changes in distribution tariff structures, namely the introduction of power-based tariffs, can affect the profitability. Better load forecasts also increase the profitability of energy storages. In our simulations, approximately one third of the theoretical cost benefit was lost due to the load forecasting errors.

VII. NONLINEAR OPTIMAL CONTROL OF RESIDENTIAL DETACHED HOUSES WITH NEW ENERGY RESOURCES

The previous chapter studied the optimal operation of a BES in a house with solar power using linear constrained models. It ignored nonlinearities and thermal flexibilities. Here these are included in the nonlinear optimal control model.

The need for dynamic demand side responses is increasing. Dynamic prices in electricity retail tariffs are available in Finland. More and more heat pumps and solar panels affect electricity consumption of houses. Thermal and electricity storages offer potential to reduce electricity costs by providing flexibility to the power system. The project RESPONSE studied by simulations the potential of nonlinear constrained optimization in dynamic price control of residential small houses that have such energy resources; see [17] and [18]. A ground source heat pump and electrical heating of a heat storage floor provided the controllable thermal flexibilities. The criterion was quadratic and the main nonlinearities of the heat pump and the battery energy storage were included in the model. We solved the nonlinear optimal control problem using constrained nonlinear optimization and the principle of Pontryagin; the principles of the optimal control approach are explained in detail in [19].

A. Models and methods

A nonlinear thermal dynamics model for each of the two measured houses was developed. The models included the thermal dynamics of the building with a thermal storage floor, ground source heat pump, solar panel, and BES. The model inputs include weather data and forecasts (temperature and solar radiation) and the electricity price signal. A separate model forecasts the solar power generation from the solar radiation forecast. For the nonlinear optimal control of the house energy consumption and storage subject to electricity price signals, we implemented, applied and developed a suitable method. The core method is explained in [19]. It uses a constrained nonlinear optimization method (a generalized reduced gradient method) where the gradient is calculated from the adjoint state of the thermal dynamics model using the method of Pontryagin. Several initial guesses are generated using heuristics in order to reduce the risk of local optima and other convergence problems. The method worked very well, when ground source heat pump, storing and direct electrical heating, and solar panel were included as controllable resources in the dynamic energy balance model of the house. When BES was added to the model, some problems with local optima and poor convergence were observed especially when the battery was small compared to the other controllable resources. The overall performance of the method is nevertheless already useful for most purposes.

B. Results

The benefits of optimal operation came mainly from the thermal storage capacity. The benefits from optimal price based control were not significantly sensitive to the dimensioning of the energy resources. Only the operational costs were taken into account. Fig. 8 shows annual variable electricity cost with a 5 kW solar panel system, 2.4 kW heat pump and different BES sizes and given by the method.

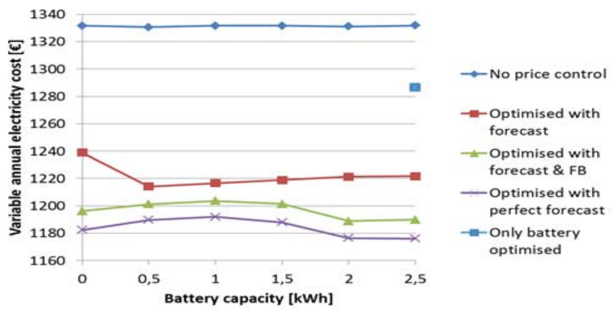

Figure 8. Benefits of the optimization with a 5 kW solar panel system, 2.4 kW HP and different BES sizes [18].

The day ahead optimization using weather forecast gave rather good cost reduction (red line), but the indoor conditions did not stay within adequate limits. When feedback (FB) control was added to keep the indoor conditions acceptable, the costs reduced further (green line). Optimization results with perfect forecasts show a reference that is impossible to achieve. Poor convergence caused the inconsistencies in the two bottom lines with battery sizes 0.5 - 1.5 kW; adding storage capacity could not reduce the benefit so much, because only operational costs were included in the analysis.

A modern Li-Titanate (LTO) battery was used in the BES in the simulations. In addition, a lead acid battery was modelled and simulated, but it was abandoned because its aging costs were roughly equal to the benefits of its use. The aging of the LTO-battery due usage was so small that it was insignificant in this application. In retrospect the power electronics of the BES were dimensioned clearly too big in the simulations, which increases the BES losses and reduces its profitability somewhat. The optimization preferred flexibilities from the heat pump and heat storage, because their control caused very little losses in the model and in the test houses used for the modelling. The annual benefit when the only price controllable resource was the 2.5 kW BES was about 45 € while the annual benefit from using only the thermal flexibilities for price control was about 136 € and with perfect forecasts about 150 €. The base case annual variable electricity cost was 1332 €.

The results show the following. 1) Forecasting solar power enables automatic optimization of price control responses. 2) Weather forecast accuracy has recently improved and is adequate for day ahead optimization. 3) For price control of storage type electrical loads, the nonlinear constrained optimization with the principle of Pontryagin is a good approach for both operational online optimization of price control responses and for offline analysis and dimensioning. However, the convergence was poor with relatively small batteries. 4) Quadratic criteria outperformed linear criteria in using the thermal flexibilities. 5) Proper optimization tools should be used in the design and dimensioning of the investments and in the operation of new energy resources. Heating, cooling, pumping, air conditioning etc. are often inexpensive sources of low loss flexibility. When they are available in the house, the investment in BES for market based demand response is most likely not justified. There are often better reasons for BES, such as backup power. 6) Optimal control gives good benefits regardless of the dimensioning of the energy resources.

VIII. Conclusion

The project RESPONSE and its results were discussed. The results support the objectives and the research hypotheses of the project. The project has succeeded in combining the strengths of different data driven and physically based modelling methods, and in developing the optimal control of load responses. The focus of the project has been on short term forecasting, related hybrid methods, and optimization of the operation of resources. In addition to loads and AD also embedded solar generation and BES are included.

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