Assessment of Residential Electricity Tariff Switching Based on Customer Response Elasticity

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Abstract— **Price-based demand response programs have recently become focus of interest due to the increased flexibility and potential to deliver greater demand responsiveness. However, the key to success of such programs highly depends on greater participation of residential customers through defining more effective dynamic tariffs. This paper aims to assess and predict the probability of switching between different tariffs based on the price response elasticity of residential customers. In this regard, different types of dynamic tariffs have been considered in contrast with a fixed price tariff. In order to investigate the variability and flexibility of household energy usage due to temporal and individual characteristics of each household, the following pricing bands are considered: day, peak, night and weekend/weekday. Moreover, the elasticity of demand relating to different pricing bands has been determined for different groups of residential customers.**

Index Terms-- **Price elasticity, demand response, electricity market, tariffs switching, residential**

I. INTRODUCTION

The UK energy consumption report released in 2016, shows significant changes in total residential electricity consumption due to a 46% increase in the number of households, as well as a 17% population increase since 1970 [1]. Rising energy consumption, along with distributed generation, can lead to system balancing issues arising within the distribution network. Time-based pricing policies such as *Time-of-Use* (ToU) tariffs have been proposed as an effective way to address this issue by offering incentives to minimize peak electricity usage [2].

Among different time-based tariffs, near-real-time (dynamic) pricing signals combined with automation in end-use systems have the potential to deliver even more benefits to both network operators and customers. Dynamic pricing allows customers to pay the fluctuating market rate for their electricity. However, in order to encourage customers to reduce demand, each customer should have an understanding of the total bill saving based on different tariffs over time. Moreover, suppliers need to characterize and assess the elasticity of customer response to changes in the electricity prices in order to define more accurate tariffs for cost optimization purposes.

The effect of dynamic and ToU tariffs on residential demand has been investigated in many papers aiming to address the required and fundamental structures for designing more effective electricity tariffs towards *Demand Response* (DR) schemes implementation [3-4]. Some studies analyse the consequences of changing from static to dynamic tariffs [5-9], indicating that unlike businesses and light industries, residential loads are less heterogeneous in terms of energy consumption patterns.

The aim of this paper is to assess the probability of different groups of residential customers to transfer from one tariff type to another. In addition to switching between *Fixed Price* (FP) tariffs to a dynamic one, switching between different ToU tariff scenarios is studied in this paper as well. ToU tariffs are varying according to the type of day (weekday/weekend) and time of day (day, peak, night).

The proposed methodology is based on clustering meter readings in order to create homogeneous groups of households based on mean aggregated load profiles using the K-means algorithm. For each cluster, demand elasticity in relation to energy price for each type of tariff has been evaluated using *Ratio of Cost* (RC), load profiles and mean power usage. Finally, the probability of switching between tariffs for different clusters of customers has been estimated. In this regard, each cluster has been characterized based on individual characteristics (educational, financial and willingness to engage in DR) as well demand elasticity for different tariff scenarios.

Residential customer load profiles have been clustered based on both a weekly and a weekend basis in order to assess the effect of type of day variations in price response elasticity. Finally, the correlation between the total demand reduction in each type of tariff with household characteristics has been analysed through a multi nominal regression model.

The rest of the paper is structured as follows. The studied dataset are elaborated in section II. Section III describes the results obtained from segmentation and characterisation of the residential customers based on average power consumption. The proposed methodology is elaborated in section IV including the RC values, price elasticity and result analysis. The conclusions and future work are presented in Section VI.

II. THE DATASET

The dataset has been selected from the *Ireland Electricity Smart Metering Trials* (IESMT) [10]. The IESMT program

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examined electricity consumption of 5028 Irish residential customers with half-hourly resolution. An in-home survey was provided with the dataset, which has been investigated in this paper in addition to the dataset to characterise the residential electricity consumption patterns and behaviours.

The dataset consists of a six month benchmark period (July- Dec 2009) and a one year test period (Jan-Dec 2010). In the test period, customers were allocated randomly to different tariff scenarios. However, the profile of the set of participants in each allocated tariff was approximately the same across behavioural, demographic and attitudinal perspectives. In this paper, data related to one summer month has been considered. In order to increase the quality of clustering results, customers with more than one missing day in their meter readings have been removed [11]. After cleaning and clearing data, 3405 customers were included in this study.

The number of customers in each cluster (population) and their power usage information are summarised in Table I. Fig. 1 shows the average power consumption resulted from aggregating households based on different tariffs allocation during a typical weekday (48 timeslots). During non-peak times, customers on fixed tariffs experienced higher power consumption comparing to those on ToU tariffs and conversely for peak times. This is due to the peak price being relatively higher than non-peak periods, while it is constant for fixed tariff at any given time. This indicates that applying ToU tariffs can provide overall demand reduction and peak shifting.

III. Dataset Clustering

A. Clustering load profiles

Residential demands are known to have an intermittent and unpredictable character when taken individually. The load profile of each customer can vary from one household to other due to their distinctive characteristics. Therefore, in this study, the load profiles have been clustered to highlight similarities in groups of households based on their consumption. The clustering result provides a basic understanding of household attitudes and the potential of demand shedding/shifting in response to different pricing bands.

The K-means algorithm [12] has been used in this paper to cluster the demand profile from benchmark periods. The clustering procedure has been applied on the July records for both weekdays and weekends (Saturday, Sunday and Bank holidays). These two distinctive segmentations regarding the type of day have been applied aiming to describe the load variation of the whole week [13]. The clustering process was

TABLE I
GROUPS AND TOU TARIFFS STRUCTURE OF IESMT [10]

Price band	**Price by tariff group (c/Kwh)**					
	A	**B**	**C**	**D**	**W**	**Control**
Night (23:00 to 08:00)	12	11	10	9	10	
Day (All other times)	14	13.5	13	12.5	14	18
Peak (17:00 to 19:00, Mon to Fri)	20	26	32	38	38	
weekend (All Weekend)					16	
N (households)	1368	511	1370	509	100	1170

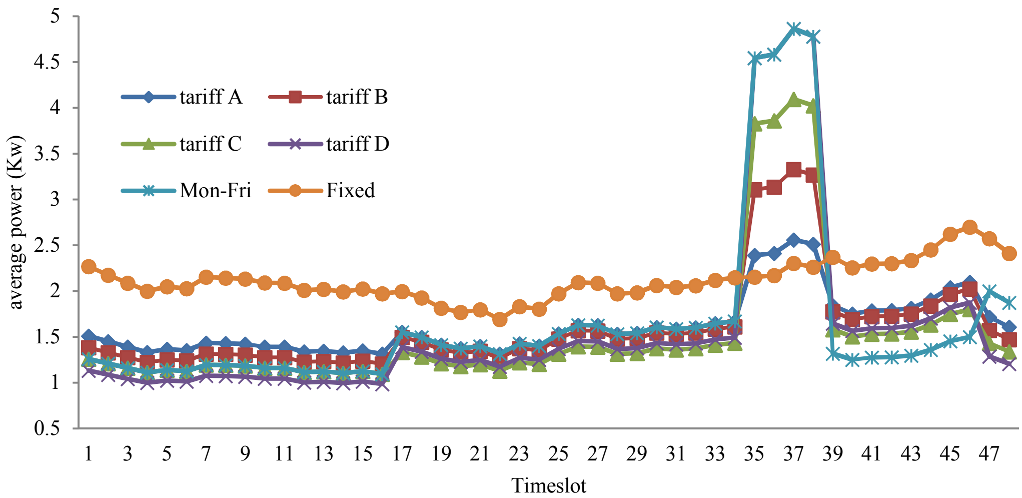

Fig. 1. Mean aggregated usage of customers in each allocated tariffs for a typical weekday in July

repeated for different initial number of clusters and evaluated by *Davies-Bouldin-Indices* (DBI). Following this procedure, seven distinctive and well separated clusters were obtained.

Table II shows the details of loads segmentation considering the population in each cluster as well as mean and *Standard Deviation* (STD) of aggregated loads. Moreover, a social segmentation for each cluster based on their attitudes towards participating in DR programs is presented in Table III.

It should be noted that the number of clusters have been sorted based on the *Mean Power* (MP) of each cluster. MP is the mean usage of all the half hour readings of each cluster of households. The *Load Factor* (LF) is defined as:

$$LF = \frac{\sum_{i=1}^{Nc}\sum_{t=1}^{48}(\overline{P}_{i,t} - P_{max,i,t})}{Nc} * 100 \qquad (1)$$

where Nc is the total number of households in c^{th} cluster, $\overline{P}_{i,t}$ and $P_{max,i,t}$ are the mean and maximum power usage of all aggregated loads for each cluster respectively.

LF does not vary significantly from cluster to cluster, as the total installed electrical equipment in residential households is of similar power consumption. A normal distribution was obtained for customers along different tariff allocation in each cluster (Fig. 2).

TABLE II: Customers clustering based on average power consumption (sorted by LF)

Cluster No.	Population	Population (%)	MP	Std	LF
			day	peak	night
5	394	21.46	413.29	15.66	31.15
2	648	19.03	350.37	15.79	31.30
7	794	43.25	344.78	15.77	31.30
4	142	4.17	163.28	15.57	31.41
1	562	39.38	152.69	15.80	31.44
3	392	24.98	118.47	15.74	31.59
6	473	15.71	31.46	17.13	32.75

TABLE III: Social segmentation of customers based on their attitude towards DR participation and occupancy characteristics (%)

Cluster No.	High motivated	Adult No	Adult Occupancy	Child No	Child Occupancy
1	80.42	91.99	82.38	36.12	21.17
2	78.70	80.25	52.47	33.95	18.98
3	78.57	68.37	52.55	22.96	15.56
4	84.50	73.24	57.75	34.51	17.61
5	79.94	72.34	56.85	26.14	15.99
6	77.16	78.22	64.48	26.00	15.86
7	81.23	88.66	76.95	33.00	21.91

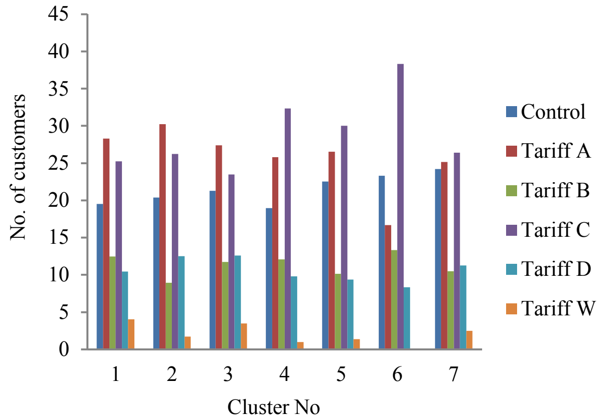

Fig.2. Distribution of population along different tariffs for each cluster

B. *Clusters characterization*

Each cluster has been characterised based on different parameters including attitude towards DR participation, social, financial and educational factors. The relationship between each factor and the usage per different periods of a day has been analysed. The results show that although most of the population have high interest in attending DR programs, the actual potential of demand responsiveness is variable among clusters due to different levels of satisfaction, comfort, option awareness of each cluster as well as financial aspects. As an example of this diversity, cluster 3 consists of mainly of retired or unemployed occupants with children that experienced considerably higher electricity use during morning time.

C. *Demand Reduction*

Electricity tariffs are mainly designed for load shedding (reduce overall demand) or load shifting (shifting peak demand to non- peak periods). Fig. 3 and Fig. 4 present, respectively, the amount and percentage (normalising data in respect to populations in each group) of overall power reduction for each cluster of customers. The demand reduced based on the time of the day is shown as percentage in Fig. 5.

As it can be seen, the potential demand responsiveness is not necessarily related to the average power consumption. For instance, the percentage of reduction in each group can be lower even when the total amount of reduction could be greater.

Moreover, each cluster presents a dissimilar behaviour depending on the type of day. This is because each cluster consists mainly of households of specific categories, which reflect the characteristics that have effect on energy consumption patterns. For instance, households in clusters no. 3, 4 and 6 are likely to have higher peak demands, compared to other groups, as they belong to educated and mostly employed customers. Therefore, they might prefer not to be disrupted when they arrive home which is mainly in peak period times.

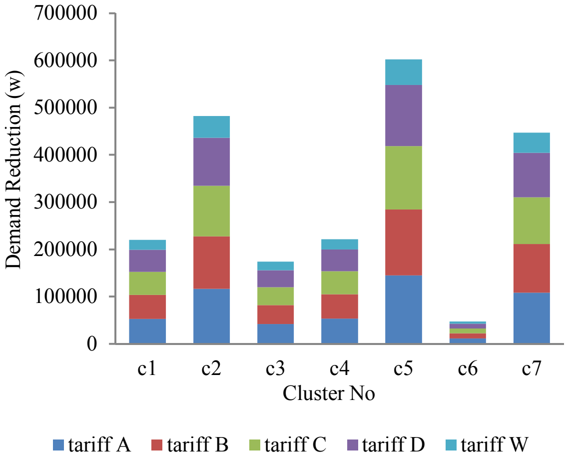

Fig. 3. Mean aggregated demand of each cluster within each tariff allocation

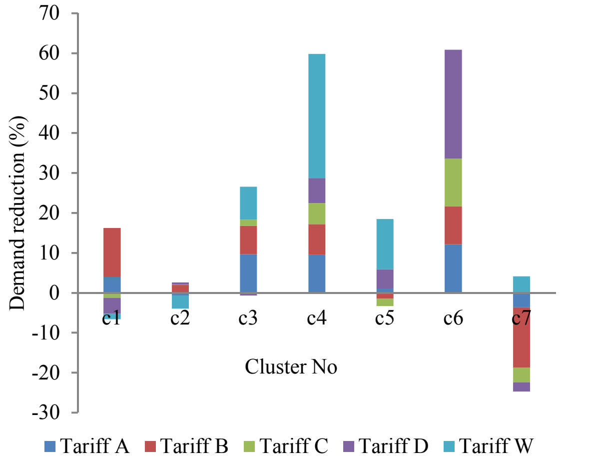

Fig. 4. Normalized aggregated demand of each cluster with respect to the population in each cluster and tariff allocation

IV. EFFECTS OF SWITCHING TARIFFS

A. *Ratio* of Cost (RC)

RC is determined using (2) in order to evaluate the ratio of tariff A compared to tariff B.

$$RC = \frac{Cost\ (Tariff\ A)}{Cost\ (Tariff\ B)} \qquad (2)$$

The RC value for each type of tariffs is presented in Table IV. For each cluster, the cost of employing tariff A and tariff B has been computed from normalising RC value with respect to time-series measurements and total cost per tariff.

B. *Price Elasticity of Demand (E_d)*

E_d is used to measure the granularity of demand responsiveness or elasticity of demand to changes in the price (depending on type of tariff) and computed as:

$$E_d = \frac{P}{C_d} \times \frac{dC_d}{dP} = \begin{cases} E_d < 1 & Inelastic \\ E_d > 1 & Elastic \end{cases} \qquad (3)$$

where P and C denote the demand and price respectively. E_d has been calculated for each cluster separately based on type of the day and tariff scenario. Fig. 6 shows the E_d of peak demand for weekdays which demonstrate that almost all clusters are elastic to changes in the price.

TABLE IV: RC values for different tariff scenarios

ToU tariff	day	peak	Night
Tariff A	1.29	0.90	1.50
Tariff B	1.33	0.69	1.64
Tariff C	1.38	0.56	1.80
Tariff D	1.44	0.47	2.00
Tariff W	1.80	1.29	0.47

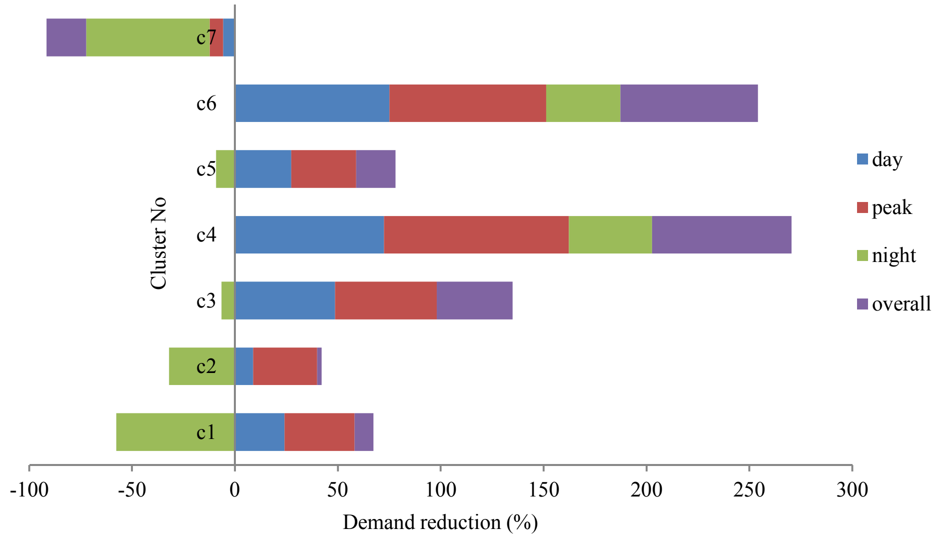

Fig. 5. Demand reduced based on the time of the day (%)

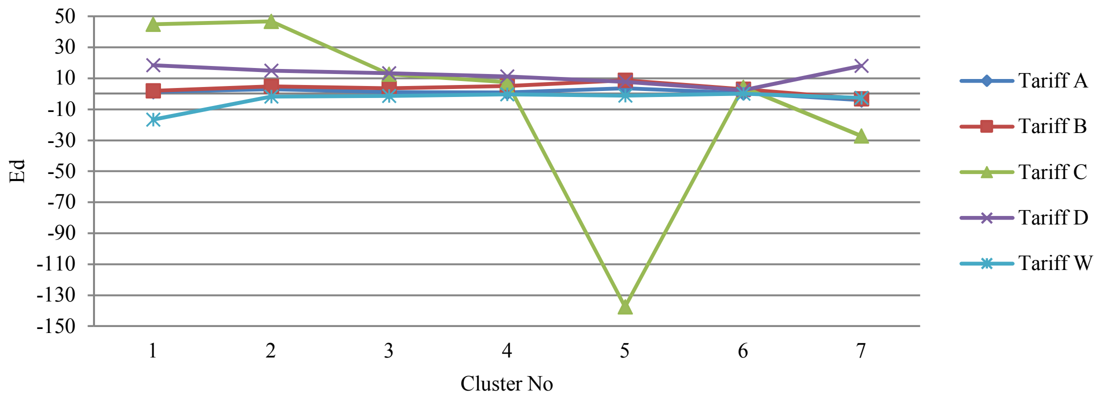

Fig.6. Ed of peak demand for weekdays

However, the quantity of Ed can vary for different tariffs in each group and some customers might be inelastic to ToU tariffs. For example, although RC for tariff A is higher, not all customers are likely elastic to this tariff compared to other tariffs. This is due to the fact that the level of incentives among customers is in order to make changes in their electricity consumptions behaviour are different customers the level of incentives.

C. *Results analysis*

As previously mentioned, each cluster has a distinctive behaviour regarding the price elasticity and potential of demand responsiveness. Therefore, each cluster can be described as a set of characteristics that results in new demand profile when switching between different tariffs. This updated load pattern of each cluster is not only related to the type of tariff (RC value) but also to the household characteristics, consumption level and current tariff of that cluster.

The typical baseline consumption over the period of time during a typical day in which the relevant price band is applied can be determined as the following function:

$$P_{base}(i,t) = f(RC,\, E_{di},\, Q_i,\, \overline{P_{i,t}},\, A_i) \qquad (4)$$

where $P_{base}(i,t)$ is the baseline power of i^{th} cluster in t^{th} timeslot during a typical day. A_i is a variable that refers to the attitudes of cluster i towards DR participation.

The correlation between each type of tariff as dependent (x_i) and peak demand elasticity as independent (p) parameters within each cluster is defined in Table V using the following equation:

$$Q\,(i) = \sum_{i=1}^{n} x_{ij}\, y_i \quad ,j = 1, \dots, p \qquad (5)$$

A multi nominal regression model based on (6) has been used in order to analyse the relation between different parameters relating to household characteristics with total power reduction within each cluster.

$$y_i = \beta_0\, 1 + \beta_1\, x_{i1} + \dots + \beta_p\, x_{ip} + \varepsilon_i \;\; ,i = 1, \dots, n \qquad (6)$$

where $\boldsymbol{y_i}$ is deponent variable, β is constant variable and ε is dummy variable.

The results of regression analysis for occupant characteristic in relation with the total peak and day demand reduction in each cluster is presented in Fig. 7(a) and Fig. 7(b) respectively.

Comparing Fig. 7 and Table V, it can be concluded that the diversity of elastic loads in changes of electricity price is highly dependent on the occupant characteristics. However load segmentation can be used as an optimum tool in order to create a series of representative load having homogeneous behaviour towards DR programs.

V. Conclusions and future work

This paper aims to assess the potential of residential demand reduction under different tariffs, particularly between

TABLE V: Coefficient results for peak demand elasticity to applying different ToU tariffs

	C1	C2	C3	C4	C5	C6	C7
A	1.0474	0.42	0.289	0.349	0.351	0.223	0.206
B	1.3411	1.452	0.999	1.206	1.215	0.772	0.772
C	2.0654	2.236	1.539	1.858	1.871	1.188	1.096
D	2.6342	2.852	1.962	2.369	2.386	1.516	1.398
W	0.9221	0.998	0.687	0.829	0.835	0.531	0.489

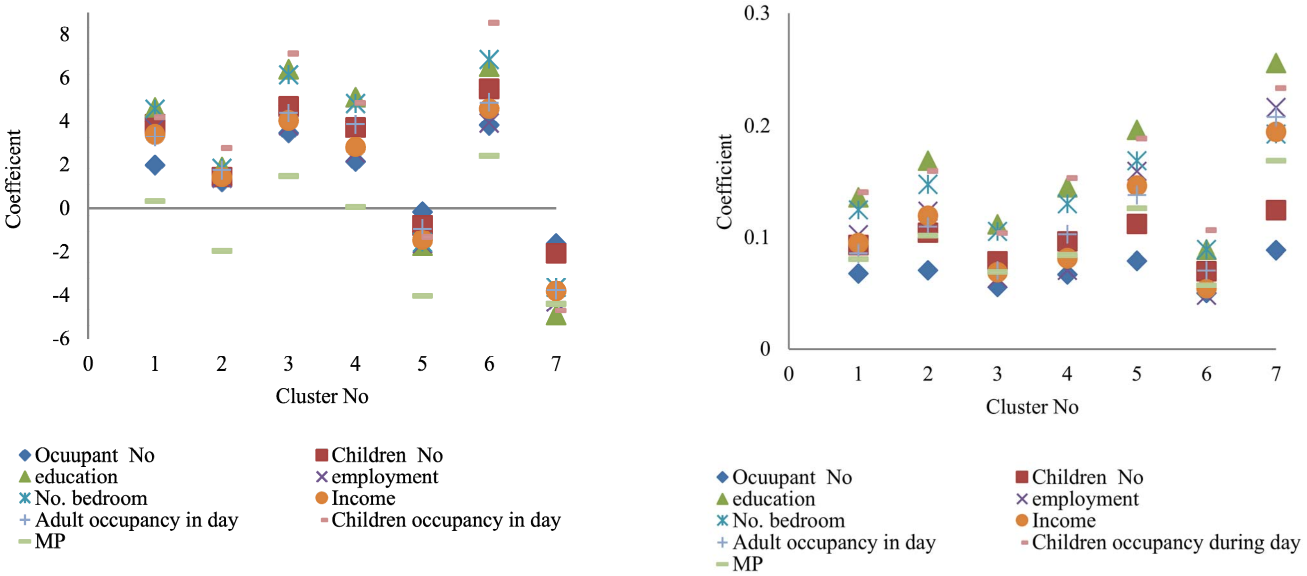

Fig. 7. Multi-nominal regression results for occupant's characteristics and demand elasticity

(a) peak demand reduction, (b) day demand reduction

fixed price and five ToU tariffs. This has been done through segmentation of households into similar groups based on distinctive parameters that can affect residential power consumption patterns. For each group of customers, demand elasticity with respect to the price in each tariff has been evaluated. Moreover, a boundary of changing the demand based on the price has been calculated with a linear regression model.

The results show that even though all clusters of customers can benefit from applying ToU pricing, the demand elasticity to price varies based on specific tariff ratio. This is due to the different potential of demand reduction, characteristics and relative financial benefits in each cluster of customers.

In terms of economic benefits and satisfaction level, the time period during which the analysis is made can highly affect the accuracy of results. Therefore, future work can include studying the effects of ToU tariffs on customer electricity use behaviour for longer periods of time.

Studying the potential of demand responsiveness under real time tariffs (dynamic tariffs) should also be investigated in depth, looking into the economic benefits for both suppliers and customers.

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