How Smart and Green? A Simulation Model of Demand Cost Perception in the Electricity Market

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***Abstract*—Nowadays energy demand is an issue regarding the vitality of cities and the welfare of citizens. The exponential growth of the cities and the consumers' demand obliged the energy producer to find a modern solution to overcome these problems. The solution was found in decentralised structures all connected through the Internet and capable of allowing all actors in the system to interact together. In this study, the effect on the smart grid's energy demand of different numbers of consumers, their behaviour and the energy price variations will be discussed. A few consumers' behaviours will be illustrated and taken into account, how they react to the energy provider's price schemes, impelling them into making a decision on whether to shift or not their demand according to their characteristic parameters and show how their expenditures and incomes for the electricity market operator change.**

***Index Terms*—Smart Grids, Agent-based Modelling, Social Simulation, Demand Modelling.**

I. Introduction

Due to the exponential growth of the cities' facilities and an ever-increasing need for a higher demand of energy, high power quality and a more critical assortment of extra services, the power industry struggles to address the issues of modern digital society and the consumers' needs. Among the power system society, it is commonly assumed that electricity will have a larger share of the overall energy consumption in the future [1].

This concept takes advantage of the large diffusion of internet access in most homes and the continuing spread of smart devices, so that they transmit information in such a way that enables the whole infrastructure to quickly respond to changes in smart grid condition systems and bring big contributions improving the overall efficiency, reducing waste of energy and leading to lower power prices. In this context, the concept of the smart grid arose to indicate an electrical system that uses information, bidirectional communication technologies and computational intelligence in a collaborative manner that allows the energy distribution and consumption more effectively and efficiently in an integrated way [2].

In this scenario, creating consumer profiles is very important in order to predict and avoid peaks using price strategies to keep the Grid as stable as possible [3]. Accounting for this novel paradigm, and assuming that consumers follow predefined behaviours, this paper presents a sensitivity analysis on the consumption profiles with respect to an awareness parameter defining the profile, and the number of consumers in each profile. We also look into how the price of the energy affects consumers' willingness to shift their demand as a means to reduce their energy costs.

The remaining parts of the paper are organised as follows. In Section IIthe related work is revisited. Section III discusses the mathematical mode and its implementation. Experiments and results are discussed in Section IV. Conclusions and future work are presented in Section V.

II. Related Work

Designing an effective demand response program requires a deep understanding of energy consumer behaviour and a precise estimate of the expected result. One way to support network reliability is to mitigate peak demand (at all times) and prevent exposure of its infrastructure to critical stress. The shift in demand or a change in prices creates new peaks, which are avoided by attributing to the consumer a reactivity to the change in prices that can be collected through direct interviews as suggested in [4]. In [5] it is discussed the necessity to include small *prosumers* behaviour in the planning of the electrical system and map all the factors (and their interactions) that dominate their behaviours and model the system load profile. While in [6] is presented a conceptual model of multi-markets environments and the processes that define the electricity tariffs.

In this changing environment, predicting energy demand becomes a very complex process. It is necessary to include the behavior of small *prosumers* in the planning of the electrical system, thus being able to map all the factors (and their interactions) that dominate the behaviors and subsequently model the system load profile. The Smart Grid concept is not yet limited within a given layout, but it is expected that future investments will be in existing and new electricity grid infrastructures [7].

Another aspect to consider is the definition of an appropriate pricing strategy for this intelligent environment, which represents a very important and complex task to define and manage. In this regard, demand response programs can be based on both incentives and prices. These tariff schemes are now applied dynamically and an attempt is made to define

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a "bridge" between the two methods, so that the consumer reacts immediately to changes in energy prices and tries to adapt his demand as much as possible in order to save money [8]. A possible pricing scheme is given by characterizing in a dynamic way a model that focus on demand-supply optimization under various and specific interaction with a spot market [9].

The method of a pricing scheme proposed by [10] is to introduce an incentive towards consumers who reduce consumption. Connectivity is at the heart of this new network infrastructure, provided by the Internet of Things (IoT). Thus an enormous volume of data was introduced which requires techniques far superior to conventional methods for adequate analysis and decision-making. Big data analysis and machine learning techniques are essential to achieve these benefits. Security also becomes a critical issue [11]. In [12] is presented a survey of management methods of consumption peaks based on individual consumer behaviour.

This paper proposes a study focused on the consumer side, in particular on 3 classes of them, and on their daily energy habits and how these vary depending on the sensitivity and the change in the price of energy during a day.

III. The Model

The following model consider the effect consumer's behavioural pattern (cost minimisation) has on the operator's pricing strategies (profit maximisation) and vice-versa.

A. Theoretical Setup

Within a given market we consider a number of $N \in \mathbb{N}$ individuals. Each individual falls within one of the three consumer types (Type A, Type B, Type C) with $N_i,\ i \in \{A, B, C\}$, representing the number of agents of type i.

Each of the types has its own parameter of awareness, denoted by S_A , S_B and S_C. These parameters lie within the interval $[0\%, 100\%]$ and represent their willingness to change their demand due to changes in prices. Some consumers may be stubborn, with $S_i, i \in \{A, B, C\}$, being low, whereas others might think more ecological, with $S_i,\ i \in \{A, B, C\}$, being higher. We also assume that every type of consumer has a different demand of consumption during one day and therefore represents a different kind of household.

Table I shows the initial setup of the baseline model. We consider a consumer pool with 60 agents of type A, with medium awareness ($S_A = 30\%$) and a demand profile with a small peak in the morning and a big peak in the evening (working household). Also there are 25 agents of type B which are considered very stubborn ($S_B = 10\%$) and their electricity demand shows a small peak in the afternoon and a big peak in the night (night owl). Finally there are 15 type C agents, which behave more ecological ($S_C = 80\%$) and have a nearly constant demand of electricity during the day with a small peak at night (home-office household).

TABLE I
Baseline model for 100 agents

	Agents	Awareness	Demand
Type A	$N_A = 60$	$S_A = 30\%$	working household
Type B	$N_B = 25$	$S_B = 10\%$	night owl
Type C	$N_C = 15$	$S_C = 80\%$	home-office household

Given a setup, we will calculate the electricity expenditures for each type of consumer during one day given by the formula

$$C_i = \sum_{t=1}^{24} P_t D_t^i,$$

where $C_i,\ i \in \{A, B, C\}$ represents the expenditures for electricity of a certain type of consumer for one day, P_t describes the price of one kWh at time $t \in \{1, ..., 24\}$ and D_t^i represents the demand for electricity of a consumer of type i at time t in kWh. We will refer to these values C_i as the baseline expenditures.

In order to analyse how changes in prices affect the behaviour of the consumers, we need to consider both, the parameter of awareness and the magnitude of price changes. Therefore we assume that the grid operator charges new prices given by $\tilde{P}_t, t \in \{1, ..., 24\}$. This will be done in the following way. Each agent i has a possibility of increasing or decreasing the demand at time t given by:

$$q_t^i := \min\left\{100, a_1\left|\frac{\tilde{P}_t - P_t}{P_t} \times 100\right| + a_2 S_i\right\},$$

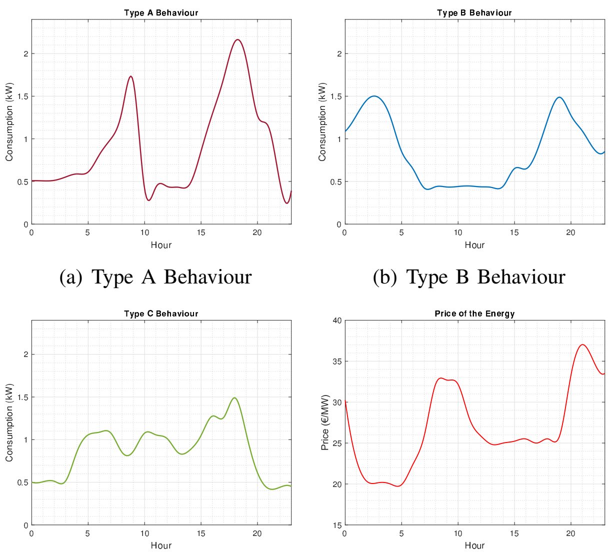
with $a_1,\ a_2 > 0$ and $a1 + a2 = 1$. The parameters a_1 and a_2 represent the weight of changes in prices relative to the parameter of awareness of each type of consumer. Taking the minimum of 100 and the weighted sum ensures the admissibility of using q_t^i as a probability in percentage.
We ensure that the total amount of used electricity during one day stays the same, which means that all the demand reduced at one point needs to be added at another time of the day. Therefore the condition:

$$\sum_{t=1}^{24} D_t^i = \sum_{t=1}^{24} \tilde{D}_t^i, \quad i \in \{A, B, C\},$$

has to hold, where $\tilde{D}_t^i$ represents the amount of electricity used by type i at time t after making changes to his demand.
We also assume that every consumer i has a certain level of minimum demand for electricity $d^i = \min_{t\in\{1,...,24\}} D_t^i$ at every time of the day, so it is not allowed to shift all its demand at once. This is ensured by the constraint

$$\tilde{D}_t^i \geq d^i, \quad \forall t \in \{1, \ldots, 24\}, \forall i \in \{A, B, C\}.$$

From this constraint also follows that the grid operator has to provide a minimum capacity of $N_A d^A + N_B d^B + N_C d^C$ of electricity at every time t in order to keep the grid stable.
In order to fulfill cost reduction for the consumers, the demand is always shifted to the time of the day with the lowest price which is allowed for changes.



(a) Type A Behaviour (b) Type B Behaviour

(c) Type C Behaviour (d) Energy Prices

Fig. 1. Type of Behaviour and Prices

B. Data

In order to achieve meaningful results with this simulation, we need the most reliable data possible, so we build our behaviour profiles using the profiling work done in the paper [13]. The plots of the demand profiles can be seen in Figure 1.

Using some typical households consumption value, we construct the following Table II.

Another important parameter for our work is the hourly energy price €/MW. Due to difficulty to retrieve a reliable source, we used the ComEd website (https://hourlypricing.comed.com) to take data and then we manipulated them to create a Plot of the energy price during the day as can be seen in Figure 1(d).

TABLE II
DIFFERENT BEHAVIOUR CONSUMPTION (KW)

Hour	Type A	Type B	Type C
0:00	0.508	1.088	0.502
1:00	0.507	1.276	0.506
2:00	0.513	1.466	0.512
3:00	0.552	1.481	0.514
4:00	0.588	1.254	0.856
5:00	0.611	0.849	1.056
6:00	0.815	0.648	1.087
7:00	0.997	0.423	1.079
8:00	1.324	0.438	0.851
9:00	1.67	0.435	0.863
10:00	0.412	0.441	1.077
11:00	0.433	0.447	1.056
12:00	0.441	0.437	1.012
13:00	0.432	0.429	0.844
14:00	0.468	0.445	0.877
15:00	0.855	0.652	1.049
16:00	1.291	0.647	1.276
17:00	1.708	0.861	1.259
18:00	2.14	1.249	1.491
19:00	1.933	1.488	1.073
20:00	1.27	1.274	0.611
21:00	1.133	1.093	0.425
22:00	0.478	0.886	0.442
23:00	0.392	0.852	0.451

C. Simulation Setting

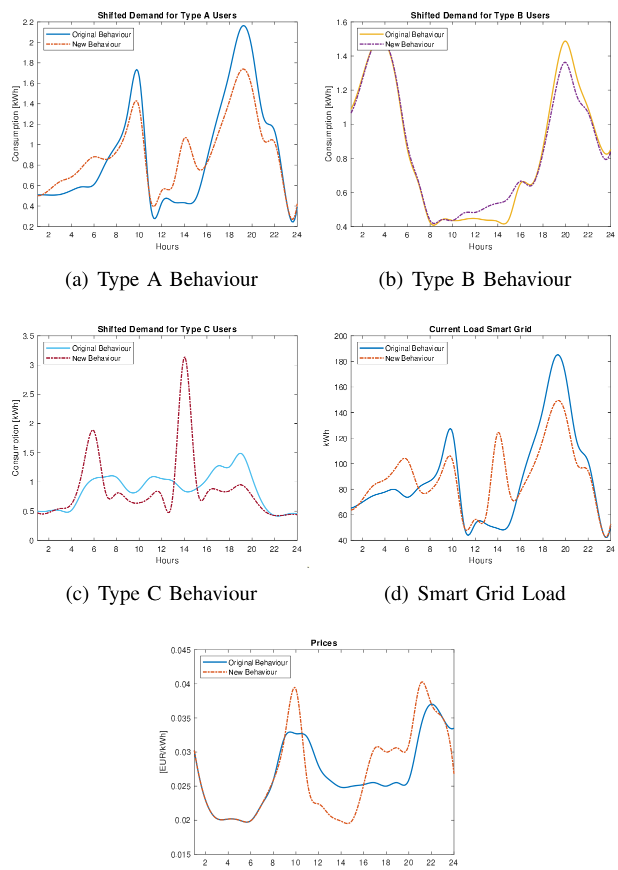
We simulate a vector with 24 entries, where each component $j \in \{1, ..., 24\}$ follows a Bernoulli distribution with probabilities q_j^i for the realisation 1 (the consumer is allowed to increase or decrease the demand during this hour) and $(1 - q_j^i)$ for the realisation 0 (the consumer is neither allowed to decrease demand, nor to shift demand to this time). We run the simulation 10000 times and considered the average consumption of every type of consumer.

The new prices $\tilde{P}_t$ are obtained in the following way: the prices for the six hours with the highest electricity demand are increased by 20% compared to the initial prices P_t, the prices for the six hours with the lowest electricity demand are decreased by 20%. The other prices stay unchanged.

IV. RESULTS

A. Baseline Model

In the baseline model we run the simulation with the parameters given in Table III. Also, the price vector is plotted



(a) Type A Behaviour (b) Type B Behaviour

(c) Type C Behaviour (d) Smart Grid Load

(e) Price Variation

Fig. 2. Base Model plots

TABLE III
BASELINE PARAMETERS

a_1	a_2	Change in Prices	Price Vector
0.5	0.5	20%	PV1

in Figure 1(d) that shows how it evolves over time.

As we can see in Figure 2 all agents changed their behaviour. Noteworthy is that agents of type C are the only one who could save more money due to their high parameter of awareness, and created a new peak in their demand around 14 o'clock. But due to their small amount, this did not make any difficulties to the grid stability, see Figure2(d).

TABLE IV
OUTPUT BASE MODEL/1

	A	B	C	SG operator
EXPENDITURES(%)	+2.39	+1.69	-5.02	-
INCOME(%)	-	-	-	+1.16

As the variance of the demand as a measure for balanced consumption during a day, the highest peak and the sum of the three highest demands decreased dramatically, this case can be considered a success for the grid operator.

TABLE V
OUTPUT BASE MODEL/2

	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	693.3	-50.01%
Highest Peak (KWh)	181.9	147.3	-19.1%
Sum of 3 Peaks (KWh)	494.15	410.5	-16.9%

B. First Variation

In this first variation changes were made to the weight of the awareness a_1 and the weight of the price changes a_2.

TABLE VI
FIRST VARIATION PARAMETERS

RUN	a_1	a_2	Change in Prices	Price Vector
1	0	1	20%	PV1
2	0.25	0.75	20%	PV1
3	0.75	0.25	20%	PV1
4	1	0	20%	PV1

1) First Variation: RUN 1

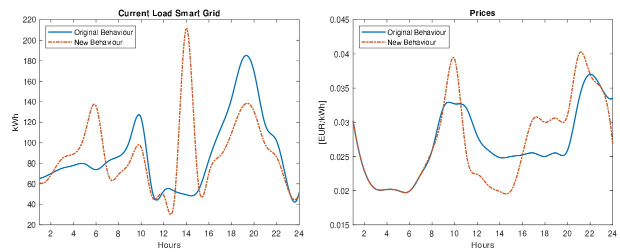
TABLE VII
OUTPUT RUN 1/1

	A	B	C	SGoperator
EXPENDITURES(%)	+0.27	+1.83	-9.14	-
INCOME(%)	-	-	-	-0.71

As in this case only the parameter of awareness influences the behaviour, type C agents could even save more money. But due to their high willingness to change the demand, a new peak is generated around 14 o'clock. This leads to a higher demand variance and even a higher peak.

TABLE VIII
OUTPUT RUN 1/2

	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	1410.3	+1.66%
Highest Peak (KWh)	181.9	212.2	+16.5%
Sum of 3 Peaks (KWh)	494.15	483.7	-2.12%



(a) Smart Grid Load (b) Price

Fig. 3. First run plots

2) First Variation: RUN 2

TABLE IX
OUTPUT RUN 2/1

	A	B	C	SG operator
EXPENDITURES(%)	+1.33	+1.83	-7.05	-
INCOME(%)	-	-	-	+0.24

In this scenario we can see that the new demand peak at 14 o'clock still exists, but it is smaller.
The demand variance, the highest peak and the sum of the three peaks all decreased, but all less than compared to the baseline model.

TABLE X
OUTPUT RUN 2/2

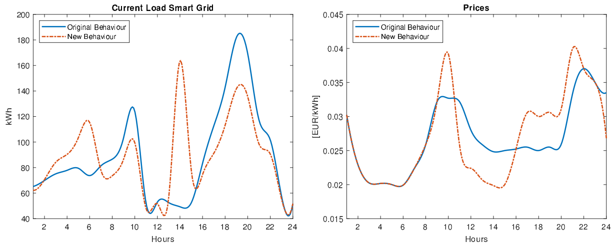
	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	899.5	-35.2%
Highest Peak (KWh)	181.9	163.8	-9.97%
Sum of 3 Peaks (KWh)	494.15	441.23	-10.7%

3) First Variation: RUN 3

TABLE XI
OUTPUT RUN 3/1

	A	B	C	SGoperator
EXPENDITURES(%)	+3.54	+1.69	-2.67	-
INCOME(%)	-	-	-	+2.21

As the weight of price changes gets more and more important, the high parameter of awareness for agents of type C



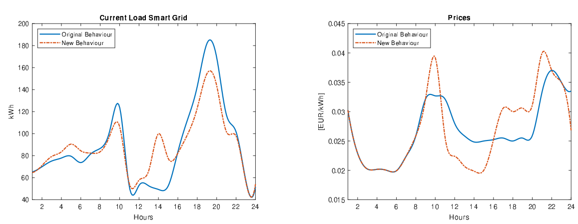
(a) Smart Grid Load (b) Price

Fig. 4. Second run plots

does not affect their behaviour that much anymore. And due to the low parameter of awareness for type B agents, increasing the influence of price changes makes them spend less money. The demand variance, the highest peak and the sum of the three peaks all decreased in a similar amount as in the baseline model.

TABLE XII
OUTPUT RUN 3/2

	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	676.8	-51.2%
Highest Peak (KWh)	181.9	154.6	-15.1%
Sum of 3 Peaks (KWh)	494.15	421.52	-14.7%



(a) smart grid Load (b) Price

Fig. 5. Third run plots

4) *First Variation: RUN 4*

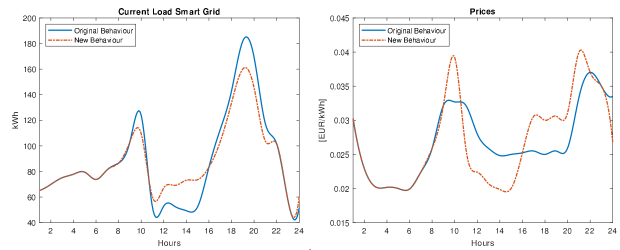
TABLE XIII
OUTPUT RUN 4/1

	A	B	C	SGoperator
EXPENDITURES(%)	+4.62	+1.62	-0.15	-
INCOME(%)	-	-	-	+3.21

In a scenario where the parameter of awareness does not affect the behaviour of agents anymore, there is no difference among their reactions, as all of them face the same price changes.
The demand variance, the highest peak and the sum of the three highest demands all decreased, but slightly less than to the baseline model.

TABLE XIV
OUTPUT RUN 4/2

	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	743	-46.4%
Highest Peak (KWh)	181.9	160.1	-12%
Sum of 3 Peaks (KWh)	494.15	439.08	-11.1%



(a) Smart Grid Load (b) Price

Fig. 6. Fourth run plots

C. *Second Variation*

In this second variation we are analyzing the effects of different amount of agents from type A,B and C, but keeping the sum up to the original population of 100.

TABLE XV
SECOND VARIATION PARAMETERS

RUN	a_1	a_2	Change in Prices	Price Vector	A	B	C
1	0.5	0.5	20%	PV1	25	25	50
2	0.5	0.5	20%	PV1	25	50	25
3	0.5	0.5	20%	PV1	50	25	25

1) *Second Variation: RUN 1*

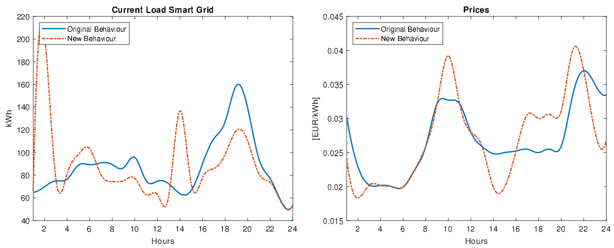
TABLE XVI
OUTPUT RUN 1/1

	A	B	C	SG operator
EXPENDITURES(%)	+1.93	-0.38	-4.35	-
INCOME(%)	-	-	-	-1.72

Due to the high flexibility and the increased number of type C agents, new peaks of electricity demand appear. They are higher than the original ones. This scenario would be a clear disadvantage compared to the baseline model.
Noteworthy is also, that in this scenario the income of the grid operator decreases due to the increased number of type C agents.

TABLE XVII
OUTPUT RUN 1/2

	INITIAL	FINAL	% VARIATION
Demand Variance	652.6	1027.2	+57.3%
Highest Peak (KWh)	159.3	203.5	+27.7%
Sum of 3 Peaks (KWh)	425.6	459.9	+8.04%



(a) Smart Grid Load (b) Price

Fig. 7. First run plots

TABLE XVIII
OUTPUT RUN 2/1

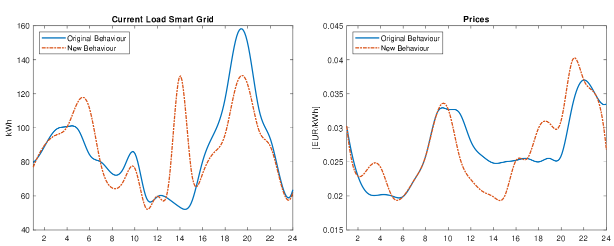
	A	B	C	SGOperator
EXPENDITURES(%)	+1.10	+2.74	-5.64	-
INCOME(%)	-	-	-	+0.23

2) *Second Variation: RUN 2*

In a scenario with more agents of type B, the highest peak get decreased. Also the variance and the sum of the three highest peaks decreased, but all less than in the baseline model. Difficult could be the fact that in the new scenario there are three peaks of nearly the same height. Turning on and off an external source of electricity multiple times during a day could be expensive for the supply side.

TABLE XIX
OUTPUT RUN 2/2

	INITIAL	FINAL	% VARIATION
Demand Variance	706	504.1	-28.6%
Highest Peak (KWh)	153.22	130.7	-14.7%
Sum of 3 Peaks (KWh)	420	381.5	-9.16%



(a) Smart Grid Load (b) Price

Fig. 8. Second run plots

3) *Second Variation: RUN 3*

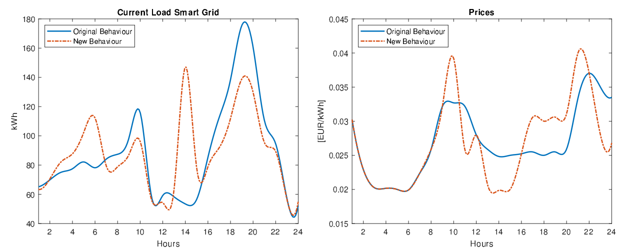
TABLE XX
OUTPUT RUN 3/1

	A	B	C	SGOperator
EXPENDITURES(%)	+2.36	+1.11	-4.5	-
INCOME(%)	-	-	-	+0.4

This scenario is very similar to the baseline model. The number of type A agents is decreased by ten, while this amount is added to type C agents. As the results show, the new peak around 14 o'clock is even higher than in the baseline model.

TABLE XXI
OUTPUT RUN 3/2

	INITIAL	FINAL	% VARIATION
Demand Variance	1122.5	672.3	-40.1%
Highest Peak (KWh)	175.5	147.2	-16.1%
Sum of 3 Peaks (KWh)	474.6	415.9	-12.4%



(a) Smart Grid Load (b) Price

Fig. 9. Third run plots

D. *Third Variation*

In this third variation the initial price vector is changed. In particular a price vector is used (https://energy-charts.de/).

TABLE XXII
THIRD VARIATION PARAMETERS

a_1	a_2	Change in Prices	Price Vector
0.5	0.5	20%	PV2

In this scenario with a new price vector the effects are exacerbated compared to the baseline model. This means that in this given setup, the grid operator can decrease the demand variance, the highest peak and the sum of the three highest peaks dramatically. As the income for the grid operator stays nearly the same, this can be considered a win-win situation for the grid operator.

TABLE XXIII
OUTPUT 1

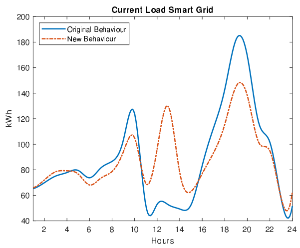
	A	B	C	SGOperator
EXPENDITURES(%)	+1.16	+2.95	-8.9	-
INCOME(%)	-	-	-	0.12

E. *Fourth Variation*

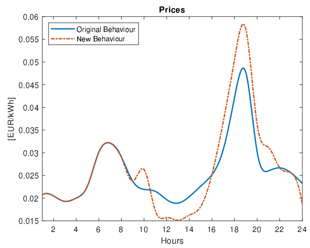
In the last variation the change in prices in percentage is decreased and increased once.

TABLE XXIV
OUTPUT 2

	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	582.9	-57.9%
Highest Peak (KWh)	181.9	145.3	-20.1%
Sum of 3 Peaks (KWh)	494.2	412.9	-16.4%



(a) Smart Grid Load



(b) Price

Fig. 10. Second run plots

TABLE XXV
FOURTH VARIATION PARAMETERS

RUN	a_1	a_2	Change in Prices	Price Vector
1	0.5	0.5	10%	PV1
2	0.5	0.5	40%	PV1

TABLE XXVI
OUTPUT RUN 1/1

	A	B	C	SG operator
EXPENDITURES(%)	+0.56	+0.89	-4.5	-
INCOME(%)	-	-	-	-0.09

1) Fourth Variation: RUN 1

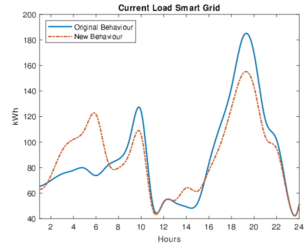
When the prices of the six hours with the highest demand are increased only by 10% and the prices for the six hours with the lowest demand are decreased by 10% less demand is shifted. This leads to a scenario where there is no new peak around 14 o'clock. The demand variance, highest peak and sum of three peaks all decreased.

TABLE XXVII
OUTPUT RUN 1/2

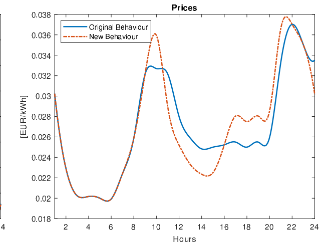
	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	870.2	-37.2%
Highest Peak (KWh)	181.9	153.4	-15.6%
Sum of 3 Peaks (KWh)	494.2	423.7	-14.3%

2) Fourth Variation: RUN 2

When the prices are changed with a higher magnitude than in the baseline model, the peak around 14 o'clock appears again. In this scenario it is nearly as high as the highest peak in the initial electricity demand. Therefore the situation for the grid operator did not improve, as the peak is only shifted to another time.



(a) Smart Grid Load



(b) Price

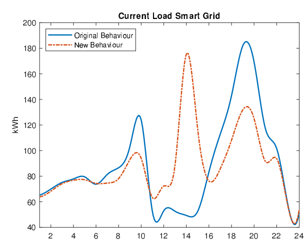
Fig. 11. First run plots

TABLE XXVIII
OUTPUT RUN 2/1

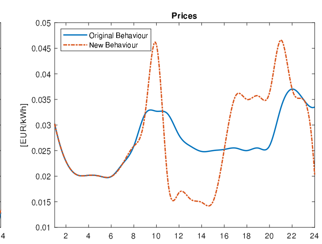
	A	B	C	SG operator
EXPENDITURES(%)	+2.7	+1.94	-10.4	-
INCOME(%)	-	-	-	+0.62

TABLE XXIX
OUTPUT RUN 2/2

	INITIAL	FINAL	% VARIATION
Demand Variance	1387.1	754.3	-45.6%
Highest Peak (KWh)	181.9	175.6	-3.53%
Sum of 3 Peaks (KWh)	494.2	432.4	-12.5%



(a) Smart Grid Load



(b) Price

Fig. 12. Second run plots

F. Discussion

Overall, looking at the baseline model it's easy to see how there is an important peak reduction in the Smart Grid Load (Fig.3d) around 19% and also a reduction of the variance(50%) relaxing the situation.

As long as a big importance is given to the parameter of awareness the most ecological agents (type C) will save more money and the Smart Grid operator will see his income reduced, whilst if more weight is given to the price, it can be seen easily that the income will grow significantly. For the same reason it is easy to see in the *Second Variation* that if the population of 100 Agents is formed by the most part of type C agents, the overall income for the smart grid operator is reduced, compared to the scenarios where the majority of the population is made by A or B agents. Even though the peaks for the Load in all these situations have been reduced and spread along the 24h.

In the third variation there is a try to see how changing the initial price vector affects the overall behaviour. As can be seen in the *Third Variation* there are even more effective price settings, which can be conducted by the grid operator. Finally in the *Fourth Variation* it's easy to see how increasing too much the price change weight doesn't lead to a better result because there is just a shift of the peaks, so the right choice is to have an appropriate price change weight in order to avoid peaks.

V. Conclusions

The objective of this work was to highlight the importance of taking into account the consumers' behaviour in planning an efficient pricing strategy in order to reduce workload at specific peak hours. A mathematical model for modelling the behaviour of consumers and smart grid operators is provided. This model involves the possibility to create a heterogeneous population of consumers by varying the number of each consumer profile (in terms of an awareness parameter and a level of consumption) and an initial price vector and analyse how they affect the price and the smart grid's load evolution. Therefore this simulation-based methodology can be seen as a guideline and as a decision support tool for the grid operator to choose the right prices to ensure peak reduction. In order to use this model in a more efficient way future research has to be done in terms of considering not only the variations in the consumption profiles but also in the load profiles.

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