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# Home Energy Management Benefits Evaluation Through Fuzzy Logic Consumptions Simulator

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*Abstract*— **In recent years the European Union and, moreover, Italy has seen a rapid growth in the photovoltaic (PV) sector, following the introduction of the feed in tariff (FIT) scheme known as Conto Energia. In July 2013 the Italian government definitively cut FITs, leaving only tax benefits and a revised net metering scheme (known as "Scambio sul Posto") for new PV installations. In this scenario, the design of a new PV plant ensuring savings on electricity bills is strongly related to household electricity consumption patterns. This paper presents a high-resolution model of domestic electricity use based on Fuzzy Logic Inference System. Using as inputs patterns of active occupancy and typical domestic habits, the fuzzy model give as output the likelihood to start each appliance within the next minute. The focus of this work is the use of this novel fuzzy model to correctly size a residential photovoltaic plant and evaluate the economic benefits of energy management actions in a case study. A cost benefits analysis is presented to quantify its effectiveness in the new net metering Italian scenario.**

## I. INTRODUCTION

The amount of new solar power installed in Europe fell sharply for the first time in more than a decade in 2013, in an arresting sign of how the region's dominance of the global market is drawing to an end. Incentive programs, although cut worldwide, have been replaced by new mechanisms to promote the direct consumption of energy in the building where a PV system is located (the so called self-consumption) in several European countries. In some cases, pure net-metering schemes have been developed (such as in Belgium, Denmark, the Netherlands), while other countries have favored mechanisms promoting self-consumption. Various intermediate schemes exist between these two approaches. Nowadays Italy and Germany represent the two most developed European PV markets, respectively with 17 and 32 GW of total PV power installations. They have been pioneers of self-consumption promotion schemes. The evolution in Germany towards promotion of self-consumption started in 2011 with a premium incentive tariff for self-consumed electricity. The remuneration was even higher if a rate of self-consumption over 30% was reached, encouraging the so called prosumers (producers and consumers of energy) to increase their direct consumption ratio.

In Italy the government took the decision to cut PV incentives on June 2013, instead of 2016 as previously expected. To provide support to PV industry a new net metering scheme has been amended [1] and came into effect on $1st$ January 2013. Under this decree PV system owners can get credits for the value of the excess of electricity fed into the grid over a time period. Further encouraging self-consumption, the Italian Revenue Agency introduced tax breaks for off-grid PV systems installed on buildings. On the same time the Ministerial Decree of July 6th 2012 established new procedures aimed at supporting the production of electricity from Renewable Energy Source-Electricity (RES-E) plants (other than the PV ones). Concerning wind energy, tariffs are granted only if the plant reaches 80% of the yearly planned production quota [2], thus forcing engineers to investigate and solve the efficiency problem, as shown in [3], [4].

In this European scenario, it is clear that overall cost-saving by PV-generation systems would only have a marginal impact if the energy consumption pattern of the household does not match the most beneficial generation pattern and no actions of energy management (EM) are performed. Households EM is widely recognized as a priority [5] to reach PV grid parity all over the world, see, e.g., [6], [7] and, combined to control, forecasting and monitoring techniques, to reduce overall energy usage [8], [9], [10], [11]. On the same time there is an increasing number of studies on microgrids [12], [13] and smart homes and the benefits of demand-side management [14], [15], [16].

Accordingly the forecast and simulation of households' electricity consumption patterns received strong interest in literature, see, e.g., [17], [18], [19], [20]. Most of the existing models and analysis focus on data from specific geographic regions and try to explain the results in a local perspective [21], [22]. It is well known that overall cost-saving by distributed generation would only have a marginal impact if the demand pattern does not match with the production one. Photovoltaic sizing is an important research field in this area but most of the works concern with the optimization of stand alone systems without an analysis of the demand response scenario for grid connected users, see e.g. [23], [24], [25]. In this scenario only the knowledge of the typical demand pattern for each household will make possible the proper sizing of a photovoltaic plant, the design of demand response techniques and energy management actions. The pattern of electricity use for any individual domestic dwelling is highly dependent upon the activities of the occupants and their associated use of electrical appliances. In this paper we present a high-resolution model of domestic electricity use, based upon a combination of patterns of active occupancy and daily activity profiles (typical appliances usage frequency and starting time). The model is built using a "bottom-up" approach, according to [26]. The basic building block is the appliance, i.e. any individual domestic electric load. The model, managing the start of each appliance in the

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household through a fuzzy logic inference system, gives as output the $1-minute$ resolution electricity usage pattern. The main differences with respect other approaches proposed in literature by [26], [27], [28] derive from the novel fuzzy approach that allow to model a specific household energetic behavior and customize the model without acquiring a large amount of data. In fact it is possible to add every appliance and predispose a ”seasonal behavior” for some of them using the flexibility of the fuzzy inference systems. This model has been used for a case study on the proper sizing of a PV plant (in the central east region of Italy) and the evaluation of Energy Management potential benefits based on a costs benefits analysis (CBA). The installation in a dwelling of all the devices necessary to actuate proper EM policies has a relatively high cost compared to that of a PV system [29], [30]. The focus of the paper is to set an upper limit for the equipment cost in order to obtain real savings for a specific household through the CBA.

In this paper, Section II provides a brief introduction of the Fuzzy Inference System used, followed by a presentation of the simulator. Model implementation and samples on how fuzzy rules can vary are presented in Section III. In Section IV is presented the application of the simulator to evaluate EM benefits for different PV plant sizes.

## II. Fuzzy Home Consumption Simulator

In this paper we develop a model of the electricity use pattern for any individual domestic dwelling using a ”bottom-up” approach, according to those proposed by [26]. The basic building block is the appliance, i.e. any individual domestic electric load, such as a television, a washing machine, a dishwasher. This approach requires a classification of the appliances into different categories, each one modeled in the same way. The main categories are:

- Continuous use appliances (e.g. Refrigerator, freezer, Wi-fi router, cordless phone, clock radios)
- Periodical use appliances without human interaction (e.g. Oven and microwave oven, dishwasher, washing machine, cooker hood)
- Periodical use appliances with human interaction This category (e.g. Vacuum cleaner, cooking appliances, hair dryer)
- Multimedia appliances
- Lighting

The modeling of the appliance’s usage has been performed with a LFM approach to determine if wether or not it is going to be started.

The usage pattern, depending on the appliance’s category, can be related to many variables, such as the number of active people in the house, the typical frequency of the appliance, the time of the day, the temperature. For example, when people are not at home, most appliances will not be used (only the so called continuous use appliances). In work days daily appliance electricity profile, the occupants use virtually little power (stand by and fridge-freezer) while in the evening, the meal is cooked, television is watched, lights are on, etc. This typical pattern can drastically change during the weekend and holidays and, moreover, it can change from dwelling to dwelling due to different life styles. The main factors influencing occupancy pattern and appliances usage are: the number of occupants, the time the first person gets up in the morning and last person goes to sleep, the periods house is unoccupied during work days, holidays and weekends. When analyzing the households load profile we need information on the active occupants of the dwelling. To compute the overall occupancy pattern for work days and holidays an interview to dwelling occupants can be performed. Starting from basic information in this paper we build a 1-minute resolution daily active occupants pattern for each day of the week. To compute the number of the busy occupants a counter is used; this counter is increased every time an appliance that requires interaction with a person is switched on, and decreased every time it is switched off. The number of unoccupied people in the dwelling can be computed from the active occupants pattern and the current value of the busy occupants counter. Knowing this value for each time of the day, we can enable or interdict the switching on of the appliance. A further important feature is to identify the typical frequency of each appliance’s starting for each household. This parameter is rarely a crisp value, e.g. ”the washing machine starts usually from 2 to 3 times a week”, and often related to the time of the day, e.g. ”the television starts some hours a day usually at night”. In this work all information regarding occupancy, appliances frequency and typical start time are taken with a brief interview. The former are used to build the active occupancy pattern and the latter to build fuzzy rules.

### A. Appliances Fuzzy Inference System

The membership functions of the input variables (a sample is shown in Fig. 1) consist of triangular asymmetric and trapezoidal functions. The trapezoidal function is totally represented with four points, known also as fuzzy set: $A = (a_1, a_2, a_3, a_4)$. This representation is interpreted as membership functions:

$$\mu_A(x) = \begin{cases} 0\,, & x < a_1 \\ \frac{x-a_1}{a_2-a_1}\,, & a_1 < x < a_2 \\ 1\,, & a_2 < x < a_3 \\ \frac{a_4-x}{a_4-a_3}\,, & a_3 < x < a_4 \\ 0\,, & x > a_4 \end{cases} \tag{1}$$

When $a_2 = a_3$, the triangular function can be considered as a particular case of the trapezoidal one. The input variables for the FIS inference are the time $h(t)$ of the day, the percentage $p(t)$ of unoccupied people in the dwelling and $DT/T(t)$ that is the time elapsed since the last appliance start normalized on his period. Table I shows the fuzzy sets for the input variables.

A sample of the fuzzy control rule base for a ”Periodical use appliance without human interaction” (e.g. the dishwasher) is shown in Table III; the Max-Min fuzzy inference

**TABLE I:**
Considered fuzzy sets for input variables.

| h(t) | Abbr. | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
|---|---|---|---|---|---|
| Early Morning | EM | 0 | 0 | 300 | 450 |
| Morning | M | 300 | 400 | 750 | 800 |
| Afternoon | A | 650 | 750 | 1000 | 1150 |
| Evening | E | 1050 | 1100 | 1250 | 1300 |
| Late evening | LE | 1250 | 1300 | 1440 | 1440 |
| **DT/T(t)** | | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
| Very Advance | VA | 0 | 0 | 0.3 | 0.6 |
| Advance | A | 0.5 | 0.75 | 0.75 | 1 |
| In Time | IT | 0.9 | 1 | 1 | 1.1 |
| Late | L | 1 | 1.25 | 1.25 | 1.5 |
| Very Late | VL | 1.4 | 1.8 | 2 | 2 |
| **p(t)** | | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
| Very Low | VL | 0 | 0 | 0.2 | 0.4 |
| Low | L | 0.2 | 0.3 | 0.4 | 0.5 |
| Medium | M | 0.3 | 0.5 | 0.7 | 0.9 |
| High | H | 0.7 | 0.8 | 1.0 | 1.1 |
| Very High | VH | 1.0 | 1.1 | $inf$ | $inf$ |

algorithm is considered, [31] . The outputs of the FIS engine are the probability $P(t)$ to start a certain appliance: (N) None, (VL) Very Low, (L) Low, (M) Medium, (H) High, (VH) Very High and the total time $D(t)$ the appliance will be on: (VL) Very Low, (L) Low, (M) Medium, (H) High, (VH) Very High. Output membership functions, shown as example in Fig. 2, consist of sigmoid functions with different values for each appliance category. As described in section II, there are 5 different categories of appliances and each one has different fuzzy input-output variables. In particular Table II contains inputs and outputs for each category. Concerning the defuzzyfication we use the modified Center of Area defuzzyfication method since the centroid method evaluates the area under the scaled membership functions only within the range of the output linguistic variable and the resulting crisp output values could not span the full range. The fuzzy logic controller uses the following equation to calculate the geometric center of the full area under the scaled membership functions:

$$\mathrm{mCoA} = \frac{\int \mathrm{f(x)} \cdot \mathrm{xdx}}{\int \mathrm{f(x)dx}} \tag{2}$$

where mCoA is the modified center of area. The interval of integration is between the minimum membership function value and the maximum membership function value. Note that this interval might extend beyond the range of the output variable.

## III. Model Implementation

The aim of the simulation tests is to evaluate the potentialities of an energy management technique applied for different households, in order to evaluate the economic benefits users can obtain. The model has been realized using LabVIEW, the graphical programming environment of National Instruments. In particular the FIS has been realized using the LabVIEW fuzzy toolkit while the input-output membership functions and the rule set with the fuzzy system designer. As the

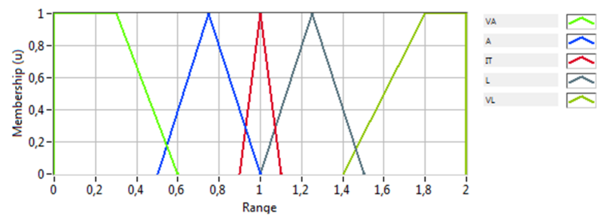


**Fig. 1:** Membership function of the input variable $DT/T(t)$. The x-axis is the ratio between the time elapsed since the last start and the average starting period.

**TABLE II:**
Fuzzy input output variables for the different appliance's categories.

| Category | IN | IN | IN | OUT | OUT |
|---|---|---|---|---|---|
| **Continuous** | - | - | - | - | - |
| **Periodic without human** | $h(t)$ | $DT/T(t)$ | - | $P(t)$ | - |
| **Periodic with human** | $h(t)$ | $DT/T(t)$ | - | $P(t)$ | - |
| **Multimedia** | $h(t)$ | $DT/T(t)$ | $p(t)$ | $P(t)$ | $D(t)$ |
| **Lighting** | $h(t)$ | $DT/T(t)$ | $p(t)$ | $P(t)$ | - |

simulator is not time driven when a simulation runs one-min resolution electricity demand data can be generated for a specified time period using two nested FOR loops (the outer for the days of the year and the inner for the minutes of each day). Each single appliance block, implemented as a functional global variable, is in the inner loop and runs in two phases. During the first iteration of the simulation all the configuration parameters are loaded, e.g. the fuzzy rule set of the appliance, the consumption profile, the maximum power, the typical starting frequency, number of people typically interacting with the appliance (all the mentioned parameters are fully editable in text files and fuzzy rules through LabVIEW graphical interface). After the first iteration the likelihood an appliance will start within the next minute is evaluated with a time resolution of one-minute (except for the so called "Continuous use appliances"). In particular, since the FIS output is a probability value, to manage the start of an appliance this value is multiplied by a calibration factor (equal to the difference in hours between the average period of use of the appliance and the time elapsed since the last

**TABLE III:**
Dishwasher FIS sample. Input $DT/T(t)$ is in the first row, while $h(t)$ is in the first column. Probability $P(t)$ are the central values of the table.

| | VA | A | IT | L | VL |
|---|---|---|---|---|---|
| **EM** | VL | VL | VL | VL | VL |
| **M** | VL | VL | VL | L | L |
| **A** | VL | VL | L | L | M |
| **E** | VL | L | M | H | VH |
| **LE** | VL | VL | VL | VL | VL |

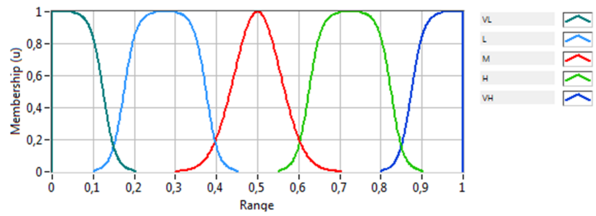


**Fig. 2:** Membership function of the output variable $P(t)$. The x-axis is the probability to start an appliance.

start), as stated in [26]. The result is then compared with a random number (within the real interval $0-1$). The appliance will start if:

- this number is less than the scaled probability
- there is at least one person in the house
- there are sufficient active people in the house (only for some appliance's categories)
- the sum between the current electrical consumption and the max power of the appliance is less than the power the customer can absorb from the grid.

Table II shows the need of taking into account also the number of active people in the dwelling for "Periodical use appliances with human interaction" and "Multimedia Appliances". Starting from the typical pattern of people in the household we decrement this number when an appliance of one of these categories starts and increment this number when the appliance is turned off. To simulate EM actions, fuzzy rules have been modified to approximate a different user behavior regarding the starting time of the two main shiftable appliances (dishwasher and washing machine). As an example, without any action, fuzzy input sets for "periodical use appliances without human interaction" are:

- the time of the day $h(t)$
- the time elapsed since the last appliance start multiplied his typical start frequency $DT/T(t)$

and a typical rule formulation is:
**if** $h(t)$ *is afternoon* **and** $DT/T(t)$ *is late*, **then** *the probability to start the appliance is low*.
The installation of a PV plant can have a great impact on the energy behavior of users. they can use an energy manager, forecasting tools or simply plan to start appliances according to weather forecast. To model this behavior a new input $DX(t)$ is added in the model, the time distance from the peak power production time of the next day. According to this new input, the same rule discussed above will change:
**if** $h(t)$ *is afternoon* **and** $DT/T(t)$ *is late* **and** $DX(t)$ *is very low*, **then** *the probability to start the appliance is very high*.

In the energy management problem considered in this work the two shiftable tasks are the dishwasher and the washing machine. In particular since in this model we represent the typical user behavior, for what regards the starting of one of these two tasks we consider the best time to start the appliance according to the algorithm described in [32].

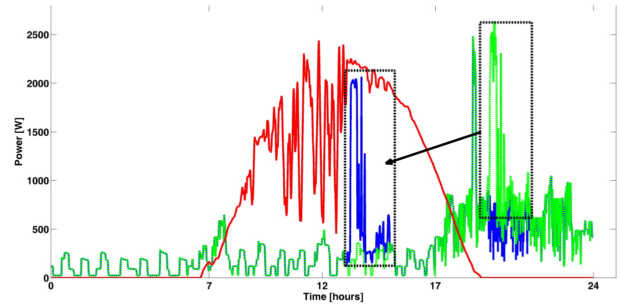


**Fig. 3:** Sample of the energy management actions performed. Red line is the PV production, green line is the original household consumption profile, blue line is the consumption profile after the shifting of a load.

$6-seconds$ resolution data of most of the household appliances (e.g. washing machine, dishwasher, multimedia appliances, iron, oven, microwave) have been extracted installing individual appliance monitors (IAMs from Current Cost company) in the dwellings. It is important to emphasize that the differences between single appliance blocks for the different dwellings are taken into account changing the fuzzy rules, the occupancy profile and using different consumption patterns from the database (according to the different appliances and categories). An example of $24h$ comparison between the simulated and measured demand profile for a single dwelling is shown in Fig. 4. Further details on the software implementation, experimental setup and model validation can be found in [33].

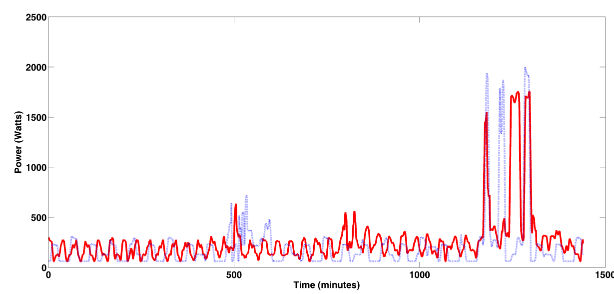


**Fig. 4:** March 23 2012. 1-min resolution data for one of the considered households in Ripatransone (AP), Italy. The dotted blue line is the simulation load profile, the red continuous line is the measured one.

## IV. Economical evaluation of EM benefits

Due to the random nature of solar energy, great effort must be made to design PV systems that optimize energy savings, self consumption and costs. Furthermore the growing interest in innovative energy management techniques suggests that the installation of a proper system able to actuate them can be drastically economically advantageous. In this section we propose economical analysis for both:

- a PV sizing case study;
- the evaluation of real economic benefits from the shifting of the two main loads of a dwelling;

The following analysis are based on the consumption pattern simulated for a household with an overall annual electrical consumption of 2300 $KWh$. The main appliances in the dwelling are: a dishwasher, a washing machine, 3 televisions, a microwave and an electrical oven, an iron, an hi-fi system, a refrigerator and a freezer. The key of the proposed analysis is the self consumption percentage, computed by the simulation tool. A 3 year historical solar irradiance data set is used to calculate the output of a varying size PV plant (1 to 3.5 KWp) and compared with the consumption pattern computed by the simulator in order to obtain the self consumption percentage for each considered PV plant size. A financial evaluation technique is used to compare the different investments under the revised Italian net metering scheme known as "scambio sul posto" in which GSE pays a contribution $E_t$ to the customer equal to:

$$E_t = C_t \cdot \min(F_t, W_t) \tag{3}$$

where $F_t$ and $W_t$ are respectively the injected and withdrawn electricity in $KWh$ and $C_t$ represents a coefficient comprehensive of the electricity cost and net services cost in $eur/KWh$. For the global cost of the PV plant, an average of the main solar installer prices in the considered area has been considered.

### A. ECONOMICAL ANALYSIS

The cost-benefit analysis (CBA) is a financial valuation technique used to predict the effects of a project, a program or an investment, verifying its benefits. CBA, as an alternative to traditional methods of economic analysis, represents also a method of ex-ante evaluation by external parties that have to decide on the financial viability of an investment or have to choose how to allocate scarce financial resources among different possible investments. To evaluate the economic convenience of PV systems on the considered building we carried out the CBA of different sizes of PV plants to choose the best one.

Maintenance cost and effort residential systems is usually very low in comparison with the initial investment afforded (approx $0.5 - 1.0\%$ of investment). The annual electrical energy output of the PV system is computed from the historical irradiance profiles and results to be between the performance range typical of the considered latitude (between 1200 and 1250 kWh/kWp). We assumed that the PV system performance will degrade $20\%$ in 25 years. By considering this fact a derating factor of $0.5\%$ is used for the first 8 years and $1.0\%$ from the $9th$.

The discounted cash flows generated from each investment have been calculated for 20 years, equal to the period in which PV module producers guarantee at least $85\%$ of their initial performance. The net present value (NPV), calculated for each PV plant size, is:

$$NPV = \sum_{t=0}^{K} \frac{C_t}{(1+r)^t} \tag{4}$$

Where $C_t$ is the cash flow at time $t$, $r$ the discount rate (equal to $5\%$ in our case) and $K$ the considered lifetime of the investment. The cash flow $C_t$ is the difference between the discounted annual cash inflows $I_t$ and outflows $O_t$. In particular $I_t$ consists of the annual directly saved energy by self consumption (considering a $3\%$ annual increase of the unitary energy price), the net metering contribution $E_t$ and government contributions ($50\%$ of the plant cost in taxes deduction for the first 10 years). $O_t$ consists instead of the initial cost of the plant (we assume that the bank does not allow a loan without feed in tariffs) and the annual maintenance costs ($0.5\%$ of the initial cost per year). Considering that NPV calculation strongly depends on the used reference discount rate $r$ used (for which the same investment may be convenient or less in relation to its value) it is useful to consider as financial indicator also the IRR (internal rate of return), calculated as the rate $r^*$ for which results:

$$NPV(r^*) = 0 \tag{5}$$

Table IV reports the unitary costs (Cost), the self consumption percentages of two simulated scenarios (user performing EM actions and user maintaining the same behavior) and CBA results for different PV plant sizes in the analyzed case study. The values of NPV, which range between 790 and 2070 €, IRR, between 6.89 and 9.71 %, show better results for a 2.25 KWp plant. In particular revenues decrease from 2070 to 1360 €with a 3 KWp plant and IRR decrease of $2\%$, emphasizing the need of the correct sizing of the plant. We have furthermore analyzed the situation in which the user performs basic EM actions to fix a target equipment cost for each specific household to analyze. As shown in table IV the NPV difference between the best and worst case can be $140\%$ (which results in more than $1,200$ €). Furthermore the economical benefits of energy management actions (shifting of the two main appliances) varies from 250 to 600 €(depending on the plant size) thus imposing cost limitation for the EM equipment.

## V. CONCLUSIONS

This paper introduces a novel Fuzzy approach to model household electrical consumptions. Our model differs from the ones existing in literature, see e.g. [26], for the chance to easily customize it exploiting the potential of Fuzzy Systems. Indeed it has been possible its use to correctly size a residential photovoltaic (PV) plant and simulate the effects of energy management techniques only changing few fuzzy rules. According to a cost benefits analysis (CBA) we computed net present value (NPV) and internal rate of return (IRR) for different PV plant sizes in a case study. Results show that the convenience to install a new PV plant in the actual scenario is strongly related to the matching of production and consumption patterns and the cost of home

**TABLE IV:**
Unitary costs, self consumption percentages (SC) and CBA results (NPV and IRR) for the considered case study with and without energy management actions.

| Size (KWp) | Cost (€/KWp) | No EM actions SC (%) | NPV (€) | IRR (%) | EM actions SC (%) | NPV (€) | IRR (%) |
|---|---|---|---|---|---|---|---|
| 1.00 | 3850 | 41.1 | 787 | 7.91 | 53.4 | 1005 | 8.64 |
| 1.25 | 3750 | 35.3 | 937 | 7.85 | 47.3 | 1208 | 8.60 |
| 1.50 | 3500 | 31.3 | 1251 | 8.35 | 42.9 | 1566 | 9.11 |
| 1.75 | 3150 | 27.4 | 1711 | 9.28 | 38.5 | 2067 | 10.07 |
| 2.00 | 2950 | 24.2 | 2048 | 9.71 | 35.2 | 2443 | 10.51 |
| 2.25 | 2750 | 22.5 | 2069 | 9.47 | 32.9 | 2501 | 10.30 |
| 2.50 | 2700 | 20.6 | 1730 | 8.51 | 30.6 | 2198 | 9.36 |
| 2.75 | 2500 | 19.4 | 1716 | 8.42 | 29.4 | 2215 | 9.32 |
| 3.00 | 2450 | 17.5 | 1363 | 7.60 | 26.9 | 1888 | 8.51 |
| 3.25 | 2320 | 16.2 | 1310 | 7.46 | 25.8 | 1879 | 8.44 |
| 3.50 | 2260 | 15.7 | 1047 | 6.89 | 24.7 | 1624 | 7.85 |

automation devices to perform EM actions can not exceed 600 €in the best case.

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