X SICEL 2021

Transición energética en la 4ta revolución industrial

Universidad Tecnológica de Pereira

UNIVERSIDAD NACIONAL DE COLOMBIA

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Transición energética en la 4ta revolución industrial

Review of charging load modeling strategies for electric vehicles: A grid-to-vehicle probabilistic approach comparison

Daniel F. Florián

Miguel A. Rojo

Sergio D. Saldarriaga

Carlos D. Zuluaga

Institución Universitaria Pascual Bravo

Contents

I. Introduction (I)

Due to the current debate concerning global warming, many countries have created numerous strategies to combat this issue.

Source: Greenpeace

I. Introduction (II)

Source:Precision Agriculture

Source: Pexels

Some strategies are:

- Electric vehicles (EVs)
- Renewable Energy Integration
- Agricultural robotic solutions
- Nanomaterials
- Replacing harmful materials with sustainable alternatives

Source: Science Examincer

Source: Pexels

I. Introduction (II)

Some strategies are:

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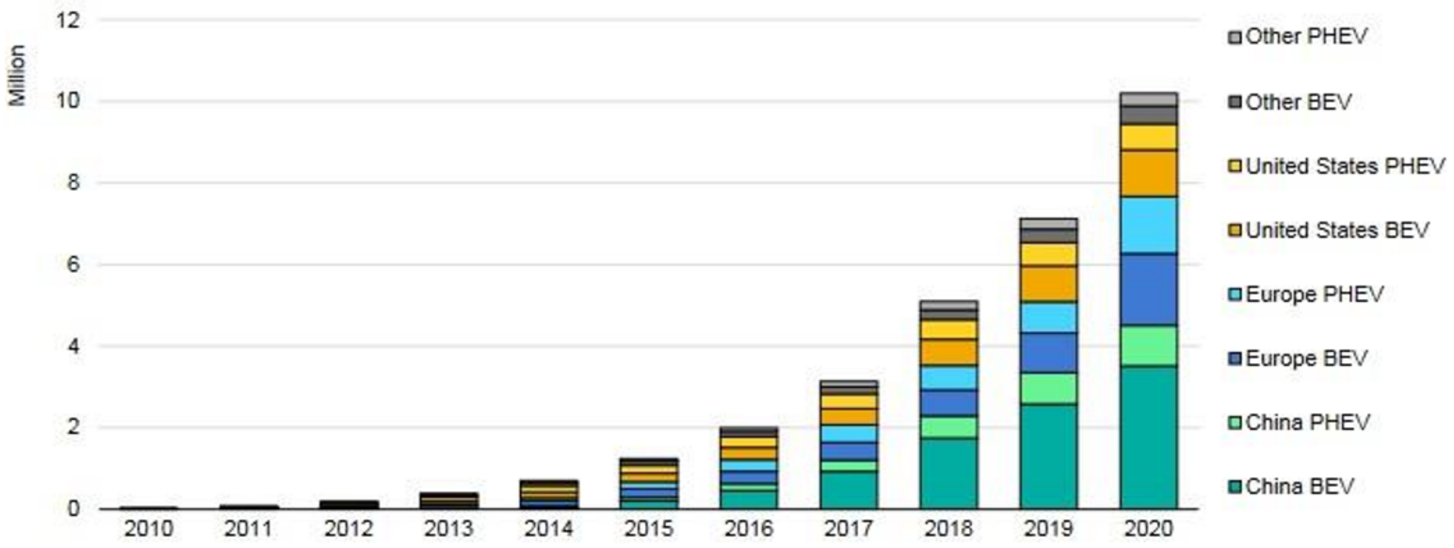
I. Introduction (III)



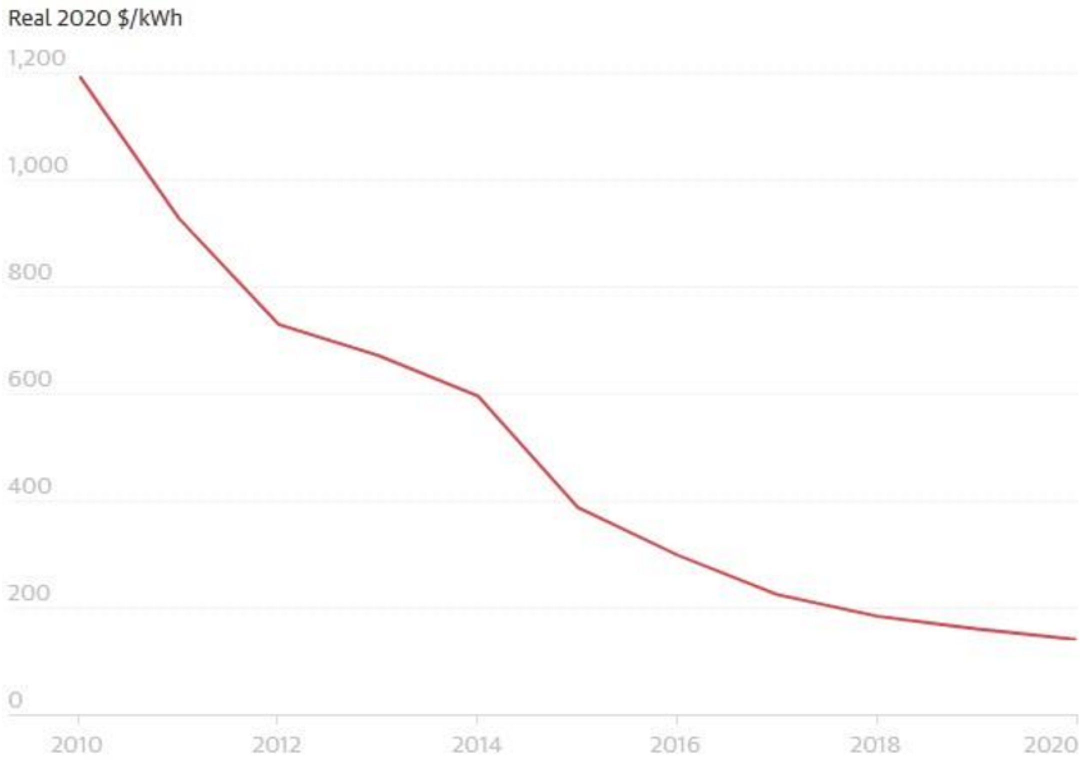
Source: International Energy Agency

- There were 10 million electric cars on the world's roads at the end of 2020, following a decade of rapid growth.
- Electric car registrations increased by 41% in 2020.

I. Introduction (IV)

- Supportive regulatory frameworks.
- Additional incentives to safeguard EV sales from the economic downturn.
- Battery cost continued to fall.

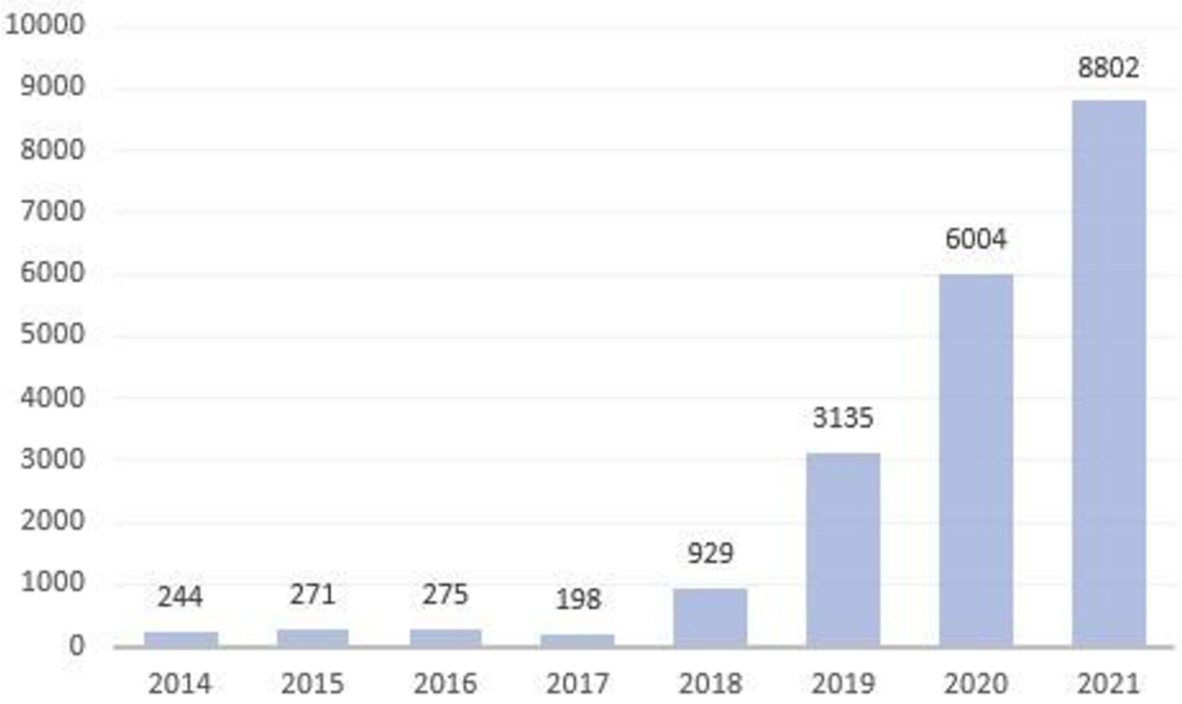
I. Introduction (V)



Lithium-ion battery pack prices. Source: The Guardian

BloombergNEF's analysis predicts lithium-ion battery costs will fall to the extent that electric cars will match the price of petrol and diesel cars by 2023

I. Introduction (VI)



Electric vehicles and hybrid vehicles registration in Colombia. Source: Fenalco, July 2021.

I. Introduction (VII)

The inclusion of EV technology allows:

- To fight against global warming.
- This penetration can also achieve efficient operation of the power grid [1]

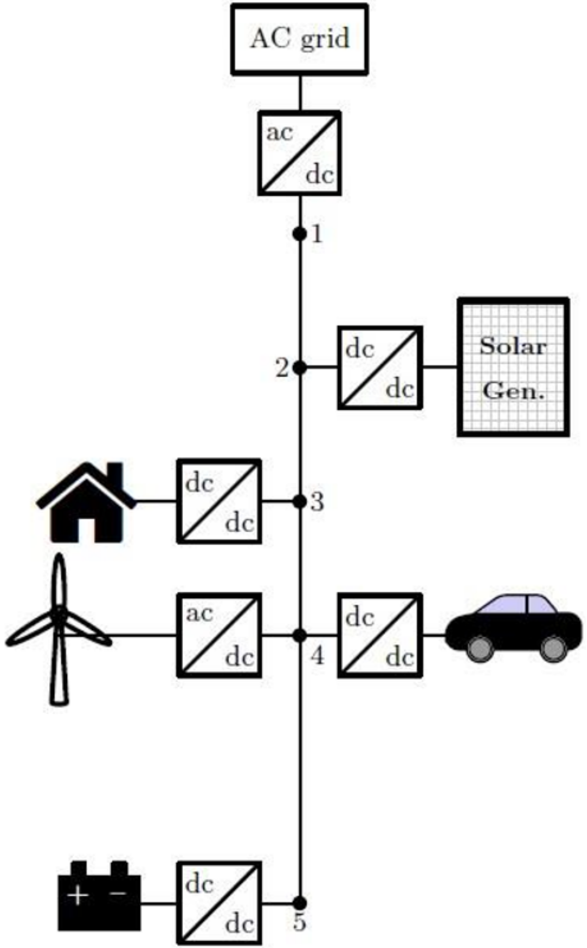
I. Introduction (VIII)

However, with the penetration of EVs:

- It is not only evident an increased amount of the electricity consumption in the power grid.
- Introduction of new load variations.
- Impacts on transportation, manufacturing or economy [2]

I. Introduction (IX)

These factors must be considered in the operation, planning and analysis of the modern power grids like active distribution networks or grid-connected microgrids [2]



I. Introduction (X)

The penetration of EVs in power network analysis studies has been widely addressed [3]:

- Unidirectional charging.
- Bidirectional charging.
- Uncontrolled charging.
- External charging strategies
- Individual charging strategies

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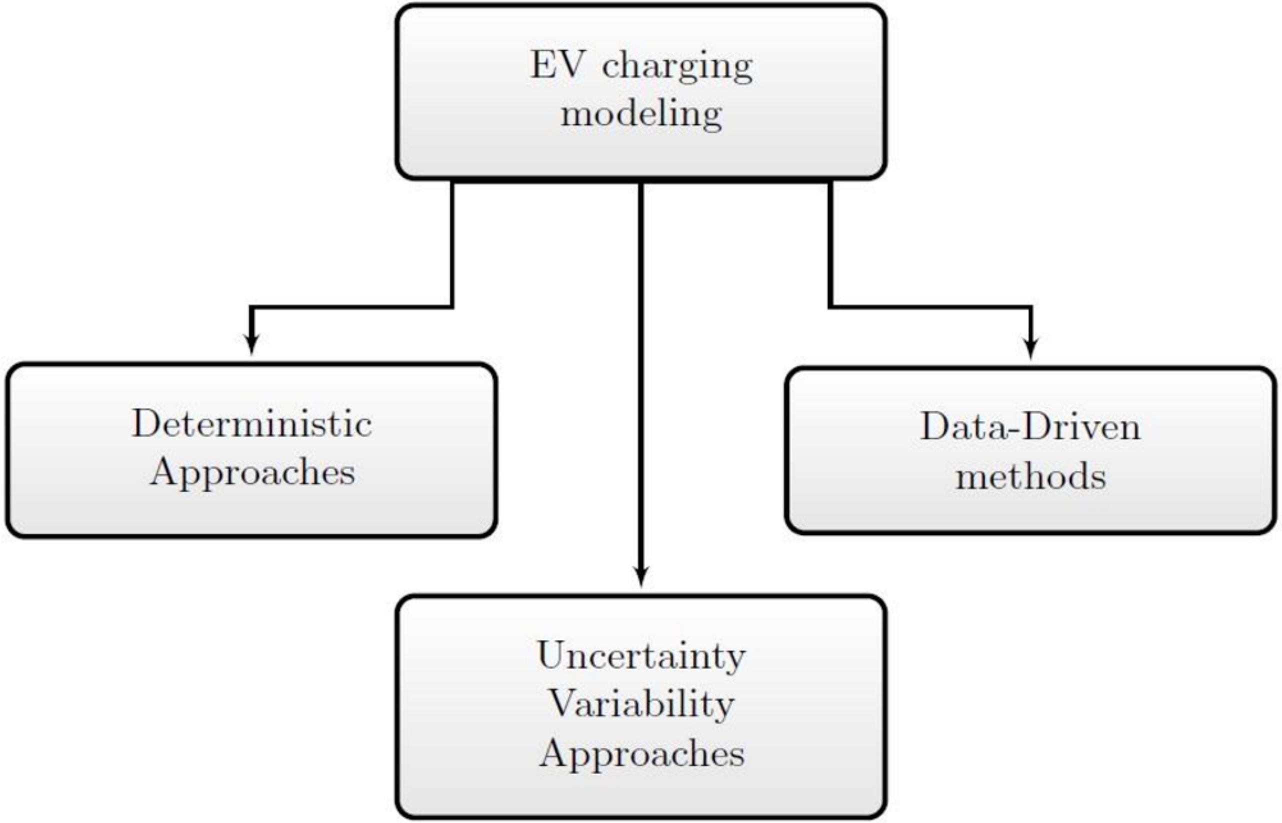
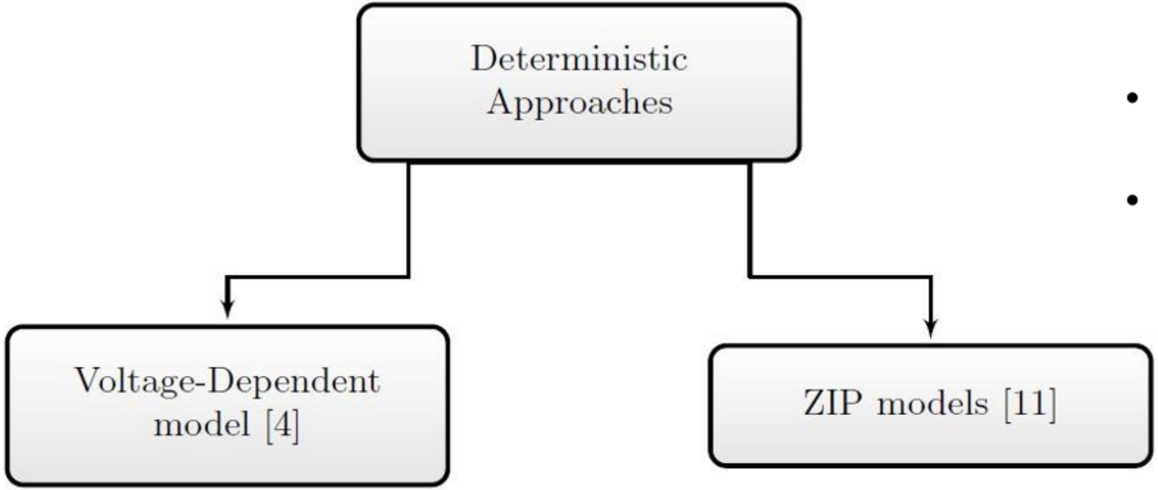
II. EV charging Load Modeling (I)

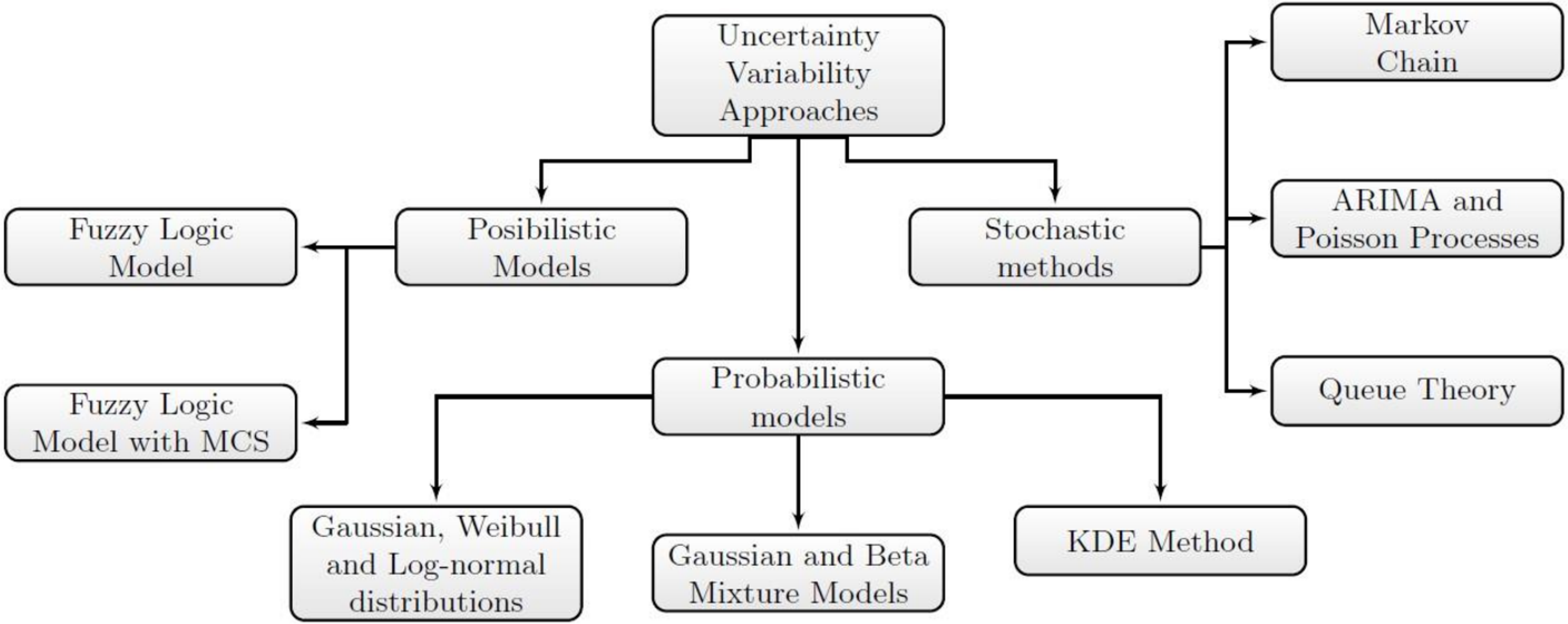


II. EV charging Load Modeling (II)



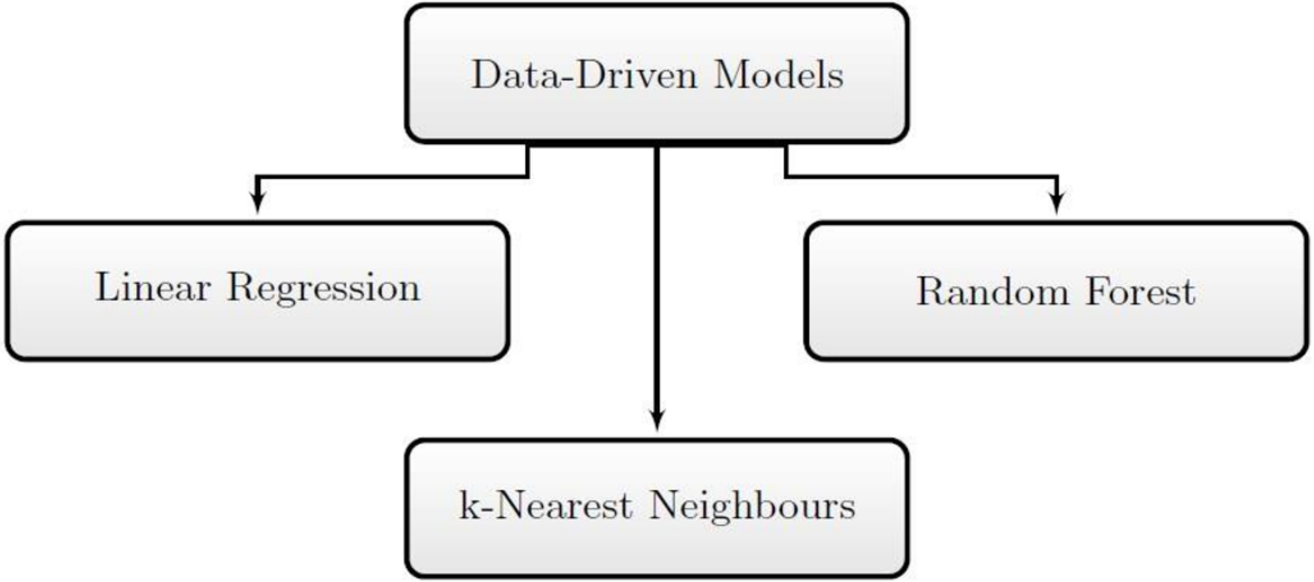
- Low computational time
- The uncertainty and driving patterns are not considered

II. EV charging Load Modeling (III)



These methods require computational effort, experience and many input data samples to determine the EV demand. However, the uncertainty is appropriately modeled.

II. EV charging Load Modeling (IV)



These methods concentrate many of the patterns associated with the dynamics of the EVs. However, they need large amounts of data to generalize the behavior of the EV demand,

III. Electric Vehicle Charging Probabilistic (EVCP) Modeling (I)

- We use Monte Carlo Simulation (MCS) for probabilistic modeling of the EV charging demand.
- We consider five predefined EV fleet.
- We show the comparison of three Electric Vehicle Charging Probabilistic (EVCP) Models.

III. EVCP model 1

- We have considered the model presented in [24].

- Two random variables were assumed. Daily travel distance d and plug-in time t_p.

III. EVCP model 1

$$SOC_{ij} = 1 - \frac{d}{D\eta}$$

$$P_{EV} = \sum_{i=1}^{5} \sum_{j=1}^{N} P_{EV_{ij}}$$

$$P_{EV_{ij}} = \begin{cases} P_c & t_p \leq t \leq t_d \\ 0 & Other\ time \end{cases}$$

- D is the average daily travel distance.
- η is the efficiency of battery power in driving cycles in EV.
- P_c is the rated charging power, j is the MCS iteration and i represents ith EV in the specific predefined EV fleet

III. EVCP model 2

- We have proposed a model with three random variables: daily travel distance d, the leaving time from home t_l and the time period that the EV user is away from home t_a.

III. EVCP model 2

$$t_{mcd}^{j} = \frac{(\eta - SOC_{ij})C_{ap}}{P_c}$$

$$t_{fc}^{j} = t_a^j + t_l^j + t_{mcd}^j$$

$$P_{EV} = \sum_{i=1}^{5} \sum_{j=1}^{N} P_{EV_{ij}}$$

$$P_{EV_{ij}} = \begin{cases} P_c & t_p \leq t_{fc}^j \leq t_d \\ 0 & Other\ time \end{cases}$$

- C_{ap} is the battery capacity.
- η is the efficiency of battery power in driving cycles in EV.
- t_l and t_a are random variables that represent the leaving time from home and the time period that the EV user is away from home.
- t_{mcd}^j and t_{fc}^j are the minimum charging duration time and the fully charging time
- P_c is the rated charging power, j is the MCS iteration and i represents ith EV in the specific predefined EV fleet

III. EVCP model 3

- We have modified the model presented in [27] to include the specific predefined EV fleet of the EVCP model 1.
- The home arrival time, home departure time, travelled distance are Gaussian random variables, and battery efficiency is uniformly distributed.
- The rated charging power P_c is modelled as a nonlinear function of the SOC.

III. EVCP model 3

$$SOC_t = SOC_{t-1} + \frac{100P_c\eta}{C_{ap}}$$

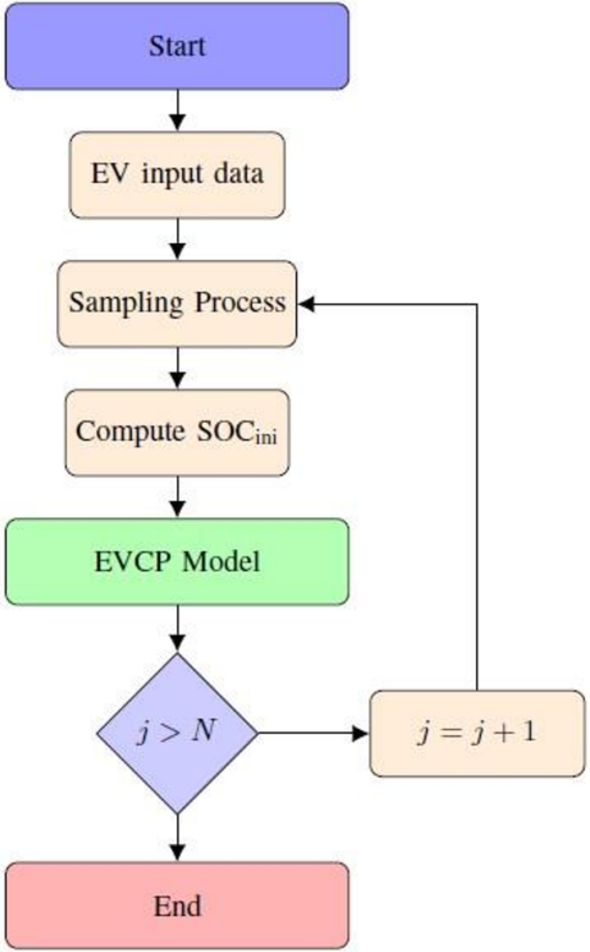
$$P_{EV} = \sum_{i=1}^{5}\sum_{j=1}^{N} P_{EV_{ij}}$$

$$P_{EV_{ij}} = \begin{cases} P_c & t_p \leq t \leq t_d \\ 0 & Other\ time \end{cases}$$

- D is the average daily travel distance.
- η is the efficiency of battery power in driving cycles in EV.
- P_c is the rated charging power, j is the MCS iteration and i represents ith EV in the specific predefined EV fleet

IV. Experimental Evaluation (I)

- We use the information in [24] as the battery capacity, EV types, charging power and full endurance mileages.
- We repeat $N = 5000$ times the procedure shown in the figure to obtain the histogram for the EV electric energy consumption.



IV. Experimental Evaluation (II)

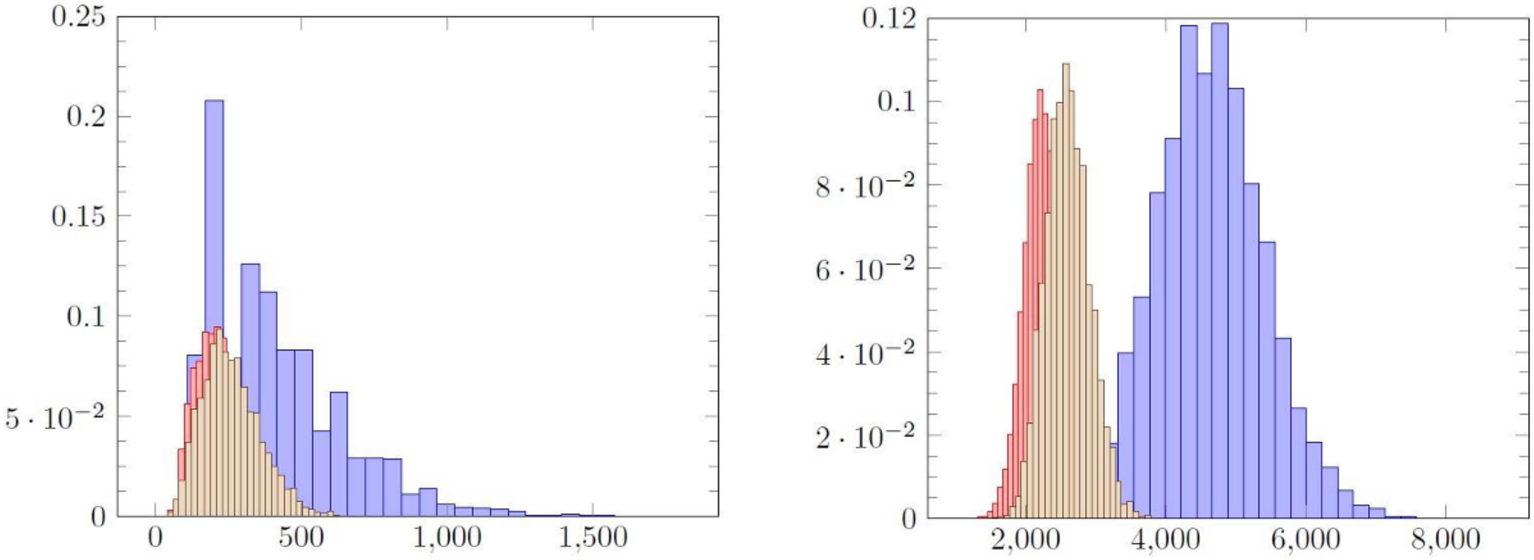
- We consider that 80% of the private EVs plug in to the power grid from 18h to 7h, and the remaining 20% is recharged during working hours, that is, from 9h to 17h.
- We contemplate three penetration scenarios using 20, 200, 2000 and 20000 EVs. To determine the number of EVs, we use a Poisson distribution with expected value λ.

IV. Experimental Evaluation (III)

EV types	Model	Battery Capacity (kWh)	Charging Power (kW)		Full Endurage mileage (km)
			Slow charging	Fast charging	
Private Vehicle	Nissan Leaf	24/40	6.6	11	150/250
Utility Vehicle	Nissan Leaf	40	6.6	11	250
Commercial Vehicle	Nissan Leaf	40	-	11	250
Goods truck	EMS 18 Series	240	-	80	250
Bus	AUT-BUS	202	-	50	200

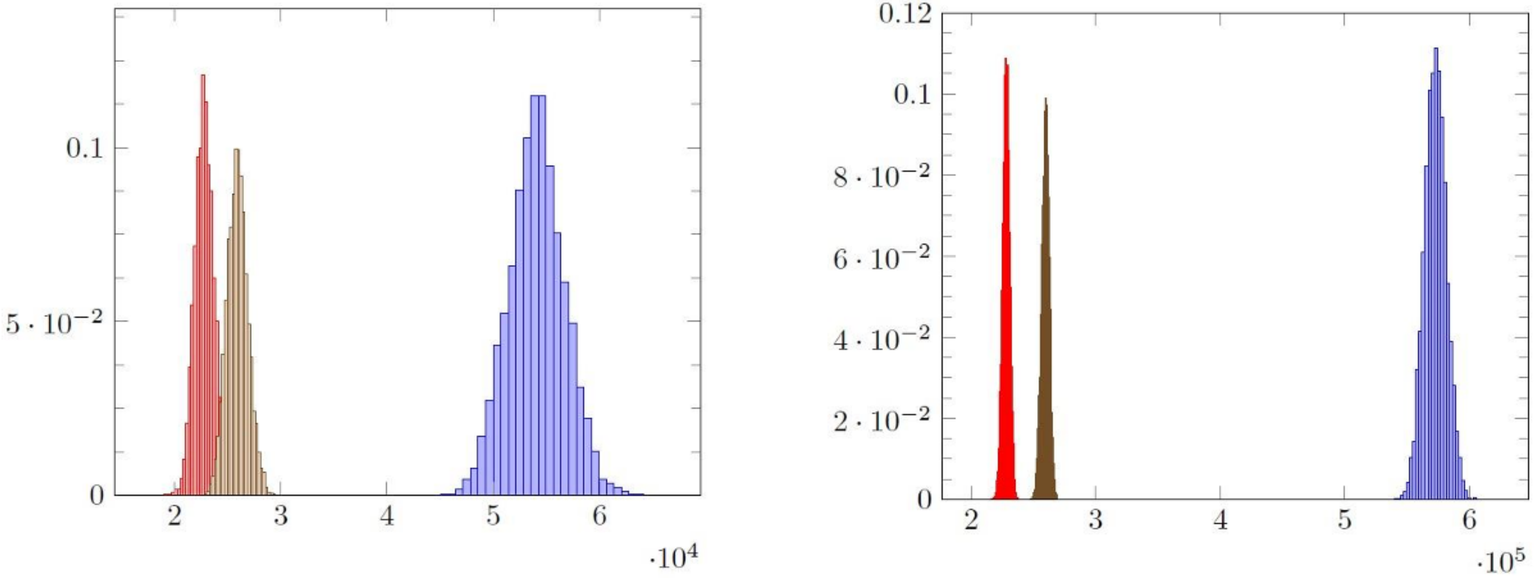
Charging parameters of five types of EV models.

IV. Experimental Evaluation (IV)



Histograms of the EV charging demand when we apply MCS to the three EVCP models considering a penetration of 20 (left) and 200 (right). The brown, red and blue bars represent EV charging demand the EVCP model 1, 2 and 3, respectively.

IV. Experimental Evaluation (V)



Histograms of the EV charging demand when we apply MCS to the three EVCP models considering a penetration of 2000 (left) and 20000 (right). The brown, red and blue bars represent EV charging demand the EVCP model 1, 2 and 3, respectively.

IV. Experimental Evaluation (VI)

- We applied a similarity measure of how one probability distribution is different from a second, that is, we compute this distance between the real probability distribution (it obtained by MCS) and a proposed distribution.
- We compute the Wasserstein distance [36] to measure the similarity between the true data distribution and some proposed distributions.
- We analyze the Gaussian, Lognormal, Gamma and Weibull distributions.

IV. Experimental Evaluation (VII)

Distribution	Wasserstein Distance			
	20	200	2000	20000
Gamma	17.928 ± 3.2997	18.634 ± 2.5456	58.565 ± 2.3555	235.03 ± 47.933
Log-normal	21.463 ± 1.7000	26.194 ± 10.059	60.434 ± 18.760	160.02 ± 42.010
Normal	49.735 ± 6.1031	48.164 ± 8.0598	69.243 ± 17.408	169.34 ± 27.718
Weibull	28.133 ± 1.5911	136.55 ± 21.603	545.91 ± 26.603	1913.2 ± 83.372

Wasserstein Distance applied between the real probability distribution and the proposed distribution of the EV demand. As proposed distribution, the Gamma, log-normal, normal and Weibull distribution were analyzed.

V. Conclusions

- A review of the state of the art of the modeling of electric vehicles under a G2V approach was presented, where three groups are identified.
- An experimental comparison was made with three probabilistic models based on Monte Carlo simulation.
- From this comparison, we observed that the PEBCP model 3 and the gamma distribution can be appropriate for modeling the penetration of EVs in probabilistic load flow analysis or for stochastic planning studies for active distribution networks.

VI. Questions

Some references

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[3] P. Grahn, J. Rosenlind, P. Hilber, K. Alvehag, and L. Söder, "A method for evaluating the impact of electric vehicle charging on transformer hotspot temperature," in 2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies, 2011, pp. 1–8.

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