A Survey on Deep Learning Applications for Electric Vehicles in Micro Grids

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Abstract— **Due to the increasing demand for energy and the environmental and economic challenges of reducing air pollution, while a large portion of the energy required comes from fossil fuels, distributed renewable energy generation systems seem to be viable solutions to this problem. Micro Grids are considered as the central part of the distributed generation system's body, while their management and control are of great importance. In recent years, the management and control of Micro Grids, their connection time to the leading network, and their disconnection time have been considered by many researchers since the optimization of these materials directly impacts economic benefits and consumer costs. In the interest of electric vehicles' nature and characteristics, they are connected to the power grid at the distribution level. The set of electric vehicles that are connected to the Micro Grids can cause problems for the grid to operate, such as voltage drops, increased losses, and unwanted clockwork during off-peak hours. In the last two years, deep learning methods have been used to address these challenges and other security and management challenges. This article surveys the applications of Deep Learning-based methods in Electric vehicles as a part of the Micro Grid.**

Keywords-component; Electric Vehicle Micro Grid; Deep Learning; CNN.

Abbreviation	
SG	Smart Grid
EV	Electric Vehicle
CNN	Convolutional Neural Networks
DNN	Deep Neural Networks
RNN	Recurrent Neural Networks
V2G	Vehicle to Grid
SOC	State of charge
MAE	Mean Absolute error
RMSE	Root Mean Square Error
MAPE	Mean absolute percentage error
DRL	Deep Reinforcement Learning
LSTM	Long short-term memory

I. Introduction

The increasing expansion of industries and electrical consumers is one of the major problems of the electricity generation industry. Due to this consumption growth, production units should be built every year to increase consumption. Increased production and construction of new power plants will cause the operation of production and transmission equipment such as lines near their permissible limits, which threatens the system's safety and stability. These causes instability of the production and transmission system.

The widespread entry of electric vehicles into the market will create an unfortunate link between the two industries of electricity and transportation. It is now the electricity industry that must be prepared to accept such changes from now on. If mismanaged and poorly planned, changes can become a challenge for the electricity industry and, in turn, an opportunity if a proper implementation framework is in place.

Improperly managed and planned, these issues can become challenges in the electricity industry and, on the other hand, can be recognized as an opportunity if a proper implementation framework is in place. The concept, which in today's scientific literature is interpreted as vehicle connection to the network or V2G for short, is a collaboration between the field of transportation and the field of electricity supply[1], the optimal implementation of which requires embedding electric vehicles in the complex puzzle of the electricity industry. In recent years, electric vehicles have entered the road transport market, and the infrastructure needed to implement V2G is growing.

Electric vehicles act as an alternative to internal combustion engines, representing an attractive economic approach based on electrification of major parts of transportation and manufacturing. Recent studies have shown that electric vehicles have an advantage over other conventional energy-saving technologies[1], including the ease of implementation and repair, and their environmental friendliness[2]. These studies are reviews and analyzes on the use of electric vehicles in a V2G system, emphasizing the benefits and costs offered by such a system. To create an easily accessible network system to increase the charge of the EV battery, various aspects must be considered.

In general, EV offers many benefits, including an increase in charging system efficiency, a reduction in oil dependence, and a reduction in CO_2 emissions[3]. Electric vehicles also offer a unique advantage in terms of technology known as V2G. The idea of V2G helps us create a complete and accessible set of distributed energy storage devices instantly. We consider the two main connections required to implement the V2G concept:

1- The first is the connection and connection of electricity used to transfer electrical energy to the vehicle and receive energy from the vehicle.

2- The second is the control of connections, which helps us give feedback signals, when we need electricity, or in which direction we should send electricity. To implement this in electric vehicles, electric vehicles' design requires a program code and some power electronic devices.

the concept of V2G application can help increase a network's performance in terms of system efficiency, reliability, stability and load distribution of electric vehicles. It can act as a bar or also as a distributed storage device. When electric vehicles are connected to the distribution network, the vehicle battery can provide power to a network during peak hours, thus increasing system reliability. This concept leads to V2G usage.

Network reliability, the balance of supply and demand, and transfer of power from the source to the buyer can be maintained with the ancillary services required in a power system. Since the V2G system is two-way, it can provide higher quality ancillary services, better voltage regulation and frequency control, peak power maintenance, load management, and efficient stock rotation. We can use each vehicle separately or as part of a set.

Deep learning techniques have been found to be very useful in the automotive industry, as they help with advanced driving guidance systems and automated driving. These are just deep learning applications in vehicles. Deep learning technology also plays a vital role outside of the vehicle environment - during production, sales, and after-sales service. Even in services where technology has seemed somewhat obscure so far, deep learning technology has made a difference and made great strides.

The remainder of the paper is organized as follows. Section II has an overview of the overall structure of the Micro Grid. Section III presents a thematic taxonomy of deep learning for EVs.This section includes a table that reviews the articles discussed and focus on in this paper. Finally, Section VI concludes the paper.

II. Review of the Micro Grid

Due to problems such as fossil fuel shortages, population growth, environmental issues, increased reliability, and reduced losses, the tendency to use distributed generation has increased. Scattered generators include wind turbines, solar cells, micro turbines, fuel cells, and more. Due to the large presence of distributed generation, new technical challenges to control and protect power systems have emerged that have led to the emergence of Micro Grids' new concept.

The components of small power systems with the ability to connect and disconnect from the national power grid are Micro Grids. Micro Grids are small distribution and transmission production networks connected and can separate and connect to the network. Generally, a Micro Grid is a system for generating and distributing electrical energy that consists of various components, including distributed generation, energy storage systems, loads, and protection equipment. A Micro Grid is an autonomous system that can control and manage itself. Sometimes in an energy Micro Grid, consumers receive heat energy for heating and cooling in addition to electricity. One of the basic characteristics of Micro Grids is that they can work in two modes connected to a network or an island (separate from the network). When connected to the grid, the Micro Grid exchanges electrical energy with the grid. Fig 1 shows the overall view of Micro Grid. In this perspective, The Battery of electric vehicles can be used as a potential storage capacity to be used in the Micro Grid.

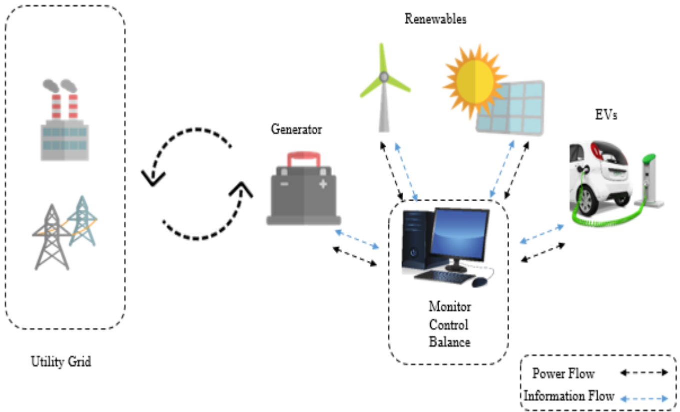

Figure 1. A Schematic of a Micro Grid

Micro Grids are used at remote points that are not connected to the main power grid and facilities related to critical missions such as military installations. However, technological advances and increasing energy resources have made these Micro Grids available to commercial and government organizations. This process of building and operating a Micro Grid makes it a more economical and feasible solution now and in the future.

III. Deep Learning Algorithms for EVs

Deep learning is part of a larger family of machine learning that focuses on artificial neural networks. Reinforcement learning is one of the subsets of machine learning. The subject of this type of learning is how software agents should operate in an environment that increases their cumulative rewards. Reinforcement learning is one of the main branches of machine learning concepts, while the other two branches are supervised learning and unsupervised learning. Contrary to what happens in supervised learning, reinforcement learning does not require a label. Instead, this type of learning focuses on maintaining a balance between discovery and the use of experience. The environment of a reinforcement learning problem is generally expressed in terms of the Markov decision-making process[4].

Supervised learning algorithms try to model the relationships and dependencies between the intended predicted output and input characteristics; To be able to predict output values for new data based on relationships learned from the previous data set. As a result, in the supervised learning algorithm, in order to teach the deep learning model, we need tagged data.

Thematic Taxonomy of deep learning applications for EVs in Micro Grid is shown in figure 2. According to the studies that have been done on the type of algorithms used related to electric vehicles, it can be said that most of the deep learning methods use supervised and reinforced learning. Table 1 shows a summary of cases which present different applications of deep learning for EVs. It should be noted that the results placed in the *performance field* are mostly the best reports of studies.

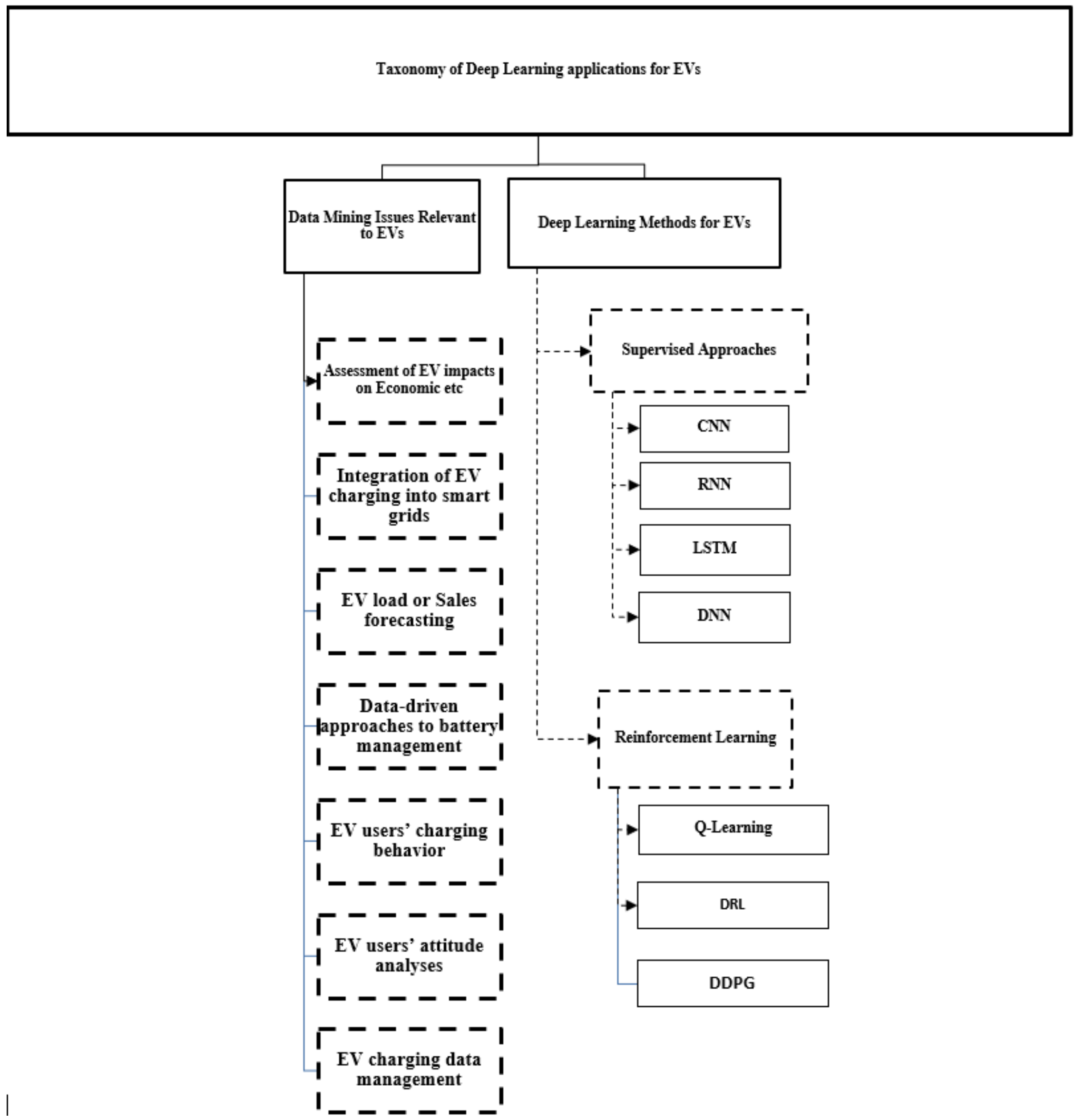

Figure 2. Taxonomy of Deep Learning applications for EVs

TABLE 1. SUMMARY OF CASES WHICH PRESENT DIFFERENT APPLICATIONS OF DEEP LEARNING FOR EVS IN MICRO GRIDS

Work	Year	Application	Approach	Data Set	Performance
[5]	2020	EVs Charging Scheduling	Deep Q-learning	Based on charge bar	Total charging Time = 369.383 sec
[6]	2020	Charging Profile Extraction	CNN	Pecan Street Dataset	Accuracy= 0.98% Precision= 0.80% Recall= 0.98% F1 SCORE= 0.79%
[7]	2020	V2G Scheduling	LSTM	Based on Electric vehicles monitoring and service center data set	MAPE=5.76% RMSE in V2G schedulable charging and discharging power prediction is 1.5969 and 1.2635
[8]	2020	SOC Estimation Of Li-Ion Battery (A Battery Management System)	DNN	Center for Advanced Life Cycle Engineering (CALCE) Battery Research Group	RMSE= 3.68% MSE= 0.13%
[9]	2020	Dynamic Pricing For PEV Charging Demand Coordination	Deep Q-learning	Based on Simulation	the pricing policy achieves a 100% QoS level for all service classes most of the time
[10]	2020	Recognize The Changing Pattern Of Traffic Flow	LSTM	the highway data of the suburban area in California, USA	At loss rate 10%: RMSE=167.8% MAPE=1.68
[11]	2020	Cyber Attack Detection	deep auto encoder	Collected	accuracy detection=93.76%
[12]	2020	Ev Charging Scheduling	Deep Q-learning	Based on Simulation	Compared with that before DQN, the cost of day-ahead trading has been reduced by about 85%, and the cost of future trading has been reduced by about 61%.
[13]	2020	Energy Management	deep deterministic policy gradient	Based on Simulation	Fuel Consumption of DDPG+TL = 2.9641 While Common DDPG= 3.2896 TRAINING TIME of DDPG+TL = 0.79 While Common DDPG =21.46
[14]	2020	Energy Storage System Control	DRL model	Based on Simulation	Relative increase of the total electricity bill = 21-25% At least 10% better than compared

					articles
[15]	2019	Energy Management	Deep Q-learning	Based on Simulation	the average proportion of fuel/electricity costs of DDPG-PR-SCN-TRA (63.13% fuel cost) is close to that of the global optimization model DP (64.45% fuel cost)
[17]	2019	Ev Charging Scheduling	DNN	Day-ahead and historical RTP/HSS prices. Ameren Illinois. [16]	the constraint violation ratio=55:27%
[18]	2019	Ev Charging Navigation	Deep Q-learning	EVCS of Xi'an city	Average Total Time: Case 3: Value per hour ($/h): 1.0 Average total time (h): 0.36 Case 4: Value per hour ($/h): 2.0 Average total time (h): 0.35
[19]	2019	Load Forecasting	RNN GRU LSTM DNN	Based on company Dataset	One hidden GRU Test-NRMSE=2.89% Test-NMAE=0.77%
[20]	2019	Ev Charging Scheduling	Deep Q-learning	Based on Simulation	Average inference time=0.002714Sec
[21]	2019	Load Forecasting	LSTM	Collected	MAE=04782% RMSE=0.9546 R2=0.9953%
[22]	2019	Energy Management	LSTM	real mobility traces of taxis in Rome Italy	MSE=0.00032 MAE=0.0119 RMSE=0.041
[23]	2018	Demand-Side Management	DNN	Collected	mean ratio of 0.95%
[24]	2018	Fault Detection	CNN	Based on two different examples	DC link capacitor Healthy samples: acc ~100% Faulty samples: 89% DC link capacitor failure Healthy samples: acc 100% Faulty samples: 95%
[25]	2018	Ev Charging Scheduling	deep Q-learning algorithm	Collected real world dataset	MPC with real future price reduces the charging cost by 86.29%. Comparing the results of MPC

IV. Discussion

Most of the applications are EVs Charging scheduling, vehicle-to-Grid scheduling, Cyber security and Energy Management. The more we move towards the production of large and massive data that inherently have a constant production time of different types of data, the more they need to be managed and processed by algorithms that are capable of analyzing them. In the discussion of resource management and optimization, it can be seen that the use of algorithms based on reinforcement learning has been more successful[6, 9, 13, 15, 26]. This is due to the nature of reinforcement learning algorithms such as deep Q learning, which based on the reward system and its policies can be suitable for Scheduling purposes.

V. Conclusions

In today's modern society, having a sustainable energy source plays an important role. There are growing concerns about continued access to the energy used and the deterioration of electricity transmission and distribution network infrastructure. There are security, sustainability, and quality challenges in energy supply sources. Micro Grids are networks that are made up of many small generators that provide a small amount of load in their range and can be connected to produce an extensive, high-power network that can be replaced by current networks. Moreover, at the same time, when necessary, re-break into the small networks that make them up. Since the transportation industry is one of the essential industries consuming fuel, the replacement of electric vehicles and electric motors with internal combustion vehicles is on the countries' agenda. Rechargeable electric vehicles are one of the best candidates to replace fossil fuel-based vehicles due to their low pollution and high efficiency, which is why we are witnessing remarkable advances in the battery industry and charging facilities in these countries. In recent years, many researchers have used deep learning methods to manage electric vehicles' current and potential challenges. This article examines the various applications of deep learning in the industry and management of electric vehicles. The results show that most of these applications are dedicated to car charging planning and battery charge forecasting. At the same time, less effort has been made for the security and privacy of electric vehicles.

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