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Optimization of Multi- Agent Control for Electric Vehicle Charging

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Abstract: **An increasing share of non- dispatchable and intermittent renewable energy plants cause probabilistic behaviour at the power grids' supply side and therefore the expected penetration of electric mobility at the demand side offers the opportunity of controllable load. For future smart grids their optimal coordination is one major concern. Therefore, a multi-agent system is proposed. In this system, according to a given strategy, each electric vehicle (EV), i.e., the agent acts in response to dynamic condition in its environment. Optimizing these strategies based on evolutionary computation is used. For representing the problem and evaluating the solution simulation models are applied. It allows the modelling of complex as well as probabilistic systems, necessary for the defined problem. In the end, the optimized strategies satisfies the energy demand of individual vehicles end-users and secure power grid operation is guaranteed throughout the considered grid using power from renewable plants.**

Keywords: **EV, Charging Control, Grid, Policy Optimization.**

I. INTRODUCTION

Various researchers investigate the integration of electric vehicle (EV) charging into modern power grids and their control strategies. Designing these strategies is a challenging task due to the stochastic nature of individual behaviour. Additionally power plants like wind power or photovoltaic further complicates the power grid by their fluctuating and weather- dependent power output. The combination of electric mobility and probabilistic supply is therefore a highly fruitful method, since controlling EV charging leads to a dispatchable distributed load. Therefore, a simulation-based optimization approach that uses evolutionary algorithms is used. This approach is applied for optimizing policies within a multi- agent system. The computed optimal policies of the electrified car fleet satisfy energy demand of individual car users as well as include the physical characteristics of the electric power grid under the special condition of probabilistic supply. Constraints can be integrated that ensure reliable operation and maximize utilization of renewable energy since the electric power grid will be considered through load flow simulations. Thus, the integration of power grid model into optimization process is enabled.

To solve such a scheduling problem, one way is to calculate a solution that consists of a fixed charging schedule for each vehicle which considers its forecasted behaviour as well as power system conditions in advance. However, planning ahead is difficult, when the system is dynamic and situation changes on the fly. In such cases, it would be more appropriate to take decisions as they come up by reacting to a new order situation very quickly. Therefore, optimization of a flexible and reactive charging policy for EVs (agents) is applied, that allows them to react to dynamic conditions. Even though the policy is principally same for all EVs, using input data from agent's individual environment it leads to agent-specific charging behaviour.

II. EXISTING SYSTEM

EV users are interested in finding an energy optimal route with appropriate charging stops while not spending unnecessary time at the charging station which will allow them to extend the driving range. For EV fleets this situation is even more critical. Very few works have been proposed in literature which tries to address this problem by considering various parameters and optimization criteria.

A. Energy Optimization Criteria

Authors in [2] address the optimal routing problem for individual EV considering the energy losses along the path. The optimization criterion is energy and the problem formulation is based on an adoption of a general shortest path algorithm, using an energy graph. A similar approach, with some enhancements has been discussed in [3] which consider the battery charging limit and discharge along the route. However, these approaches do not consider the charging stops for vehicles along the route which is essential for EVs. Another energy optimal routing is proposed in [4] where authors optimize the energy consumption along the route. This approach is limited to a single vehicle with no charging stops.

B. Time Optimization Criteria

Apart from energy optimization, few approaches are based on time optimization. One such approach is discussed in [6] which consider the time required to charge a vehicle at the charging station. However, it assumes that a charging station is always available when a request is made which is not the case in reality. Authors in [7] also propose a time based optimization algorithm for electric vehicles, but in this approach the vehicles travel at a constant speed and hence the time of arrival at the charging station can be predicted in a deterministic way and also the charging station is available when the request is made.

C. Distance Optimization Criteria

A distance based optimization for EV fleets is proposed in [10]. However, it is assumed that vehicles can complete the entire trip in a single charge and no charging stops are needed midway. To compute efficient routes an Electric Vehicle Routing Problem (EVRP) is first defined. The problem includes transport capacity, time and energy constraints. In a second step the charging schedule for vehicles is computed by including the state of charge, charging price and battery degradation. However, in this approach the charging and the route are treated as different problems and charging station concurrent use is not taken into consideration.

III. PROBLEM DEFINITION

Optimal electric vehicle charging is our problem and it can be defined as follows. We are given a fleet of EVs within a distribution grid and each EV must receive a specific amount of energy satisfying its daily demand. EV users are also interested in finding an energy optimal route with appropriate charging stops while not spending unnecessary time at the charging station which will allow them to extend the driving range. For EV fleets this situation is even more critical. Our aim is to supply power to each of the charging station from the power grid and hence to satisfy the energy demand of individual users by minimizing the financial costs associated with power supply.

IV. SCENARIO DESCRIPTION

The proposed scenario can be explained using two models. They are:

1. Distribution grid model
2. Simulation optimization architecture model

The outline of the distribution grid model is depicted in Figure 1.

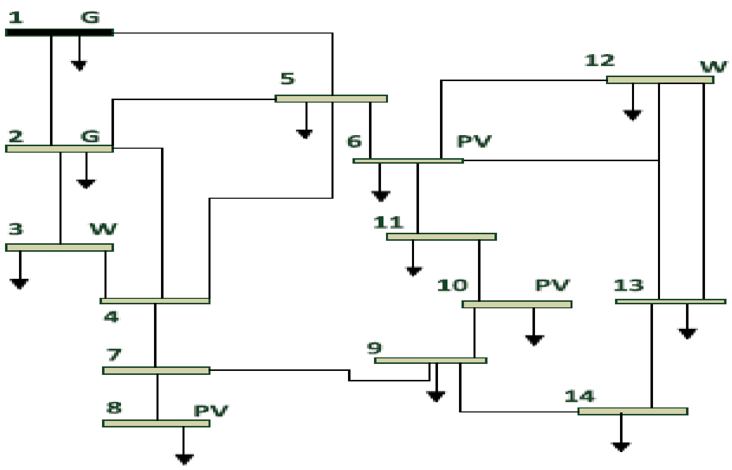

Fig. 1- Distribution Grid Model

The outline of the distribution grid model shows different interconnected buses as well as their characteristics. The black bar shows the slack bus and is necessary for power flow calculation. There are three buses in the system that serves as generator buses which supplies energy from photovoltaic. Two buses inject electricity from wind power plants, and additionally to the slack bus. One bus serves as a deterministic generator which injects power according to a defined profile. All buses are assumed to be load buses additionally.

Simulation optimization architecture model is shown in Figure 2. The simulation model consists of three components. They are:

- distribution grid model
- probabilistic supply model and
- traffic model which describes the behaviour of EVs.

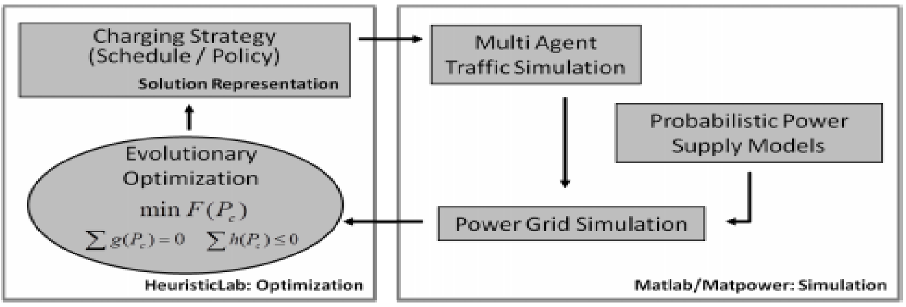

Fig. 2- Simulation Optimization Architecture

The traffic model simulates synthetic driving profiles that describe location, time step as well as duration of residence of all single EVs. A charging station may exist according to a certain probability at each location in the simulated system, which provides actual real-world activities in charging infrastructure implementation plans. The probabilistic supply model describes the expected injection of power from renewable plants using probability distributions from the renewable point of view. The distribution grid model takes the resulting load of electric vehicle charging and the simulated input from renewable supply for calculating the final power flow calculation. In the end, the computed solution satisfies each EV users' energy demand as well as considering all constraints from the distribution grid model point of view for ensuring secure power grid operation.

V. SOLUTION REPRESENTATION

Two different solution representations are discussed in this work. The first approach tries to compute the solution statically in advance, considering forecasted behaviour through simulation. However, planning ahead is difficult, when the system is dynamic and situation changes on the fly. In such cases, it would be more appropriate to take decisions as they come up by reacting to a new situation very quickly. Therefore, optimization of a flexible and reactive charging policy for EVs (agents) is applied, that allows them to react to dynamic conditions.

A. Computing Static Schedules in Advance

This solution representation contains solution as real-valued vector, which ensures optimal behaviour beforehand considering forecasted behaviour of the system. This representation seems to be the easiest and most intuitive way for tackling this problem, but can lead to solution space explosion. In this case, clustering is applied, where agents (EVs) with similar behaviour and similar local appearance in the power grid get clustered using the same solution, thus reducing the solution space drastically. Within this study, EVs are clustered to group sizes of 60 (based on the availability of node), which is valid according to the defined problem dynamic conditions.

B. Multi- Agent Policy Optimization

When trying to find optimal behaviour within a volatile and uncertain system, it's more adequate for each agent to make decisions as they come up, reacting optimally to its individual environment. This can be realized using a policy-based approach, where each agent (EV) in the system receives a flexible policy rather than a static charging schedule. This policy lets him react to influences quickly, but in an optimal manner.

The principle of optimizing a multi- agent system based on policies is a common approach in operations research, for example, in the field of production logistics. Here, for example each job within a process chain serves as agent that acts according to a policy which describes its priority at a certain point in the process. This priority decides its position within a waiting queue of a specific service. It is based on a policy which is computed using agent- specific input data such as actual waiting time, service time, or other logistical metrics. Serving a number of electric vehicles with power by considering restrictions from the supply infrastructure can be seen as a similar problem; hence, the concept of policy optimization can be applied now. The aim is to compute the optimal charging power of an agent at a specific time step in the process and to compute its optimal priority at a specific point.

In our system, the value "priority" is substituted by the amount of power a car is desired to charge relative to its maximum charging power. A similar work with the aim of demand response has already been performed in the field of electric engineering along with the application of policy-based optimization which provides a large number of established priority rules in production plant logistics. These priority rules are generally dependent on logistic metrics, but can be adapted to the herein defined problem. Such logistical rules prioritize jobs according to their remaining number of operations, imminent operation time, information about their remaining time or distance to due date. Such simple rules can be easily adapted to the problem of charging control.

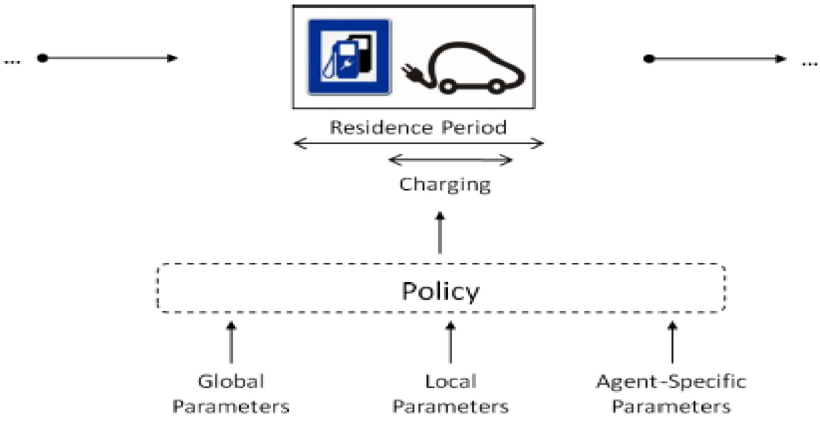

Fig. 3- Illustration of Policy Principle

Instead of computing a job's priority based on imminent operation time or its remaining number of operations, values like an EV's remaining energy demand or its remaining residence time at a charging spot can be taken for computing its necessary charging power. Therefore, the adaptation of existing rules and their formulation with EV and power grid specific metrics is absolutely valid as well as feasible for handling the defined problem. Additionally to the adapted rules coming from logistics, further rules have to be defined that consider electricity generation and distribution metrics for regarding the power grid situation as well.

In the end, the policy defines the charging behavior of each single EV. Even if the policy is principally the same for all agents, using situation- specific input data it leads to individual and (near-) optimal behaviour. An illustration of the principle is shown in Figure 3.

Clustering is applied, where agents (EVs) with similar behaviour and similar local appearance in the power grid get clustered using the same solution, thus reducing the solution space drastically. Within this study, EVs are clustered to group sizes of 60 (based on the availability of node), which is valid according to the defined problem dynamic conditions. Since there exist generally a high variety of possible rules, those have to be selected, that are suitable for the formulated problem. Base load data is used with the intention of shifting charging to off-peak hours. Price data is used as well since the objective function of the optimization problem aims at minimizing financial costs.

In order to represent local distribution grid aspects, data from connected branches is included as well as information about how many EVs are remaining at the same bus during the considered time steps, using local information. Additional information is important considering each rule: namely if this rule leads to a higher or lower charging rate. For example, ETTD (Estimated Time to Departure): an EV that has a relatively high remaining time left at the charging station should get a lower charging rate at the actual time step. This is intrinsically clear, since there is much time left to get charged, probably more than for other agents. Therefore, this rule is getting inverted. "Prioritize minimum" is thus added. For all these rules it is theoretically assumed that the needed information can be obtained. Flexible policy rather than a static charging schedule is used. This policy lets him react to influences quickly, but in an optimal manner.

VI. WORKING

Simulation- based optimization with evolutionary algorithms is applied for handling the defined problem. The central idea of this approach is the application of simulation for evaluating the fitness of a solution candidate generated by the meta-heuristic optimization algorithm.

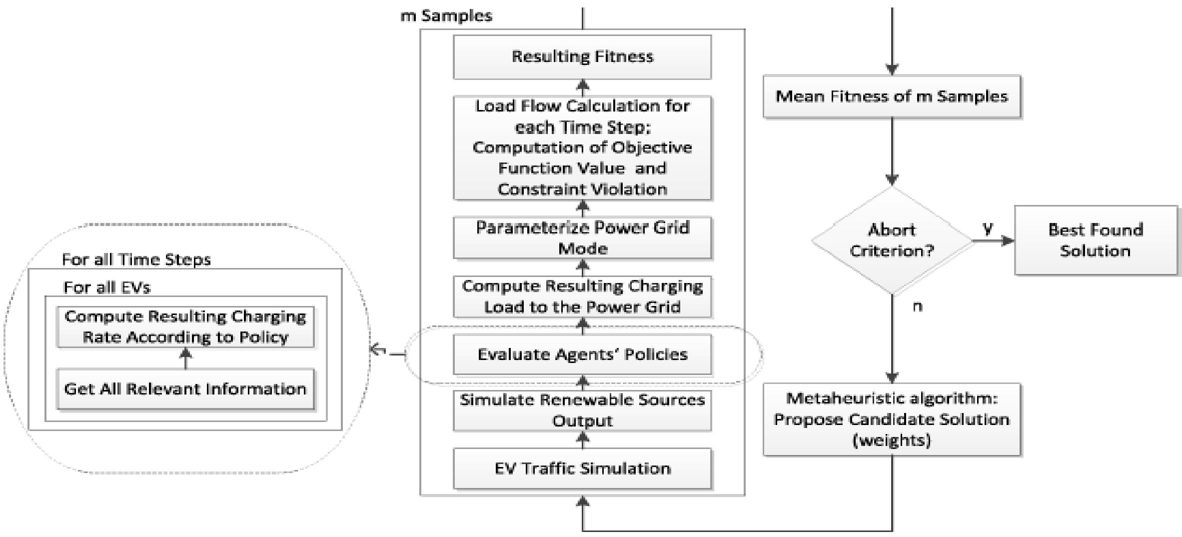

Fig. 4- Optimization Process Flow

During evaluation, the solution is computed from the policy for each agent directly in the simulation for the policy-based approach. For the static approach the whole solution is computed explicitly by the optimization algorithm. Given the so computed charging rates, the resulting fitness of the solution candidate is evaluated through simulation. This evaluation will be sampled a sufficient number of times in order to overcome uncertainty of the stochastic system. The stochastic system is represented through simulation. Uncertainty in this case occurs because of probabilistic models of intermittent supply on one hand, but because of the uncertain individual traffic behaviour on the other hand. The optimization process especially for the policy-based multi-agent approach is shown in Figure 4.

The solution evaluation is the more interesting part now: as known from the problem description, the model consists of different parts including electric distribution grid model, electric vehicle traffic model and probabilistic supply model. These three simulation models are aggregated for evaluating a solution candidate. At the beginning of the evaluation, the traffic models as well as the renewable sources are simulated. Using this data, for the policy-based approach the resulting charging rate is computed for each agent over all time steps, serving as input data for the distribution grid model. Using load flow simulation, all constraints as well as the resulting fitness value are computed. Constraints are incorporated using the concept of penalization, where the fitness of a solution candidate is penalized by the degree of constraint violation.

Principally, evolution strategies (ES) are used as evolutionary algorithms, which have been successfully proved to be performant for real-valued optimization problems. In principle, ES is a nature-inspired population-based optimization algorithm that tries to improve a set of solution candidates until a certain stopping criterion is reached. Contrary to other related algorithms, ES selects the best individuals within each generation and improves them where mutation is the main evolutionary operator. It is generally proven to be a powerful and efficient meta- heuristic algorithm for real- valued optimization problems, supplied by its special ability of self- adaptiveness within the search process.

Since time for evaluation is the main critical issue for simulation-based optimization, the optimization algorithm has to be adapted accordingly. Evaluation of the policy principally takes longer than the evaluation of the static schedule. Thus, experiments for policy optimization have been performed with drastically reduced population sizes as well as number of resulting total evaluations. With these configurations, solutions have been found that will be com- pared to each other consequently.

VII. CONCLUSION

A simulation-based evolutionary optimization approach has been presented that is used for computing optimal intelligent charging strategies for a fleet of electric individual vehicles that exist within a distribution grid, building a multi-agent system. The concept of using simulation for evaluation enables that probabilistic influences of both individual traffic behaviour as well as intermittent energy supply can be incorporated during the optimization process. In the end, intelligent strategies have been found that satisfy operation constraints from the electric power grid point of view while supplying energy demand by individual vehicle users.

Two different solution representations have been discussed. First a static one was introduced where individual charging strategies for all agents during a specific time interval are computed in advance. Since in such a dynamic and uncertain environment it is more appropriate for an agent's behavior to make decisions as they come up, a more sophisticated approach is introduced that optimizes a generic policy. This policy is the same for each agent, but using agent-specific input data from the environment, it leads to individual charging behavior. Comparisons showed that it is possible for the static approach to produce compatible results, but in order to meet higher problem sizes, using optimization of generic policies will be more accurate.

VIII. ACKNOWLEDGEMENT

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