ISSN 1311-0829

# ГОДИШНИК НА ТЕХНИЧЕСКИ УНИВЕРСИТЕТ-СОФИЯ

## Том 64, книга 4, 2014

**VI-та КОНФЕРЕНЦИЯ НА ЕЛЕКТРОТЕХНИЧЕСКИ ФАКУЛТЕТ „ЕФ 2014“**

**15 – 17 септември 2014 г., Созопол, България**

# PROCEEDINGS OF TECHNICAL UNIVERSITY OF SOFIA

## Volume 64, Issue 4, 2014

**VI-th CONFERENCE OF FACULTY OF ELECTRICAL ENGINEERING “EF 2014”**

**September 15 - 17, 2014, Sozopol, Bulgaria**

*Годишник на Технически Университет - София, т. 64, кн. 4, 2014*
*Proceedings of the Technical University of Sofia, v. 64, book 4, 2014*

# ПОДХОД ЗА ОЦЕНКА НА ВЛИЯНИЕТО НА ЗАРЯДНИ УСТРОЙСТВА ЗА ЕЛЕКТРОМОБИЛИ ВЪРХУ РАЗПРЕДЕЛИТЕЛНИТЕ МРЕЖИ

**Рад Станев, Методи Георгиев, Анастасия Кръстева**

***Резюме:*** *Тази статия представя бърз и изчислително ефективен аналичен подход за оценка на влиянието на зарядните устройства за електромобили (ЕМ) върху разпределителните мрежи посредством квази-динамични симулации на процесите за продължителен период от време. Въз основа на променливите във времето електрически параметри на зарядните устройства на електромобилите, товарите и разпределените производствени мощности за всеки възел е получено изменението на параметрите на мрежата във времето. Изследван и представен е набор от типични товарови графици на режими на зареждане на електромобили. Представена е софтуерна реализация и представителен тестов пример на 24 часов анализ в областта на времето за разпределителна мрежа ниско напрежение с присъединени зарядни устройства за електромобили. Въз основа на представения подход са разграничени основните проблеми в мрежата, които възникват поради зареждането на електромобилите.*
***Ключови думи:*** *заряд на електромобили, разпределителни мрежи, интелигентно управление на заряда на електромобили, интелигентно управление на електрическите мрежи, управление на устройствата за съхранение на електрическа енергия, устойчивост на електроенергийните системи, товарови профили на заряд на електромобили*

# AN APPROACH FOR ESTIMATION OF THE IMPACT OF ELECTRIC VEHICLE CHARGING DEVICES ON DISTRIBUTION NETWORKS

**Rad Stanev, Metody Georgiev, Anastasia Krusteva**

***Abstract:*** *This article presents a fast and computationally efficient analytical approach for estimation of the impact of electrical vehicle (EV) charging devices on the distribution networks using quasi-dynamic long-term simulations. Based on the time varying electrical parameters of the EV charging devices, loads and local distributed generation in each node the time variation of the grid parameters is obtained. A set of typical load profiles of EV charging modes is studied and presented. A software realization and a representative test case of 24h time domain analysis of low voltage distribution network with EV charging devices is presented to illustrate the methodology. Based on the approach presented the main problematic grid issues arising due to the EV charging are distinguished.*
***Keywords:*** *electric vehicle charging, distribution networks, smart EV charging, smart grid management, storage control, power system stability, EV charging load profiles*



*ISSN 1311-0829*

## 1. INTRODUCTION

The electric vehicle (EV) charging devices promise to be one of the most significant challenges for the contemporary microgrids and distribution networks [1,2] . The European Commission urges the member states to increase their EV share and charging stations infrastructure [5]. The EV chargers represent significant loads for the low voltage distribution networks due to the ability of these devices to influence substantially the network parameters. Since the distribution networks are not originally intended for such kind of loads a special attention and analysis of both network parameters and charging processes has to be performed in order to guarantee proper interoperability of these devices within the network. Considering the fact that the electrical networks are already built and the upgrades are difficult, time consuming and expensive a new charging control strategies have to be defined smart and grid oriented in order to allow adequate penetration of the electrical vehicle charging devices in the network.

When properly done the electrical vehicle storage is not necessarily problematic. If the EV storage device is unidirectional, (i.e. it can only consume power) the charging process can be used as a dispatchable load, which gives a potential for load profile improvement. Moreover if the EV storage device is bidirectional (i.e. is able to consume power in charger mode and emit power in inverter mode) it can be used for power balancing and many other grid support services.

The main purpose of this article is to present an approach for estimation of the impact of electric mobility charging devices on the distribution networks using long-term quasi-dynamic simulation analysis.

## 2. METHODOLOGY

Different power system analysis techniques are currently available. The classical power flow analysis offers very fast and accurate computation of the network state parameters even for multi node power system. However, it is limited to only one operational state and since the EV charging process proceeds in a specific manner over the time this simple and computationally efficient approach cannot give a deep insight.

On the other side, the conventional time domain simulations using differential equations are complicated and very time consuming for multi nodes power systems especially when analyses of slow dynamic processes with duration from tens of hours to days are performed.

In this work, a “quasi-dynamic” simulation approach using modified nonlinear algebraic equations is proposed for slow dynamics time domain analysis of the EV charging devices operation in the network. Its applicability has been already proved [3] and well accepted for long- term analysis of networks with distributed energy resources. The approach uses a concept of division of the variables in “fast” and “slow”, with very different time constants, under the assumption that fast transients settling time is shorter than the time step used for the slow variables simulation.

Focusing on the slow variables, the evolution of the grid parameters over the time is simulated as a sequence of steady state snapshots. Then for each snapshot, a static grid model is used for studying the power system behavior in response to slow variation of loads, generations and other input settings. The “quasi-dynamic” type of simulations is characterized by time constants of tens of seconds to hours. Since the processes and the variables are very slow, the typical simulation time steps are within the same range.

The “quasi-dynamic" analysis is best suited for time domain simulations with duration from several minutes to several weeks [3]. These types of simulations are useful for interoperability analysis between the EV charging devices and the other network players and components. Moreover it is also useful for analyses of the power system behavior due to slow variations, studies on power and energy management, active and reactive power balancing, demand side management, voltage control strategies, determination of the proximity to operating limits, power system stability etc. The main variables of interest for the quasi-dynamic analysis of the electrical power system are the node and branch variables: voltage magnitude, voltage phase, active and reactive power. The state of each node in each individual snapshot is given by the state equations:

$$P_k = \sum_{m \in k} V_k V_m (G_{km} \cos\theta_{km} + B_{km} \sin\theta_{km}) \quad (1)$$

$$Q_k = \sum_{m \in k} V_k V_m (G_{km} \sin\theta_{km} - B_{km} \cos\theta_{km}) \quad (2)$$

Where $P_k$ is the active power at node (bus) k;

$Q_k$ - Reactive power at node k;

$V_k$ - Voltage magnitude at node k;

$V_m$ - Voltage magnitude at node m,

$\dot{Y}_{km} = G_{km} + jB_{km}$ –Element *k, m* from the bus admittance matrix;

$\theta_k$ - Voltage angle at node k;

$\theta_m$ - Voltage angle at node m,

and $\theta_{km} = \theta_k - \theta_m$.

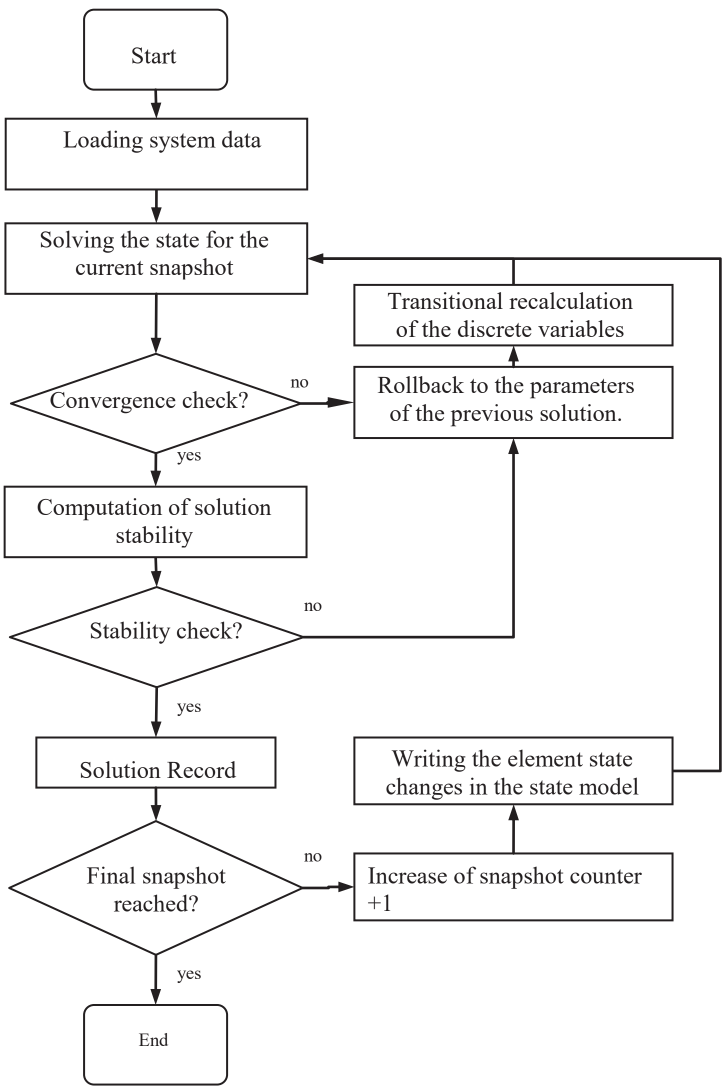


**Fig.1.** Basic block diagram of algorithm for quasi- dynamic analysis.

A basic algorithm is shown on Fig.1 in order to illustrate the approach [3]. After loading the system data, a solution for the initial snapshot is made. If the iteration process is not convergent, a rollback to the last solution is performed after which a recalculation of the variables is made. In case of convergent iteration process, the stability of the obtained solution is checked. If the solution is stable the state parameters are recorded and a calculation for the next snapshot is made.

The iteration methods for solving the state of each snapshot do not always guarantee reaching of stable solution. For this reason a module of the program for power system analysis called *STATUS* is developed in order to overcome this problem.

The module for transitional recalculation uses some special computation techniques with improved convergence and improved solution stability.

In case of non-convergent iteration process, a rollback to the parameters of the last stable solution is done and the technics described in [3] are performed. At each step, the solution received is recorded and used for obtaining a predictor for the following solution.

## 3. COMPONENTS MODELING

Each individual EV charging device in each network node is modeled using its load profile. The loads and the distributed generators are similarly represented.

When EV storage interaction is studied, each device is represented via the node vectors of the active and reactive power over the time. In case of smart grid management power flow control the charging devices node variables are set as dependent on network parameters at the point of common coupling. If bidirectional EV charger-inverters are present the active and reactive power consumption and generation is defined.

An analysis of the charging parameters of the best-sold EV's is made.

Based on this a set of the most commonly used typical load profiles is extracted and presented in this work. The load profiles presented are constrained and dependent from the battery initial state of charge (SOC), battery capacity, battery maximum acceptable current, battery resistance, battery temperature, charger maximum acceptable power etc.

In order to estimate the impact of the electrical vehicles on the grid four typical charging modes as defined in IEC 62196 and IEC 61851 are considered.

Fig. 2 presents load profiles of 3,6kW Mode 1 and a 6,6kW Mode 2 charging process of EV with 16 kWh batteries, starting from 15% initial state of charge (SOC).

Fig.3 presents load profiles of 3,6kW Mode 1, 6,6kW Mode 2, 22kW Mode 3 and fast DC charging Mode 4 of EV with 24 kWh batteries, starting from 40% initial state of charge (SOC).

Fig.4 presents load profiles of fast charging Mode 4 of EV with 60 kWh and 85 kWh batteries, starting from 10% initial state of charge (SOC).

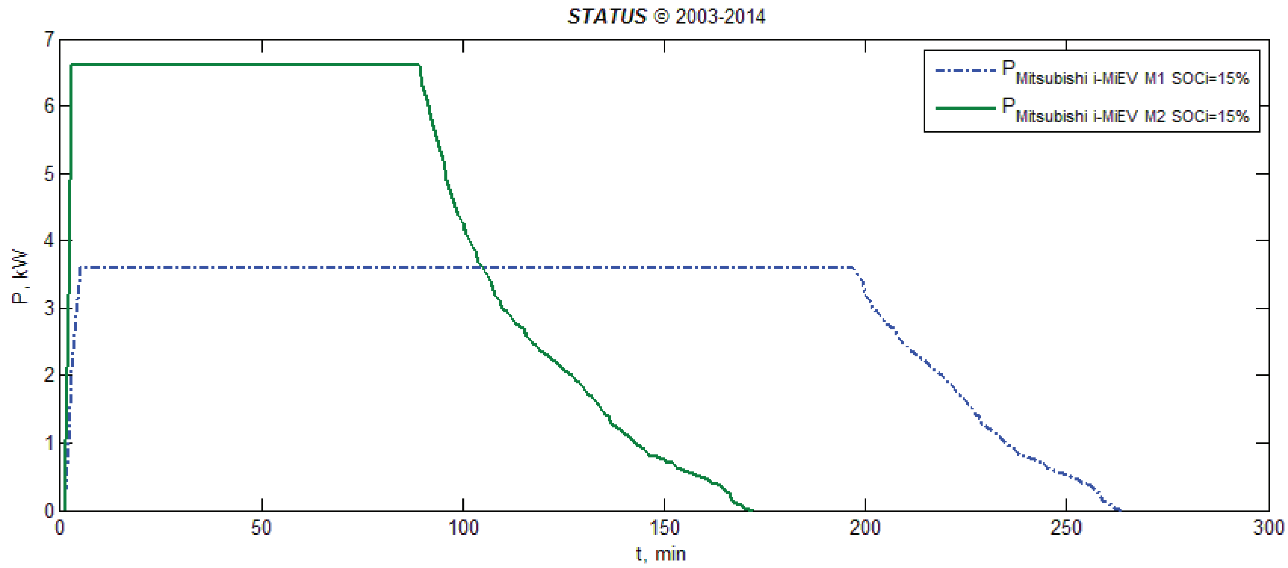


**Fig.2.** Load profiles of 3,6kW Mode 1 and a 6,6kW Mode 2 charging.

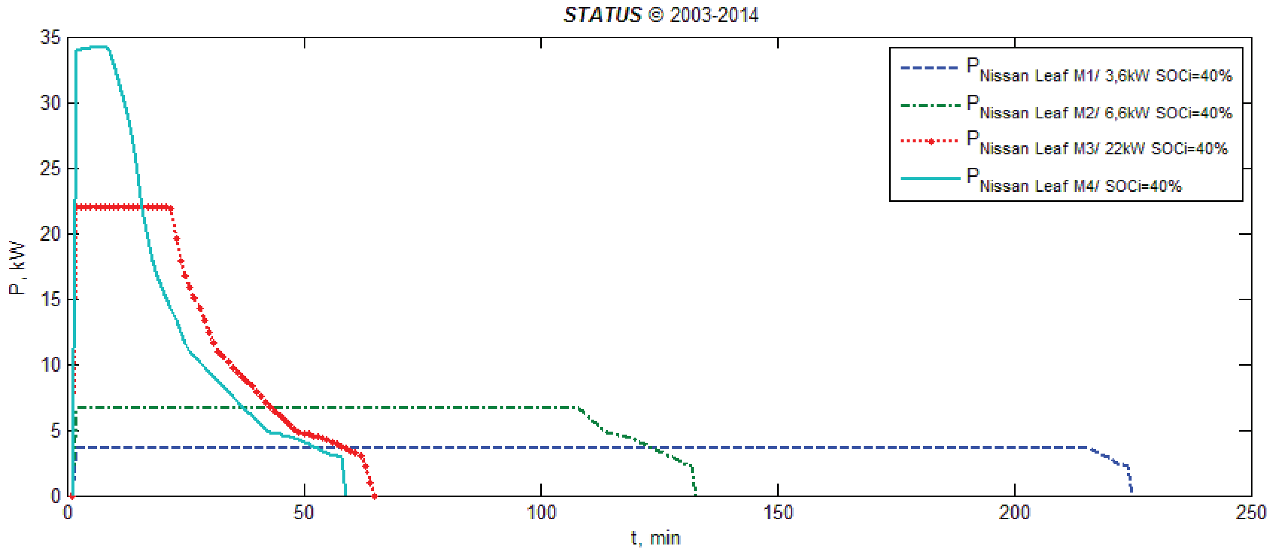


**Fig.3.** Load profiles of 3,6kW Mode 1, 6,6kW Mode 2, 22kW Mode 3 and fast charging Mode 4.

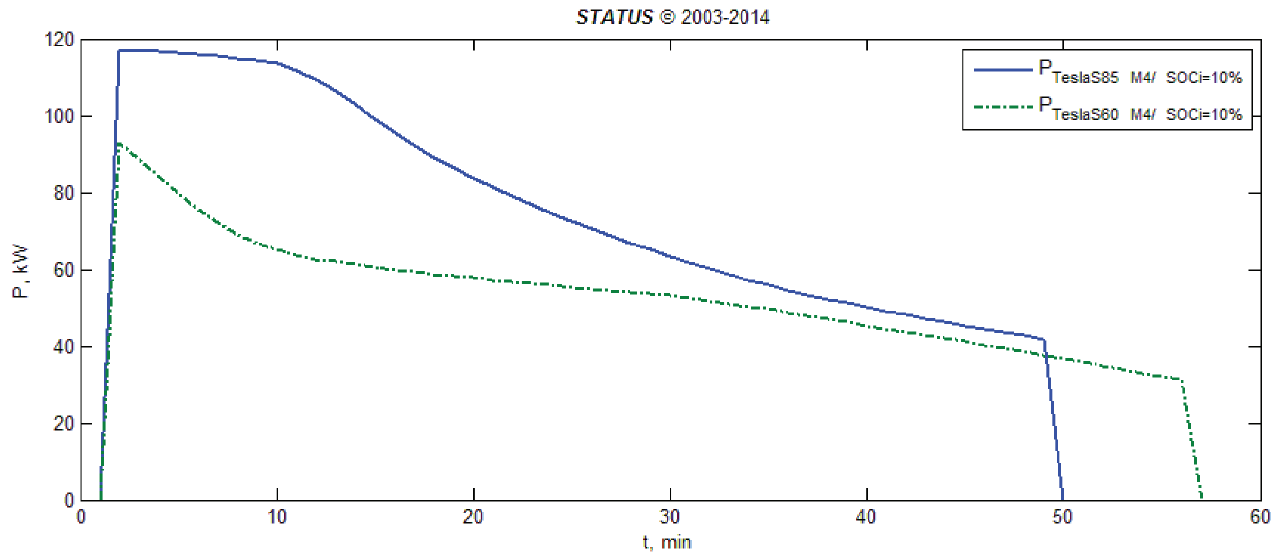


**Fig.4.** Load profiles of Mode 4 fast charging of EV with 60 kWh and 85 kWh batteries

## 4. TEST CASE

A representative simulation test case of existing 0,4 kV, 21 bus distribution network of a village near Sofia, Bulgaria is presented (Fig.5) [4].

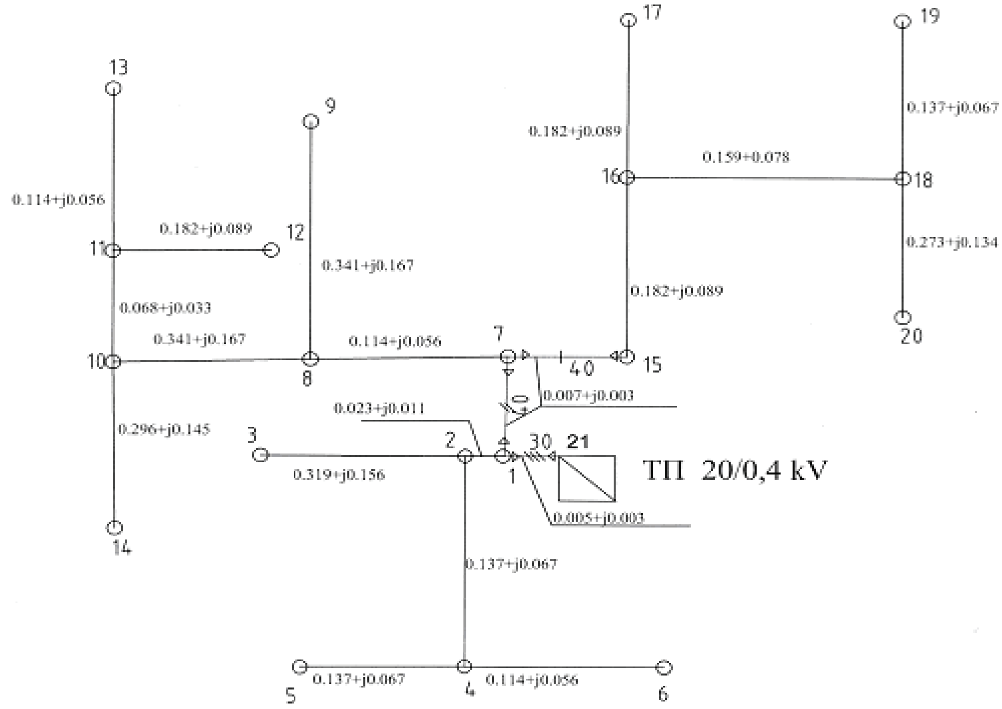


**Fig.5.** One-line scheme of the tested system

The network (Fig.5) has uniformly distributed, symmetric, predominantly active load. The minimal and the maximal system loads without EV charging are Pmin=33,2 kW and Pmax=110,8 kW respectively. Two inverter tied photovoltaic generators are interconnected at bus 10 and at bus 18. The photovoltaic generator G1 with nominal power PG1=30 kW is connected at bus 10. The photovoltaic generator G2 with nominal power PG2=50 kW is connected at bus 18.

A presence of 10 electrical vehicles totaling 7% of the vehicles in the village is assumed. The average daily run per vehicle is 64 km achieved using 13,2 kWh. A probabilistic distribution of the EV charger placement, starting moment of the charging and the initial SOC is applied similarly to the purpose in [3 and 4]. It is supposed that the most EV users will start the charging after returning home after work which occurs most probably at 18:30h.

The case study represents a quasi-dynamic simulation over a typical 24 h period. The simulation time stamp is 1 minute. Based on the network data and the load, generation and charging profile data for each individual node the system parameters over the time are computed. In order to obtain specific and clear results the interaction of the protection devices is prohibited.

The following scenarios are studied:

1) *Scenario 1* Base case scenario of network operation without EV charging. The load is supplied from the transformer station and local PV generation;

2) *Scenario 2* Multiple EV applying charging Modes 1, 2, 3 and 4;

3) *Scenario 3* Multiple EV applying charging Mode 1 and 2.

Table 1 presents the EV charging load profile data in scenario 2 and 3 giving the load profile pattern, initial moment of charging start $t_i$, min and the charging device interconnection node *Bus №* .

**Table 1**

EV charging load profile description

| | *Scenario 2* | | *Scenario 3* | |
|---|---|---|---|---|
| Bus № | $t_i$, min | Charging device load pattern | $t_i$, min | |
| 12 | 1144 | Mitsubishi i-Mi, Mode1, SOCi=15% 3,6kW | 1144 | Mitsubishi i-Mi, Mode1, SOCi=15% 3,6kW |
| 14 | 1112 | Mitsubishi i-MiEV, Mode2, SOCi=15% 6,6kW | 1112 | Mitsubishi i-Mi, Mode2, SOCi=15% 6,6kW |
| 13 | 1045 | Mitsubishi i-Mi, Mode1, SOCi=15% 3,6kW | 1045 | Mitsubishi i-Mi, Mode1, SOCi=15% 3,6kW |
| 17 | 821 | Mitsubishi i-Mi, Mode2, SOCi=15% 6,6kW | 821 | Mitsubishi i-Mi, Mode2, SOCi=15% 6,6kW |
| 4 | 1087 | Nissan Leaf Mode1, SOCi=40%, 3,6 kW | 1087 | Nissan Leaf Mode1, SOCi=40%, 3,6 kW |
| 20 | 1020 | Nissan Leaf Mode2, SOCi=40%, 6,6 kW | 1020 | Nissan Leaf Mode2, SOCi=40%, 6,6 kW |
| 18 | 1121 | Nissan Leaf Mode3, SOCi=40%, 22 kW | 1121 | Nissan Leaf Mode3, SOCi=40%, 22 kW |
| 10 | 230 | Nissan Leaf Mode4, SOCi=40%, fast charge | 230 | Nissan Leaf Mode4, SOCi=40%, fast charge |
| 16 | 972 | Tesla S 60, SOCi=10%, Mode fast charge | 972 | Mitsubishi i-Mi, Mode2, SOCi=15% 6,6kW |
| 8 | 1097 | Tesla S 85, SOCi=10%, Mode fast charge | 1097 | Mitsubishi i-Mi, Mode2, SOCi=15% 6,6kW |

Fig.6 presents the aggregated domestic load, PV generation and EV load.

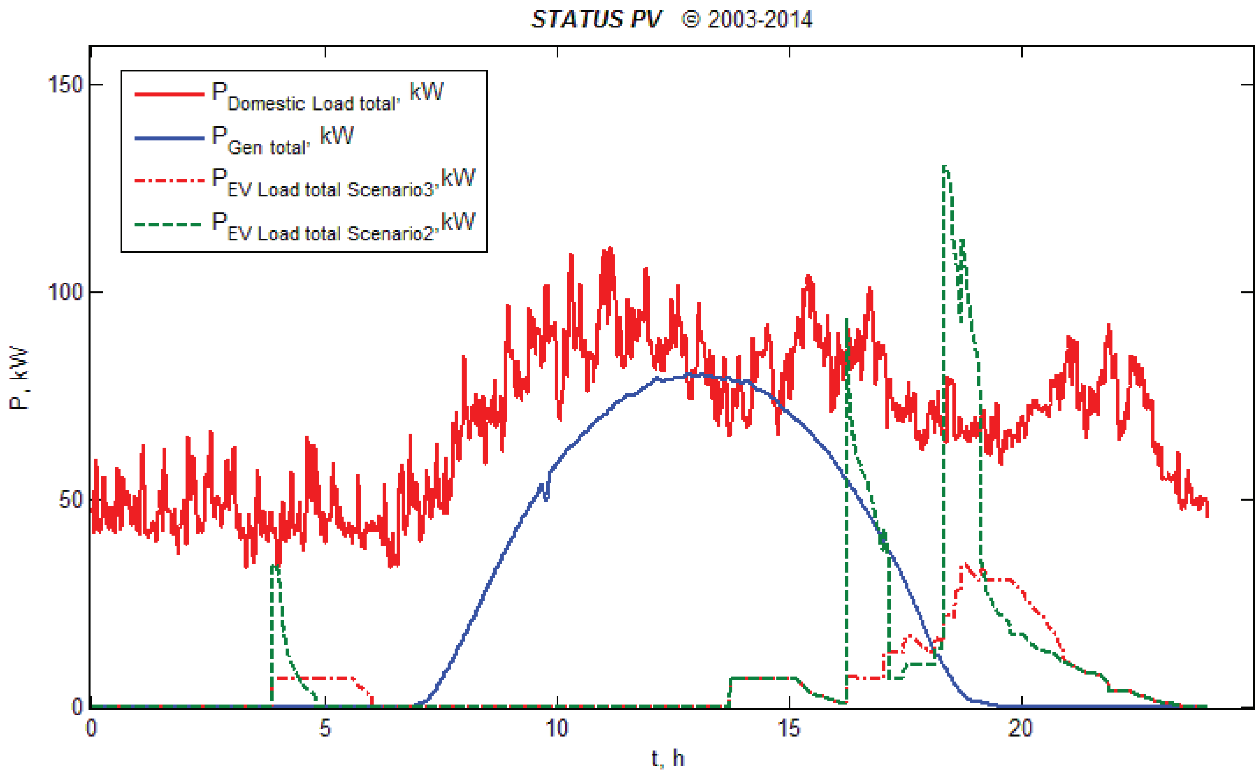


**Fig.6.** Aggregated load and PV generation profile without EV charging.

## 5. RESULTS

The following results for the test case simulation scenarios are obtained:

1) *Scenario 1* Fig.7 presents the voltage variation in each bus over the time when EV charging is not present. The active power injection of the PV generators causes

significant voltage rise during the midday generation maximum. With transformer tap setting of V=1.00 p.u. the maximum voltage reaches 428 V and the voltage variation band is 72V correspondingly (Fig.7). Due to the presence of distributed generation close to the load the electrical distance between the sources and the consumers remains small which finally results in admissible power and energy losses (Fig.10). The energy losses in this case are 42,25 kWh.

2) *Scenario 2* Fig. 8 presents the voltage variation in each bus over the time when Mode 1, Mode 2, Mode 3 and Mode 4 EV charging is applied. The EV charging devices cause significant and unacceptable voltage deviations and power line overloading- especially during the Mode 4 fast charging processes (Fig.8). The maximum voltage remains 428 V and the minimum voltage value reaches 310 V. The voltage variation band is 118V. The line overloading during the fast charging modes results in significantly increased power and energy losses in this scenario (Fig.10). The energy losses in this case reach the remarkable value of 71,92 kWh.

3) *Scenario 3* The EV charging devices cause significant voltage deviations also when Mode 1 and Mode 2 charging is applied. Fig.9 presents the voltage variation in each bus over the time. The maximum voltage remains 428 V and the minimum voltage value reaches 335 V. The voltage variation band is 93V. The energy losses in this case are 56,90 kWh. Although the system state is not admissible it has to be however noticed that it is still less critical than in Scenario 2.

Table 2 summarizes the results obtained for each scenario.

**Table 2**

Simulation results summary

| *Scenario* | *Umin,V* | *Umax,V* | *ΔU,V* | *ΔE,kWh* |
|---|---|---|---|---|
| 1) Operation without EV charging | 356 | 428 | 72 | 42,3 |
| 2) Mode 1,2,3 and 4 EV charging | 310 | 428 | 118 | 71,92 |
| 3) Mode 1 and Mode 2 EV charging | 335 | 428 | 93 | 56,90 |

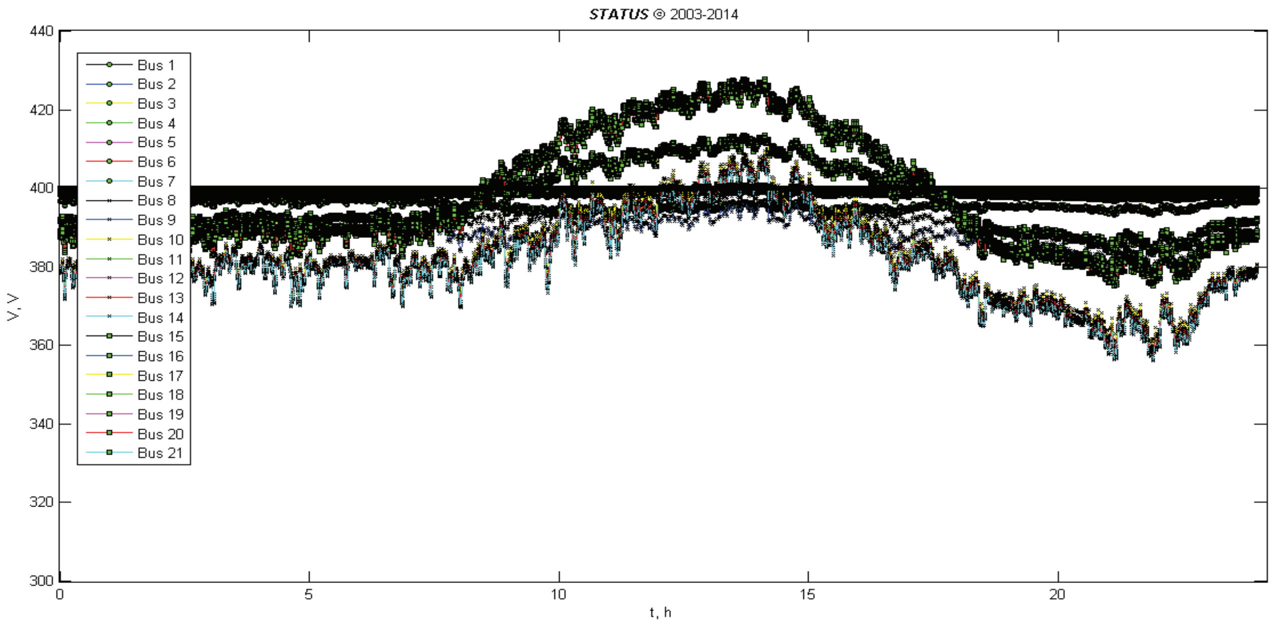


**Fig.7.** Voltage profile evolution without EV charging (Scenario 1).

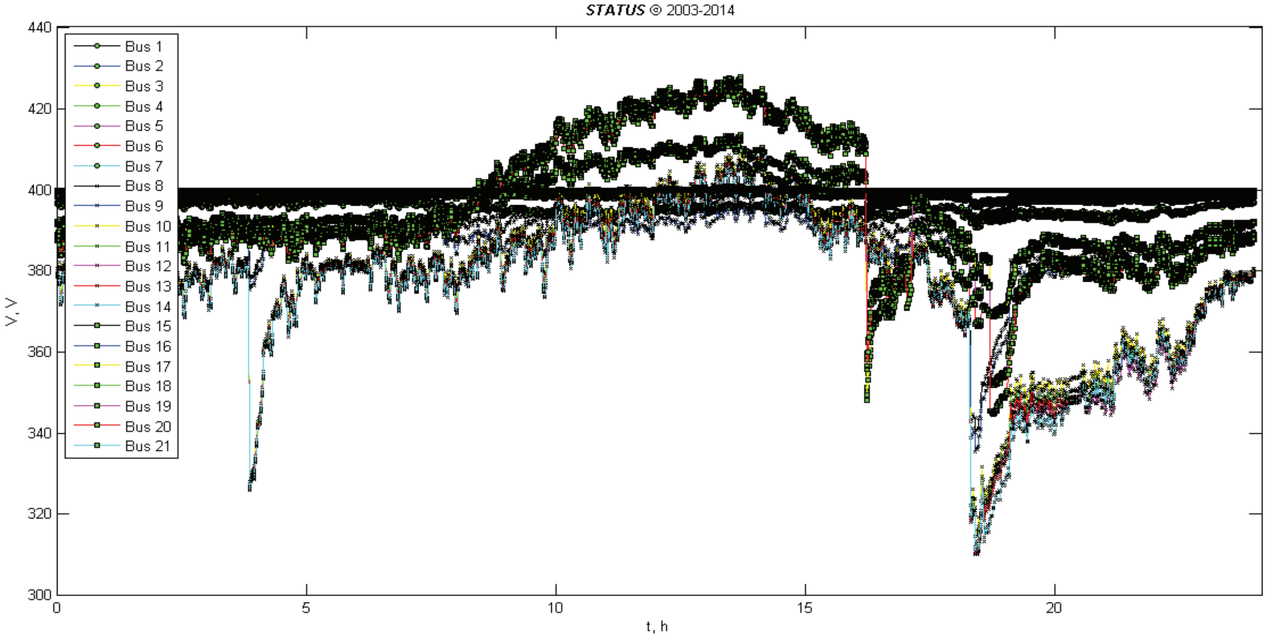


**Fig.8.** Voltage profile evolution with Mode 1, 2, 3 and 4 EV charging (Scenario 2).

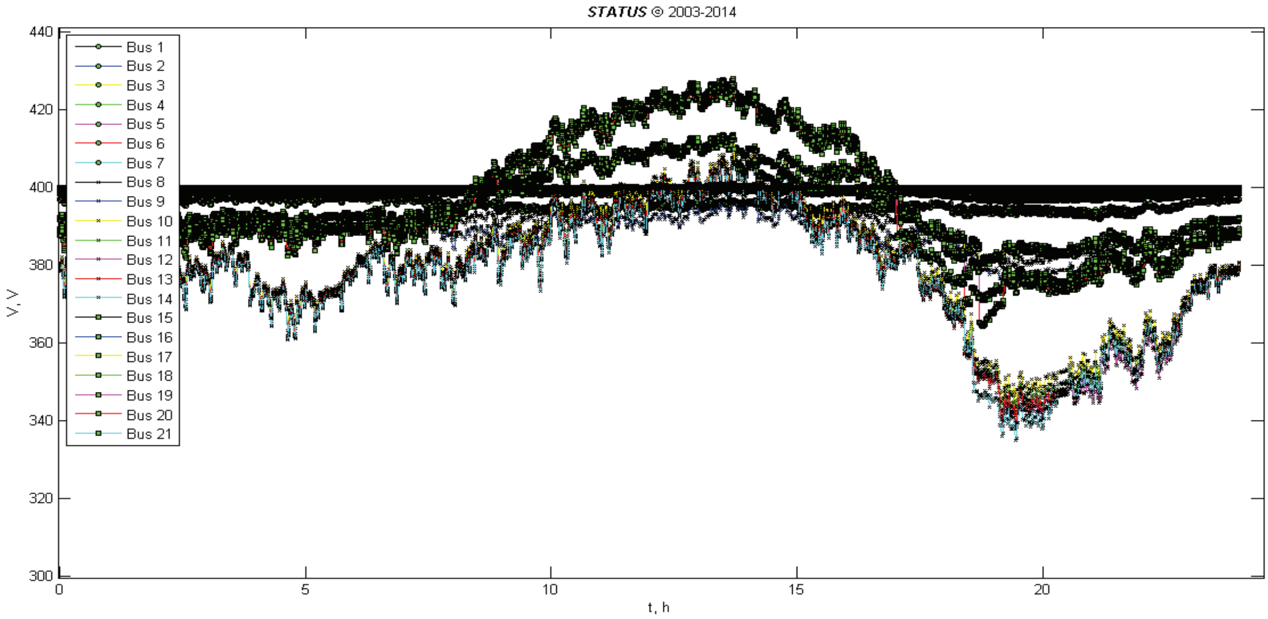


**Fig.9.** Voltage profile evolution with Mode 1 and Mode 2 EV charging (Scenario 3).

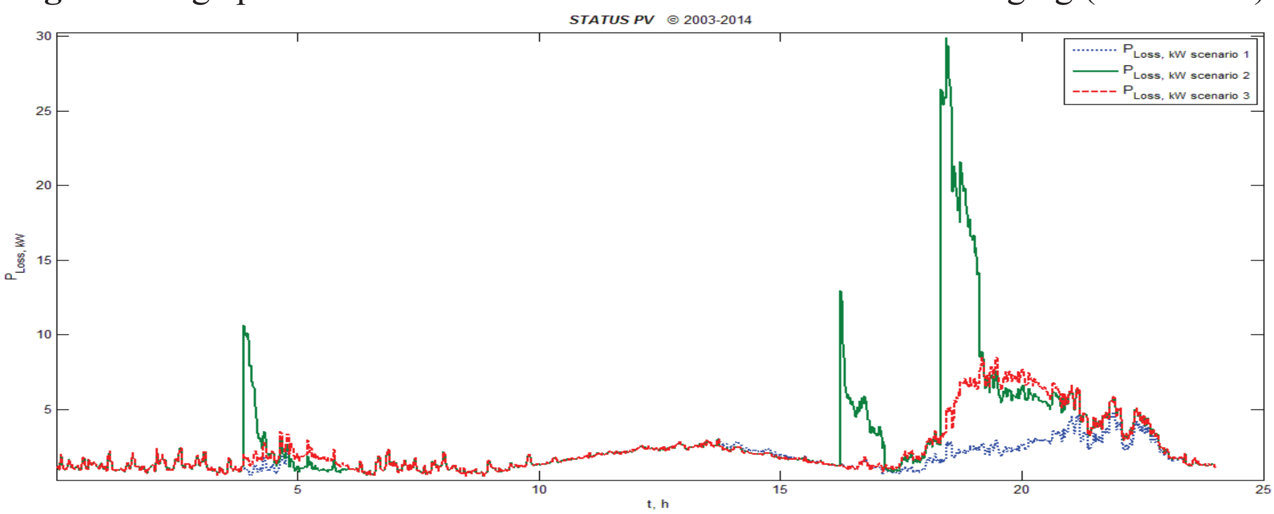


**Fig.10.** Aggregated power losses evolution during Scenario 1, 2 and 3.

## 4. CONCLUSIONS

A promising and computationally efficient approach for dynamic analysis of distribution network with EV charging and DER is presented. The approach is adequate for the majority of the power system studies like control algorithms testing, EV and DER hosting capacity evaluation, EV interoperability testing, grid stability analysis and smart grid power management testing. The results of the test dynamic simulations obtained show that, the EV charging is a significant issue, which has to be studied. New properly selected smart grid control concepts have to be defined and analyzed in order to allow stable and reliable network operation with EV charging.


## БЛАГОДАРНОСТИ

Авторите изказват своята благодарност към Министерството на образованието и науката на Република България и Европейската комисия за подкрепата в рамките на проекта DERri GA No 228449 по FP7 http://www.der-ri.net, съфинансиран от МОН по договор № ДКОФ7РП02/4-03 на НИС при ТУ– София.

## ACKNOWLEDGEMENT

The authors thank the Bulgarian Ministry of Education and Research and European Commission for the support from the FP7 project DERri, GA No 228449 *www.der-ri.net* co-financed from Bulgarian Ministry of Education and Research, Contract No ДКОФ7РП02/4.


## REFERENCES


[1] Yijia Cao, Shengwei Tang, Canbing Li, Peng Zhang, Yi Tan, Zhikun Zhang, et al, ***An optimized EV charging model considering TOU price and SOC curve*** , IEEE Transactions on smart grid, Vol. 3, NO. 1, p. 388- 393, March 2012

[2] P. Papadopoulos, "Integration of electric vehicles intro distribution Networks," Ph.D. dissertation, Cardiff University, 2012

[3] Stanev R., A. Krusteva, C. Tornelli, C. Sandroni, ***A quasi-dynamic approach for slow dynamics time domain analysis of electrical networks with distributed energy ressources***, Fifth Scientific Conference of EF 2013, 02.09.-05.09.2013, Proceedings of the TU- Sofia, V 63, Issue 6 (2013), pp. 273-281, ISSN 1311-0829

[4] R. Stanev, ***"Voltage control strategies for distribution networks with distributed energy resources"*** Fifth Scientific Conference of EF 2013, 02.09.-05.09.2013, Proceedings of the TU- Sofia, V 63, Issue 6 (2013), pp. 263-271

[5] Concepts, Capacities and Methods for Testing EV systems and their interoperability within smart grids FP7 EU project 2013-2016 *www.cotevos.eu*



**Autors:** Rad Stanev, Associate professor PhD, Electrical Power Engineering Department, Technical University of Sofia, E-mail adress: *rstanev@tu-sofia.bg* ; Anastassia Krusteva, Associate professor PhD, Power Electronics Department, Technical University of Sofia; Metody Georgiev, Associate professor PhD, Faculty of Automation, Technical University of Sofia



**Received:** 15 December 2015 **Reviewer:** Associate professor PhD N. Matanov