EVALUTION OF RESILIENCE OF A DISTRIBUTION GRID AFTER ADDITION OF HEAT PUMPS AND ELECTRIC VEHICLES AS HOME AUTOMATED LOADS OPERATING UNDER MULTIPLE CASE SCENARIOS FOR ALL HOUSEHOLDS

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Abstract

The increasing integration of heat pumps (HP) and electric vehicles (EV) in Finland's households as home automated loads may cause overloading in distribution grids. Furthermore, the inadequate cybersecurity of these automated loads might make already strained grid susceptible to coordinated load attacks. Hence, to analyse grid resilience under such scenarios, medium and low voltage network in the region of South Savo, Finland operated by distribution system operator (DSO) Suur-Savon Sähkö Group is tested. For each household in the network, heat pump consumption is modelled using two methods: HP-Model 1 and HP-Model 2; whereas the EV load is modelled for two charging powers: 1.84 kW and 11.1 kW. In total, 8 different cases are formulated for normal and post-hacking operation of these home automated loads. Then, for each case, existing customer load profiles are modified to test the effect on all service points, conductors and transformers throughout the network. It is found that heat pumps and EV (1.84kW) do not pose significant risk to grid capacity. However, EV (11.1 kW) causes some overloading and undervoltage issues for the grid in normal operation and deteriorates network health massively in post-hacking scenario.

1 Introduction

Evolution of houses, from caves to modern homes have been centered around the fundamental aspects of safety, security, and comfort. Modern home automation systems not only enhance the aforementioned characteristics but also offer energy efficiency. However, there are multiple risks associated with the home automation systems particularly in the realm of cybersecurity. The current condition is evaluated by [1] in which it is assessed that approximately 80% of home automation devices are susceptible to hacking. In particular, research analysis done in [2] identifies weak encryption layer, outdated protocols, and firmware failure to be main vulnerabilities within home automation systems. It is also analyzed by [3] that rules and regulations have not developed at same pace as advancement of IoT industry.

In Finland, the penetration rate of smart home automation systems is projected to grow significantly, rising from 29.8% in 2024 to 69.8% by 2028 [4]. Nordic and Global trends suggest that this growth is closely aligned with the electrification of households, particularly with the growing adoption of heat pumps and electric vehicles [5]. Hence, for this research paper, future scenario of 100% penetration rate of these loads controlled through home automation systems is simulated for the households located in the region of South Savo, Finland. Then, load manipulation strategies are formulated as post-hacking scenarios for these loads. It must be noted that existing research on load manipulation through cyberattacks primarily focus on power system models, such as the IEEE 39-bus system or Nordic 32 bus system. In contrast, this research paper adopts a novel approach by utilizing real customer data to individually model heat pump and EV loads for each household, and the impacts are then analysed on an actual medium and low voltage grid.

2. Methodology

Each user point belonging to residential houses is individually assigned with one heat pump/EV. This modelled load is then allocated to service points based on the number user points connected to them. Moreover, time resolution of one hour, and simulation timespan of one year is used.

2.1 Heat Pump Load Modelling

Over 81% of heat pumps sold in Finland in 2022 were air-air heat pumps [5]. Based on this trajectory, each household is assigned one air-air heat pump with the target to cover complete space heating requirements. Hence, air-air heat pump will be referred as heat pump onwards. Moreover, as

the area under study is in Northern Hemisphere with cold climate, it is assumed that heat pump is used only for heating purpose. To model heat pump consumption for each household, following steps are taken:

2.1.1 Input Parameters: Outdoor temperature data is taken from Partala observation station of Finnish Meteorological Institute which has smallest Euclidean distance from South Savo. Hourly temperature data is collected over ten-year period from 2013 to 2022 from which hourly average temperature for one year is extracted. This averaging technique ensures avoidance of extreme cold temperatures which is important to avoid oversizing of heat pump. Indoor temperature representing heating degree day (T_{HDD}) is set at 17°C [6]. Indoor Set Point Temperature (T_{in}) is set at 20°C as per the guideline of National Building Code of Finland [7]. In-blast Temperature (T_{ib}) is the temperature of heated up air exiting condenser of heat pump which is set at 35°C for this simulation based on combined study by Aalto University and VTT [8]. Moreover, according to Nordic Council of Ministers, nominal coefficient of performance (COP_N) of heat pump in Nordic climate is 3.5 at 7°C Outdoor and 20°C indoor set point temperature in accordance with SFS-EN 14511-2 [9]. Seasonal Performance Factor (SPF) is taken to be 2.75 in this simulation for Nordic Climate [9].

2.1.2 Sum of Heating Degree Days: For South Savo, sum of HDD provides basic estimation of overall heating demand during extended period which in this case is one year. Its calculation methodology is explained in this research paper [8].

2.1.3 Final Coefficient of Performance of Heat Pump ($COP_F(t)$): Initially, theoretical coefficient of performance ($COP_T(t)$) is calculated through following formula [8]:

$$COP_T(t) = \frac{T_{ib}}{T_{ib} - T_{Outdoor}(t)}$$

$COP_F(t)$ is then derived by multiplying loss factor (f) with $COP_T(t)$ [8].

2.1.4 Annual Space Heating Requirements of each Household (Q): Annual electricity consumption of each service point is used as an indirect way to estimate annual space heating requirement of each household. For this estimation, it is also considered whether the household belongs to electric or non-electric heated load group. For electric heated load groups, heat pumps replace certain portion of space heating already being provided by electric heating. For non-electric heated load groups, heat pump load is simply added to existing customer load. Furthermore, it is unknown which households already have heat pump installed, and how much space heating requirements are they already fulfilling. Hence, two different methods are utilized in this regard. In first method (HP-Model 1), it is assumed that no household has heat pump installed initially. In second method (HP-Model 2), it is assumed that each household has certain amount of space heating already being provided by heat pump depending upon Finland's National statistics. Detailed calculation information can be found in this thesis [10]

2.1.5 Hourly Space Heating Demand ($I_{Spaces\_demand}(t)$) and its Consumption Requirement ($e_{Spaces\_Demand}(t)$): Hourly space heating demand and its electricity consumption requirement for each household can be calculated through the following formula [8]:

$$I_{Spaces\_demand}(t) = \frac{Q(T_{HDD} - T_{Outdoor}(t))}{Sum\ of\ HDD}$$

$$e_{Spaces_{Demand}}(t) = I_{Spaces_{Demand}}(t) \times COP_F(t)$$

2.1.6 Heat Pump Consumption: To size heat pump for all households, smallest heat pump of 0.25 kW output capacity is allotted to the house having least amount of annual consumption. For smallest sized heat pump, hourly space heating demand ($(I_{Spaces_{SingleHP}}(t))$) and electricity consumption ($(e_{Spaces_{SingleHP}}(t))$ is calculated [8]. In the next step, each heat pump is sized ($(I_{HPSpacesMax}(t))$ by comparing ($(e_{Spaces_{SingleHP}}(t))$ to ($e_{Spaces_{Demand}}(t)$) [8]. Then, actual heating output ($I_{HP}(t)$) and actual electricity consumption ($e(t)$) of each heat pump is calculated [8]:

$$if\ max.of\ I_{Spaces\_Demand}(t) > max.of\ I_{HP_{Spaces_{Max}}}(t)$$

$$I_{HP}(t) = I_{HP_{Spaces_{Max}}}(t)$$

$$else\ I_{HP}(t) = I_{Spaces\_Demand}(t)$$

$$e(t) = \frac{I_{HP}(t)}{COP_F(t)}$$

2.1.7 Heat Pump post-Hacking Scenario Formulation: Worst post-hacking scenario is when all heat pumps of all households are compromised and operated at maximum capacity with the intention to cause a static load attack on the grid. In this scenario, electricity consumption of each heat pump throughout the year will be equal to its maximum possible electric input ($e\_maximum$).

$$e\_maximum = \frac{I_{HP\_Spaces\_Max}(t)}{COP_F(t)}$$

Moreover, hourly hacking capacity of each heat pump, measured in terms of electricity consumption is:

$$e_{hacking}(t) = e_{maximum} - e(t)$$

Figure 1 provides comparison of consumption versus hacking capacity of a heat pump for a random household. It

can be seen that as heat pump consumption increases, its hacking capacity decreases and vice versa. Hence, heat pump is not an ideal device for load attack because its consumption pattern has direct, and hacking capacity has inverse correlation with grid loading conditions especially for very cold or very hot climates. For instance, in Finland, peak loading conditions are in winter when heat pump consumption would already be high thus leaving very little capacity of heat pumps for static load attack on the grid.

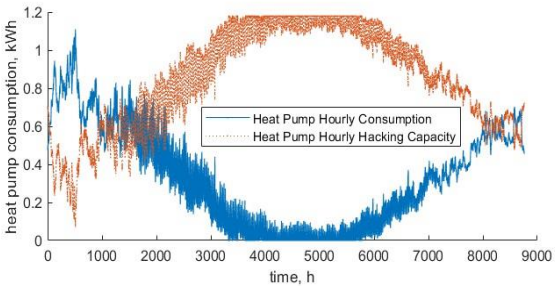

Fig. 1 Comparison of Heat Pump Electricity Consumption

2.1.8 Addition of Heat Pumps to Customer Load: Heat pump hourly consumption is added arithmetically to customer hourly consumption both representing the expected values of normal distribution. This is done for all households for heat pump normal operation as well as post-hacking scenario respectively.

2.2 Electric Vehicle Load Modelling

The EV load is considered constant over the entire charging period, with self-discharge effects neglected, and only home charging stations utilized for EV charging. It is also assumed that driving behaviour of people will remain the same after replacement of internal combustion engine vehicles with EVs.

2.2.1 Input Parameters: First parameter is daily driving distance for which the mean value is 46 km with standard deviation of 20 km in Finland [11]. Secondly, daily mean arrival time of 16.53h is used with 3.99h standard deviation [11]. Furthermore, two different charging powers of 1.84 kW and 11.1 kW are set for home charging stations respectively. Charging efficiency is kept constant at 90% for whole charging timespan [11]. Moreover, EV consumption is set at constant value of 0.25 kW/km throughout the year for all EVs [11]. Furthermore, generalization is made that each EV is connected to home charging station each day for 16 hours since arrival time due to 8-hour office working time.

2.2.2 Assignment of Driving Distance and Arrival Time to each Household: Normal random distribution pattern is formulated to allocate daily driving distance as well as arrival time for all households based on mean and standard deviation values. Through this method, tens of thousands of EV charging load curves would be formulated. As the software tool used to alter load profiles takes significant time to handle single load curve change, processing it tens of thousands of times is not practically feasible. Hence, a grouping technique is utilized to limit the number of unique load curves to 24, with separate methods for 1.84 kW and 11.1 kW charging to ensure accuracy. This grouping technique can be studied in detail in this thesis [10].

2.2.3 Calculation of Charging Timespan: Charging timespan for each EV is calculated through the following formula [11]:

$$Timespan = \frac{Distance \times EV\ Consumption/km}{Charging\ Power \times Efficiency}$$

2.2.4 Allocation & Addition of EV Charging Load to Customer Load: Hourly EV consumption is calculated based on charging duration, power, and arrival time which is then integrated arithmetically into the existing customer load for the entire year. This process is repeated twice for normal operation of EV charging, assuming all customers first use a 1.84 kW and then an 11.1 kW charging power.

2.2.5 EV Charging post-Hacking Scenario Formulation: As the battery of EV gets depleted only a certain amount throughout the day, load shifting technique is used rather than load maximization. One strategy could be to initiate EV charging load during high price/peak loading hours. However, one major aspect mostly missing in this methodology is the consideration of number of EVs connected to the network during those peak hours. Based on arrival time and overnight EV connection to the grid, simulation is done to calculate descending order of number of EVs connected to the grid. It was found that most EVs connected are connected to the grid at 01:00, followed by 24:00, 02:00, 23:00, 22:00, 03:00, 21:00, 04:00, 05:00, 20:00, 06:00, 19:00, 07:00, 18:00, 08:00, 17:00, 09:00, 16:00, 10:00, 15:00, 11:00, 14:00, 12:00, 13:00. It shows that order of number of EVs connected to the grid do not correspond directly to the evening peak load hours, however, if all EV load gets compromised and is maximized together, it can formulate its own peak which could cause very damaging effects for the grid. Hackers would delay EVs from charging when plugged in, and for the next 16 hours until EV stay plugged in, would charge EVs based on descending order total vehicles connected to the network irrespective of existing grid load.

3 Results

Eight simulations are conducted, and their results are compared to their own base case. Real Network Information System and customer data is utilized for each simulation. Normal operation and post hacking represent state of operation of HP/EV load after integration to existing customer load profiles. For result analysis, it is important to

consider that electric heating consumes nearly twice as much electricity as heat pumps [12]. In households with existing electric heating, replacing these systems with heat pumps significantly reduces overall consumption. This reduction outweighs the additional load introduced by heat pumps in these houses, and to some extent may neutralize the heat pump load addition in those houses which do not have prior electric heating system. Also, for Finland, heat pumps do not prove to be ideal loads for static load attacks because of low hacking capacity during peak load in winters. Moreover, for EV (1.84 kW), this charging power seems too insignificant cause major changes. However, EV (11.1 kW) poses most significant issues for the network especially in post-hacking scenario.

3.1 Effects on Service Points

In the whole network, there are 79488 service points. However, for EV (1.84 kW) simulations, data for only 68952 service points is available. So, each simulation case should be evaluated against its own base case. Average loading level and number of service points overloaded beyond 100% can be seen from tables 1 and 2 respectively. Moreover, table 3 represents number of service points experiencing undervoltage below 95%.

Table 1 Average load level of all service points

Simulation	Base Case	Normal Operation	Post Hacking
HP-Model 1	24.93%	22.59%	23.67%
HP-Model 2	24.93%	16.51%	18.51%
EV (1.84 kW)	24.791%	24.791%	24.792%
EV (11.1 kW)	24.93%	34.43%	53%

Table 2 Number of service points loaded beyond 100%

Simulation	Base Case	Normal Operation	Post Hacking
HP-Model 1	903	517	545
HP-Model 2	903	575	693
EV (1.84 kW)	776	776	776
EV (11.1 kW)	903	1864	15639

Table 3 Number of service points experiencing undervoltage below 95%

Simulation	Base Case	Normal Operation	Post Hacking
HP-Model 1	9845	10029	12064
HP-Model 2	9845	5905	8050
EV (1.84 kW)	8770	8771	8759
EV (11.1 kW)	9845	17762	52474

3.2 Effects on Transformers

In the whole network, there are 9465 transformers for all cases, except for EV (1.84 kW) simulation, where only 4742 transformers are analysed. Table 4 presents average loading level, whereas table 5 presents number of transformers overloaded beyond 100%.

Table 4 Average load level of all transformers

Simulation	Base Case	Normal Operation	Post Hacking
HP-Model 1	33.83%	33.89%	35.72%
HP-Model 2	33.83%	25.58%	29.04%
EV (1.84 kW)	34.89%	34.90%	34.90%
EV (11.1 kW)	33.83%	42.32%	73.36%

Table 5 Number of transformers loaded beyond 100%

Simulation	Base Case	Normal Operation	Post Hacking
HP-Model 1	48	52	72
HP-Model 2	48	27	37
EV (1.84 kW)	23	23	23
EV (11.1 kW)	48	226	2491

3.3 Effects on Conductors

In the whole network, there are 244284 conductors for all cases, except for EV (1.84 kW) simulation, where data of only 227308 conductors is available. Table 6 presents average loading level, whereas table 7 presents number of conductors overloaded beyond 100%.

Table 6 Average load level of all conductors

Simulation	Base Case	Normal Operation	Post Hacking
HP-Model 1	8.20%	7.70%	8.10%
HP-Model 2	8.20%	5.60%	6.34%
EV (1.84 kW)	8.4828%	8.4832%	8.4838%
EV (11.1 kW)	8.20%	11.11%	18.90%

Table 7 Number of conductors loaded beyond 100%

Simulation	Base Case	Normal Operation	Post Hacking
HP-Model 1	226	172	179
HP-Model 2	226	148	172
EV (1.84 kW)	205	205	205
EV (11.1 kW)	226	421	3905

4 Analysis

The outputs of both heat pump simulations suggest no significant adverse impacts on the network. On the contrary, most key performance indicators (KPIs) demonstrate an improvement in network health. This improvement can likely be attributed to the substitution of electric heating with heat pumps for houses in electrically heated load groups, resulting in reduced overall energy consumption. However, certain challenges for the network are observed. In the HP-Model 1, two KPIs indicate negative effects: increment in number of service points experiencing undervoltage and in the number of overloaded transformers. Particularly, percentage of service points with voltages below 95% increased by 1.8% during normal operation, and by 22% in post-hacking scenario as compared to the base case. Moreover, number of transformers operating above 100% capacity rose from 48 in the base case to 52 during normal operation, and 72 in the post-hacking scenario.

For EV (1.84 kW), no major impact on network elements is observed under normal operation or the post-hacking scenario. This suggests that either 1.84 kW charging power is too small to cause notable issues or the chosen hacking strategy may not have been optimal, as this level of EV load may be insufficient to create a distinct peak load. EV (11.1 kW) reveals significant adverse effects on network elements. Under normal operation, some adverse effects in terms of overloading and undervoltage can be observed. However, extreme situation arises during post hacking scenario where nearly 20% of all service points exceed 100% capacity, over 66% of all service points experience undervoltage below 95%, and more than 25% of all transformers become overloaded. Number of conductors overloaded beyond 100% increase seventeen-fold compared to base case, though they account for mere 1.59% of total conductors in the network. Thus, the post-hacking scenario of EV (11.1 kW) proves to be most detrimental.

5 Conclusion

This research paper investigates the impact of heat pumps and electric vehicles (EVs) as home automated loads under pre and post-hacking scenarios for the distribution grid in South Savo, Finland. The key findings indicate that integration of heat pumps and EVs (1.84 kW) to households even with 100 % penetration rate do not pose significant threat to the network even for post hacking scenario. However, if all households were to charge their EVs using 11.1 kW home charging stations daily, this could potentially strain the network. More critically, load-side attack involving 11.1 kW EV home chargers in a post-hacking scenario could lead to severe overloading of service points, transformers, and conductors; and undervoltage issues for service points across the grid. To mitigate such risks, mandatory emergency actions like supply voltage dependent charging or expensive grid reinforcement would be necessary in advance. In conclusion, this research provides foundation for further investigation into impacts of integration of home automated loads as well as coordinated load side attacks on medium and low voltage networks.

Acknowledgement: The paper has received funding from Sähkötutkimuspooli (Energiateollisuus ry) and Business Finland project “Integrated automation for distribution grid and DERs”.

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