POTENTIAL FOR IMPROVING ECONOMIC FEASIBILITY OF AUTONOMOUS ROBOTIC SYSTEMS BY USING WIRELESS CHARGING SYSTEMS

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Abstract. This research examines the economic viability of converting autonomous robotic systems to use wireless power transfer (WPT) for their dynamic charging during operation. Existing static robot charging models were compared to wireless charging, The analysis was made by developing Matlab model to analyse the process of charging autonomous service robots dynamically wirelessly versus statically by traditional means. The results demonstrated that wireless dynamic charging can potentially significantly increase the productivity for service robots and is economically feasible for the WPT technologies.

Keywords: wireless charging, electric vehicles, lead-acid batteries, battery lifetime.

Introduction

This research focuses on a very specific niche – wireless charging for robotic systems in warehouses. Robots are researched in thousands of articles; as they are becoming more and more widespread in all areas, they are also becoming an important part of a modern warehouse operation [1]. Many areas of the warehouse operations have been extensively examined to enhance the running of warehouses, from general planning to picking optimisation, including performance improving algorithms [2], which are applicable for robots as well as human operators. Also wireless charging lately has been examined very extensively, however, generally from the technical point of view, as wireless energy transfer, not as an economically feasible means of efficiency improvement. Furthermore, there has been little to no research work done on the techno-economic analysis on how the wireless charging can benefit the warehouse operations – which is surprising, since in practice WPT have been used for years already [3].

This is a first of a series of articles dedicated to wireless charging of industrial service robots as a means of improving the economic feasibility of warehouse operations, and it is intended as a general introduction of wireless charging of industrial service robots to assess the potential of the technology.

Materials and methods

In order to evaluate the possible effects of wireless charging, a battery degradation model was created in MatLab, which in detail has been described in the previous research[4]. This model depicts the degradation of lead-acid batteries, which are still widely used for robotics in industrial applications, depending on charging scenarios, like the depth of discharge (DoD) and charging speed.

This model was expanded for this research, to include also dynamic wireless charging, as robots move along wirelessly electrified pathways. For that, the energy flow modules were modified to permit simultaneous energy inflow from wireless charging and outflow from the robots' movement during dynamic charging, which would result in either net charging or discharging of the battery. Additional blocks were included in the model to allow simulation of various randomly generated robot paths, and driving conditions.

The energy flow scenario parameters for the model have been clustered in the following groups:

- constant (limiting) parameters –include the factors that have been assumed to stay constant for the purposes of this model. They include initial robot parameters and some charging infrastructure parameters;
- variable parameters – this group includes variables that are randomized, depending on the possible outcomes as well as modelled (robot operation and charging) parameters that are changed to evaluate specific scenarios, namely wireless dynamic versus static charging.

The model includes two operational scenarios (A and B) and three charging scenarios (α, β and χ).

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Constant (limiting) parameters

The following robot parameters were used as constant during the scenarios, based on the Lesla wirelessly charging robot shown in Figure 1.

- Battery initial capacity (before degradation) C_{nom} = 1400 Wh at battery state of charge (SoC) 100 %.
- V – robot's speed. $V_{\max} = 0.8\ \mathrm{m \cdot s^{-1}}$ In this paper it is assumed that the robot is moving constantly on maximum constant speed to do the calculations for the worst case dynamic charging scenario.
- Robot net weight – W_n = 13.7 kg; Maximum cargo weight 50 kg.

Fig. 1. **Lesla industrial service robot**

Robot operation parameters

In this paper it is assumed that the robot's power consumption depends on two variable parameters: robot's state of operation and robot's full weight (including its load).

The model assumes four possible states of robot: 1: doing nothing (receiving a new task); 2: loading/unloading the load; 3: driving empty; 4: driving with the load. These states correspond to the following modes of the robot operation (Fig. 2) – the states are noted in parentheses.

In this model we have assumed optimum operation, that the robot never drives empty, but it delivers a new load to the warehouse, whilst it is picking up a new cargo from the warehouse. Thus, the effective emulation algorithm can be shortened to four stages:

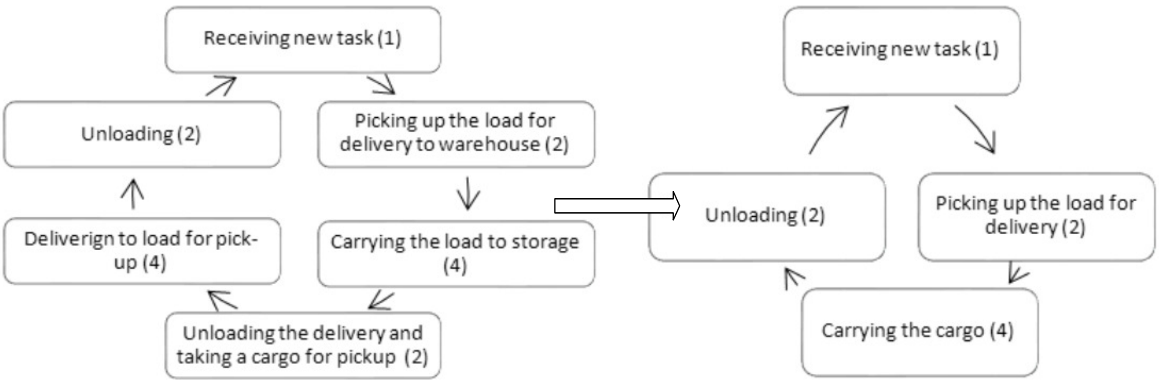

Fig. 2. **Modes of robot operation for model's purposes**

The maximum trip distance the robot was doing in one task was 100 meters, the minimum distance – 20 meters. In this simulation 700 000 trips were generated in two operational scenarios – A: random and B: optimised.

The scenario A assumes that the load location is not optimised and that the cargo can be located anywhere in the warehouse – we have used uniform random distance distribution for this scenario.

The optimised scenario B assumes that the most frequently bought merchandize is located in the shelves nearer to the shop, so that the driving distance for these products is shorter. The exact distribution would largely depend on the specifics of the particular business. In our research just for demonstration purposes we have used the Pearson distribution with kurtosis of 2.7.

The distributions of the distances for both scenarios are presented in Fig. 3.

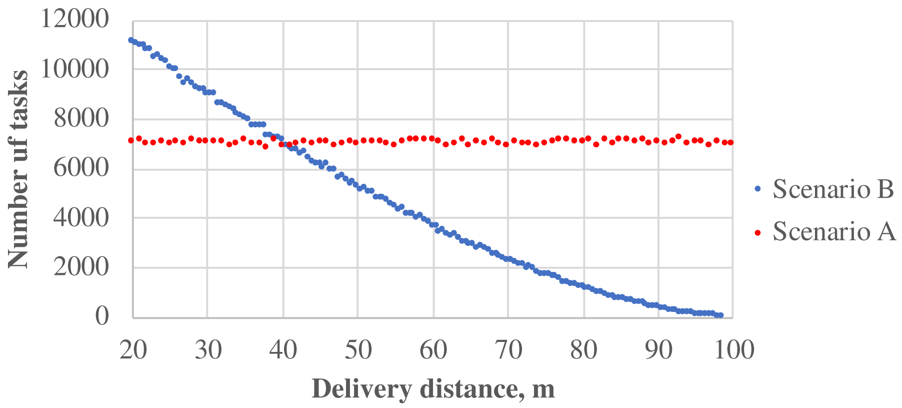

Fig. 3. **Modelled distributions of task distances for scenario A and B**

The robot's power consumption data for various modes of operation are presented in Table 1 together with the times of the operations used in the model for energy consumption calculation purposes.

Table 1

Robot's energy consumption parameters

State	Mode of operation	Energy consumption, Wh	Time, sec
0	Charging (stationary)	5	modelled, charging scenario α only
1	Receiving a new task Loading Unloading	5	3 10 10
3	Driving empty	16	(unused)
4	Carrying the cargo	16-18 modelled, depending on load	modelled, scenarios α and β

The robot's energy consumption while carrying load is variable, depending on the weight of the cargo. The energy consumption for this research has been obtained from the empirical measurements of the Lesla robot energy consumption, and it varies from 16 Wh up to 18 Wh for full load weighting 50 kg.

The table of weights for the simulation tasks was generated using uniform distribution as for a generic warehouse (Fig. 4). The same set of weights was used for all operation and charging scenarios.

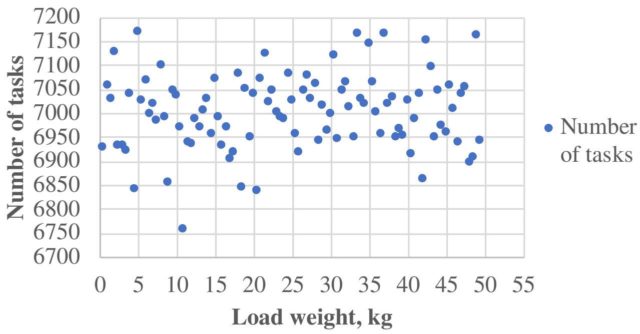

Fig. 4. **Modelled distribution of task weights**

Charging parameters

There have been three robot charging scenarios emulated for the analysis. The first charging scenario α assumes that the robot is charged using traditional plug-in methods. Two other charging scenarios – β and χ – use wireless charging. Scenario β assumes that wireless charging happens stationary during the robot states 0 and 1: respectively, when the robot is standing still during loading, unloading and during dedicated charging time. In scenario χ wireless charging happens both while the robot is stationary as well as dynamical during the movement. Scenario χ is further analysed in three sub scenarios: if the charging line is laid in 10 %, 30 %, 50 % or 70 % of the warehouse roads (i.e. the dynamic wireless charging process happens respectively 10 %, 30 %, 50 % and 70 % of the driving time).

In the simulation battery charging is set from 20 % SoC to 80 % SoC (Fig.5), which was selected by two factors: (1) the charge acceptance in this battery SoC range is the highest, which allows the fastest charging times (so called "bulk" and "boost" stages of the charging process) [5], and (2) the cycle life of lead-acid batteries decreases dramatically as discharged more than 80 %DoD.

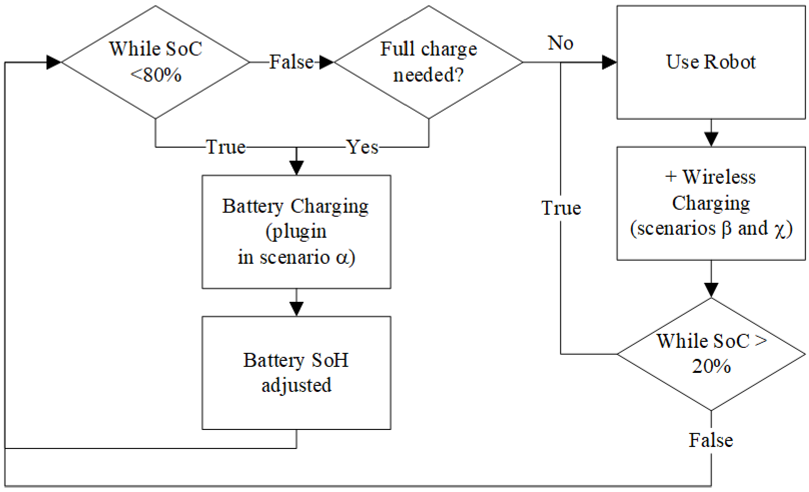

Fig. 5. **General robot charging algorithms**

However, each 4th time the batteries are charged fully up to 100 %, to prevent battery sulphation and faster capacity loss[6]. The battery remaining cycle life is adjusted in the model after each charging cycle, using the manufacturers data, which for this particular battery (U.S. Battery US 2200 XC2) is approximately 1000 cycles at DoD 80 % [7].

The following five charging scenarios have been analysed:

Table 2

Robot's charging scenarios

State	**Charging type**	**Charging periods – robot state**	**Charging power, W**	**Additional coefficients**
α	Charging (stationary)	0 – base charging	21	none
β	Wireless charging (stationary)	+ 1.Receiving a new task 2. Loading Unloading		parking precision over charging pad
$\chi 1$	Wireless charging (dynamic)	+ 4. While moving 10 % of time		driving precision over charging line
$\chi 2$		30 % of time		
$\chi 3$		50 % of time		
$\chi 4$		75 % of time		

In the traditional plugin charging scenario α charging happens (manually) at the dedicated spot until the set SoC is reached. In the stationary wireless charging scenario β and all three dynamic charging scenarios $\chi 1$ το $\chi 4$ the charging power is additionally discounted by the amount of the precision the robot moves itself over charging lines. The empirical data observed from the Lesla robot movement over charging lines demonstrate that usually the robot stays within 3 cm limits, so the charging alignment precision table for each task was generated using normal distribution with $\sigma = 3$ cm.(Fig. 6).

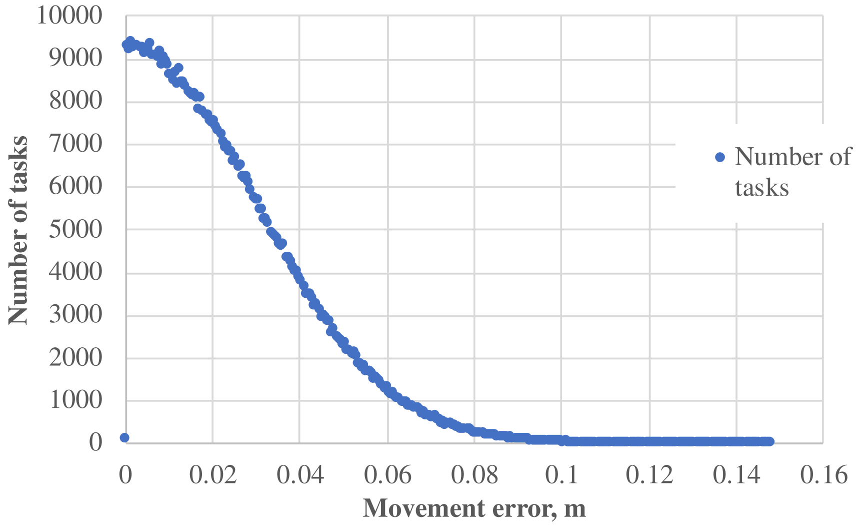

Fig. 6. **Distribution of robot's movement precision over charging lines**

The scenarios were run until the simulated battery reached the end of life. The battery end of life has been reached, when the maximal actual battery capacity falls below 20 % of nominal capacity, as per the battery standard EN 60896-11:2003[8].

Results and discussion

The battery end of life was reached in all scenarios but three – $\chi 3$(B) and $\chi 4$ (A and B) (see Figure 7), where the simulation limit of 700 000 tasks was reached by days 662, 929 and 612 respectively.

The battery end of life expectation difference between the distance distribution scenarios (A and B) is the smallest at the ordinary plug-in charging scenarios – only 11 days (or 5 %), however, this difference increases with wireless charging, reaching 169 days (32 %) between the scenarios A and B at 30 % dynamic wireless charging, which can be reasonably assumed that the effect from dynamic wireless charging is more distinct at longer driving distances between the charging events.

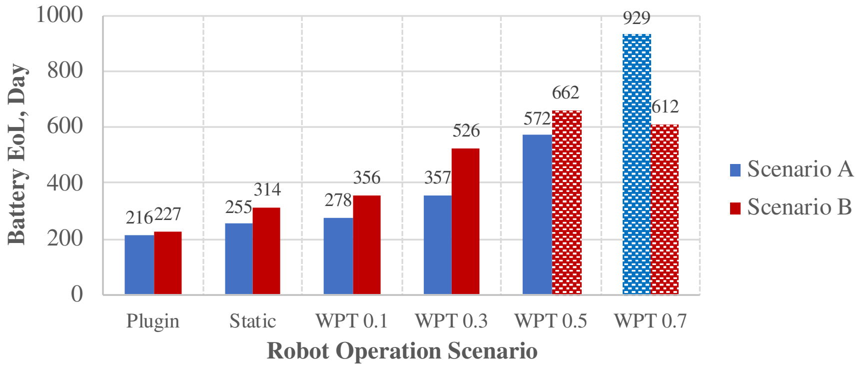

Fig. 7. **Battery expected end of life at various robot charging scenarios**

It can be assumed that this trend would continue, as because of different battery SoC during charging, the battery deterioration is quite lower during wireless charging than during ordinary charging (see Figure 10). As demonstrated in the scenario $\chi 4$(B), when the proportion of dynamic charging reaches 70 % of the road, the battery almost stops deteriorating.

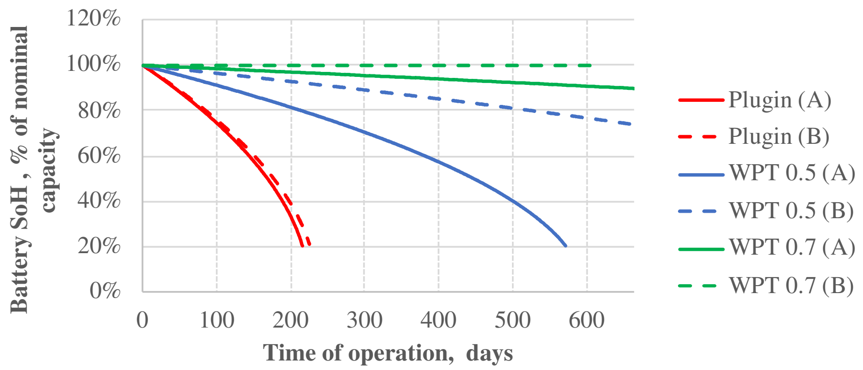

Fig. 8. **Battery SoHat various robot charging scenarios**

This is because the battery basically is never discharged below 80 % SoC, as the energy spent during 30 % of the road not covered by wireless charging is regained during cargo loading and unloading times (See Fig.9).

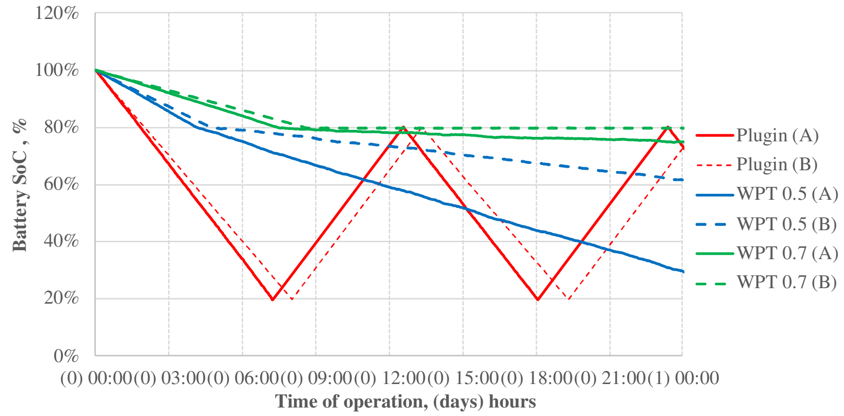

Fig. 9. **Battery SoC during 24 hour cycle at various robot charging scenarios**

Economic implications

There are both direct and indirect economic effects from dynamic wireless charging for robots. These effects can be analysed from capital and operational expenditure perspective. Direct capital expenditure includes installation of the charging infrastructure and robots; the operational expenditure includes the energy costs, service (battery replacement) costs etc. Indirect economic effects come from increase of the income gained from increased operation of the warehouse. To evaluate the effects correctly, the indirect effects have to be included, by assessing differences in the robot's productivity under various scenarios.

During simulation of traditional plug-in charging, the robot on average carried out 396 and 607 tasks per day in the distribution scenarios A and B, respectively (Figure 10).

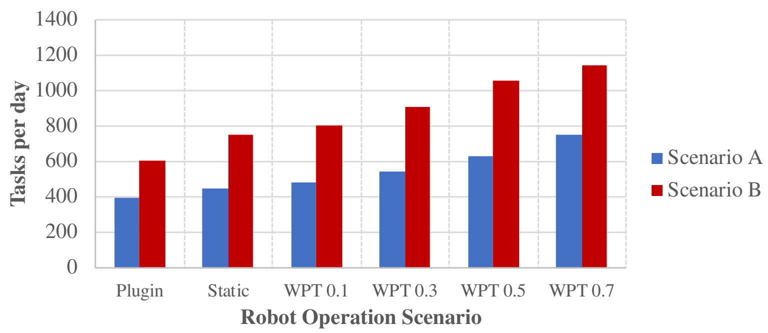

Fig. 10. **Effective tasks per day at various robot charging scenarios**

In static wireless charging scenarios these figures were 453 and 757 tasks per day, already reaching respective 14 % and 25 %improvement over plug-in charging. However, with dynamic wireless charging the robot productivity reached 750 and 1140 tasks per day or 90 % improvement over plugin charging.

It was noteworthy that throughout the whole range of dynamic wireless charging proportions, the effect was slightly larger for the optimised scenario B than for the uniformly distributed scenario A, except for the last one, which suggests diminishing return on increasing the dynamic wireless charging ratio.

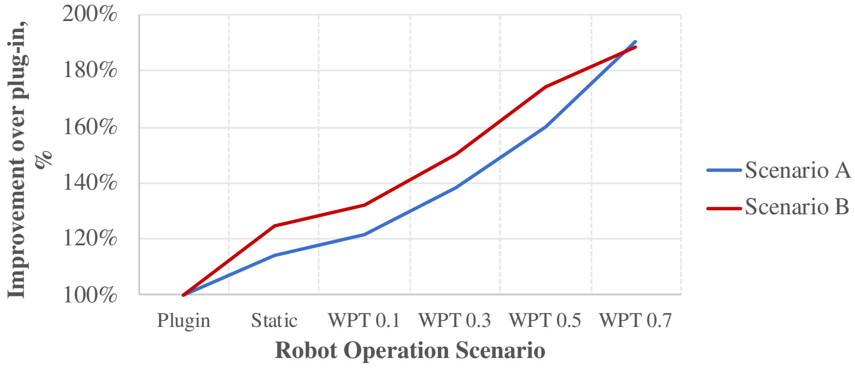

Fig. 11. **Improvement on effective tasks per day at various robot charging scenarios vs plug-in charging**

This also might be explained that by 70 % wireless charging in principal the point has already been reached, where there is no need for additional wireless track installation, as no further benefit can be achieved.

In order to get a preliminary effect of wireless charging on the cost of ownership for warehouse robots, the main economic factors are presented in the table. They can be attributed either directly to the task (direct costs), attributed indirectly to the tasks (battery lifetime), or attributed to the time (robot lifetime, infrastructure costs).

The following costs have been used for the calculations: cost of the warehouse robot – 5000 EUR (estimated retail cost of the Lesla robot), static charger – 21 EUR [9], Wireless charger costs about the same, around 20 EUR$\cdot$m^{-1} (estimated Lesla dynamic wireless charger cost per m), however, one static charger can be used at maximum for three robots (assuming, they do not have to be charged simultaneously), while the wireless charging infrastructure can be used by all robots. Therefore, the average infrastructure costs have been calculated assuming that 10 robots are using the dynamic charging infrastructure. The costs for electricity are calculated using the average electricity price in the EU 0.121 EUR$\cdot$(kWh)$^{-1}$ [10].

As the energy flow modelling was done up to failure of the batterySoH, all the calculations have been attributed to the tasks based on the end of the lifetime (EoL) cycle.

For this particular robot application, the cost of the robots (depreciation) is the most expensive part of the cost structure, amounting up to 95 % of the total costs for the operations. Therefore, the productivity increase plays much more important part than the increase of the battery lifetime or losses due to the wireless energy transfer inefficiency. It demonstrates that by increasing the robot productivity wireless charging can bring the operation costs down by 50 %.

Several directions for further research have been identified, which shall be addressed in further articles:

- an option of trickle charging for wireless dynamic charging will be realized in the model to keep the battery SoC in the range of 0.9 to 1 for lead-acid batteries, thus maximizing the battery lifetime – a feature that is not possible using the traditional plug-in charging,
- the model will be adapted for use of Li-Ion batteries, which currently still have not been used widely in industrial service robots because of the prohibitive costs, however, with constant decrease of the Li-Ion battery prices and additional benefits from wireless charging their use might become more economically justified,

- investigation of charging effectivity vs infrastructure costs based on deployment case study will be included for full economic benefit analysis,
- detailed implementation of distance optimisation algorithms will be carried out based on specific industry data to determine the optimum amount of charging lines needed for real-life conditions.

Table 3

Robot's cost of ownership at various charging and operational scenarios

Charging scenario	Charger costs, Static, EUR	Dynamic track, % of the distance	Electric track, m	Total infra-structure costs, EUR	Infrastruc-ture EUR, per robot (for 10 robots)	Days till battery EoL	Robot depr. / bat-tery EoL
αA	22	x	0	22	7	216	6 %
αB	22	x	0	22	7	227	6 %
βA	20	x	0	20	7	255	7 %
βB	20	x	0	20	7	314	9 %
χ1A	x	10	30	600	60	278	8 %
χ1B	x	10	22	440	44	356	10 %
χ2A	x	30	50	1000	100	357	10 %
χ2B	x	30	30	600	60	526	14 %
χ3A	x	50	70	1400	140	572	16 %
χ3B	x	50	38	760	76	662	18 %
χ4A	x	70	90	1800	180	929	25 %
χ4B	x	70	48	960	96	612	17 %
Charging scenario	**Robot depr., EUR per 1000 tasks**	**Battery costs, EUR per 1000 tasks**	**Number of tasks before EoL, 1000**	**Total energy, Wh per battery life**	**Energy, Wh per 1000 tasks**	**Energy, EUR per 1000 tasks**	**Total costs, EUR per 1000 tasks**
αA	3.46	0.23	85.6	61242	716	0.09	3.78
αB	2.26	0.15	137.8	61370	446	0.05	2.46
βA	3.02	0.17	115.6	78606	680	0.08	3.28
βB	1.81	0.08	237.8	96777	407	0.05	1.94
χ1A	1.94	0.10	196.2	88974	454	0.05	2.10
χ1B	1.70	0.07	286.1	113756	398	0.05	1.82
χ2A	1.35	0.06	363.3	123995	341	0.04	1.44
χ2B	1.50	0.04	479.7	182151	380	0.05	1.59
χ3A	2.16	0.06	362.5	219150	605	0.07	2.29
χ3B	1.30	0.03	700.0	253145	362	0.04	1.37
χ4A	1.82	0.03	700.0	402167	575	0.07	1.92
χ4B	1.20	0.03	700.0	272434	389	0.05	1.27

Conclusions

1. The calculations illustrate that wireless charging can decrease the costs by half, compared to static plug-in charging.
2. The model showed that the robot battery lifetime can be prolonged by using wireless charging and that the lifetime increase is significant, reaching almost constant SoC level at 70 % dynamic wireless charging ratio.
3. Apart from financial benefits from the increased battery lifetime, the robot productivity is increased reaching 190 % compared with plug-in. Economic calculations illustrate that robot depreciation is the largest cost item, and therefore increase of productivity is of primary importance.
4. The distance distribution has notable impact on robot productivity and its battery lifetime.

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