Efficient Scheduling of Electric Vehicle Charging via Tabu Search and Exact Optimization Techniques

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***Abstract*—The growing adoption of electric vehicles (EVs) necessitates efficient scheduling of charging operations to optimize limited infrastructure and maximize demand satisfaction. This study addresses the Electric Vehicle Charging Scheduling Problem (EVCSP) with the objective of maximizing the number of fulfilled charging requests. We propose two complementary solution frameworks. The first is an enhanced global mathematical programming model that captures the full problem structure and delivers high-quality solutions, even for large-scale instances. The second is a hybrid optimization approach that decomposes the problem into two interrelated components: EV-to-charger assignment and energy delivery optimization. A tabu search (TS) algorithm explores diverse assignment configurations, while each generated assignment is evaluated via exact mathematical programming to optimize energy allocation. Computational experiments show that both frameworks significantly outperform conventional approaches in solution quality and efficiency. These results highlight the potential of the proposed methods for scalable and effective EV charging management, supporting the operational needs of increasingly complex EV networks.**

***Index Terms*—Electric Vehicle, Charging Scheduling Problem, Mathematical programming, Tabu Search, Hybrid Optimization**

I. Introduction

The rapid adoption of electric vehicles (EVs), driven by the global transition toward low-emission mobility, has placed increasing pressure on charging infrastructure [1], [2]. While EV deployment continues to accelerate, infrastructure development has not kept pace, leading to congestion and limited access to charging services [3]. This imbalance highlights the need for efficient and fair management of available resources, which is addressed by the Electric Vehicle Charging Scheduling Problem (EVCSP) [4]. The EVCSP involves allocating limited charging capacity to a set of time-constrained demands under various operational constraints. Although classical optimization techniques—such as linear, nonlinear, and dynamic programming—have been applied to solve this problem, they are generally limited to small- or medium-scale instances due to their computational complexity [5]. As a result, recent research has increasingly focused on metaheuristic approaches, which offer greater scalability and flexibility for solving large and complex instances of the EVCSP [6]–[8].

Beyond optimization techniques, another important aspect of EVCSP research is the adoption of strategic frameworks for scheduling, such as preemptive charging. Preemptive charging strategies allow interruption and reallocation of charging sessions, which helps reduce delays and improve system responsiveness [9]. Preemptive methods also contribute to lower operational costs and better infrastructure utilization [10].

As research on the EVCSP has matured, greater attention has been given to incorporating practical constraints to improve real-world applicability. Liu et al. [11] considered limited charger availability and introduced time-of-use pricing to enhance operational feasibility, though their focus remained largely on cost reduction. While minimizing operational costs is important, financial objectives alone may neglect critical aspects of service quality and system reliability. Recent efforts have increasingly shifted toward demand-oriented objectives that better address energy requirements and user satisfaction. In this direction, Zaidi et al. [12] developed a preemptive scheduling model to minimize the gap between the desired and actual battery state of charge. This model has laid the groundwork for subsequent advances, including the evaluation of metaheuristic performance for improved scalability [6], [7] and the use of surrogate models to accelerate computational processes [13].

Building upon this foundational work, Zaidi et al. [14] shifted the optimization focus from minimizing deviations in the state of charge to maximizing the number of fulfilled charging requests. Their study introduced a linear programming model supported by a heuristic method and a metaheuristic combining simulated annealing with iterated local search. This shift reflects a more practical objective, aligning with the operational goals of EV charging networks, where maximizing service coverage under resource constraints is essential. By prioritizing demand fulfillment, the proposed approach offers a more realistic representation of the challenges faced by charging infrastructure.

While the study by Zaidi et al. [14] represents a key reference for demand maximization under grid capacity constraints, certain limitations highlight the need for further progress. Their mathematical programming model struggles with scalability, as the high dimensionality of decision variables and the complexity of constraints prevent it from reaching optimal solutions within a one-hour time limit, even for small instances. Moreover, although the simulated annealing-based metaheuristic promotes broad exploration, it often fails to produce consistent, high-quality results in large-scale scenarios, particularly when jointly optimizing vehicle-to-charger assignments and energy delivery.

In response to these limitations, the current study proposes an integrated solution framework that advances both modeling and algorithmic aspects of the EVCSP. First, an improved mathematical programming model is developed, designed to reduce variable dimensionality and better handle scalability challenges in large instances. Second, a hybrid decomposition framework is proposed, dividing the EVCSP into two interrelated components: vehicle-to-charger assignment and energy delivery optimization. The assignment sub-problem is tackled using a tabu search algorithm, while the energy delivery phase is solved through exact mathematical programming. This integration of metaheuristic flexibility with exact optimization accuracy offers a robust and scalable approach for real-world EV charging scenarios.

The remainder of this paper is organized as follows. Section II defines the problem, and Section III presents the mathematical model. The hybrid solution method is detailed in Section IV, followed by results in Section V and conclusions in Section VI.

II. Problem Definition

This study considers the preemptive EVCSP introduced by Zaidi et al. [14]. For further technical details, readers may consult the original work. A concise overview is provided here for clarity.

The problem involves a set of charging demands $J = \{1, \ldots, n\}$ to be scheduled over a set of chargers $M = \{1, \ldots, m\}$ during a discrete time horizon $\mathcal{T} = \{1, \ldots, T\}$. Each charger i operates at a fixed power rate w_i (kW), and the total grid capacity w_G (kW), typically lower than the combined maximum demand, limits the simultaneous power consumption across all chargers.

Each demand j is defined by an arrival time r_j, departure time d_j, and an energy requirement e_j (kWh), which must be satisfied by its departure. The uninterrupted charging time required for demand j on charger i, denoted p_{ij}, is calculated as $p_{ij} = \frac{e_j}{w_i}$. This implies that demand j must receive p_{ij} time units of charging before departure. A demand can be either accepted or rejected; if accepted, it must be entirely satisfied within its availability window $[r_j, d_j)$.

Each charger may serve only one demand at a time. Although a charger is exclusively occupied until the departure of the vehicle, charging may be paused and resumed, allowing preemption. This flexibility enables better adaptation to resource constraints, as long as the full energy requirement is delivered on time. For example, consider a case where an EV with a relatively long charging duration is being served, and a second EV with a much shorter demand arrives. In a preemptive scheme, the ongoing session can be temporarily interrupted to serve the shorter task first, thereby reducing overall waiting times and improving system performance. Such operations are feasible in practice through modern charging stations equipped with smart energy management systems capable of handling controlled interruptions.

The time horizon is discretized into uniform intervals τ, and the objective is to maximize the number of fully satisfied demands while respecting charger availability, grid capacity, and temporal constraints. This preemptive EVCSP variant is NP-hard [14].

III. Mathematical Model Formulation

To model the assignment and scheduling of charging demands under system constraints, two binary decision variables are introduced. The variable x_{ij} equals 1 if demand j is assigned to charger i, and 0 otherwise. Likewise, y_{it} equals 1 if charger i is active at time t, and 0 otherwise. Together with the notations defined in Section II, these variables form the basis of a mathematical model that maximizes the number of satisfied demands while ensuring compliance with operational and technical constraints. The full formulation is presented below:

$$\max \sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij} \tag{1}$$

Subject to:

$$\sum_{i=1}^{m} x_{ij} \leq 1, \quad \forall j \in J \tag{2}$$

$$x_{ij} + \frac{1}{n} \sum_{k \in \sigma_j} x_{ik} \leq 1, \quad \forall i \in M,\ j \in J \tag{3}$$

$$\sum_{t=r_j}^{d_j-1} y_{it} \geq p_{ij} \cdot x_{ij}, \quad \forall i \in M, j \in J \tag{4}$$

$$\sum_{i=1}^{m} w_i \cdot y_{it} \leq W_G, \quad \forall t \in T \tag{5}$$

The proposed model aims to maximize the total number of accepted demands, as defined in the objective function (1). Constraint (2) ensures that each demand j is assigned to at most one charger. Constraint (3) prevents overlapping demands from being scheduled on the same charger by enforcing that if $x_{ij} = 1$, no other demand in the conflicting set σ_j is assigned to charger i. Constraint (4) ensures that for any accepted demand j, the total active time slots of charger i within $[r_j, d_j)$ meet the required charging duration p_{ij}. This guarantees sufficient charging time while allowing for scheduling flexibility. Finally, constraint (5) enforces the grid capacity limit, ensuring that total power consumption at any time slot does not exceed W_G.

IV. The hybrid solution method

The previous section introduced a mathematical model for the EVCSP, capturing the joint optimization of EV-to-charger assignment and energy allocation over time. While the model is comprehensive, exact methods become computationally impractical for large instances due to the NP-hard nature of the problem [14]. To address this, metaheuristics offer an effective alternative for exploring complex solution spaces and generating high-quality solutions.

Given the dual structure of the problem, which involves the interdependent subproblems of EV-to-charger assignment and energy allocation, this work adopts a decomposition-based hybrid approach that treats each component separately while preserving their interaction. The assignment subproblem is solved using a TS algorithm, a well-established method for combinatorial optimization [15]. A dedicated heuristic is first employed to generate a feasible and efficient initial solution. TS then refines it through neighborhood exploration, tabu restrictions, and aspiration criteria to escape local optima. For each assignment, the energy allocation is handled by the exact model, ensuring feasible and accurate resource distribution.

To evaluate the trade-off between performance and computation time, the heuristic is also tested as a standalone alternative to TS for the assignment phase. In this variant, the heuristic performs the assignment, and the exact model is retained for energy allocation. This enables a comparative analysis between the TS-based and heuristic-based hybrid variants. The next subsections detail the structure and implementation of the TS algorithm.

A. Solution representation

solution is encoded as a matrix with $m + 1$ rows, where the first m rows represent chargers and the last stores rejected demands. Each row lists the demands allocated to a specific charger, ordered by their arrival times. If two demands overlap, the latter one is classified as rejected.

B. Heuristic for generating the initial solution

To construct an initial feasible solution, we apply a greedy heuristic described in Algorithm 1. Each demand j is assigned an energy demand rate, defined as the average power required over its time window. Demands are sorted in non-decreasing order of this rate and considered one by one for assignment. For each demand, the algorithm attempts to assign it to the first charger that can potentially satisfy its requirements. If no such charger is found, the demand is temporarily marked as rejected. The feasibility of each assignment is then validated through a mathematical model shown in Section IV-C, which determines the final set of accepted demands and allocates the corresponding charging time slots while ensuring compliance with grid capacity constraints.

C. Solution evaluation

Since the assignment produced by the algorithm - whether heuristic or metaheuristic - may not satisfy the constraints of the energy and the grid, a mathematical model is used to validate and refine the solution. This model ensures that selected demands are feasible with respect to system limitations and aims to maximize the number of accepted requests.

Let A denote the set of demands selected by the assignment algorithm, and let M_j be the index of the charger assigned to each $j \in A$. A binary variable x_j is defined such that $x_j = 1$ if demand j is accepted and assigned to charger M_j. Another binary variable $y_{jt} = 1$ indicates that demand j is being charged at time slot t. Given this terms and sybols, the model is defined as follows:

Algorithm 1 Constructive Greedy Heuristic for Demand Assignment

Input: Set of demands J, each with a time interval and energy requirement
Output: Accepted demands and their assigned time slots
for each demand $j \in J$ **do**
    Compute the energy demand rate as $\rho_j = e_j/(d_j - r_j)$
end for
Sort demands in J in ascending order of ρ_j
for each demand j in the sorted list **do**
    Assign j to the first available charger satisfying its requirements
    if no charger is available **then**
        Mark j as rejected
    end if
end for
Evaluate the assignment using the model in Section IV-C
Return the accepted demands and their assigned time slots

$$\max \sum_{j \in A} x_j \tag{6}$$

Subject to:

$$\sum_{t=r_j}^{d_j-1} y_{jt} = p_{M_j,j} \cdot x_j, \quad \forall j \in A \tag{7}$$

$$\sum_{j \in A / t \in [r_j, d_j)} w_{M_j,j} \cdot y_{jt} \le W_G, \quad \forall t \in T \tag{8}$$

In this model, the objective function (6) maximizes the number of accepted demands. Constraint (7) ensures that each accepted demand receives its full energy requirement within its time window, and constraint (8) enforces the grid capacity limit across all time slots.

D. Steps of the Developed Tabu Search Algorithm

This section presents the TS algorithm developed to enhance the assignment of charging demands to chargers, with the objective of maximizing the number of accepted requests. The algorithm iteratively explores the solution space while leveraging memory-based mechanisms to avoid cycling and escape local optima. A formal representation of the procedure is provided in Algorithm 2. The key components of the algorithm are detailed in the following paragraphs.

a) Initialization: An initial feasible solution is generated using the heuristic in Section IV-B, and its objective value is evaluated via the model in Section IV-C. This solution is set as both the current solution S_{current} and the best-known solution S^*_{best}. The Tabu List is initialized as an empty FIFO queue storing pairs (i, j), where demand j was removed from charger i.

b) Neighborhood Generation: At each iteration, a charger $c \in \{1, \ldots, m+1\}$ is randomly selected, where $m + 1$ denotes a virtual charger for rejected demands. If c contains at least one demand, a demand d assigned to it is randomly chosen. The algorithm then attempts to reassign d

Algorithm 2 Tabu Search Algorithm

Input: Demand set J, chargers m, max iterations NB_ITER, Tabu List size T
Output: Best solution S^*_{best} with objective value f^*_{best}
$S_{\text{current}} \leftarrow$ HeuristicSolution()
$f_{\text{current}} \leftarrow$ Evaluate(S_{current})
$S^*_{\text{best}} \leftarrow S_{\text{current}}$, $f^*_{\text{best}} \leftarrow f_{\text{current}}$
Initialize empty Tabu List $\mathcal{T}$ as FIFO queue
for $iter = 1$ to NB_ITER **do**
  Randomly select charger c with at least one demand
  Randomly select demand d from charger c
  $bestNeighbor \leftarrow \emptyset$, $f_{bestNeighbor} \leftarrow -\infty$
  for each $c' \in \{1, \ldots, m+1\} \setminus \{c\}$ **do**
    if $(c, d) \notin \mathcal{T}$ **then**
      Generate S' by moving d to c'
      $f' \leftarrow$ Evaluate(S')
      if $f' > f_{bestNeighbor}$ **then**
        Update $bestNeighbor$, $f_{bestNeighbor}$, $bestMove$
      end if
    end if
  end for
  if $bestNeighbor \neq \emptyset$ **then**
    $S_{\text{current}} \leftarrow bestNeighbor$
    Add $bestMove$ to $\mathcal{T}$; remove oldest if $|\mathcal{T}| > T$
    if $f_{bestNeighbor} > f^*_{\text{best}}$ **then**
      Update S^*_{best}, f^*_{best}
    end if
  end if
  if $|\mathcal{T}| = T$ **then**
    Remove the first 1/3 of the moves from tabu list
  end if
end for
return S^*_{best}, f^*_{best}

to every other charger $c' \in \{1, \ldots, m+1\} \setminus \{c\}$, generating one neighbor per move. A move (c, d, c') is admissible only if (c, d) is not in the Tabu List. The objective function is evaluated for each admissible neighbor, and the best one among them is selected for potential acceptance. To preserve temporal order, demands are inserted into the new charger respecting their arrival times. Each admissible neighbor is evaluated, and the best one is selected.

c) Tabu List Management: Once a move is executed, the corresponding pair (c, d) is added to the Tabu List. If the list exceeds its fixed size T, the oldest entry is removed. This prevents the algorithm from revisiting recent configurations and encourages exploration.

d) Update and Termination: The best admissible neighbor becomes the new current solution. If it improves upon S^*_{best}, the best solution is updated. The process continues for a fixed number of iterations NB_ITER, or until a time limit is reached. Upon termination, the algorithm returns the best solution found.

V. Computational Results

Computational experiments were performed on a system with an Intel Xeon W-2295 CPU (3 GHz), 128 GB RAM, and Windows 10. All implementations were developed in C++ and integrated with CPLEX via its API to solve the linear programming models.

As the instances from [14] were not publicly available, a new benchmark dataset was generated by replicating their methodology. Experiments were conducted across four instance groups, varying by the number of demands $n \in \{10, 40, 50, 100\}$, chargers $m \in \{15, 24, 27, 30\}$, and grid capacities $w_G \in \{50, 75, 100, 125\}$. Chargers were categorized into three types: one-third with $w_1 = 11$ kW, one-third with $w_2 = 22$ kW, and the remainder with $w_3 = 43$ kW. For each configuration, five random instances were generated as follows:

1) Vehicle arrival times r_j were drawn from a uniform distribution over the interval $[0, 0.2n]$ (in hours).
2) The energy demand e_j of each vehicle was randomly sampled from a uniform distribution within the range $[5.5, 66]$ kWh.
3) For every vehicle $j \in J$, the charging time p_{1j} (in hours) was calculated based on type 1 chargers (11 kW), using the formula $p_{1j} = \frac{e_j}{11}$.
4) The departure time d_j for each vehicle was determined as:

$$d_j = r_j + (1 + \alpha) p_{1j} \tag{9}$$

where α is a random variable selected according to the value of p_{1j}. The ranges for α are provided in Table I, which specifies the intervals corresponding to the calculated charging times.

TABLE I
Intervals for α Based on Charging Times (p_{1j})

$p_{1j} \in$	**[0.5, 1)**	**[1, 2)**	**[2, 3)**	**[3, 4)**	**[4, 5)**	**[5, 6]**
$\alpha \in$	$[0.1, 1]$	$[0.1, 0.9]$	$[0.1, 0.8]$	$[0.1, 0.7]$	$[0.1, 0.6]$	$[0.1, 0.5]$

The results obtained from the proposed methods on various benchmark instances, each with different charger configurations, are presented in Tables 2–5. The first column identifies the tested instances. The second column reports results from the mathematical model, including the achieved objective value, the upper bound provided by CPLEX, and the computational time. The third and fourth columns present the objective values and corresponding runtimes of the hybrid TS and heuristic approaches, respectively. The final column includes the objective value and computation time of the simulated annealing method from the reference study, applied to the same instances. All times are reported in seconds.

The parameters of the TS algorithm were fine-tuned through iterative adjustment, with a stopping condition of 500 iterations or a maximum runtime of 5 minutes. In contrast, the CPLEX solver was given a time limit of 30 minutes, which aligns with common practice in evaluating exact methods for scheduling problems. The shorter time limit for TS reflects its intended use as a fast, scalable heuristic, whereas the longer time budget for CPLEX ensures a fair evaluation of the exact model under standard conditions. The tabu list size was fixed at 20. For consistency, all benchmark instances were generated with the same sizes and time granularity used in [14], with a time step of $\tau = 0.1$ hours (6 minutes).

The results from the computational experiments demonstrate both the effectiveness and practical applicability of the proposed solution techniques. In contrast to the reference study by Zaidi et al. [14], where the mathematical model struggled to reach optimality for smaller instances involving 10 demands and 15 chargers, the mathematical model introduced in this work shows significant performance improvements. The mathematical model proposed in the reference study exhibited poor performance on larger instances of the problem, as evidenced by the low-quality solutions it produced and the substantial discrepancy compared to the solutions obtained by their simulated annealing algorithm. In contrast, the enhanced mathematical model introduced in our study demonstrates a significantly improved capability, yielding acceptable solutions with other developed solution approaches, especially in small and medium instances. The results obtained from solving the mathematical model and the proposed hybrid TS framework consistently demonstrate the superior performance of the TS approach. This superiority becomes more pronounced as the size of the problem instances increases. Furthermore, with its significantly reduced computational time, the hybrid TS framework proves to be a more effective and scalable solution for addressing the studied problem.

The results obtained from the TS algorithm across all considered instances demonstrate its superior performance in maximizing the number of accepted demands compared to the simulated annealing algorithm proposed in [14]. When executing the source codes provided in the reference work, the findings consistently highlight the superiority of the solution approaches proposed in this research over the simulated annealing method from the original study. Notably, the simulated annealing approach exhibits performance comparable to the heuristic method introduced in this work. The heuristic method, while unable to achieve the same solution quality as the mathematical model and the hybrid TS, offers a notable advantage in terms of computational efficiency. Its rapid execution time makes it particularly suitable for scenarios requiring real-time decision-making, where solution speed takes precedence over optimality. Moreover, it holds potential as a warm-start mechanism for other solution methods, where providing an initial feasible solution may guide the search process more effectively and contribute to reducing overall computational effort.

VI. Conclusion

This study addresses the Electric Vehicle Charging Scheduling Problem (EVCSP), with the objective of maximizing the number of satisfied charging demands while ensuring the efficient utilization of limited resources. The problem is formulated as a novel mathematical programming model that incorporates the relevant operational constraints. As an initial step, the model is solved using an exact solver to obtain optimal solutions. However, given the inherent complexity of the problem, particularly for large-scale real-world instances, solving the model directly using exact methods may become computationally challenging or infeasible.

To overcome these potential challenges, we proposed a hybrid optimization framework that decomposes the problem into two interdependent subproblems: the assignment of vehicles to chargers and the optimization of energy delivery. The assignment subproblem is addressed using a tabu search (TS) algorithm, which begins with an initial solution generated by a specifically developed heuristic algorithm. The energy delivery subproblem is solved using an efficient mathematical programming model, ensuring precise resource allocation for each assignment solution generated by the TS. To evaluate the efficacy of the framework, we also tested an alternative approach where the heuristic solution for the assignment is directly used, bypassing the TS, to compare its results in terms of solution quality and computational efficiency.

The computational experiments confirm the effectiveness and practicality of the proposed solution techniques. The introduced mathematical model demonstrates significant improvements over existing methods, effectively addressing challenging instances. The hybrid TS framework achieves results consistent with the mathematical model, with minor deviations in larger instances, while requiring substantially less computational time. The heuristic method, though less accurate, offers exceptional computational efficiency, making it suitable for scenarios where quick solutions are essential.

For future research, promising directions include the design of more scalable solution strategies, such as hybrid metaheuristics that combine tabu search with complementary approaches to address very large-scale instances more effectively. The integration of machine learning techniques remains valuable for enhancing adaptive parameter control and decision-making under uncertainty. Additionally, conducting the sensitivity analysis on key parameters and extending the model to incorporate dynamic system characteristics such as time-varying grid capacity driven by renewable energy fluctuations would provide deeper insights into the robustness and operational resilience of the proposed framework.

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TABLE II
RESULTS FOR n = 10 DEMANDS AND m = 15 CHARGERS

id	Mathematical Model			Hybrid TS		Heuristic		SA [14]	
	z	UB	Time	z	Time	z	Time	z	Time
1	**10**	10.00	0.15	**10**	86.17	9	0.04	**10**	1.35
2	**10**	10.00	0.27	**10**	134.66	9	0.03	**10**	5.88
3	**9**	9.00	15.22	**9**	139.18	8	0.03	8	9.50
4	**10**	10.00	0.21	**10**	120.22	**10**	0.04	**10**	1.27
5	**9**	9.00	19.45	**9**	149.89	8	0.04	8	6.42

TABLE III
RESULTS FOR $n = 40$ DEMANDS AND m = 24 CHARGERS

id	Mathematical Model			Hybrid TS		Heuristic		SA [14]	
	z	UB	Time	z	Time	z	Time	z	Time
11	32	40.00	1805.52	**33**	360.59	32	0.27	32	21.78
12	29	39.00	1802.11	**30**	320.56	29	0.74	29	23.14
13	**30**	39.00	1805.66	**30**	360.96	29	0.47	28	19.82
14	**30**	40.00	1805.68	**30**	360.74	**30**	0.74	27	23.49
15	**27**	37.10	1801.91	**27**	360.91	**27**	0.61	26	26.74

TABLE IV
RESULTS FOR n = 50 DEMANDS AND m = 27 CHARGERS

id	Mathematical Model			Hybrid TS		Heuristic		SA [14]	
	z	UB	Time	z	Time	z	Time	z	Time
21	**44**	50.00	1807.29	**44**	361.06	43	0.70	42	37.26
22	**44**	50.00	1801.05	43	361.16	43	0.43	42	32.68
23	**42**	48.00	1808.55	**42**	360.87	41	0.39	40	39.45
24	**45**	50.00	1802.09	**45**	360.87	**45**	0.91	**45**	43.1
25	46	50.00	1809.30	**46**	360.48	45	0.98	45	28.09

TABLE V
RESULTS FOR n = 100 DEMANDS AND m = 30 CHARGERS

id	Mathematical Model			Hybrid TS		Heuristic		SA [14]	
	z	UB	Time	z	Time	z	Time	z	Time
31	86	100.00	1809.71	**87**	360.29	**87**	6.78	85	189.47
32	88	100.00	1810.88	**89**	379.54	88	6.76	88	114.06
33	86	98.00	1823.91	**87**	361.13	86	2.73	84	170.93
34	92	100.00	1815.45	**93**	360.97	92	2.59	91	94.91
35	86	99.00	1802.48	**89**	360.46	88	3.25	86	182.82

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