Empirical Comparison of AC and DC Power Flow Models in Transmission Expansion Planning

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***Abstract*—Expansion planning models often rely on the DC power flow approximation for the sake of computational tractability. The AC power flow model, however, is the full representation of a power system's steady-state behavior, while DC power flow is a linear approximation, so it is important to understand how well the DC approximation performs in this context. In this paper, we investigate the impact of utilizing the nonlinear AC power flow model versus the DC power flow linearization in transmission expansion planning. We compare investment decisions obtained from the IDAES-GTEP package on a 5-bus and 9-bus test systems under several scenarios that vary line parameters. Our results show that, for standard parameter ranges, AC and DC formulations yield nearly identical expansion plans, whereas under extreme parameter variations that exaggerate losses or reactive effects the models can select different investment decisions, but with the AC formulation requiring substantially more computation time and similar final investment costs.**

***Index Terms*—Expansion planning, AC power flow, DC power flow**

I. Introduction

With the growth in power demands, extreme weather events, and use of inverter-based energy resources, the electric grid is becoming increasingly stressed. Expansion planning is an important tool for developing long-term investment strategies to mitigate this stress and imbue reliability and resiliency into future power systems [1]. However, transmission and generation expansion planning (TEP and GEP) are some of the most computationally challenging problems in power system analysis [2]. TEP and GEP are typically formulated as large mixed-integer programming (MIP) problems with numerous binary investment decisions, network constraints, and spatial/temporal considerations [3].

Due to the inclusion of the nonlinear AC power flow equations, AC expansion planning is formulated as large mixed-integer quadratically constrained programs (MI-QCP). The DC approximation of the power flow equations is often employed to reduce the expansion planning problem to a mixed-integer linear program (MILP) to exploit the maturity of linear programming solvers [3]. DC power flow makes several assumptions, namely lossless networks, small angle differences, close to nominal voltages, and ignoring reactive power, that may be violated in the study of expansion planning. In light of recent advances in mixed-integer nonlinear solvers such as in Gurobi that make it increasingly practical to solve AC-based formulations directly, it is timely to investigate how the choice between AC and DC power flow models affects expansion planning investment decisions.

In this paper, we utilize the IDAES-GTEP framework to evaluate the impacts of incorporating the nonlinear AC power flow equations versus the DC power flow approximations on infrastructure expansion decisions. Our main findings indicate that differences between AC and DC formulations are minimal unless unusual line parameter values are used to emphasize power flow modeling differences.

The paper is organized as follows. Section II lays out a literature review of the comparison of AC and DC power flow and their differences in many different analyses. Section III describes the formulation of the GTEP framework used to solve the expansion planning problem. Section IV presents our numerical results and their discussion. Section V concludes the paper and points towards future work.

II. Background

The choice between the nonlinear AC power flow model and its linear DC approximation represents a trade off between physical accuracy and computational tractability. While the DC approximation has been the cornerstone of much practical analysis and large-scale optimization, considerable work has gone into understanding this accuracy–tractability trade off for various applications [4]. This section reviews literature comparing AC and DC power flow models across several applications and indicates the need for similar analyses for expansion planning problems.

A. AC vs. DC Power Flow

Power flow (or load flow) analysis refers to computing a steady-state solution of the network equations: given net active and reactive power injections and specified generator voltage magnitudes (and angle at a slack bus), the goal is to find the voltage phasors that satisfy Kirchhoff's laws. In this work, AC power flow denotes the full nonlinear set of equations relating the voltage phasors to the complex power injections, whereas DC power flow denotes a linearized approximation that retains

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only active power, assumes flat voltage magnitudes and small phase-angle differences, and neglects losses.

The fundamental tradeoffs between AC and DC power flow have been studied extensively, with many works empirically quantifying the accuracy of DC models for steady-state analysis. In particular, [5]–[7] assess DC power flow accuracy by solving both AC and various DC formulations on a range of test systems and operating conditions, then comparing errors in bus voltage angles, line flows, and losses. While these studies have shown DC power flow is reasonably accurate for a number of practical problems, there has been a struggle to understand DC power flow accuracy for a particular problem and system of interest. Additionally, some prior work has conducted theoretical analyses bounding worst-case error [8], [9] for DC power flow relative to AC power flow. More recently for general linearizations, which include DC power flow, worst-case [10] and average-case [11] theoretical analysis relative to the AC power flow equations have also been explored. Taken together, these empirical and theoretical results primarily characterize AC versus DC discrepancies at the level of individual operating points, while much less is known about how such modeling errors propagate into long-term expansion planning models with discrete investment decisions, which is the focus of this work.

B. AC vs. DC Power Flow Models for Optimal Power Flow

The tradeoffs associated with AC versus DC power flow models in the context of optimal power flow (OPF) problems have been particularly well studied due to the centrality of OPF problems in power system operations and economic dispatch. A key finding is that the generator setpoints from a standard DC OPF are never AC feasible due to the DC power flow's lossless assumption [12]. The economic impact of this gap have been a major area of study. Reference [13] showed that while DC-based locational marginal prices (LMPs) can match fairly closely with AC LMPs in systems where congestion is the dominant price driver, the inaccuracies can still lead to economic inefficiencies. The Federal Energy Regulatory Commission (FERC) has estimated that the cumulative cost of such suboptimal operations could have significant savings on national and global scales [14]. Analysis of locational marginal pricing under AC vs. DC models for systems with high penetrations of renewable energy have also shown an insufficiency in operational revenue [15]. On the environmental side, [16] showed that standard DC OPF produces generator setpoints that generally yield higher carbon emissions than AC OPF setpoints.

C. AC vs. DC Models for Security and Reliability Analyses

In power system security, the choice between AC or DC model typically depends on the context of the problem. For example, as reviewed in [17], in typical $N-1$ contingency analysis, the DC model is used during an initial screening phase to rapidly identify potential thermal overloads. This reduced list of critical contingencies is then re-analyzed in detail using a full AC power flow model to verify the severity of overloads and check for voltage or line flow violations.

For more severe events like cascading failures, the DC power flow approximation's limitations have been shown to be more pronounced. Comparative studies simulating large-scale cascades have consistently shown that DC-based models are overly optimistic in their predictions of system resilience [18]. This is because the DC power flow is blind to voltage collapse and reactive power relationships, which are often the primary drivers of widespread blackouts. A DC power flow approximation may continue to return a solution for a system that, in reality, would have already experienced voltage instability, leading to an underestimation of its risk [18], [19].

D. AC vs. DC Models for Optimal Transmission Switching

Topology control problems such as Optimal Transmission Switching (OTS) introduce discrete decisions on line status (on/off) in addition to continuous operational variables. Most early OTS work relies on DC power flow, but several studies have examined the consequences of this choice and the benefits and costs of more accurate AC-based formulations.

Reference [20] develops primal and dual bounds for OTS using formulations that more faithfully reflect AC equations, quantifying the optimality gaps of DC-based solutions and highlighting cases where DC models misrepresent congestion and reactive power effects. Reference [21] proposes correcting DC-based OTS solutions by reanalyzing the resulting topologies with AC power flow and adjusting switching decisions to restore feasibility. Similarly, [22] investigates the impacts of topology control on AC optimal power flow (ACOPF), showing that switching decisions derived under DC assumptions can significantly alter AC-feasible operating points and costs. More recently, [23] studies the Optimal Power Shutoff problem under different power flow formulations and documents explicit trade-offs between long solution times for AC-based models and reduced solution quality when using DC or other approximations.

E. Choice of Model in Expansion Planning

While the operational discrepancies of model choice are well-studied, as shown above, its impact on long-term expansion planning investment decisions is an area of active research. The primary motivation for using DC power flow in expansion planning is to transform a Mixed-Integer Nonlinear Program (MINLP) into a more tractable Mixed-Integer Linear Program (MILP). There have been some comparisons between AC and DC power flow in expansion planning; for example, [24] and [25] confirm the potential for a gap between DC and AC TEP and evaluates the applicability of alternative linearizations. Reference [26] showed that for transmission expansion planning, the full AC model tends to choose to invest in fewer lines compared to the DC model for the 19 bus model of Egypt's 220 kV transmission network.

Relative to these studies, our work applies recent advances in mixed-integer nonlinear solvers to globally solve AC-based formulations from the IDAES-GTEP expansion planning framework, considering two test cases with systematically varied line parameters. Our results share some commonality with the prior observation that AC formulations can differ in line investments compared to DC for large changes in parameter values, but we also find that for more typical parameter ranges the AC and DC formulations produce nearly identical total costs.

III. GTEP Formulation

Capacity expansion planning provides a structured optimization framework for selecting transmission and generation additions (and retirements) that satisfy anticipated demand and reliability targets over many years. Generation expansion planning, in particular, determines when and where to build, maintain, or retire units across space and time. With accelerating electrification, variability in renewable output, and an emphasis on resilient infrastructure, substantial public and private investment is expected for the foreseeable future. To prioritize those investments under budget constraints, models must couple network physics with costs in a consistent way.

This study uses the IDAES-GTEP Python package, a modular environment for constructing expansion models at multiple spatial and temporal resolutions [27]. The framework is built on Generalized Disjunctive Programming (GDP) [28], which allows high-level logical relationships among assets and operating modes (whether a line is built and, if so, whether it is in service) to be expressed directly and then reformulated for mixed-integer optimization. Implementations rely on Pyomo [29] and Pyomo.GDP [30] and interface with standard optimization solvers. This section summarizes the IDAES-GTEP formulation and we refer the reader to [27] for complete details.

IDAES-GTEP organizes decisions on three nested time scales: *investment* periods, *commitment* periods, and *dispatch* periods. Investment periods span years to decades and determine which assets are constructed (e.g., new generators or transmission lines between specified substations). Commitment periods capture discrete unit-status choices, and dispatch periods enforce the network physics and balance constraints. In the experiments that follow, the economic and logical layers are held fixed while the power flow model is alternated between the AC and DC equations to isolate the impact of the power flow representation on long-horizon investment outcomes.

Within each investment period, IDAES–GTEP represents operating variability by a set of *representative operating periods* (e.g., representative days). These representative periods are sampling constructs rather than a fourth decision timescale: they aggregate many similar hours into a smaller number of weighted scenarios so that uncertainty in load, weather, and renewable output is reflected without explicitly modeling every hour of the horizon. Each representative operating period is further decomposed into hourly *commitment* intervals and subhourly *dispatch* intervals. The decision variables during commitment intervals are the discrete statuses of each generator subject to ramping and minimum up/down-time constraints; this collection of decisions and constraints corresponds to a standard unit commitment problem.

Finally, within each commitment period in IDAES-GTEP are a number of economic dispatch periods. Economic dispatch represents the minute-to-minute operations of the grid and are at the core of this paper's investigation. It is at this stage that the model must constantly balance generation and load while satisfying either the nonlinear AC power flow equations or their linear DC approximation.

A high-level, abstract representation of this multi-level GDP formulation is given as:

$$
\begin{aligned}
\min \quad & C^I + C^O + C^P && \text{(1a)}\\
\text{s.t.} \quad & Ax + Bz \le c && \text{(1b)}\\
& \bigvee \begin{bmatrix} U \\ Mx + Nz \le e \\ \bigvee \begin{bmatrix} W \\ Dx + Ez \le h \\ \begin{bmatrix} \textbf{DCPF} \\ p_\ell = -b_\ell(\theta_i - \theta_j), \quad \forall \ell = (i,j) \end{bmatrix} \\ \textbf{OR} \\ \begin{bmatrix} \textbf{ACPF} \\ p_i = \Re\left\{ V_i \sum_j Y_{ij}^* V_j^* \right\}, \quad \forall i \\ q_i = \Im\left\{ V_i \sum_j Y_{ij}^* V_j^* \right\}, \quad \forall i \end{bmatrix} \end{bmatrix} \end{bmatrix} && \text{(1c)}\\
& \Omega = True && \text{(1d)}\\
& x \in X \subseteq \mathbb{R}^n && \text{(1e)}\\
& U, W \in \mathbb{B}^p && \text{(1f)}\\
& z \in Z \subseteq \mathbb{Z}^m && \text{(1g)}
\end{aligned}
$$

Here, (1a) represents an objective function that minimizes total cost, with C^I, C^O, and C^P representing investment, operational and maintenance, and penalty costs, respectively. Constraint (1b) represents global linear constraints on the real-valued variables x and the integer-valued variables z. These constraints are operational limits such as generator output limits, transmission line thermal limits, or other system-wide bounds.

The disjunctive block (1c) encodes the nested logical structure of the model. The outer disjunct, indexed by the Boolean variables U, represents the *investment-period decisions*. In practice, these Booleans capture the logical state of each asset across the long-term horizon: whether a generator or transmission line is built, extended, retired, or disabled in a given investment period. When a particular investment choice is selected, the associated linear constraints $Mx+Nz \le e$ are enforced for that asset and period.

Nested within an investment configuration is an inner disjunct, indexed by the Boolean variables W, which represents the *commitment-period decisions*. These Booleans capture short-term operating modes such as whether a generator is on, off, starting up, or shutting down, or whether a controllable branch is in service or opened. The corresponding constraints $Dx + Ez \le h$ then enforce unit-commitment logic, ramping limits, and switching constraints consistent with the chosen operating modes.

The innermost blocks represent the *dispatch-period physics*, enforced when assets are available and online. Under the DC power flow (DCPF) representation, p_ℓ denotes the active power flow on line $\ell = (i, j)$, b_ℓ is the series susceptance of that line, and θ_i and θ_j are the voltage phase angles at buses i and j. Under the AC power flow (ACPF) representation, p_i and q_i denote the net active and reactive power injections at bus i; V_i is the complex voltage at bus i; Y_{ij} is the (i, j) entry of the network bus-admittance matrix; the superscript * denotes complex conjugation; and $\Re\{\cdot\}$ and $\Im\{\cdot\}$ denote the real and imaginary parts, respectively. In this work, we construct two model variants: one in which the dispatch-level constraints are instantiated with the DC equations and one with the full AC equations. This choice between DCPF and ACPF is manually chosen a priori at the model-construction stage. The logic constraint (1d) collects the first-order logic relationships among all Boolean variables, and (1e)–(1g) specify the domains of the continuous, Boolean, and integer decision variables.

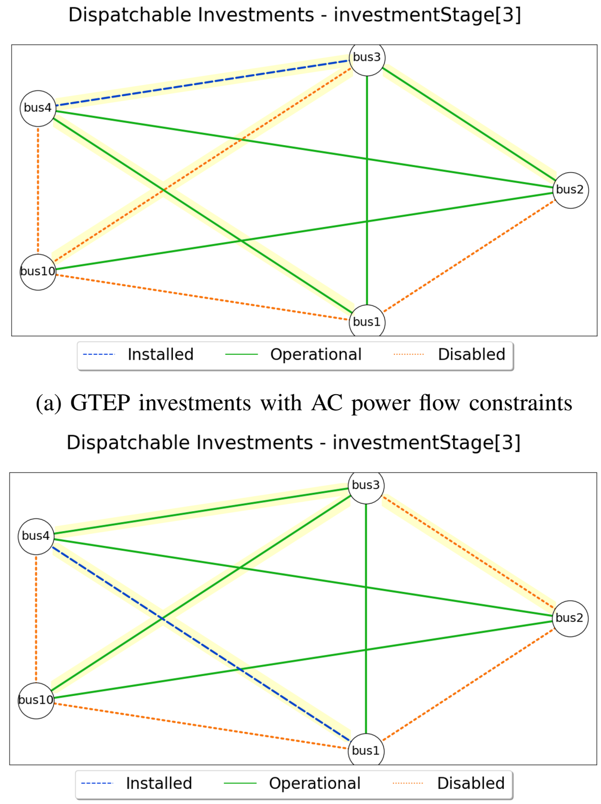
IV. Numerical Results

We conducted a series of numerical experiments using the IDAES-GTEP model on their 5- and 9-bus test systems [27] to investigate the differences between AC and DC power flow constraints in expansion planning. All simulations are completed on Gurobi 12.0.0 [31] on an AMD Ryzen 7 3700X eight-core processor @ 3.59 GHz with 16 GB of memory and a tolerance of 1×10^{-4}. The investments decided by the GTEP model with DC constraints were evaluated on the model with AC power flow constraints. Then the best-known objective is compared with the best objective found by the investment decisions from the AC-constrained model by taking a percentage difference between the two respective objective values. This allows us to gauge a relative difference between the two models on our test cases.

A. 5- and 9-Bus Test Case

We study 5- and 9-bus power systems with both nominal and modified branch data that includes three distinct types of candidate lines that the formulation is allowed to construct. We refer to the "primary" line as the original, unmodified branch parameters from the test case, the "secondary" line as a line with reduced resistance values, and the "tertiary" line as a line with reduced line-to-ground capacitance values. This setup allows for a direct comparison of how the AC and DC models value different line parameters when making investment decisions. All other costs and system parameters were held constant. Table I shows the difference in computational times and optimality gaps between power flow model across each scenario. The computational times with AC power flow constraints are consistently at least two times slower than with DC power flow, and sometimes over ten times slower on the 5-bus system. The relative objective difference of the DC investment to the AC constrained model across all scenarios are low, at most 0.007262% different, providing evidence that the DC investments are nearly as good as AC investments.

This gives confidence that for many planning studies within typical parameter ranges, a DC formulation is an effective first step. A practical workflow is to solve the GTEP model



(a) GTEP investments with AC power flow constraints

(b) GTEP investments with DC power flow constraints

Fig. 1: Final investments for 5-bus complete network variation for AC and DC models. Highlighted lines are the differences between investments.

with DC constraints to screen investments and then validate the selected portfolio by running the investments on the GTEP model with AC constraints; reoptimize with AC only when infeasibilities or material cost differences arise, or when networks exhibit a large R/X ratio, tight voltage/reactive limits, or significant shunt effects.

1) Complete Network Availability: In this experiment, we give the solver the ability to construct a line between any pair of buses to test how the IDAES-GTEP model with AC and DC constraints invest in lines when any pair of connections are allowed. The line parameters of the original network are unchanged, and the candidate line between any pair of buses have line parameters $R = 0.01\Omega$, $X = 0.1\Omega$, $B = 0.2\Omega$ which are similar to line parameters in the original network.

In the 5-bus system, the IDAES-GTEP model with an AC power flow model chose to invest in a line between buses 2 and 3, whereas the DC model chose to invest in a line between buses 3 and 10. However, for the 9-bus test case, the DC model chose to install a branch between buses 4 and 8 whereas the AC model chose to not install this line.

2) Moderate Parameter Variations: In this experiment, the candidate lines were modified to test the sensitivity to active power losses and reactive power characteristics. For the secondary candidate lines, the resistance was halved ($R_{sec} = 0.5 \times R_{pri}$), making them more efficient in terms of I^2R losses.

Case			Runtime (s)	Objective optimality
System	Scenario	PF		Percent Difference Relative to AC
5-bus	Complete	AC	102.23	–
		DC	16.85	0.006443%
	Moderate	AC	104.50	–
		DC	13.29	0.000112%
	Extreme	AC	106.55	–
		DC	10.75	0.007262%
9-bus	Complete	AC	185.84	–
		DC	60.10	0.001043%
	Moderate	AC	100.11	–
		DC	35.23	0.000057%
	Extreme	AC	106.97	–
		DC	36.55	0.000184%

TABLE I: Computation times for AC/DC GTEP runs on 5- and 9-bus systems. The investment decisions found by GTEP with DC constraints were evaluated in the AC model to calculate the percentage difference between its best feasible objective from the best bound found by the AC model investments.

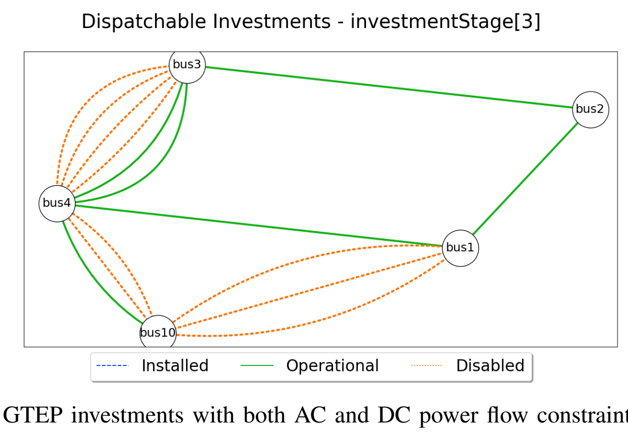


Fig. 2: Final investments for 5-bus moderate parameter variation.

For the tertiary candidates, the line-to-ground capacitance was halved ($B_{ter} = 0.5 \times B_{pri}$).

When the model was solved with these candidate lines, the investment decisions from the AC and DC formulations were largely identical. For the 5-bus test case, there was no difference between its investments to the extreme line parameter investments. For the 9-bus case, both formulations chose to invest in the same set of new lines except for `b5_sec`, the branch between buses 6 and 7. The DC model chose to build `b5_sec`, whereas the AC model did not due to taking into account of reactive power flows and resistance loss of transmission lines.

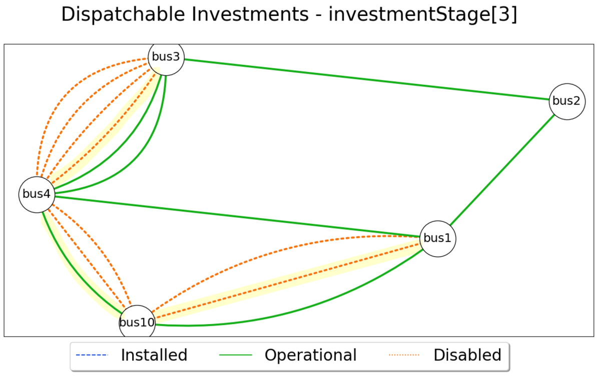
3) Extreme Parameter Variations: In this experiment, the secondary candidate lines resistances was set to zero ($R_{sec} = 0$), representing a hypothetical line with no active power losses. For the tertiary candidates, the shunt susceptance was set to zero ($B_{ter} = 0$), representing a line with no reactive power charging.

For the 5-bus test case, the AC model invested in the primary and secondary candidate lines between buses 4 and 5, and invested none between buses 1 and 5. However, the DC model invested in the primary and secondary lines between buses 1 and 5, and did not build a line between buses 4 and 5. For the 9-bus test case, there were differences in investment decisions for branch `b9` which connects buses 4 and 9. The AC model chose to invest only in the original, unchanged line, `b9_pri` rejecting both `b9_sec` ($R = 0$) and `b9_ter` ($B = 0$). The DC model made a different decision, investing only in `b9_ter` ($B = 0$) and not `b9_pri` nor `b9_sec`. These differences occur since by setting the line resistance to zero changes the overall line admittance in the AC equations. This can shift both the active and reactive flows in a way that tightens line limits elsewhere in the system.

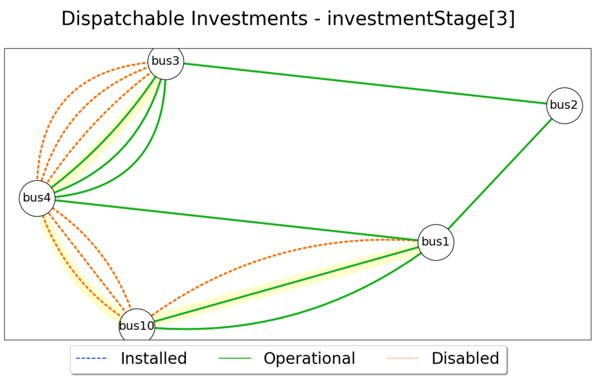
V. Conclusions

This paper compared AC and DC power flow representations within the IDAES-GTEP expansion planning framework. We constructed separate AC and DC constrained models and solved them on 5- and 9-bus test systems across nominal and perturbed line parameter scenarios. The goal was to isolate how the power flow formulation alone influences long horizon investment outcomes when the surrounding economic, logical, and temporal structure is held fixed.

Across the studied cases, the DC power flow constrained case produced investment decisions and best objective costs that closely matched those from AC power flow based planning under typical parameter ranges, while requiring less computation time. When the line parameters were altered to exaggerate resistance and charging susceptance to line susceptance ratios, the two different formulations selected some different transmission line investments. However, the relative percentage difference between the objective costs of these different investments evaluated on the AC constrained model were very small, at most 0.007262% different.



(a) GTEP investments with AC power flow constraints



(b) GTEP investments with DC power flow constraints

Fig. 3: Final investment for 5-bus extreme parameter variation.

This study is limited to small systems, deterministic costs, and stylized parameter perturbations, and it does not evaluate convex AC relaxations or stability/security constraints. Future work will scale the experiments to larger networks, more realistic data such as uncertainty in demand profiles and effects of weather events, and compare investment decisions of alternative relaxations and linearization models.

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