

Applications of Stochastic Processes in Engineering: The Poisson Process and a Simulation Study of Vehicle Arrivals

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Abstract: Stochastic processes are important to model systems that have components of randomness, and that develop over time; they are useful in engineering. Of those, arguably the most basic and indispensable is the Poisson process which is also used to describe the likelihood of random, independent events to occur in various applications such as telecommunication, reliability, transportation, manufacturing and energy systems. Drawing upon mathematical theory the Poisson process is defined by its rate parameter which is λ , and also explains that it possesses nice features such as independent and stationary increments which make it suitable for modelling real-life phenomena. Communication systems apply the Poisson process to model packet arrivals and enhance the performance of the application, and reliability engineering uses it to estimate the failure rate and plan for maintenance. In transport, the process is useful in modelling ways of managing traffic and even the schedule of a public transport system. Manufacturing systems use quality assurance and inventory control modeling while energy systems use the Poisson process for power outages and renewable energy systems planning. The article also discusses generalizations of non-Poisson processes for practical situations where the rate assumptions and events are correlated. To move from description to demonstration, the paper further reports a Monte Carlo experiment in which 500 one-minute intervals of vehicle arrivals are generated from exponential interarrival times at a mean rate of $\lambda = 20$ vehicles per minute. The simulated counts are compared with the theoretical Poisson distribution through a time series, a histogram, an interarrival plot and a quantile-quantile plot, and are tested formally by a chi-square goodness-of-fit test ($\chi^2 = 7.40$, $df = 6$, $p = 0.285$); the interarrival times are tested against the exponential law (Kolmogorov–Smirnov $D = 0.012$, $p = 0.122$). Neither test finds evidence against the Poisson model, and the experiment quantifies how much minute-to-minute variation an engineer should expect around a constant mean rate — a result with direct consequences for signal timing and capacity margins.

Keywords: stochastic processes, Poisson process, engineering applications, random events, probability theory, Monte Carlo simulation, traffic flow.

INTRODUCTION

Stochastic Processes

Stochastic processes in this case are an excellent way of modeling systems that change with time, and the process involves inherent randomness. These processes are characterized by the occurrence of

chance events that are sometimes unpredictable yet can be modelled (Wolpert et al., 2024). Thus stochastic process is widely used in engineering where traffic flow, communication networks, reliability of the systems, etc., have to be modeled as there is much variability and uncertainty involved. These processes make it easy for engineers to decide on the system, optimize the system, and measure the risks concerned (Doyle et al., 2019).

Poisson Process

The Poisson process is a highly employed stochastic process, especially in queuing theory, telecom and reliability engineering areas. It explains the chance that occurred haphazardly and it does not depend on other previous occurrences, and they have a fixed mean rate per unit of time. Stochastically, the Poisson process is characterized by one rate parameter – λ – which is the expected number of events in a unit time interval (Nakagawa, 2011). The applications of the Poisson process are based on the fact that it describes real-world schemes, for instance, the call arrivals at the call centre, failure of systems at production lines or accidents at certain crossings. The Poisson process possesses the memoryless feature; the events in the Poisson process are said to be independent of one another as well as the number of occurrences in the disjoint interval (Tijms, n.d.).

Objective and Scope

Existing treatments of the Poisson process tend either to present the mathematics in isolation or to list application areas without demonstrating that the model actually reproduces the behaviour observed in the field. This article will describe how this stochastic process can be integrated to estimate and simulate different engineering systems, ranging from telecommunication networks to transportation systems and manufacturing lines. In the article, numerous examples and case studies will be used to explain and demonstrate the applicability of the Poisson process to issues arising in engineering in terms of randomness and chance. Areas covered by the article are the definition of the Poisson process and its characteristics, with emphasis on the possibilities of its usage by engineers. In addition to this descriptive treatment, the paper contributes a small, fully reproducible simulation experiment (Section V) that generates synthetic arrival data from first principles, compares them with the theoretical distribution, and translates the comparison into practical design guidance.

MATHEMATICAL FOUNDATION OF THE POISSON PROCESS

The Poisson process is the discrete-time stochastic process that is widely used to examine the randomness of events occurring in continued time. The parameter is the characteristic that defines it which is λ which is the probability of occurrence in each slot of time which is usually $N(t)$ per time unit (Basic Concepts of the Poisson Process, 2021). A Poisson process satisfies three primary properties: In the calculation of probabilities: independent increments, stationary increments, and no two events can happen at the same time. The unpredictability of independent increments implies that we have events corresponding to disjoint time intervals and that these events are independent. Stationary increments would mean that margined events will be a function of the interval size and not the position. Last but not least, no simultaneous events enable the formulation of a way to prove the impossible of one or more events to happen in a very short time gap (Chen, 2021).

The following assumptions must be met for a process to be considered as a Poisson process. The first one is stationarity which makes the occurrence process a homogeneous process where the rate of events remains the same with time. The second assumption we have is common and independent observations, that is the assumption that source measurements in two different time intervals are independent of one another (Cressie, 1994). The third assumption is “no two events happen at once”, meaning that the

chance of experiencing more than one event in a small Δt is virtually nil. Although these assumptions are made the Poisson process is particularly well suited for modeling independently and randomly occurring events over time (Kissell & Poserina, 2017).

It is possible to present the Poisson process mathematically in two different ways. First, the number of events $N(t)$ occurring in a time interval t follows the Poisson distribution, given by (1). Here, λ is the average rate of events and t is the interval length, so that the expected event count is λt . Second, the time between two consecutive events is called the interarrival time and has the exponential distribution given by (2).

$$P(N(t) = k) = \frac{(\lambda t)^k e^{-\lambda t}}{k!}, \quad k = 0, 1, 2, \dots$$

$$f_T(t) = \lambda e^{-\lambda t}, \quad t \geq 0$$

(1), (2)

III. APPLICATIONS IN ENGINEERING

Stochastic processes, but especially the Poisson process, are being used in many fields of engineering since it is very useful in modelling the occurrence of events in time.

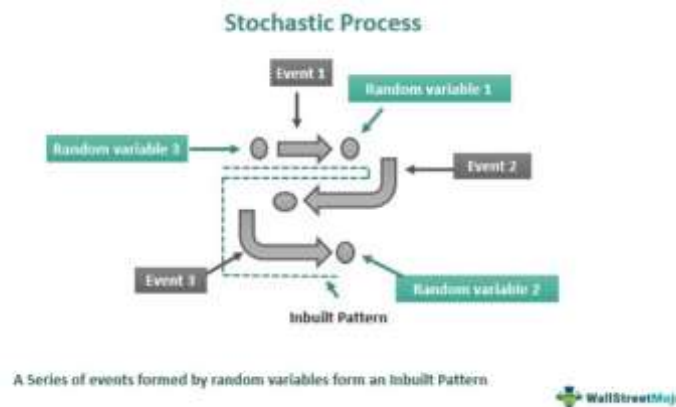


Fig. 1. Stochastic process basic framework.

This section explores practical implementations across five key areas: communication structures, reliability management, transportation structures, production systems, and power systems.

Communication Systems

The Poisson process is widely used in the design and analysis of current communications technologies. In packet-switched networks, particularly at routers or servers, the packet arrival rate is often considered to follow a Poisson process to spearhead performance analysis of the system. For instance, to enable efficient management of time and eliminate as many instances of packet loss as possible, the data packets as they enter a network queue can be modelled (Sudha & Thangaraj, 2016). The Poisson process is used to model the packet arrivals, and thus engineers can estimate average queue length and waiting time to design the most efficient buffers needed. Another important use can be seen in telecommunications, especially in call-centre or mobile communications systems. Here, the Poisson process describes phone calls or data requests so that blocking probabilities or mean service times can be established (Michela Becchi, 2008). For instance, it assists in more efficient things like the

prognostication of bandwidth consumption and server utilization. Call-centre performance forecasting and network capacity planning represent core applications according to research (BYJU'S, 2021).

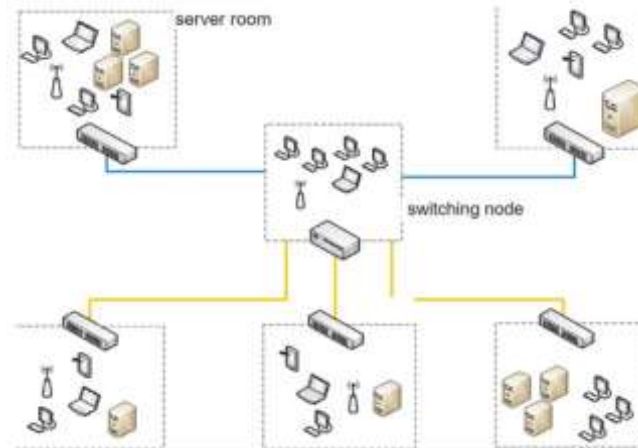


Fig. 2. Call centre incorporating the Poisson process.

Reliability Engineering

The Poisson process for failure data analysis is widely applied in reliability engineering for the prediction of failures in components of large systems. The process assists in modelling the failures' occurrences over time granted that they occur independently at a fixed average rate. It is particularly essential in the characterization and design of dependable systems and in evaluating risks. Predictive maintenance is also another application where failure rate data is modelled using the Poisson process (Andrzejczak et al., 2018). For instance, when a machine is employed in an effort manufacturing process or electrical circuits, then the failure of the machine or electronic devices in question can be modelled based on past failure data. This makes it possible to predict when maintenance should be conducted in a bid to avoid unnecessarily long periods of idleness of the system (Dalzochio et al., 2020). Machinery upkeep scheduling requires special attention in this context according to Michela Becchi (2008).

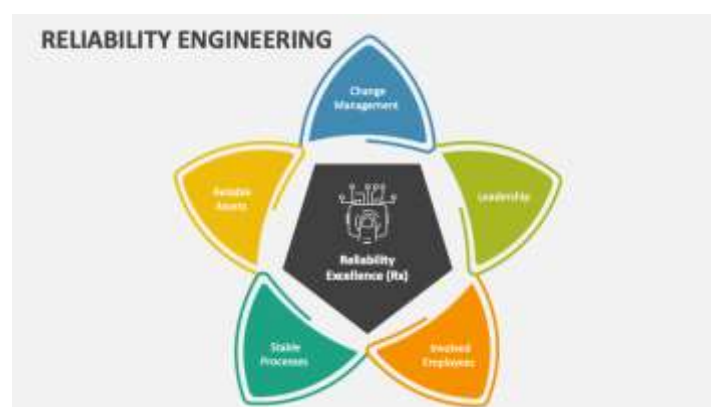


Fig. 3. Reliability engineering.

Transportation Engineering

In the area of transportation engineering, the Poisson processes find application when studying traffic flow. For instance, the arrival of vehicles at intersections or toll booths can be modelled under a Poisson process since the arrival of the vehicle occurs at random and is independent. This aids in designing the right traffic signals, and the position and number of toll booths that should exist so that the amount of traffic congestion does not obstruct the free flow of traffic (Gerlough & Schuhl, 1955). Another field of application relates to the timetable and the route plan of means of transport of public transportation.

Just suppose that the number of arriving passengers follows the Poisson model because poor service timing increases passenger waiting time on bus or train, hence improving the reliability of the service timing function will enhance improved performance and operation. With the aid of data obtained from this modelling method, policymakers gain an understanding of possible high utilization times and how transportation systems can be defined and enhanced (Li & Shalaby, 2024). The system assists organizations by both modelling intersection traffic patterns and improving public transit timetable efficiency (Chen, 2021).

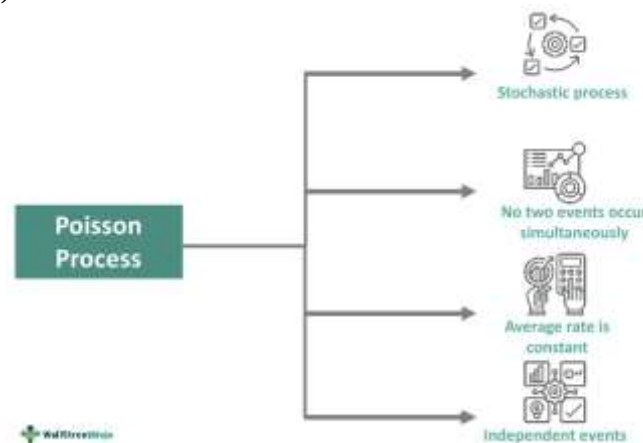


Fig. 4. Application in transportation systems.

Manufacturing Systems

Manufacturing systems make use of the Poisson process for quality assurance and inventory control. For instance, when the non-conforming product reaches a production line it is possible to model this as a Poisson process. This allows engineers to control and solve defective products effectively, so achieving the quality of the products and minimizing wasting resources. In the supply chain, the Poisson process is typically applied to describe demand for inventory products (Berling & Sonntag, 2022). This means that, understanding the randomness of customers' demand and its volatility, inside organizations one can regulate inventory to achieve the greatest profitability/quality of service ratio. For example, it explains the way to set the reorder points and safety stocks that facilitate the smooth circulation of material and products (Thomas, 2016). For quality control and inventory optimisation, Poisson processes show great value (ScienceDirect, 2025).



Fig. 5. Application in energy systems and manufacturing systems.

Energy Systems

The Poisson process is applied in the energy sector to estimate failures and outages in the electrical power network. Power outages or system breakdowns, in general, are abrupt and uncorrelated with one another, making use of the Poisson process to study the randomness of blackouts in the network. This information is then used by engineers in an attempt to provide more reliable and better-optimized artefacts of the grid, or, in other words, in an attempt to design more stable and mechanically useful variants of the grid, along with all the backup systems that are required to maintain its functionality. The Poisson process also applies to the renewable energy system, especially wind turbines. Turbine failure rates that can be dependent on some environmental characteristics are predicted to detect the required maintenance and boost the turbine availability time (Ünsal Bekir & Tunaboğlu, 2022). Likewise, the stochastic Poisson process may be applied to model the occurrence of certain solar energy generation events or other stochastic processes occurring in autonomous renewable energy systems to address some issues related to energy storage and distribution (ScienceDirect, 2025). Putting the power outage and renewable energy breakdown analysis belongs to the essential work area of energy system modelling.

CASE STUDY: TRAFFIC FLOW MODELING

A perfect example of a Poisson process is in traffic modelling to estimate traffic jams and to manage traffic networks in the built-up environment. Transportation of vehicles at intersections, toll barriers or roundabouts can best be described by a Poisson process in which the likelihood of arrival of vehicles at any point in time is independent of that at any other point in time. Thus, by using this model, traffic engineers can approximate the mean number of auto arrivals per minute and congestion probability within the peak period of auto arrivals (Guerrieri, 2024).

For instance, let us assume that there is a cross-road with an average arrival rate $\lambda = 20$ cars per minute. By employing the Poisson distribution given in (1) the engineers can estimate the probability of k vehicles arriving within a particular interval of time. This insight facilitates the control of signal lights to help reduce waiting times and thereby congestion. In addition, the distribution of the interarrival times in an exponential manner gives the data to design responsive traffic signal systems, which enable green light for particular interarrival duration. Such applications increase people's transportation efficiency and help decrease emissions from parked cars (BYJU'S, 2021).

SIMULATION STUDY OF THE INTERSECTION CASE

The intersection scenario of Section IV is treated there purely analytically. This section carries it one step further by generating synthetic arrival data for the same scenario, comparing those data with the theoretical distribution, and drawing out what the comparison means for design. The purpose is twofold: to verify that the analytical result survives sampling variability, and to make visible the amount of ordinary random fluctuation that a constant mean rate still produces.

Simulation Design

A deliberate methodological choice was made not to draw Poisson counts directly. Instead, arrivals were generated one vehicle at a time from the exponential interarrival distribution of (2), the arrival epochs were obtained by cumulative summation, and the counts per interval were then obtained by binning those epochs, as in (3). Constructed this way, the Poisson count distribution is an output of the experiment rather than an input to it, so the agreement reported below is genuine evidence rather than a restatement of the assumption.

$$T_i = \sum_{j=1}^i X_j$$

$$N_m = \# \{ i : (m-1)\Delta t < T_i \leq m\Delta t \}$$
(3)

The procedure is as follows. First, the parameters of Table I are set and the pseudo-random generator is seeded. Second, independent interarrival times $X_i \sim \text{Exp}(\lambda)$ are drawn. Third, the arrival epochs T_i are formed by cumulative summation and truncated at the end of the observation window T . Fourth, the number of arrivals N_m in each one-minute interval is counted. Fifth, the empirical distribution of the counts is compared with $\text{Poisson}(\lambda\Delta t)$ and the empirical distribution of the gaps with $\text{Exp}(\lambda)$. The experiment was implemented in Python using NumPy (Harris et al., 2020) and SciPy (Virtanen et al., 2020); the seed is fixed at 42 so that every figure and every number reported here can be reproduced exactly (Law, 2015).

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Mean arrival rate, λ	20 vehicles / minute
Observation window, T	500 minutes
Counting interval, Δt	1 minute
Number of intervals	500
Arrivals generated	10,108
Generation mechanism	Exponential interarrival times
Random seed	42

The window of 500 minutes corresponds to roughly 8.3 hours of continuous observation, comparable to a full working-day traffic count.

Arrival Counts per Interval

Fig. 6 presents the first 100 intervals of the simulated series. The counts move between 10 and 36 vehicles per minute around a mean rate that is, by construction, perfectly constant at 20. There is no trend and no drift, which is exactly what the stationary-increments property predicts. The practical warning is immediate: swings of roughly ± 50 percent from one minute to the next occur routinely in a process whose underlying demand never changes at all, so a run of “busy” or “quiet” minutes in a field count is not, on its own, evidence that traffic demand has shifted.

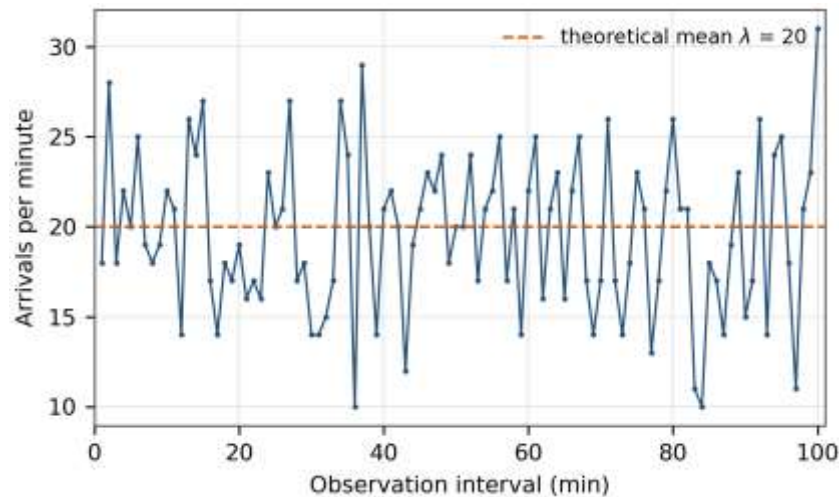


Fig. 6. Simulated arrivals per minute over the first 100 intervals, against the theoretical mean rate.

Fig. 7 collapses all 500 intervals into an empirical distribution and superimposes the theoretical Poisson probability mass function. The two agree closely across the whole support, with the residual bar-to-bar roughness being the expected consequence of a finite sample. Table II reports the corresponding summary statistics.

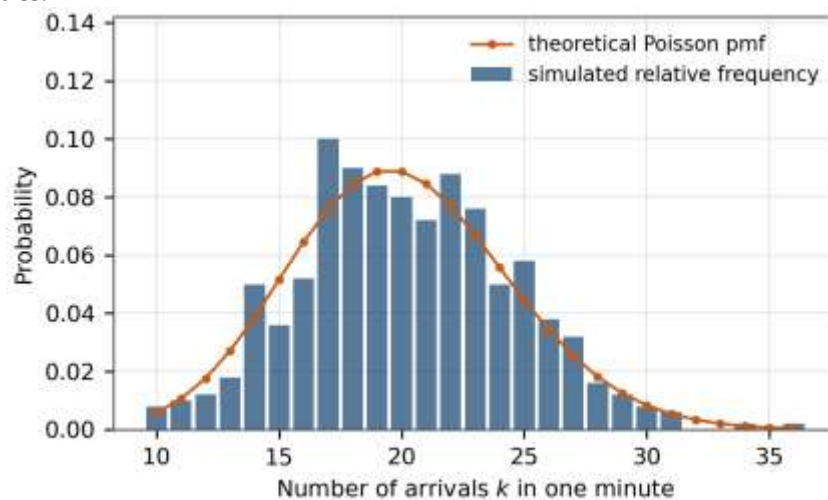


Fig. 7. Simulated relative frequency of arrival counts against the theoretical Poisson probability mass function.

TABLE II

SIMULATED VERSUS THEORETICAL STATISTICS

Statistic	Simulated	Theoretical
Mean count, $E[N]$	20.216	20.000
Variance, $\text{Var}[N]$	18.847	20.000
Standard deviation	4.341	4.472
Variance-to-mean ratio	0.932	1.000
Mean gap (s)	2.968	3.000
SD of gap (s)	2.978	3.000
Minimum count	10	—
Maximum count	36	—

The mean count deviates from λ by 1.1 percent and the variance by 5.8 percent, both well inside the sampling error expected from 500 observations. The variance-to-mean ratio of 0.93 is the most diagnostic single figure in the table: equidispersion, a ratio of exactly one, is the signature property of the Poisson law, and a value close to one is what distinguishes genuine Poisson behaviour from the overdispersed clustering that real traffic often shows. Fig. 8 confirms the same agreement in quantile terms, with the simulated order statistics lying along the line of perfect agreement over the whole range and departing from it only in the extreme upper tail, where a handful of observations carry all the sampling noise.

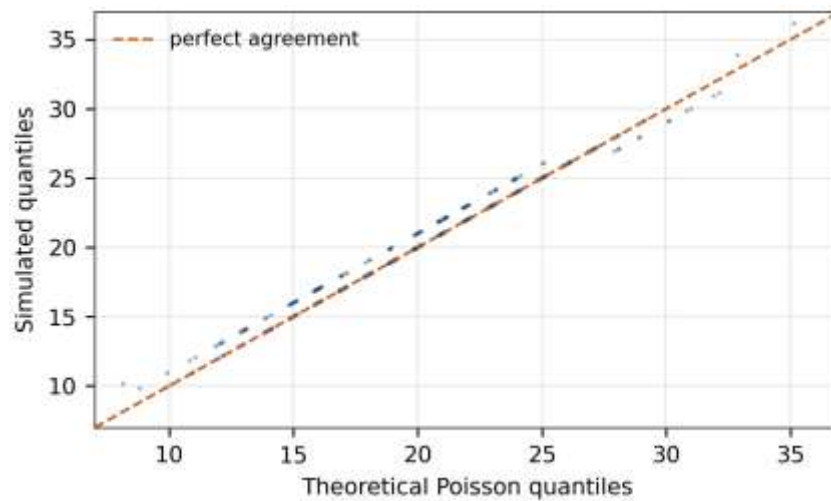


Fig. 8. Quantile-quantile comparison of simulated counts against the theoretical Poisson quantiles (points jittered for legibility).

Interarrival Times

Because the process was built from gaps rather than counts, the interarrival distribution provides an independent check on the construction. Fig. 9 shows the histogram of the 10,108 simulated gaps against the theoretical exponential density. The mean gap is 2.968 s against a theoretical $60/\lambda = 3.000$ s, and the standard deviation is 2.978 s. The near-equality of mean and standard deviation is the characteristic fingerprint of the exponential law and reflects its memoryless property: the expected waiting time to the next vehicle is three seconds regardless of how long one has already been waiting. A Kolmogorov–Smirnov test against $\text{Exp}(\lambda)$ gives $D = 0.012$ with $p = 0.122$, so the exponential hypothesis is not rejected at the 5 percent level.

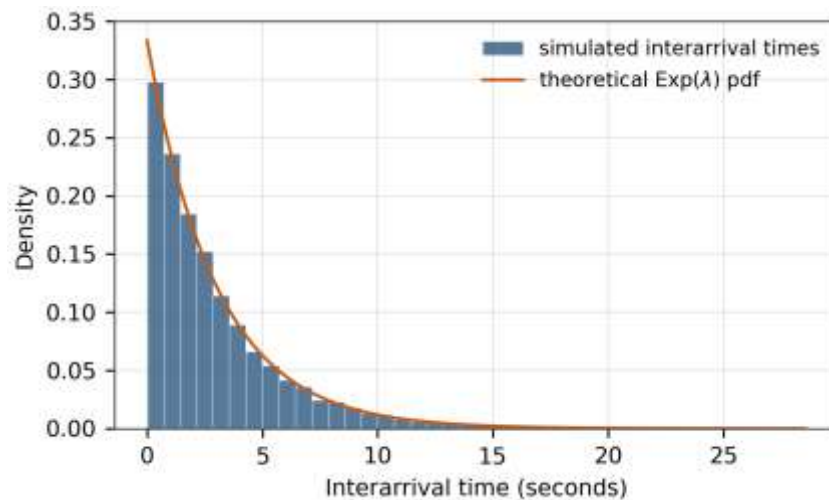


Fig. 9. Simulated interarrival times against the theoretical exponential density.

Goodness-of-Fit Assessment

A formal chi-square test was applied to the counts. The observations were grouped into seven classes chosen so that every expected frequency comfortably exceeds five, and the test statistic of (4) was computed. Because λ was fixed in advance rather than estimated from the data, no degrees of freedom are lost to parameter estimation and the statistic has $C - 1 = 6$ degrees of freedom.

$$\chi^2 = \sum_{c=1}^C \frac{(O_c - E_c)^2}{E_c} \quad (4)$$

TABLE III
CHI-SQUARE GOODNESS-OF-FIT FOR ARRIVAL COUNTS

Class (k)	Observed	Expected	(O-E) ² /E
≤ 12	15	19.5	1.043
13–15	52	58.8	0.780
16–18	121	112.5	0.647
19–21	118	131.1	1.313
22–24	107	99.8	0.523
25–27	64	52.1	2.703
≥ 28	23	26.2	0.393
Total	500	500.0	7.402

$\chi^2 = 7.402$, $df = 6$, critical value at $\alpha = 0.05$ is 12.592, $p = 0.285$.

Since the computed statistic falls far short of the critical value, the null hypothesis that the simulated counts follow Poisson(20) cannot be rejected. Together with the Kolmogorov–Smirnov result of Section V-C, this gives concordant evidence from two independent angles — the count distribution and the gap distribution — that the generated data behave as a Poisson process should.

Practical Interpretation

The value of the experiment for engineering practice lies less in the confirmation itself than in the numbers of Table IV, which turn the distribution into design quantities.

TABLE IV
DESIGN-RELEVANT PROBABILITIES

Quantity	Simulated	Theoretical
$P(N \geq 25)$ per minute	0.174	0.157
$P(N \geq 30)$ per minute	0.018	0.022
95th percentile of N	27	28
$P(\text{gap} > 6 \text{ s})$	0.133	0.135

Three implications follow. First, a signalised approach dimensioned on the mean demand of 20 vehicles per minute will be over-saturated in roughly one minute out of every six, because that is how often at least 25 vehicles actually arrive. Designing to the average is therefore designing to fail about half the time; the relevant design figure is the 95th percentile of 28 vehicles per minute, some 40 percent above the mean. Second, the tail matters but is thin: minutes carrying 30 or more vehicles occur about twice in every hundred, which is the level at which occasional queue spillback should be planned for rather than engineered out. Third, in a vehicle-actuated controller using a six-second gap-out threshold, about 13 percent of headways exceed that threshold, so the green phase would terminate on a random gap that often; the threshold must be tuned against this figure rather than against the average headway of three seconds.

A further observation concerns the amount of field data required. The theoretical standard deviation of the count is $\sqrt{\lambda}$, so relative variability falls as λ rises and high-volume approaches are, in relative terms, more predictable than low-volume ones — the latter therefore need proportionally larger safety margins. In this experiment roughly 8.3 hours of continuous observation brought every empirical statistic to within a few percent of its theoretical value, which offers a rough practical guide to the observation effort needed before a Poisson assumption can be accepted or rejected with any confidence at a real site.

LIMITATIONS AND EXTENSIONS

Difficulties of the Poisson Assumption

Nevertheless, as has been shown before, the Poisson process is applicable in a very large variety of situations, even though it has its limitations in real life. The key assumptions of the constant intensity parameter (λ) and independent events could also be violated in dynamic conditions. For instance, vehicle arrivals may not be independent of each other and have underlying structures in terms of temporal arrivals which are affected by time of day, weather, road, etc., hence do not meet the stationarity assumption. There is another thing that needs to be mentioned: the Poisson process does not allow the dependence of the occurrence of events, for example, several vehicles can arrive at a certain time in the morning or the evening (Gustafsson, 2010). It is worth noting that the simulation of Section V satisfies these assumptions by construction; its role is to establish the behaviour of the idealised model as a baseline, against which departures observed in real data — an inflated variance-to-mean ratio, in particular — can be recognised and measured.

Extensions to Non-Poisson Processes

To cope with these issues, extensions such as the renewal processes and the Markov-modulated Poisson processes (MMPP) are used. Renewal processes extend the model and weaken the requirement of the exponential distribution of interarrival times. As a result, MMPP includes time-varying rates to capture dependencies and non-stationary behaviours. These extensions offer a better description of systems

such as traffic flow under variable conditions than existing conventional models (Hani et al., 2024). The simulation framework of Section V generalises to these cases with little modification: a non-homogeneous rate function $\lambda(t)$ can be handled by thinning, and a Markov-modulated rate by switching λ according to a background chain, in both cases leaving the comparison and testing procedure unchanged (Ross, 2014).

CONCLUSION

The Poisson process is a useful theory, well applicable in engineering practice for modelling the random events taking place in traffic engineering and reliability as well as in communication systems. The simulation reported in Section V supports this claim quantitatively: 500 minutes of synthetic arrivals generated purely from exponential interarrival times reproduced the theoretical Poisson distribution to within a few percent on every statistic examined, and neither the chi-square nor the Kolmogorov–Smirnov test found evidence against the model. Equally important for practice, the experiment made the scale of ordinary random variation explicit — roughly one minute in six carried at least 25 percent more traffic than the mean — which is precisely the margin that deterministic, average-based design overlooks. Setting up this framework also enables more sophisticated stochastic processes such as renewal and Markov-modulated ones. Future research can cover the use of these models with real-time data and machine learning algorithms to extend the models' predictive power and usability, and can replace the synthetic data used here with observed counts from an instrumented intersection so that the departures from the Poisson baseline can be characterised directly.

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