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Review Paper

Review of intelligent transportation systems methodology models

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ABSTRACT

Intelligent transportation systems have been integrated and adapted to our daily lives. Transportation is one of the sustainable systems and an essential aspect of the shift toward a digital economy and intelligence. Here, we explore the theory of transportation services by exploring a mathematical model using queueing theory. Several methodologies have been employed for this theory, including micro- and Macro-simulation models. They have been used for the purpose of enhancing the analysis of intelligent transport systems. Intelligent transportation systems (ITS) are revolutionizing the management of transportation networks, leveraging advanced technologies to improve efficiency, safety, and sustainability. Operations research (OR) plays a crucial role in designing and optimizing these systems and providing mathematical models and computational techniques to address complex transportation challenges. This paper reviews the integration of OR methodologies and their role in developing and managing ITSs, including optimization, queuing theory, simulation, and network modeling. We assess technical applications for optimizing traffic flow, congestion, and instantaneous decision-making in transportation systems. OR contributes to ITS by using optimization models for route planning and traffic queue management. Simulation techniques also used to evaluate the system performance under different scenarios. The paper highlights the increasing trend of addressing multifaceted modern transportation networks by hybridizing models of multiple OR approaches. We aim to gather insight into current ITS methodology models, applications, and limitations by synthesizing recent advancements. Additionally, our aim is to identify emerging trends and future research directions, with a focus on big data, autonomous vehicles, and smart cities. This is a valuable resource in leveraging OR tools for ITS operations and designs.

Keywords: *Autonomous vehicles , Congestion management, Hybrid models, Intelligent transportation systems, Queuing theory, Smart cities, Traffic flow*

1 INTRODUCTION

In daily life, people often find themselves stuck in traffic due to congestion and accidents without prior warning. A revolution of technologies has launched throughout the world in an enormous way. These developments were designed to be implemented in conjunction with the available information, ultimately providing an opportunity to overcome the challenges. ITSs have become a cornerstone of modern transportation networks and offering solutions that enhance mobility, safety, and efficiency in the face of increasing urbanization and environmental concerns. ITS harnesses emerging technologies, such as sensor networks, machine learning, and real-time data analytics, to optimize traffic flow, reduce congestion, and improve overall system performance. As transportation networks become more complex, the role of operations research in analyzing, modelling, and optimizing these systems has become increasingly crucial. OR provides a suite of mathematical and computational tools, including optimization, simulation, and queuing theory. These tools can be used to design more efficient transportation systems, mitigate traffic congestion, and improve decision-making in real-time [1,2].

ITS has delivered various services to improve traffic flow efficiency, increase safety, minimize traffic congestion, and reduce trip times. Our goal is to focus on the system function, particularly the model section. Queueing theory is a major function that can model one of these services. The queuing theory is proposed in this paper as the primary analytical tool to model and analyze proposed systems and services, thereby establishing a suitable methodology and tools that can ultimately bring innovations to the transportation area.

2 THE OBJECTIVE

The transportation system has become a significant concern for both the government and the public, as it has a profound impact on almost every aspect of our daily lives. Over the last few decades, rapid and dramatic advances in technology have significantly impacted all aspects of our lives. Given that the transportation network is essential to our lives, it is extremely important to incorporate technological advancements in this sector. Meanwhile, it is crucial to continue assessing and updating the impacts of such technology in this field. Queuing theory has been widely applied to problems such as these, as it demonstrates the capacity to solve, evaluate, and improve various road network challenges and services offered by ITS, utilizing queueing theory. It has been demonstrated that one of the most widely used mathematical tools for evaluating the performance of these systems is queueing theory. This paper introduces a wide range of queueing theory models to present the fundamental knowledge of mathematical models for researchers, enabling them to apply these models in their investigations and studies.

Two aims pushing scientists to study queueing theory:

- As much as possible to understand real-life queueing situations.
- To make it easier to adapt.

In addition, this review explores the integration of operations research methodologies in the design and management of intelligent transportation systems. Specifically, our focus is on how techniques such as queuing theory, optimization algorithms, and simulation models can be applied to enhance traffic flow, reduce delays, and improve the performance of transportation networks. By evaluating these methodologies, this review seeks to identify best practices for implementing ITS solutions and provide insights into their impact on system efficiency. Additionally, this review aims to demonstrate how advanced operations research tools can offer both predictive and prescriptive insights that can be applied to urban transportation problems, ranging from congestion management to resource allocation in real-time.

3 SIGNIFICANCE OF THE STUDY

The significance of this review lies in its potential to enhance the application of operations research in intelligent transportation systems, which is critical to the effective management of modern transport networks. As cities continue to grow, transportation systems must evolve to meet the demands of increasing traffic volume, changing mobility patterns, and the need for sustainability. Operations research can offer critical contributions through the optimization of traffic flow, the development of real-time decision-making models, and the simulation of different traffic management strategies. The review bridges the gap between theoretical models and practical applications, offering a comprehensive approach to improving the performance of ITSs. By utilizing cutting-edge OR tools, the review will contribute to the development of smarter, more efficient urban transport solutions [3,4].

4 INTELLIGENT TRANSPORTATION SYSTEMS

This section offers a brief overview of the main topic of this report. ITSs are defined, followed by a review with a discussion of their different dimensions. The section below is primarily based on the review titled "An Introduction to ITS," which is available on the MIT OpenCourseWare. These sections were also prepared using additional resources, which include [5–8].

Most developed countries have sophisticated transportation systems. Traffic congestion and safety factors can be considered as the major difficult problems that have emerged, leading to time and money losses. Therefore, these complicated conditions were addressed by developing ITS. They are a component of the digital economy agenda continuously in the transportation sector of the government.

ITS is defined as "products, services, and systems” for rapidly emerging transportation that relies on advanced technology like electronics, computers, and communications. Also, the definition was given as: "A set of instruments for transportation applications that integrate contemporary computing and communication technologies". The phrase "ITS" describes efforts to combine communications and information technology (CIT) into vehicles and infrastructure to monitor things that typically conflict, like routes, vehicles, and loads. ITS aims to decrease vehicle accidents, journey times, and fuel consumption while enhancing safety issues.

Dynamic feedback and automation are the hallmarks of ITS, which encompasses all information technologies utilized in transportation and enables the efficient movement of people and goods. These new technologies have recently gained popularity as a new mode of transportation. As a result, CIT, like computing, sensing, communications, and algorithms, is utilized by ITS. It incorporates a variety of communication and technology tools to enhance the transportation systems. The technology used in ITS varies, from applications of monitoring like security CCTV systems to basic management systems like traffic signals and car navigation. Therefore, the systems' appendices contain all information regarding the state of the existing route and may offer an alternate solution to any issues.

5 MODELS OF SIMULATION

A variety of models and programs are being introduced for various traffic network problem situations, and each model depends on different boundaries. These problems can be treated and resolved by multi-disciplinary approaches such as simulation and optimization models. For most simulation models, some traffic specialists have chosen tools that were designed for their purposes and have adopted them. While others preferred to choose particular programs that were created for the evacuation situation [9]. Over time and with the development of science, the need for quick solutions to road issues increases, leading to the adoption of more models and tools. In 2008, Hardy and Wunderlich compared 30 simulation models based on traffic computer programs. The system's complexity served as the basis for the comparison. The study also examined the distinctions among the three simulation classes-micro, macro, and meso-simulation models [9, 10]. Additional models can also be found in [11]. For every simulation model, a few examples were examined and defined at many resources, some but not limited to, as presented by these references [12–23].

6 TRAFFIC MODELS METHODOLOGY

Simply, the theory of queueing is “Theory Mathematical for Waiting Lines” [24–28]. The queueing theory could be presented under a wide range of names, including theories of traffic, congestion, and stochastic service systems. Among them, the queueing theory has become the most widely used. It has been described as one of the most important modelling tools for analyzing transportation systems. Therefore, many researchers have published related works that are extremely influential in addressing the queue problems. Queueing models will be utilized in this section, emphasizing that these models are suitable for tackling such problems. The phrase "service systems" essentially has the same meaning as the phrase "queueing system," as the road users expect to obtain the service. The customer will get the service right away if the server is available; otherwise, the customer either leaves the system or waits in the queue until another server becomes available.

In queueing theory, every investigation aims to discover the system's basic performance metrics (probabilistic properties), including the mean, variance, density function, and distribution function for the variables listed below, as in [29]:

- Customer numbers enrolled in the system.
- Customer numbers are waiting for a service.
- Take advantage of the server or servers.
- The customer's response time.
- Waiting time of the customer.
- Idle time of the server.
- Busy time of the server.

As outlined earlier, this model can be defined according to three variables:

The input process: The distribution of time periods between successive customer arrival moments.

The service mechanism: The length of time and number of servers required to provide customer service.

The queue discipline: The customer either leaves the system or waits in the queue because the servers are busy.

6.1 Theory of stochastic and probability processes review

In this section, some theoretical aspects of the theory of stochastic and probability processes will be described, which could interpret the basic concept of the queueing theory:

6.1.1 Random variables

It is important to emphasize that the majority of models are predicated on the assumption that the random variables involved are independent and distributed exponentially [29]. In the middle of the nineteenth century, Pafnuty Chebyshev (1821–1894) introduced the concept of random variables, defining them as "A real variable which can take on various values with various probabilities" [30]. Under the identical conditions, the customers have to achieve the same performance on the road. Means that this situation can remain steady over a long-run relative frequency, and this behavior can be explained using probability theory. Practically, probability theory has been developed mathematically, and it has proved that it can give excellent models because it represents the interface between the mathematical and intuitive aspects. Random variables: each event that can be expressed in numerical terms in different ways. Mainly, there are two types of random variables: discrete random variables and continuous random variables.

6.1.2 The statistical equilibrium

Initial conditions do not affect the state probabilities $\{P_0(0) and P_1(0)\}$ and sum to unity if a system is worked for a long time. The system is called “equilibrium” in terms that all the boundaries of the system do not change frequently, which means the system is approximately in a state of stationarity. In the late 19th century, Maxwell (1860), Boltzmann (1871), and Gibbs (1902) developed statistical equilibrium methods in physics, which were initially used to solve relatively straightforward problems of thermodynamics. Statistical mechanics makes statistical and probabilistic claims regarding systems' macroscopic behavior based on the known microscopic properties of those systems [31].

6.1.3 Processes of birth and death

Feller (1939) introduced processes of birth and death, which are now utilized as models for epidemiology's queue formation, population growth, and numerous other theoretical and applied domains [32, 33]. A continuous Markov chain time that tracks particle numbers in a system over time is defined by the name "processes of birth and death". The birth and death rates at any given time are determined by the number of currently existing particles, and each particle has the ability to either live or die. In evolution, birth-death processes are popular modeling tools [32]. It has been preferred to give a simple example of the birth-death processes because the queueing theory relies heavily on this process, which is known as the Poisson process.

Birth-and-death processes consist of some models, which are as follows:

- Models of birth and death queueing.
- Multidimensional birth and death queueing models.

6.2 A few significant distributions of probabilities

6.2.1 The bernoulli distribution

A random variable that has only two possible values, often 0 and 1, is known as a Bernoulli random variable. These random experiment models have two possible outcomes, which are sometimes called "success" and "failure." [34]. A random variable X, sometimes entitled (success and failure), because it has two possible results ($X = 0$, and $X = 1$), its probabilities are shown as $P\{X = 0\} = q$and $P\{X = 1\} = p$, where $p + q = 1$.

6.2.2 The binomial distribution

This distribution represents the number of the same type of (n) Bernoulli trials (either success or failure), and thus it is a sequence of (n) independent experiments [35, 36]. According to a proof by Swiss mathematician Jakob Bernoulli published in 1713 posthumously, the expansion of the binomial equation $(p + q)n$, where $q = 1 - p$, has a kth term (where k starts with 0) that represents the probability of k such occurrences in n repetitions. This is where the "binomial distribution" first appeared.

6.2.3 The multinomial distribution

In finance, the type of probability distribution is called the multinomial distribution and is used to determine things such as how likely a company will post earnings higher than expected, while rivals will post disappointing earnings. The process of determining the results of experiments with independent events and two or more distinct possible results is referred to by this term [37].

Supposing we have:
n: Sequence of independent trials. r: Number of possible results in each trial, $r \geq 2$. Then, the probability of those n trials the (ith) outcome occurs K_i times is:

$$P\{N_1 = K_1, \cdots, N_r = K_r\} = \frac{n!}{K_1! \cdots K_r!} p_1^{K_1} \cdots p_r^{K_r} \quad (1)$$

6.2.4 The negative-binomial distribution (pascal distribution)

The Pascal random variable is an extension of a geometric random variable. It is sometimes referred to as the "Kth-order interarrival time of the Bernoulli process" because it describes the number of trials required to reach the Kth success. The negative binomial distribution is also known as the Pascal distribution [38].

6.2.5 The uniform distribution

Even though the distribution of uniform is the most basic probability distribution, it plays the most fundamental role in statistics since it is effective in random variable modeling [39]. Suppose that:
U: Values of a continuous random variable taken in $(0, t)$, then it has a mean and variance as below:

$$E(U) = \int_0^t x f(x) dx = \frac{t}{2}, \quad V(U) = \int_0^t \left(x - \frac{t}{2}\right)^2 f(x) dx = \frac{t^2}{12} \quad (2)$$

6.2.6 The negative-exponential distribution

The probability distribution that describes the time interval between events in the Poisson process is called the exponential distribution (also known as, negative-exponential distribution).

The Poisson distribution and the exponential distribution are closely related. Let's say, for example, the number of births during a given interval time is modeled by a Poisson distribution, and the time between births can be modeled using an exponential distribution [40].

Let X : Continuous random variables, has distribution function $\mathrm{P}\{X \leq x\} = f(x)$, and

$$f(x) = \begin{cases} 1 - e^{-\mu x} & \text{if} \quad x \geq 0 \\ 0 & \text{if} \quad x < 0 \end{cases}$$

Then, X has the negative-exponential distribution with mean and variance as below:

$$\mathrm{E}(X) = \mu^{-1}, \quad \mathrm{V}(X) = \mu^{-2}$$

6.2.7 The poisson distribution

The Poisson processes find probabilities for the process's random points in time. A "process" can be anything, such as collisions at an interchange. You can use the Poisson process to predict when one of these random events will occur in time.

Assuming that the duration of service time between two successive customers is independent and identical, and: $N(t)$: Number of arriving customers on time $(0, t)$ and has $P\{N(t) = j\} = P_j(t)$. Length of time between sequences points has the exponential distribution$e^{(-\lambda h)}$. Then, the exponential distribution is:

$$\mathrm{P}\left\{X_j > t\right\} = \mathrm{e}^{-\lambda \mathrm{t}} \quad (3)$$

Furthermore, if the length of the interval is fixed, and has the exponential distribution as above, thus the probability that at least one point will occur in $(t, t + h)$ is:

$$1 - e^{-\lambda t} = \lambda h + o(h)$$

For two or more points in $(t, t + h)$ is:

$$1 - e^{-\lambda h} - \lambda h e^{-\lambda h} = o(h)$$

The probability of the number of customers in any interval of total length t is:

$$P_j(t) = \frac{(\lambda t)^j}{j!} e^{-\lambda t}$$

The Poisson distribution with mean and variance as below:

$$\mathrm{E}(N(t)) = \mathrm{V}(N(t)) = \lambda t$$

7 DIMENSIONS AND QUEUES MODELLING

The real-life queue with the queueing models that are developed to model them have been produced according to five dimensions; the dimensions will be described in fair detail below.

7.1 Single server versus multi-servers versus infinite servers

In practice, key parameters are the number of customers that are waiting to get the service, which can be written as $\mathrm{S} = 1, 1 < \mathrm{S} < \infty$, and $\mathrm{S} = \infty$. And these assumptions are mathematically more than reality.

While no expression is represented when $S = \infty$ in real-life because no systems that have an infinite number of servers can exist.

7.2 Exponential versus non-exponential

The random arrival times can be derived mathematically according to an exponential distribution, whilst the service times are derived depending on a non-exponential distribution. When the system is derived mathematically according to an exponential distribution, stationary conditions, such as $M/M/1$, $M/M/S$, and $M/M/\infty$, can be formulated as a process of Markov (as above). But, when the system is derived depending upon non-exponential, such as $M/G/1$, $M/G/S$, and $M/G/\infty$, the derivation gets harder to do. The mean number expression in the system $E(Q)$ for $M/G/1$, which is now an embedded Markov chain:

For multi-servers $M/G/S$, in this case, the phase-type distribution must be used to approximate the service time distribution.

To infinite services $M/G/\infty$, the distribution is Poisson because the behavior of the customers' number in $M/M/\infty$ and $M/G/\infty$ is the same.

7.3 Steady state versus time-dependent

As explained above, the understanding is that most real queueing systems depend on time, either in terms of the stationary state or the non-stationary state. However, the behavior of some cases is built on ignoring time. However, analytical operations have shown that analyses that depend on time can become more valuable. For instance, the M(t)/M/1 queue models, which depend on time, require groups of differential equations that can be found numerically. The same assumptions can be adopted with other queueing models, which have a high level of complexity, as in M(t)/G/S, which requires discrete approximations for the service time distribution. It was found that these approximations worked well if levels of service were high, cycle lengths were relative to the average service time, and the rate of arrival variations was small. In terms of the importance of time, the M(t)/G/∞ queueing model again shows less dependence on time.

7.4 Single node versus queues of tandem versus queues of networks

Open networks are one of the basic layouts of road networks; this means there are external network arrivals and departures at one or more system nodes. By assuming exponential service times and random arrivals, each network can be analyzed as distinct queues, which can all be expressed as $M/(M/(S)$ systems, and the product-form solution is the name given to the resulting solution. As a result, the marginal probability of each independent queue can be used to calculate the steady-state joint probabilities. The technique of modeling systems as a collection of distinct sub-systems is called "decomposition". This was a starting point for the development of approximations to systems of non-exponential functions. Open queuing networks can be modeled where service times are not required to be exponential and external arrivals are not required to be Poisson. For single-node systems, phase-type approximations are used, and each node of service is examined as a $GI/G/S$ queue. Also, this paper explains the restrictions on the capacity of buffers in queueing networks.

7.5 Extra features

Particular features can be seen on the road, such as batch arrival, bulk services, and priority systems. And can be motivated either by specific real-world issues or with the intention of enhancing comprehension of problems set.

8 QUEUE MODELING APPROACHES

In the modeling approaches, there is a big difference that has appeared clearly in the two classes, from basic mathematical formulas for queueing theory to simulation models, and these issues will be explained in this paper.

8.1 Formulae and analytic formulations

The classic theory of queueing can be seen in mathematical formulations, and these formulae can be found either by relatively simple techniques, such as resolving birth-death equations, or with more complexity by generating function methods. These sorts of formulae, which have been found in the first approach ($M/M/1$), proved that the key force in the congestion is the intensity of the road (λ/μ). The same evaluation is used for both other approaches, and the same result was realized that the traffic density ($\lambda/S\mu$) is responsible for the congestion. The performance of the queue can be clarified through the queueing theory approach. The $M/G/1$ queue models can emphasize the concept that the relation between the service time and the congestion is positive. Furthermore, based on this insight, it has been hypothesized that multi-server systems might experience similar results, and as a result, the successful method of utilizing discrete-time and phase-type approximations for $M/G/S$ systems that were mentioned earlier.

8.2 Simulation models

Simulation models have been used for a long time; the ability of the variables for a particular queueing system can be introduced by using simulation models.

8.2.1 Mapping of queues and queue modeling

It can be defined as modeling techniques for the steady-state behavior of various kinds of queueing problems, see the tables below:

Table 1 steady-state behavior of various kinds of queueing problems

	Exponential	Non-exponential
Single node	$M/M/1: AF\&F$ $M/M/S: AF\&F$ $M/M/\infty: AF\&F$	$M/G/1: AF\&F, AF\&N$ $M/G/S: AF\&N$ (approximation) $M/G/\infty: AF\&F$
Network	$Jackson: AF\&F$ $Other: AF\&N(approximation)$ $\infty server: AF\&F$	$Any: AF\&N(approximation)$ $\infty server: AF\&F$

Table 2 Modeling techniques for the time-dependent behavior of various kinds of queueing problems

	Exponential	Non-exponential
Single node	$M(t)/M/1: AF\&N$ $M(t)/M/S: AF\&N$ $M(t)/M/\infty: AF\&F$	$M(t)/G/1: AF\&N$ (approximation) $M(t)/G/S: AF\&N$ (approximation) $M(t)/G/\infty: AF\&F$
Network	$Any: SM$ $\infty server: AF\&F$	$Any: SM$ $\infty server: AF\&F$

Where:
$AF\&F$: Analytic formulations with formulas.
$AF\&N$: Analytical formulations with solution of numerical.
SM: Simulation modeling.

9 CONCLUSION

A queueing model is a mathematical model, which means an abstraction of reality. Although the drawback of the models is the complex and lengthy procedures that may lead to complicated solutions, the results of analytical solutions (using queueing theory) have proven that they are suitable and capable of providing an assessment of traffic flows. In addition, these models still have the potential to simulate the performance of the traffic flows, such as uninterrupted flows. The aspects that can help evaluate the traffic performance improved by queueing theory are congestion pricing and environmental impacts.

Queueing theory models were adopted for modeling uninterrupted traffic flows. Analytical models were developed, and most relevant elements for uninterrupted traffic flows can be described and calculated, such as road characteristics and maximum speed. This methodology was considered for both single and multiple nodes, as well as finite and infinite buffer sizes.

The results of these models provide a general form of speed-flow-density diagrams. Due to their analytical nature, the practical results demonstrated that these models are suitable for both general and analytical forms, regardless of the particular situation.

For the future recommendations, please read the summary below:

- Needs more research in networks with finite buffer sizes.
- More work needs to be done on the applications and validation of the queueing model.
- More work needs to be done with finite networks of zero buffer size.
- It can be considered that the time spent on the route is due to congestion, not just the travel time on the calculated routes.

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