Non-Technological Challenges for the Remote Operation of Automated Vehicles

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Abstract

No existing automated vehicle can operate in all conditions and environments. In order to allow unmanned operation of automated vehicles in all conditions, many developers have the capability for human drivers to operate the vehicle from a remote location using wireless communication. This practice, referred to as remote operation or teleoperation, is prevalent among industry, yet has received little attention in the legal and transportation literature. This paper describes the legal environment for remote operation of vehicles, both in terms of existing motor vehicle codes and model legislation. The operational performance of remote operation is explored, and a model is developed to estimate the number of remote operators needed to manage large automated vehicle fleets using reasonable assumptions.

Keywords: Remote operation; remote control; teleoperation; automation; outsourcing

1 Introduction

Remote operation is generally considered to be a component of most early automated driving systems, as even highly-advanced automated vehicles (AVs) require occasional human input in particularly difficult driving environments or in cases of hardware or software failure. SAE's definitions of levels of driving automation, for example, require an in-vehicle driver in levels 0 to 2, and in-vehicle backup in level 3, and allows for automated driving without human monitoring in limited situations in level 4 (SAE International, 2018). Human intervention can be performed by an operator located inside the vehicle, but to save costs it may be performed by a driver located in an off-site facility using wireless communication.

An automobile was first controlled via radio by an operator in a following vehicle in 1925 ("Radio-Driven Auto Runs Down Escort; Wireless Directs Test Car in Wobbly Course Through Heavy Broadway Traffic," 1925). Recent advancements in video allow the operator to be completely off-site, as demonstrated in mining operations (Hainsworth, 2001), agriculture (Murakami et al., 2008), and drone warfare (Gusterson, 2016). A small fleet of dockless electric scooters in Atlanta in the United States are repositioned with the help of remote operators based in Mexico City (Hawkins, 2020). By applying this technology to passenger vehicles, a licensed driver could remotely operate a vehicle with conditional automation and be available to take (remote) control given adequate warning.

California requires all companies conducting driverless testing of automated vehicles in the state to have a licensed human driver who "engages and monitors" the automated vehicle and who may also "perform the dynamic driving task," although they do not specify whether each vehicle requires its own dedicated remote operator or if oversight can be shared among several drivers (CA DMV, 2018a). As of July 2020, three entities were registered to conduct driverless testing in California: Waymo, Nuro, and AutoX Technologies (CA DMV, 2018b).

There are two main forms of remote operation. In the first, a remote operator assists a stuck vehicle with object identification and/or path planning around an object. In this situation, the remote operator does not control the vehicle's motion through steering, throttle, or braking directly but rather provides routing instructions which are executed by the vehicle's automated driving system. An automated vehicle might use this approach to navigate through an unfamiliar work zone. This approach is generally referred to as *remote assistance*, and has been used by Nissan (Davies, 2017), General Motors' Cruise, and Waymo (Higgins, 2018).

In the second form, the remote operator takes control of the vehicle's steering, throttle, and braking to perform the driving task. This approach, referred to as *remote driving,* often uses computer terminals equipped with steering wheels, pedals, and multiple monitors displaying a wide-angle camera feed transmitted live from the automated vehicle over wireless networks. The communications requirements for remote driving are more demanding than remote assistance; while the latter can be conducted over existing cell networks, the former requires highly reliable low-latency communication. Although several automated vehicle developers have filed patents for remote driving applications (Davies, 2017), most activity is with small technology startups (Davies, 2019; Sawers, 2018).

There are other, less direct ways to remotely control a vehicle. It may be as simple as a user standing on the sidewalk and supervising (and stopping, if necessary) a vehicle pulling into tight parking spot, a feature available on some Tesla models (Davies, 2016). The lead driver in a coordinated, prearranged truck platoon is, in a way, controlling the movements of driverless trucks in the platoon which are programmed to follow a lead vehicle. In another example, a construction vehicle in an active work zone could be controlled by a worker standing in safe location along the shoulder. In a more complex example, a licensed driver in India could monitor five automated taxis in the U.S., interceding when requested. Such a system would drastically reduce the costs of operating a taxi, transit, or delivery service, without the need for high/full automation.

Given the widespread adoption of remote operation in industry, there is relatively little literature on the subject. Of the 29 states that have enacted automated vehicle legislation, only five address remote operation or teleoperation directly. A draft addition to the Uniform Vehicle Code defined “remote driver,” (ULC, 2017, p. 14), but this was removed in the final version (ULC, 2019). In its most recent guidance, the United States Department of Transportation mentions remote operation only briefly in the context of agriculture and space exploration (NSTC and USDOT, 2020). Many open questions regarding remote operations remain, such as its legality, licensure and location restrictions on drivers, technical feasibility, and economic impacts. The purpose of this paper is to establish some of the critical legal, technical, operational, and economic challenges of the remote operation of road vehicles, especially automated vehicles.

2 Legal aspects

The legality of the remote operation of motor vehicles has received little attention in the literature. This section reviews relevant state legislation in the U.S. The section considers two key questions: do jurisdictions in the United States generally require a vehicle’s driver to be physically located inside the vehicle and seated at the controls, and if not, are drivers required to be physically located in the United States?

2.1 Driver’s physical presence within the vehicle

There is some ambiguity regarding whether a licensed driver can legally operate a vehicle from a remote location. As Smith notes in a 2014 study of the legality of automated vehicle operation, no state’s statutes expressly requires the physical presence of a driver in a motor vehicle, especially when considering that some jurisdictions define trailers as vehicles even though they are meant for cargo rather than human passengers (Smith, 2014).

Other rules, however, seem to imply the presence of a human driver. Smith lists seven categories where the absence of a driver makes compliance with existing law impossible or impractical: unattended vehicles, abandoned vehicles, crash obligations, safety belts, driver sight, driver interference, and control (Smith, 2014). As a brief example, drivers in many states are required to provide contact information and, in some cases, render aid following a crash. These tasks are impractical, and in some cases impossible, with remote operators.

Trimble et al. (2018) reviewed statutes and regulations in 15 states and the Uniform Vehicle Code (National Committee on Uniform Traffic Laws and Ordinances, 1968) with respect to vehicle automation. They found that most states base their requirements for an operator on the Uniform Vehicle Code. These requirements generally take the following form:

> “No person … shall drive any motor vehicle upon a highway in this state unless such person has a valid driver’s license” (National Committee on Uniform Traffic Laws and Ordinances, 1968).

Trimble et al. (2018) concluded that based on these definitions, an operator is limited to a *person* (defined either as a “natural person, firm, partnership, association, or corporation” or not defined at all) with a *valid license.* The definitions of "drive" and "operate," however, leave open questions of what driving acts might be considered as "operating" under the definitions, and whether physical presence of the driver or operator is required. Trimble et al. (2018) recommended that states review the terms "drive," "driver," "operate," and "operator" to reduce ambiguity and remove restrictions on the use of automated driving systems. They argued for a broad interpretation of the terms "drive," "operate," and "be in physical control," and proposed the following definition:

> "Human engages and can disengage vehicle (including remotely) but does not need to be physically present or seated behind the controls of the vehicle" (Trimble et al., 2018).

By including remote operators, this broader definition ensures that highly automated vehicles operating without passengers will still have legal drivers, albeit remote ones. This definition also ensures that passengers in the driver seat while the automated driving system is in control are not considered as drivers. Finally, the definition ensures that empty AVs are regulated at all. States that have not developed new definitions of driver and operator in anticipation of AVs generally require that "no person … shall drive … without a valid driver's license" (National Committee on Uniform Traffic Laws and Ordinances, 1968) but do not make the opposite requirement that "all vehicles operating in the state must be driven by persons with a valid license" (Trimble et al., 2018). Without the opposite requirement, driverless vehicles would have no driver for authorities to regulate, and therefore rules of the road would be inapplicable for an automated vehicle without a person inside the vehicle to take control.

The Uniform Law Commission recently published model legislation that addresses this responsibility gap by requiring that all automated vehicles be associated with an automated-driving provider who is responsible for rules of the road violations (ULC, 2019). The requirements to register as an automated-driving provider allow technically competent entities, such as companies involved in the development and operation of automated vehicles, to operate vehicles. The automated-driving provider does not need to be the same person or entity as the vehicle owner, and furthermore may operate the vehicle (in automated mode) without a driver's license. Finally, the model legislation stipulates that passengers in the driver's seat during a completely automated trip are not required to possess a driver's license. If this model legislation is adopted by states, it will allow automated vehicles to have legal, non-human drivers responsible for adhering to rules of the road.

2.2 Remote operator's physical presence within the United States

Every state reviewed in Trimble et al.'s (2018) legal audit recognized driver's licenses from other states as presumptively valid. If operating an automated vehicle remotely does not require a special license, then a remote operator could use a valid driver's license from any state. Unless expressly prohibited, a remote operator could also be physically located in another state; no state currently requires remote operators to be located within the state's boundaries.

Driver's licenses from foreign countries are generally recognized in the United States, although some states require drivers possess an International Driver's License along with a driver's license from his or her country of residence (USA.gov, 2019).

Several states have enacted AV legislation that addresses remote operation. A summary of relevant legislation is provided in Table 1.

Table 1. State laws and regulations addressing remote operation of road vehicles.

State	Title	Driver's License Requirements	Operator's Physical Location
California	Testing of Autonomous Vehicles	Valid driver's license required; jurisdiction not specified.	Not specified.
Florida	House Bill 311	U.S. driver's license required.	United States.
Alabama	Senate Bill 47	Valid driver's license required; jurisdiction not specified.	Not specified.
Vermont	Senate Bill 149	Valid driver's license required; jurisdiction not specified.	Not specified.
Utah	House Bill 101	Valid driver's license required; jurisdiction not specified.	Not specified.

California's AV testing regulations define "remote operator" as:

> "a natural person who: possesses the proper class of license for the type of test vehicle being operated; is not seated in the driver's seat of the vehicle; engages and monitors the autonomous vehicle; is able to communicate with occupants in the vehicle through a communication link. A remote operator may also have the ability to perform the dynamic driving task for the vehicle or cause the vehicle to achieve a minimal risk condition" (CA DMV, 2018a).

This definition covers a range of control ability both within (but not in the driver's seat) and outside the car. A person that sits in the passenger seat, engages the vehicle, and sets the speed of the autonomous driving system might be considered a remote operator under California's definition. California requires that the remote operator have a valid driver's license but does not specify if the license must be from California or another U.S. state with which California extends reciprocity. The statute does not require that the driver be physically located in either California or the United States (CA DMV, 2018a).

Florida's House Bill 311, enacted June 13, 2019, defines a "remote human operator" as "a natural person who is not physically present in a vehicle equipped with an automated driving system who engages or monitors the vehicle from a remote location." The bill requires that remote human operators be "physically present in the United States and be licensed to operate a motor vehicle by a United States jurisdiction" (Fischer, 2019).

Alabama's Senate Bill 47, enacted June 10, 2019, defines a "remote driver" as "a natural person who is not seated in a commercial motor vehicle, but is able to perform the entire dynamic driving task." (Gerald, 2019). The bill states that the remote driver "is considered to be the operator of the vehicle for the purpose of assessing compliance with applicable traffic or motor vehicle laws" (Gerald, 2019). In the event of a crash, the remote driver is deemed to have given consent to provide blood and urine for testing the presence of drugs and alcohol, "regardless of the jurisdiction in which the remote driver is physically present" (Gerald, 2019). The bill does not specify the jurisdiction of the operator's license, nor does it require any geographic location for the operator.

Vermont Senate Bill 149 was signed by the Governor on June 14, 2019. The bill defines an "operator" as "an individual employed by or under contract with an automated vehicle tester who has successfully completed the tester's training on safe driving and the capabilities and limitations of the automated vehicle and automated driving system, can take immediate manual or remote control of the automated vehicle being tested, is 21 years of age or older, and holds an operator's license for the class of vehicle being tested" (Senate Transportation Committee, 2019). The bill does not specify the jurisdiction of the operator's license, nor does it require any geographic location for the operator.

Utah's House Bill 101, enacted in March 29, 2019, defines a "remote driver" as "a human driver who is not located in a position to manually exercise in-vehicle braking, accelerating, steering, or transmission gear selection input devices, but operates the vehicle" (Spendlove, 2019). The remote driver is required to have a "valid license to operate a motor vehicle of the proper class for the motor vehicle being operated" (Spendlove, 2019) but there are no restrictions on geographic location.

3 Technical feasibility

There are two main forms of remote operation: remote assistance and remote driving. Remote assistance requires transmission of video or still images, audio, and coordinates and sensor data from vehicles to remote operators. Remote operators must have the ability to transmit audio and waypoints to the vehicle. Because the vehicles theoretically request assistance from safe location, ideally while stopped (Higgins, 2018), a reasonable amount of latency is acceptable. There is little literature on latency and bandwidth requirements for remote assistance, but given California DMV's requirements for communicating with driverless vehicles during testing (CA DMV, 2018a), as well as examples of autonomous vehicle developers using remote assistance in the field (Higgins, 2018), it can be assumed that remote assistance is feasible using existing wireless networks. The remainder of this section is therefore focused on technical feasibility of remote driving.

Remote driving requires significant bandwidth over wireless networks to allow reliable, low-latency two-way communication between vehicle and remote operator. Vehicles must be able to transmit high-resolution video and audio, as well as coordinates, sensor data, and verification of message receipt. Remote operators must be able to transmit audio (to communicate with passengers or emergency responders) and steering, brake, throttle, and signaling control inputs. Several companies have demonstrated remote driving on public roads at various ranges using wireless networks. Table 2 lists remote driving demonstrations.

There is some disagreement over the extent to which wireless networks can support remote driving. Some developers estimate less than 100 millisecond latency over Verizon and AT&T networks (Davies, 2019), while other demonstrations have experienced occasional but unacceptable loss of signal (Higgins, 2018). Several companies have demonstrated remote driving on public roads at various ranges using both existing and enhanced wireless networks, but there are few details regarding the precise technologies used. Table 2 lists remote driving demonstrations.

Table 2. Road vehicle remote operation demonstrations.

Demonstration	Year	Network	Range	Details
Huawei and Shanghai Automotive Industry Corporation	2017	5G*	30 km	240 degree HD video, 10 ms claimed end-to-end control latency (Huawei Technologies, 2017)
Telefonica and Ericsson	2017	5G*	70 km	Mobile World Cong. (González, 2017)
Phantom Auto	2018	LTE	600 km	Simultaneous AT&T and Verizon networks (Harris, 2018)

*5G standards had not been released at the time of demonstration (3GPP, 2017), suggesting these were prototypes using some 5G concepts.

Latency over wireless networks varies over time and space. The exact variation depends on many factors, but field tests have shown average video streaming latencies of 121 ms (Chucholowski et al., 2014) and 205 ms (Shen et al., 2016) over 3G networks, and 183 ms over 4G networks (Shen et al., 2016). Two-way latency was measured over LTE networks at 75–83 ms (Dano, 2013) and about 100 ms (Kang et al., 2018; Liu et al., 2017).

Latency has a significant effect on driver performance. Studies have shown that small consistent delays below 170 ms (Chen et al., 2007) and 300 ms (Neumeier et al., 2019b) have minimal effect on remote drivers. Tests of a real vehicle on a closed track with constant 500 ms delay showed a lateral offset standard deviation of 0.4 meters, demonstrating that the operator was able to safely follow a lane at 30 km/h (Gnatzig et al., 2013). Other studies have shown worse driver performance when delays are greater than 300ms (Neumeier et al., 2019b) and 700 ms (Davis et al., 2010; Vozar and Tilbury, 2014). These studies have generally been conducted in simulation or in controlled, low-risk environments; it is not clear whether results will transfer to dynamic driving environments.

While varying latency has been shown to negatively impact driver performance, these impacts can be mitigated by artificially inserting delay to produce greater but consistent latency (Davis et al., 2010; Luck et al., 2006). Liu et al. (2017) was able to reduce driving errors by half by inserting delay in data transmission, increasing a variable average delay of 97 ms to a constant delay of 358 ms. Although artificial latency can improve performance in benign conditions, it may prove disastrous when responding to sudden emergencies.

5G networks are expected to increase bandwidth and reduce latency significantly compared to 3G/4G/LTE networks. Saeed et al. (2019) used a conservative estimate of remote driving data needs, using a 3GPP (2018) estimate of required upload rates of 20 Mbps at 99.999 percent reliability. The authors found that widescale deployment of 5G infrastructure to support remote driving on all roads may be impractical due to cost of fiber backhaul, signal interference, and limited upload capacity. Instead, they recommend that remote driving occur only in designated corridors such as freight or transit routes where infrastructure needs are not cost prohibitive.

Relaxed uptime requirements may make remote driving more feasible under 5G networks. Reduced bandwidth requirements may help as well—remote driving might use digital panning to transmit video only if the driver looks in that direction (Gnatzig et al., 2013), or lower frame rates or compression might be found to have minimal effects on driver performance. Neumeier et al. (2019a), for example, estimated that 3 Mbps upload bandwidth was sufficient to provide a 180 degree view ahead and 90 degree view behind, far lower than the 20 Mbps requirement used by Saeed et al. (2019). In another example, Shen et al. (2016) were able to remotely drive a road vehicle using off-the-shelf hardware, transmitting two 640×480 pixel video streams over 4G networks with an average delay of 184 ms. Given these demonstrations and the examples in Table 2, it may be possible to safely drive a vehicle remotely with less stringent requirements than those considered by Saeed et al. (2019).

4 Staffing requirements to remotely operate a fleet of automated vehicles

None of the states regulating remote operation require that there be a single remote operator for each automated vehicle. It is also unlikely that AV developers plan to employ a one-to-one operator-to-vehicle ratio in the long term, as the only cost advantages it offers over a human driver in the vehicle are lower wages due to outsourcing. Instead, remote operators may work in teams, responsible for monitoring several vehicles and taking control as requested either by the passengers or the automated driving system.

The ratio of operators to vehicles has clear safety implications. With one operator assigned to a single vehicle, the operator is always available to take control. If instead one operator were responsible for two vehicles, there would be rare occasions when both vehicles required assistance simultaneously and one is left waiting. The number of remote operators needed to service a fleet also has economic impacts, as it serves as a rough estimate of potential job losses as vehicles no longer require their own dedicated drivers.

This section estimates the number of remote operators needed to manage all driving in the United States assuming all driving is highly automated and that vehicles can anticipate their need for human intervention with reasonable warning.

4.1 Model selection

The number of remote operators required to manage a fleet of vehicles can be estimated using queueing theory. Many call centers with known call volumes and call durations use the Erlang C formula (Erlang, 1917) to estimate the number of staff needed to achieve performance goals and minimize caller wait times (Klungle, 1997). The Erlang C formula in its original form estimates the probability P_C that an incoming request cannot be immediately served based on the number of agents *m* and the request load *a*.

$$P_C(m,a) = \frac{\frac{a^m m}{m!\,(m-a)}}{\sum_{i=0}^{m-1}\frac{a^i}{i!} + \frac{a^m m}{m!\,(m-a)}}$$

The load *a* can be defined as the average number of requests per unit time λ divided by the average number of requests than can be serviced by a single operator per unit time μ.

$$a = \frac{\lambda}{\mu}$$

The request rate λ can be calculated as the takeover request rate of an automated driving system r_v multiplied by the number of automated vehicles in the fleet n_v.

$$\lambda = r_v n_v$$

This form of the Erlang C distribution is difficult to calculate for large values of agents due to the factorial operation. For this paper, a recursive algorithm for calculating Erlang C developed by Zeng (2003) was used. To determine the number of servers *m* required to handle a known load *a* for a given probability of immediate service P_C the following algorithm is employed.

input: P_C and a
output: m
begin
Initialize m to $\lfloor a \rfloor + 1, a$
Initialize P_B to 1
for $i := 1$ to $\lfloor a \rfloor + 1$ **do**
$P_B(\lfloor a \rfloor + 1, a) := \frac{P_B(\lfloor a \rfloor + 1, a)}{P_B(\lfloor a \rfloor + 1, a) + i/a}$
Initialize simulated probability P to
$\frac{P_B(\lfloor a \rfloor + 1, a)}{1 - \frac{a}{\lfloor a \rfloor + 1}[1 - P_B(\lfloor a \rfloor + 1, a)]}$
while $P > P_C$
$m := m + 1$
$P := \frac{(m-1-a)P}{\left(\frac{m}{a} - 1\right)(m-1) - P}$
end
end

4.2 Model inputs and assumptions

The demand λ for remote operator assistance can be estimated by employing a few assumptions. The rate at which an automated vehicle might require remote takeover (r_v) is unknown. Companies testing automated vehicles in California are required to report all disengagements, defined as the "deactivation of the autonomous mode when a failure of the autonomous technology is detected or when the safe operation of the vehicle requires that the autonomous vehicle test driver disengage the autonomous mode and take immediate manual control of the vehicle…" (CA DMV, 2018b). A disengagement is not the same as an AV-initiated takeover request, as some of the disengagement were initiated by the test driver. Furthermore, a future AV may initiate takeover requests at a *higher* rate than seen in the California reports, as there were likely situations that required human intervention that the AV missed. For the purposes of this paper, and in the absence of a better metric, the disengagement rate is used here as a surrogate takeover request rate for an advanced automated vehicle.

In 2017, disengagement rates for different companies ranged from 341 disengagements in 682,894 kilometers (once per 2,003 kilometers) to 625 disengagements in 1505 kilometers (once per 2.4 kilometers) (Lv et al., 2018). Disengagement rates improved in 2018, with the top two companies reporting averages of 8,328 and 17,847 kilometers between disengagements (Herger, 2019).

In order to estimate remote operator staffing needs, the remote takeover rate must be expressed in units of time. In the disengagement reports, hours of vehicle operation were not provided. The National Household Travel Survey reported an average vehicle trip length of 15.4 kilometers and an average vehicle trip duration of 20.6 minutes, yielding an average speed of 45 km/h for all vehicle travel in the United States (FHWA, 2017). Assuming that the disengagement rate per mile holds for driving nationally, then the number of disengagements per hour can be calculated by dividing the average distance traveled between disengagements by average vehicle speed of 45 km/h.[1]

Additional takeover request rates are used in this analysis for comparison. For example, the average American travels in a vehicle for 58.6 minutes per day (McGuckin and Fucci, 2018, p. 54); a takeover request rate of once per 356 hours would equate to each person experiencing an average of one remote takeover per year. Table 3 shows a sample of average hours between takeover requests.

Table 3. Evaluated takeover request rates using automated driving disengagement rates as surrogates.

Description	Average hours between takeover requests	Takeover request rate per hour per vehicle, r_v
Once per hour	1	1
Once per 10 hours	10	10^{-1}
Waymo 2017 disengagement rate	44	2.27×10^{-2}
GM Cruise 2018 disengagement rate	185	5.41×10^{-3}
Once per year for average American	356	2.81×10^{-3}
Waymo 2018 disengagement rate	397	2.52×10^{-3}
Once per 1,000 hours	1,000	10^{-3}
Once per 10,000 hours	10,000	10^{-4}
Once per 100,000 hours	100,000	10^{-5}

The number of vehicles on the road (n_v) can be calculated from transportation surveys. The Federal Highway Administration estimates that vehicles in the United States traveled a total of 5.1 trillion kilometers in 2017, or 14 billion kilometers per day (FHWA, 2018). Vehicle travel volumes vary throughout the week. Estimates from Schrank et al. (2015). found that volumes on Fridays are 10% greater than an average day. Volumes also vary throughout a typical day. Schrank et al. (2015) provide figures displaying the percentage of daily volumes that occur in each hour of the day, categorized by congestion level, road facility type, and whether a road carries higher volumes during the morning or evening peak period.

To determine the total distance traveled for each of the day for the entire United States, first the average daily vehicle-kilometers traveled (VKT) from each state were multiplied by a Friday

[1] Both GM Cruise and Waymo test on lower speed roads in San Francisco and Mountain View, California, respectively. If their disengagements are primarily a function of time rather than distance, then a lower disengagement rate per hour should be used for national figures. Average arterial speeds in San Francisco are approximately 22 km/h compared to 45 km/h nationally (City and County of San Francisco, 2017).

adjustment factor 1.1 (Schrank et al., 2015). Then, for each hour in the day, each state's daily volume was multiplied by the appropriate hour factor for its time zone. For simplicity, states that crossed multiple time zones were assigned to the time zone with the greatest geographic coverage.

Remote operators must work in shifts to provide 24-hour coverage. Emergency response agencies that provide 24-hour service in the United States often assign employees to 12-hour shifts (Picarello, 2016). Ideally the shifts should be scheduled so that minimum staff are needed during the overnight shift, meaning that the low-volume 12-hour shift has the lowest possible peak hour volume. Hourly vehicle-kilometers traveled per hour in the United States are shown in Figure 1, along with the peak hour volumes for the preceding and following 12-hour shifts for each possible shift change hour. The hours of 8 AM and 8 PM Eastern Time show the greatest differences between peak hour volumes for each 12-hour period and is designated as the day shift.

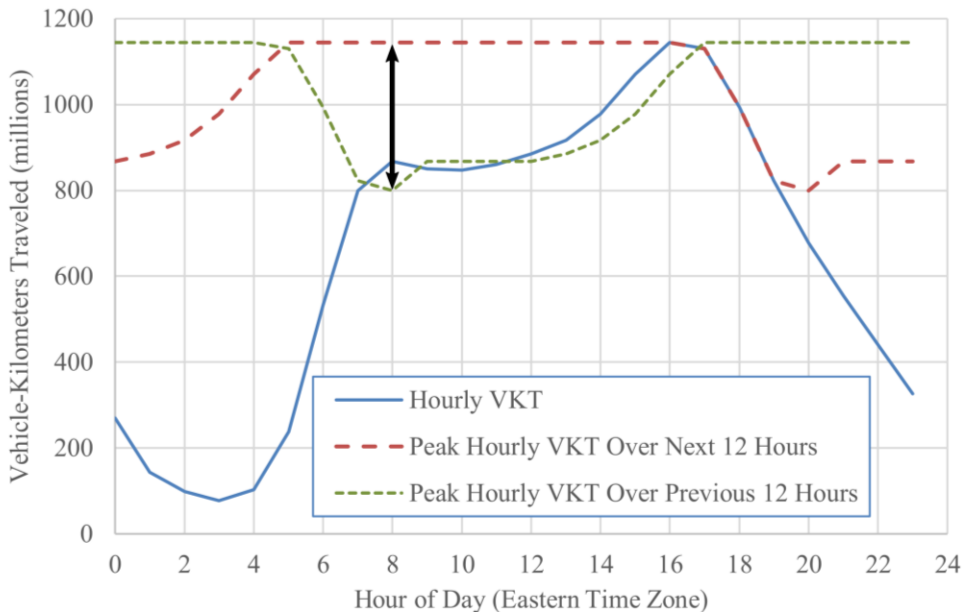

Fig. 1. Differences in peak hour vehicle-kilometers traveled for a typical Friday in the United States over a 12-hour shift. Greatest difference in demand is at 8 AM, the recommended time for shift change.

For the two shifts, the peak volumes are 1,144 million VKT and 800 million VKT. When adjusted for the 45 km/h average vehicle speed, these are equivalent to 25.3 million vehicle-hours traveled (VHT) and 17.7 million VHT, respectively. Because each peak period is exactly one hour, the 25.3 million VHT corresponds to 25.3 million vehicles on the road during the peak hour on average. (As the average vehicle trip is 20 minutes in duration (FHWA, 2017), there would be vehicles on the road over the course of the hour, but only 25.3 million vehicles on the road at any given moment.) The demand for remote operator takeover λ can then be defined as:

$$\lambda_{day} = r_v n_v = r_v(2.53 \times 10^7)$$

$$\lambda_{night} = r_v n_v = r_v(1.77 \times 10^7)$$

The service rate μ must be estimated as the California disengagement reports do not list takeover durations. A range of average remote takeover durations of one, five, and ten minutes was used, resulting in service rates μ of 60, 12, and 6 per hour.

4.3 Target failure rate selection

The Erlang C distribution outputs the probability that a request cannot be immediately handled by the agents. For remote operation of vehicles, a target probability must be established to determine staffing needs. A typical target for a call center is to answer 80% of calls within 20 seconds (Klungle, 1997). Automated vehicles, however, may request takeover during safety-critical events, necessitating a higher target.

Commercial airline travel involves considerable risk, and the Federal Aviation Administration (FAA) provides guidance of failure rates for critical systems. FAA regulations specify that some system failures (such as the failure of a door-closed indicator) be "improbable," while others (such as a door failure) must be "extremely improbable" (FAA, 2004). The Federal Aviation Administration does not specify precise failure rates, but suggests rates of 10^{-5} per flight-hour for improbable events and 10^{-9} per flight-hour for extremely improbable events (FAA, 1988).

These standards apply to an aircraft's equipment and systems and may not be applicable to a remote operator whose original function is to supplement an automated driving system that itself replaced a human driver. A better target might be the probability that a human driver becomes incapacitated in some way. This standard could be stated as: the probability that both a) an automated driving system requires takeover and b) no operator is available to provide immediate service *should be less than* the probability that a human driver becomes incapacitated. To ensure that the failure rate of the automated driving system combined with the backup remote operator is no worse than the medical event rate of a human driver, the following equation is employed:

$$\text{ADS Failure Rate } \times \text{Remote Operator Failure Rate} \leq \text{Target Failure Rate}$$

This can be rewritten using established terminology:

$$r_v \times P_C(m, a) \leq r_t$$

Solving for $P_C(m, a)$ while keeping consistent units of time yields the following equation.

$$P_C(m, a) \leq r_t / r_v$$

The probability that a human driver becomes incapacitated can be estimated from records of pilot incapacitation in commercial aviation. The population of pilots differs from the general population in age (DeJohn et al., 2004), health, and level of certification (FAA, 2006), and therefore a pilot medical event rate will likely be lower than that of the driving population. Medical event rates for airline pilots serve as a lower boundary for a human failure rate.

The FAA studied in-flight medical events involving U.S commercial airline pilots between 1993 and 1998, where medical events were defined as circumstances in which a pilot was unable to perform full flight duties (DeJohn et al., 2004). Fifty medical events were found over a six-year period, with an in-flight medical event rate of 0.058 per 100,000 flight hours. This is in agreement with studies of Air France pilots at 0.044 per 100,000 flight hours (Martin-Saint-Laurent et al., 1990) and United States Air Force pilots at 0.019 per 100,000 flight hours (McCormick and Lyons, 1991). Rates were not reported per pilot-hour, only per flight-hour, and therefore pilot-hour rates must be estimated. An estimate of 2.5 pilots per flight can be used to calculate a medical event rate of 0.0232 medical events per 100,000 pilot-hours. This translates to a target failure rate r_t of 2.32×10^{-7} per person-hour.

Four example target failure rates were established: a typical call center (no r_t but 80 percent of calls answered within 20 seconds), FAA improbable (10^{-5} per hour), FAA extremely improbable (10^{-9} per hour), and medical event for a human (2.32×10^{-7} per hour). While the target failure rates vary greatly, the number of operators required to meet them does not. In queuing theory, arrivals are typically modeled as a Poisson distribution, where the time between arrivals is represented as an exponential function. This has the effect of producing demands that are fairly uniform. When tested in this study, changing the target failure rates from 10^{-2} to 10^{-9} required only a 6.3% increase in operators assuming 5-minute durations and 397 average hours between takeover requests. The number of required operators is driven more by average call duration and mean time between takeover requests for AVs. For the purposes of this analysis, the medical event for a human of 2.32×10^{-7} is selected as the sole target failure rate per hour r_t.

A summary of all model inputs is provided in Table 4.

Table 4. Erlang C model parameters.

Parameter	Symbol	Value	Source
Operators	m	Varies	Calculated
ADS failure rate	r_v	Varies	(Herger, 2019; Lv et al., 2018)
Vehicles on road during shift peak hour	n_v	25.3 million day 17.7 million night	(FHWA, 2017; Schrank et al., 2015)
Request rate	λ	r_v/n_v	Calculated
Service rate	μ	6, 12, 60 per hour	Assumption
Requests (load)	a	λ/μ	Calculated
Target failure rate	r_t	2.32×10^{-7}	Pilot medical event rate
Remote operator missed call rate	P_C	$\leq r_t/r_v$	(Erlang, 1917; Zeng, 2003)

4.4 Model results

The Erlang C distribution was calculated for both day and night shift values of λ, ranges of μ, and ranges of P_C. For each minimum number of remote operator agents N required, the day and night shift values were added. As many emergency response agencies use 12-hour shifts with employees working four days on followed by four days off, the total number of remote operators required to manage a single day's demand was multiplied by two to represent the full staffing requirements to manage the automated vehicle demand.[2]

Table 5 and Figure 2 show the estimated number of remote operators required to manage the takeover requests for all vehicles in the United States assuming they had automated capabilities.

Table 5. Estimated number of remote operators needed to assist entire United States vehicle fleet.

Average hours between takeover requests	Minutes to service each takeover request		
	1 min/request	5 min/request	10 min/request
1	1,445,392	7,193,604	14,371,422
10	146,812	724,424	1,444,296
44 (Waymo 2017)	34,126	166,328	330,628
185 (GM Cruise 2018)	8,452	40,298	79,676
356 1x/year per American	4,518	21,214	41,786
397 (Waymo 2018)	4,074	19,072	37,538
1,000	1,710	7,772	15,184
10,000	220	878	1,658
100,000	36	112	198
1,000,000	8	14	24

[2] An anonymous reviewer noted that the vigilance, periods of low activity, and safety-actions required of remote operators might necessitate shorter shifts with more frequent breaks. Extensive human factors research on air traffic control may have applications for remote operators (National Research Council, 1997). More research is needed on human factors specific to remote operation.

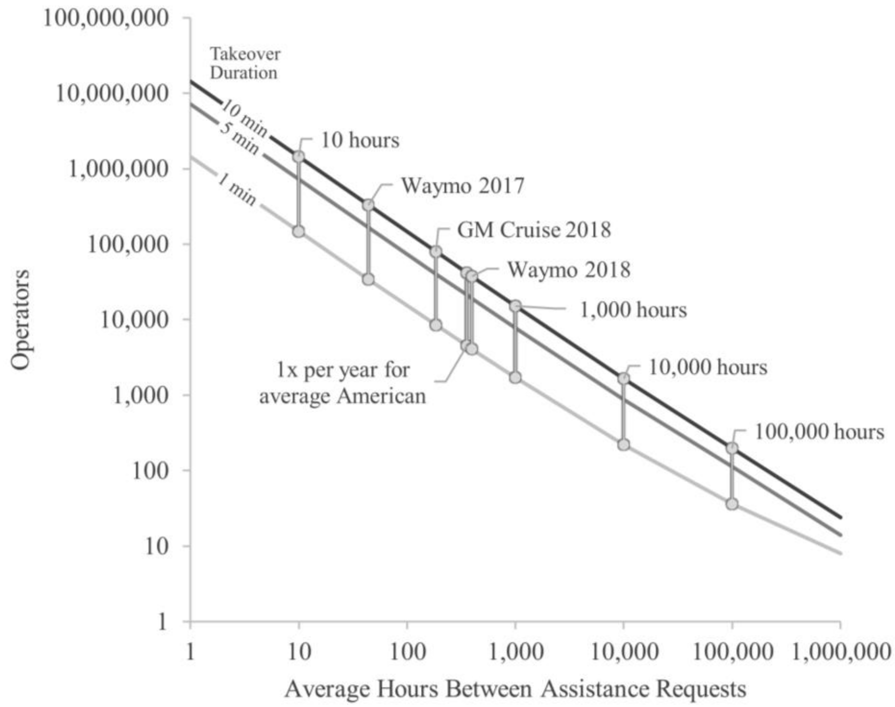

Fig. 2. Estimated number of remote operators needed to assist entire United States vehicle fleet.

4.5 Performance during severe, unplanned events

Requests for remote operation may fluctuate over time, requiring greater or fewer remote operators. Many of these fluctuations can be predicted in advanced. For these events, additional operators can be scheduled to handle the increased call demand. Hurricanes, snowstorms, and holidays are examples of events with some warning.

Other events occur with little or no warning, such as terrorist attacks, earthquakes, and tsunamis. To estimate the performance of remote operation when handling unexpected fluctuations in call volumes, a terrorist attack scenario is considered.

During the attacks of September 11, 2001, over a million people fled lower Manhattan (DeBlasio et al., 2002). Only 14% of Manhattan commuters travel by passenger car on a typical day car (Moss et al., 2012), and even fewer left by car on September 11 (DeBlasio et al., 2002). This scenario assumes that peak period travel increased by an additional million automated vehicles during the peak traffic hours of both the remote operation day and night shifts. Although this is a larger increase in vehicle travel demand than was experienced on September 11 in Manhattan, it represents an especially challenging circumstance and may more accurately reflect an attack on a less dense city. In the scenario, automated vehicles request remote operation at the usual hourly rates, which is set to once per 397 hours (approximately Waymo's 2018 disengagement rate).

Peak hour traffic volumes are 2.3 times the average hourly volumes for night shift and 1.2 times the average hourly volumes for day shift. Because the shift staffing is designed to handle peak hours, an injection of one million vehicles in any non-peak hour could be absorbed by operators without exceeding the target failure rate.

The performance during the peak hour is calculated using a procedure similar to the one described in Sections 4.1 and 4.2. The probability P_C that a request is not handled immediately can be calculated using Algorithm 4 in Zeng (2003). The average wait time W for those placed in the queue is given in the following equation (Chromy et al., 2011).

$$W = \frac{P_C}{\mu(m - a)}$$

For the night shift peak hour with an additional million vehicles in the system, 57% of requests cannot be handled immediately, and vehicles in the queue must wait an average of 8 seconds before reaching a remote operator. For the day shift, 16% of requests are not answered immediately, with an average queue wait time of less than one second.

These figures assume that all remote operators in the United States can address all U.S. requests. If the network of global remote operators could be utilized, the performance would be improved.

4.6 Economic impacts

Automation of the driving task is expected to eliminate many jobs (Milakis et al., 2017; Smith, 2017). The U.S. Department of Transportation has argued that technological advancements will create new jobs that will require drivers to attain new skills (USDOT, 2018). Many but not all professional drivers will be able to transition to jobs as remote operators due to limited demand. Based on the calculations presented in this paper, if all driving in the United States were to become automated with remote takeover requested on average once per 397 hours of operation, all driving could be handled by a team of between 4,074 and 37,538 remote operators. According to the U.S. Bureau of Labor Statistics, there are 4.4 million persons employed as drivers in the United States (Bureau of Labor Statistics, 2019a). Even if all remote operators were required to be based in the United States, this accounts for less than one percent of drivers employed today.

The entire fleet of vehicles in the U.S. need not become automated. Transportation network companies, often referred to as ridesharing services, have heavily invested in vehicle automation in recent years, with Uber spending as much as $20 million per month on its AV research program (Harris, 2019). In 2018, Uber transported passengers 41.8 billion kilometers (Uber Technologies, Inc., 2019). Accounting for both ridesharing and empty vehicle movement, *i.e.* "deadheading," Henao and Marshall (2019a) found an average distance weight passenger occupancy of 0.8. Using the same average speed assumptions of 45 km/h from the National Household Travel Study (FHWA, 2017), Uber vehicles operated for approximately 52.3 billion kilometers over 1.2 billion hours in 2018. Assuming uniform hourly demand for worldwide operations and a remote takeover request rate equivalent to Waymo's 2018 disengagement rate, Uber's entire fleet of 3.9 million drivers (Uber Technologies, Inc., 2019, p. 5) could be replaced with reliable automated driving systems and between 72 and 356 remote operators. The required number of remote operators to manage Uber's fleet under various assumptions is shown in Table 6. Many Uber drivers work part-time, while remote operators in this model are assumed to work full-time (42 hours/week on average). In terms of total person-hours, Uber requires an estimated 1.2 billion annual person-hours to operate manually compared to 158,000–780,000 annual person-hours to manage an automated vehicle fleet remotely. This represents a person-hour reduction of 99.94–99.99%.

Table 6. Estimated number of full-time remote operators needed to manage Uber global vehicle mileage.

Average hours between assistance requests	Minutes per takeover request		
	1 min/request	5 min/request	10 min/request
1	10,116	47,840	94,396
10	1,208	5,204	10,028
44 (Waymo 2017)	344	1,328	2,480
185 (GM Cruise 2018)	116	384	684
356 (1x/year per American)	76	228	392
397 (Waymo 2018)	72	208	356
1,000	40	104	168
10,000	12	24	36
100,000	4	8	12
1,000,000	4	4	4

5 Cost savings from outsourcing

If automated vehicles are able to monitor the driving environment and request assistance when needed, *i.e.* Level 3 automation (SAE International, 2018), companies can use teams of remote operators to reduce the number of drivers needed to manage a fleet. As shown in Section 2.2, only Florida specifically requires that a remote operator be physically located in the United States. Some states require that remote operators hold a valid driver's license, but do not specify a jurisdiction. As states generally recognize foreign driver's licenses, remote operators may be able to legally operate a vehicle on U.S. roads with a foreign driver's license while physically located outside the United States.

If long-range remote operation is technically feasible (which seems likely given today's high-quality international video calls and nearly lag-free intercontinental online gaming), this would allow companies to further reduce costs by outsourcing remote operation to countries with lower costs of labor. For example, one call center service provider lists hourly rates for a dedicated call center operator as $22–28 in North America and $8–15 internationally, a reduction of 47–64% (Worldwide Call Centers, 2020). These rates could create the potential for outsourcing heavy truck and tractor trailer driving jobs, which have median hourly salaries of $21 in the United States (Bureau of Labor Statistics, 2019b). There is less potential to outsource jobs for taxi drivers, ride-hailing drivers, and chauffeurs, which earn median salaries of $12.49 per hour (Bureau of Labor Statistics, 2019b). Ride-hailing drivers must also account for expenses in purchasing and maintaining a vehicle. One study found that ride-hailing drivers earned hourly rates of $15.57 gross but between $5.72 and $10.46 after expenses (Henao and Marshall, 2019b). It may be impractical to outsource these positions at current pay rates.

6 Conclusions

This paper represents the most thorough analysis of legal and operational challenges associated with remote operation of automated vehicles. In most states, remote operation is not expressly prohibited by any single statute, nor is it prohibited under most definitions of driver/operator, although a physically present driver is implied in other statutes concerning unattended vehicles, abandoned vehicles, crash obligations, safety belts, driver sight, driver interference, and control. Of the five states that address remote operation within their automated vehicle legislation, only Florida requires that the remote operator be physically located within the United States. As states generally recognize driver's licenses from foreign countries, a person operating a vehicle remotely may be able to do so using a foreign license while physically located outside the United States.

An analysis using queuing theory and assumptions about automated vehicle failure rates was used to estimate the number of remote operators required to safely manage a large fleet of vehicles while ensuring that the probability of a vehicle both requesting takeover and not receiving it from an operator was less than the probability of a incapacitating medical event for a human. Based on the analysis, if all vehicles in the United States were automated and able to automatically request takeovers at the same rate that Waymo's vehicles disengaged from autonomous control in 2018, all driving could be managed by between 4,074 and 37,538 remote operators. This would eliminate 99% of jobs belonging to the 4.4 million professional driver workforce in the United States, while simultaneously covering all non-professional driving. Employing the same assumptions, Uber's operations, currently requiring 3.9 million drivers globally, could be managed by fewer than 400 remote operators, representing a reduction of 99.94–99.99% in person-hours.

These findings have significant impacts for governments and regulators. It is difficult to overstate the economic and safety impacts of automated driving, a technology that will fundamentally alter trillion dollar industries (Clements and Kockelman, 2017) and prevent millions of crashes (World Health Organization, 2018). Remote operation may accelerate the advancement of vehicle automation by outsourcing the most difficult aspects of computerized driving—*e.g.* classifying and navigating occasional situations outside of the vehicle's operational design domain—to humans outside the vehicle. This could drastically accelerate advancement in vehicle automation. It is recommended that governments review their policies, if any, regarding remote operation's potential economic and operational impacts.

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