A Queueing Model Based Intelligent Human–Machine Task Allocator

Changxu Wu, *Member, IEEE*, Yijun Liu, and Bin Lin

***Abstract*—Automatic machines are increasingly being used to help drivers automatically complete tasks; however, the high error rate of automatic machines limits how they might reduce driver task load. Therefore, allocating tasks between human and machine becomes an important question in system design. Existing methods of task allocation do not consider several natural characteristics of human–machine systems simultaneously, including speed–error tradeoff, cognitive modeling of workload, multicriteria decision modeling, dynamic allocation, and global optimum. In this paper, a queueing model-based intelligent task allocator (QM-ITA) that covers the criteria above and optimally allocates tasks between a human operator and an automatic machine is developed. The optimal task allocation algorithm is described in four scenarios that demonstrate how QM-ITA is able to minimize the workload of human operator, minimize system error rate, propose a maximum acceptable error rate of an automatic machine, determine if an automatic machine is necessary for a system, and suggest a maximum acceptable task arrival rate. Further development of the model and the prospects for future research are also discussed.**

***Index Terms*—Cognitive model, human error rates, human workload, queueing model, task allocation and allocator, task assignment.**

I. Introduction

INCREASED use of systems and devices in automobiles requires drivers to respond to an incrementally increasing amount of electronic information. For emergency drivers, this means that they are required to process a growing amount of in-vehicle information. The development of automatic machines (e.g., voice recognition, image recognition, and other techniques in artificial intelligence) presents an opportunity that related tasks can be handled by automatic machines, thereby lessening driver process demands. This situation raises an important research question for consideration: How do we distribute or allocate the tasks between a human operator and an automatic machine?

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Quantitative methods and approaches in task allocation have been proposed in the previous studies. Fitts [1] first proposed an innovative list of statements including their descriptions about whether a human or a machine performs a certain function better [1], [2]. Recently, de Winter and Dodou [2] reviewed and summarized more than 40 studies of function and task allocation based on Fitts' original work. Although Fitts' list was criticized by other researchers (e.g., Jordan [3]), it is still an adequate approximation that captures the most important regularity of automation [2].

As technology advanced, studies using quantitative methods in task allocation are developed. These studies, summarized in Table I, can be categorized into five groups: 1) rating evaluation; 2) statistical decision theory; 3) network optimization; 4) dynamic allocation; and 5) queueing theory. Table I also demonstrates the criteria to assess those quantitative methods, which include the speed–error tradeoff, use of cognitive model, multicriteria decision, dynamic allocation, and global optimum. All these criteria came from the nature of human–machine systems. 1) One of the important information processing characteristics of human being is the speed–error tradeoff: When human operators have less time to respond to a task, they usually make more errors (e.g., [6] and [55]–[57]). A good task allocation algorithm should consider this important feature of human information processing (A. Speed–error tradeoff criteria). 2) In dynamic task situations with the task arrival rate changing very frequently, a good task allocation should be able to allocate these tasks in real time (B. Dynamic allocation criteria). If a task allocation method takes a relatively long time to calculate the allocation results by another human (e.g., workload rating [7]), it may slow down the responses of the whole human–machine system. 3) If a task allocation algorithm does not estimate the human workload, it may assign lots of jobs/tasks to the human operator, which may eventually overload the operator. To relatively and accurately estimate human workload, a quantitative cognitive model (e.g., [6]) is needed to estimate the workload (C. Usage of cognitive model criteria). 4) Unlike usage of heuristic methods in optimization (cannot guarantee the optimal solution is global, called local optimum) used by other task allocation methods, a good allocation method should be able to obtain the best allocation strategy/results in all possible cases (D. Global optimum criteria). 5) In many practical situations, usually human operators are already occupied by a primary task, and any additional information loaded on the operators may affect their performance and safety in performing the primary task (e.g., single modality in the multiple resource theory [6] and empirical results in [5]); therefore, the workload of secondary task(s) should be minimized (Criterion E1). In reality,

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TABLE I
QUANTITATIVE TASK ALLOCATION METHODS

Allocation Methods	Studies	A. Speed-error Trade-off	B. Dynamic Allocation	C. Usage of Cog. Model	D. Global Optimum	E. Multi-Criteria Decision
Rating Evaluation	Workload Rating [7]	No	No	No	No	No
	Job Process Charts [8]	No	No	No	No	Yes
	Evaluation Matrix [9]	No	No	No	No	Yes
Statistical Decision Theory	Signal Detection Theory [10]	No	No	No	-	No
	Fuzzy Signal Detection [11]	No*	No*	No*	-	No*
	Bayesian Analysis [12]	No*	No*	No*	-	No*
	Expected Value Method [13]	No	No	No	-	No
Network Optimization	Tasks-Agent Control [14]	No*	Yes	No*	No*	No*
Dynamic Allocation	Situation dependent [15]	No	Yes	No	No	No
	Flexible/adaptive allocation [16]	No	Yes	No	No	No
	Workload-based allocations [45]	No	Yes	No	-	No
Queueing Theory	Simple Queueing Model [17], [20]	No*	Yes	Yes	-	No*
	QN-MHP AWMS [5]	No	Yes	Yes	-	No
	QM-ITA Current work	Yes	Yes	Yes	Yes	Yes

-: Not mentioned in the method; No: Existing work did not cover the corresponding criterion; *: Possible major improvement of the method may able to cover that criterion.

it is very difficult to find an error-free human–machine system, and error may cause accidents and other severe problems in the system; thus, the human–machine system's error rate should also be minimized (Criterion E2). Moreover, it is very hard for an automatic machine to reach 100% accuracy, particularly for image/voice recognition systems; thus, there is a criterion of maximum acceptable error rate for the automatic machine (Criterion E3). In addition, the arrival rate of information cannot be infinite, and it has its maximum level to avoid overloading the system (Criterion E4). Overall, a good task allocation algorithm should consider all of these criteria (E1-E4) above imbedded naturally in human–machine systems to maximize or minimize the corresponding indexes (e.g., workload, error rates, etc.) (E. Multiple-criteria decision).

Rating evaluation is the first and most intuitive approach used to determine the allocation strategy through quantifying and comparing the performance of human and automatic machines. Williams [7] proposed a workload rating method for the evaluation of multiple operators. Tanish [8] provided subjective ratings sensitive to individual difference with job process charts. Finally, Papantonopoulos and Salvendy [9] applied an evaluation matrix to the analytical cognitive task allocation.

Statistical decision theory refers to statistical methods that facilitate decision by the operators to respond to (or to ignore) automated alerts and warnings. While evaluating the sensitivity of an automated machine, signal detection theory and fuzzy signal detection theory determined the threshold between true alarm rates and reduce false alarm rates [10], [11]. Similarly, Parasuraman [12] applied Bayesian analysis to determine the decision threshold and maximize the probability of a true alarm. The expected value analysis proposed by Sheridan and Parasuraman [13] compared the expected value for either human or automated control in decision making.

Shoval *et al.* [14] proposed an optimal task allocation and information transfer strategy based on network optimization. This method mapped tasks onto a task agent control space with network optimization techniques, finding the optimal path with the lowest flow value calculated from the weight and capacity matrices.

One further development of the task allocation is the concept of dynamic/adaptive task allocation. The basic principle of dynamic task allocation is that altering the allocation must be contextual and fit within "situation dependent" [15] or "flexible and adaptive allocation" situations [16]. Debernard *et al.* [45] validated workload-based task allocation mainly for task allocations between air-traffic controller and an artificial intelligence system, which considered workload while ignoring other important indexes of a system (e.g., the error rate).

Rouse [17] developed a queueing model of pilot decision making, where an allocation strategy of decision-making responsibilities between pilot and computer regulated task frequencies to improve system performance. Rencken and Durrant-Whyte [20] constructed a queueing model that predicted the task arrival rates and service rates for human and computer performance. The optimal allocation decision is made through dynamic programming algorithms based on system performance and human behavior.

However, as shown in Table I, few existing task allocation methods meet all of these five criteria simultaneously. In this paper, a queueing model-based task allocation algorithm is proposed, which addresses these criteria and finds optimal allocation strategies. Specifically, the objectives of this paper are to describe the characteristics and development of the queueing model-based intelligent task allocator (QM-ITA) and present its results in a case study. In the following sections of this paper, Section II represents a description of the general structure of the intelligent task allocator (QM-ITA), followed by the mathematical development of a queueing model. Section III illustrates the results and the application of QM-ITA referring to a case study. Finally, Section IV summarizes the major results of the current work and its applications and the limitations of the current research.

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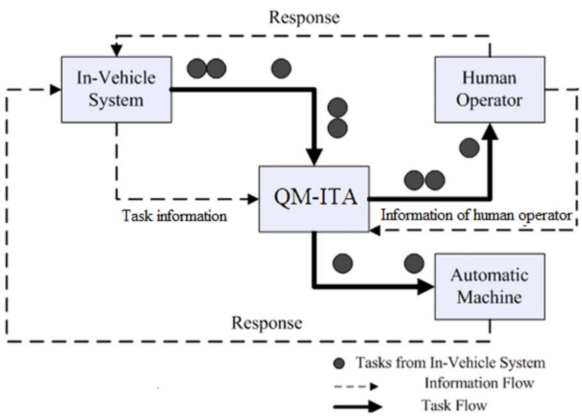

Fig. 1. QM-ITA.

II. Queueing Model-Based Intelligent Task Allocator

A. Overview

QM-ITA and other related components in the human–machine system are presented in Fig. 1. Tasks from in-vehicle system (see the big dots in Fig. 1) proceed to QM-ITA. Based on the optimal allocation strategies in QM-ITA, the tasks are allocated between a human operator and an automatic machine (see the solid line as task flow in Fig. 1). The human operator and the automatic machine process the tasks and send responses to the in-vehicle system (see the two "response" dashed information flows from human operator to the in-vehicle system and from automatic machine to the in-vehicle system in Fig. 1, respectively). Information about the human operator (e.g., the processing speed of an ongoing task) and task information from the in-vehicle system (e.g., arrival rate of the information) are sent to QM-ITA so that QM-ITA is able to allocate the tasks optimally (See the dashed lines as information flow from human operator to QM-ITA and information flow from the in-vehicle system to QM-ITA in Fig. 1, respectively).

QM-ITA is composed of a set of mathematical equations that can quantify the allocation of the tasks (called allocation or routing strategy q_j). The following sections introduce how the allocation strategies are mathematically obtained.

B. Mathematical Model Formulation and Derivation of QM-ITA

The objective of the current model is to determine the optimal allocation strategy for allocating tasks for a global optima while satisfying all the constraints. Based on Rouse's queueing model of the human operator [17], the human operator is modeled as a continuous-time Markov chain with a capacity c and a service rate μ. The capacity of the automatic machine is assumed to be infinite.

Let q_j be the probability that a task will be assigned to the human operator given the condition that there are j tasks currently in the human operator $(j = 0, 1, \ldots, c)$.[1] For example, $q_2 = 1$ indicates that a task is assigned to the human operator, given the condition that there are two tasks currently in the human operator. Within all conditions, $q_c = 0$.

[1]From a human factors point of view, tasks in the human operator mean tasks being stored and processed in the working memory of the human.

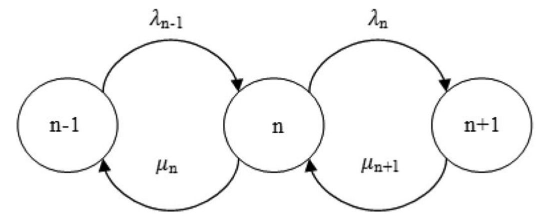

Fig. 2. Transition diagram of the Markov chain.

Let λ_j be the task arrival rate at the human operator given the condition that there are j tasks currently in the human operator. λ_j is calculated as

$$\lambda_j = \lambda \times q_j, \quad j = 0, 1, \ldots, c \tag{1}$$

where λ stands for the task arrival rate of the whole system.

Essentially, the mathematical property of the Markov chain indicates that the total flows into a state must be equal to the total flows out of that state if a stationary state exists. A transition diagram of the human operator would then appear as shown in Fig. 2, where state n indicates that there are n tasks currently in the human operator [23].

Let p_j be the probability that there are j tasks in the human operator $(j = 0, 1, \ldots, c)$. Since p_j is a probability distribution, we can have the boundary condition that

$$\sum_{j=0}^{c} p_j = 1. \tag{2}$$

Equaling flow in and flow out of state n, the following balance equation can be obtained:

$$\lambda_n p_n + \mu_n p_n = \mu_{n+1} p_{n+1} + \lambda_{n-1} p_{n-1}. \tag{3}$$

In state 0

$$\lambda_n p_n + \mu_n p_n = \mu_{n+1} p_{n+1} + \lambda_{n-1} p_{n-1}. \tag{4}$$

Combining (3) and (4), it can be determined that

$$p_j = \prod_{i=1}^{j} \left(\frac{\lambda_{i-1}}{\mu_i} p_0 \right). \tag{5}$$

By substituting q_j in (2), the value of p_0 can now be determined as

$$p_0 = \frac{1}{1 + \sum_{j=1}^{c} \left[\prod_{i=1}^{j} \left(\frac{\lambda_{i-1}}{\mu_i} \right) \right]}. \tag{6}$$

Rewriting (5) by substituting p_o, we then have

$$p_j = \prod_{i=1}^{j} \left(\frac{\lambda_{i-1}}{\mu_i} \right) \times \frac{1}{1 + \sum_{j=1}^{c} \left[\prod_{i=1}^{j} \left(\frac{\lambda_{i-1}}{\mu_i} \right) \right]}. \tag{7}$$

The error rate of the human operator e_h can be regarded as a constant or interactive as related to the arrival rate λ [see Appendix A for the derivation of (8)], i.e.,

$$e_h = \frac{0.04}{0.04 + \frac{1}{\lambda} - C} \tag{8}$$

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TABLE II
OBJECTIVES, VARIABLES, AND CONSTANTS IN THE FOUR SCENARIOS

Scenarios	Objectives	Variables	Constants
1 (Sec. 3.3.1)	Minimize mental workload	λ, ET	μ, e_m
2 (Sec. 3.3.2)	Minimize the overall error rate of human-machine system (e)	λ, U_T	μ, e_m
3 (Sec. 3.3.3)	Determine the maximum acceptable error rate of the automatic machine (e_m): Max E_m	λ, U_T	μ, E_T
4 (Sec. 3.3.4)	Determine the maximum acceptable arrival rate (λ): Max λ	E_T, U_T	μ, e_m

where C is the duration from the time point when the response of the human operator completes to the time point when a task arrives at the human operator. At this point, the system error rate can be calculated by (see Appendix B)

$$e = \sum_{j=0}^{c} p_j \left[e_h q_j + e_m(1 - q_j)\right]. \tag{9}$$

The workload of the human operator can be obtained via (see Appendix B)

$$\rho = \frac{\left(\sum_{j=0}^{c} q_j p_j\right) \lambda}{\mu}. \tag{10}$$

C. Calculation Simplification

Simplification of the mathematical calculation is reasonable by assigning q_j a binary value of 0 or 1. In this case, $q_j = 1$ indicates that the task is assigned to the human operator when there are j tasks in the human operator; $q_j = 0$ indicates that the task is assigned to the automatic machine when there are j tasks in the human operator.

In (7), there is a special property of the current mathematical model. Using (1) to substitute λ_{j-1}, (7) can be rewritten in terms of λ and q_j as

$$\begin{aligned} p_j &= \prod_{i=1}^{j} \frac{\lambda_{i-1}}{\mu_i} \times \frac{1}{1 + \sum_{j=1}^{c} \left(\prod_{i=1}^{j} \frac{\lambda_{i-1}}{\mu_i}\right)} \\ &= \lambda^j \prod_{i=1}^{j} \frac{q_{i-1}}{\mu_i} \times \frac{1}{1 + \lambda^j \sum_{j=1}^{c} \left(\prod_{i=1}^{j} \frac{q_{i-1}}{\mu_i}\right)}. \end{aligned} \tag{11}$$

Therefore, when $q_j = 0$, it is obvious that $p_{j+1} = 0$. At this point, the solution space $\{q_j\}$ is reduced from 2^c to $c + 1$ in the form of $\{q_j = 1, q_k = 0 | 0 \le k \le c, 0 \le j < k\}$.

The optimal objective is obtained by selecting an appropriate solution from the solution space given the relevant constraints. Examples of these strategies are described in detail in the case study.

D. Development of the Four Scenarios

The human–machine system model previously described are used to address four scenarios with the following objectives (see Table II): 1) to minimize workload given the task arrival rate λ and an overall error rate tolerance E_T; 2) to minimize the overall human–machine system error rate e with a given task arrival rate λ and a human operator workload tolerance U_T; 3) to determine the maximum acceptable error rate of the automatic machine e_m with a given task arrival rate λ and a human operator workload tolerance U_T; and 4) to identify the maximum task arrival rate λ with given overall error rate tolerance E_T and a human operator workload tolerance U_T. The service rate of the human operator μ is regarded as a constant since this rate is determined by a designated human operator.

In practice, the overall error rate tolerance E_T and the human operator workload tolerance U_T will be determined by the requirement for a certain human–machine system and properties of a human operator (e.g., age). For a human–machine system with a very high demand of accuracy (e.g., detecting pedestrians running across road at night), E_T can be very low. U_T can be adjusted depending on the properties of the human operator. For example, for an elder operator (age $>$ 65 years old), his/her U_T should be lower than that of a young operator (age from 20 to 30) [42].

Scenario 1: Determine q_j (allocation strategy) so that the human operator workload is minimized[2] given the task arrival rate λ and the overall error rate tolerance E_T. The problem is formulated as the following nonlinear program:

$$\begin{aligned} &\text{Minimize} \\ &\quad \rho = \frac{\left(\sum_{j=0}^{c} q_j p_j\right) \lambda}{\mu} \\ &\text{S.T.} \sum_{j=0}^{c} p_j \left(e_h q_j + e_m(1 = q_j)\right) = E_T \\ &\quad 0 \le q_j \le 1;\ e_m > e_h;\ q_c = 0;\ j = 0, 1, \ldots, c \end{aligned}$$

where E_T is the system error rate tolerance for secondary tasks, λ, e_h, e_m, and E_T are given constants, and $e_h < e_m$. In the case study, this scenario minimizes driver workload in using a radar system with an automatic machine in different arrival rates of information and overall error rate tolerances (see Section III-C1).

Scenario 2: Determine q_j (allocation strategy) so that the overall system error rate e is minimized given the task arrival rate λ and a human operator workload tolerance U_T. The problem is formulated as the following nonlinear program:

$$\begin{aligned} &\text{Minimize} \\ &\quad e = \sum_{j=0}^{c} p_j \left(e_h q_j + e_m(1 = q_j)\right) \\ &\text{S.T. } \rho \le U_T;\ e_m > e_h;\ q_c = 0;\ j = 0, 1, \ldots, c \end{aligned}$$

where U_T is the human workload tolerance; λ, e_h, e_m, and E_T are the given constants, and $e_h < e_m$. The case study

[2]Since workload (WL) = a ρ + b (see Appendix B and [42]) and a and b are constants, minimizing workload (WL) is equivalent to minimizing ρ.

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described an example of this scenario to minimize the overall system error rate when a driver is using a radar system with an automatic machine under different driver workload tolerances and different arrival rates of information (see Section III-C2).

Scenario 3: Determine q_j (allocation strategy) so that the maximum acceptable machine error rate e_m is obtained given a task arrival rate λ and a human operator workload tolerance U_T. In this scenario, the error rate of the automatic machine e_m does not need to be greater than the error rate of the human operator e_h. The problem is formulated as the following nonlinear program:

$$\begin{aligned}&\text{Determine maximum}\\&e_m = \frac{E_T - e_h \sum_{j=0}^{c} q_j p_j}{\sum_{j=o}^{c} (1 = q_j) p_j}\\&\text{S.T } \rho \leq U_T;\ 0 \leq q_j \leq 1;\ q_c = 0\\&\quad 0 \leq e_m \leq 1;\ j = 0, 1, \ldots, c\end{aligned}$$

where E_T and U_T represent the tolerance of the system error rate and human workload, respectively, and e_h, E_T, and U_T are given constants. In the case study, an example of this scenario is provided to calculate the maximum acceptable machine error rate of the automatic machine at different driver workload tolerance levels and arrival rates of information. If the derived maximum acceptable error rate of the machine is equal to 1, the automatic machine is not needed in this system (see Section III-C3).

Scenario 4: Determine q_j (allocation strategy) so that the maximum acceptable arrival rate λ can be obtained given an overall error rate tolerance E_T and a human operator workload tolerance U_T. The problem is formulated as the following nonlinear program:

$$\begin{aligned}&\text{Determine maximum } \lambda\\&\text{S.T. } \rho \leq U_T;\ 0 \leq q_j \leq 1;\ e_m > e_h;\ q_c = 0\\&e = \sum_{j=0}^{c} p_j \left(e_h q_j + e_m (1 - q_j)\right) \leq E_T\\&j = 0, 1, \ldots, c\end{aligned}$$

where E_T and U_T represent a system error rate and human workload, respectively, and e_m, e_h, E_T, and U_T are given constants, and $e_h < e_m$. In the case study, we described an example of this scenario to estimate the maximum acceptable information arrival rate of a radar system with an automatic machine at different driver workload tolerance levels and different overall system error constraints (see Section III-C4).

Appendix C describes how the objective functions are solved and the allocation strategies q_j are obtained via the optimization process in each scenario.

In addition, a conventional task allocation algorithm is introduced for comparison with the optimal algorithm: a task is assigned to the automatic machine only if the human operator is already occupied. It is a traditional way for the automatic machine to help the human operator process certain types of tasks. In other words, in a conventional algorithm, one task is processed by the human operator at one time, whereas the optimal strategy of the new algorithm presents more than one task to the human operator, depending on the allocation strategy.

Fig. 3. User interface of the radar system [24].

III. Intelligent Task Allocation

A. Case Study

Speeding is one of the most prevalent factors contributing to automobile crashes, according to a report from the U.S. National Highway Traffic Safety Administration (NHTSA). Estimated by NHTSA, in 2004, speeding was a contributing factor in 30% of all fatal crashes, and 13 192 lives were lost in speeding-related crashes. Traffic law enforcement (police officers detecting speeding and issuing speeding tickets) is one of the most critical measures for preventing speeding [5].

Based on an informal interview with the Patrol Division Supervisor of the Police Department of the University at Buffalo, it was found that one of the routine tasks for an officer is speeding detection while steering a vehicle. The police officer must read two numbers on a display of a radar system mounted on the dashboard. The first number is the speed of a target vehicle measured by the radar system, and the second is the distance from the police vehicle to the target vehicle. A speeding violation is determined by both the speed and the distance. Fig. 3 illustrates the radar system and demonstrates how the human operator (driver) responds to an incoming task.[3]

Each pair of numbers are tasks that are allocated either to the human operator or to the automatic machine by QM-ITA. In this case, the speeding detection task is either processed by the police officer or by an automatic machine that reads two numbers and turns on the siren automatically. It should be noted that, in the real world, whether the police officer thinks the vehicle is speeding depends on not only the speed and distance but the consecutive judgment after the speeding reading from the radar machine as well. The police officer uses his long-term memory to judge. Moreover, because there are always a great

[3]For example, suppose the speed limit is 55 mi/h on a road. If the speed is between 56 and 64 m/hr and the distance is less than 100 yd, the vehicle is speeding, and the officer will turn on the siren; if the distance is more than 100 yd, it is judged as not speeding. Moreover, independent of the distance, if the speed is above 65 m/hr, it is speeding, and the siren will be turned on; if the speed is below 55 mi/h, it will not be turned on.

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number of vehicles running on multiple lanes on the road, it is hard for the automatic machine to tell which vehicle is speeding by just reading two numbers. Therefore, the chance that the automatic machine makes an error to tell a vehicle is speeding is higher than the human operator, which is consistent with our assumption of QM-ITA.

B. Parameter Settings

All of the parameters in the models can be altered based on the interaction of different automatic machines, tasks, and human operators. The error rate of the human operator e_h is a variable that is relevant to the arrival rate λ. The reason to set e_h in this way is that it demonstrates existing experimental evidences: when the number of responses in a certain duration is increased as the arrival rates increase, Mulert *et al.* [25] found that the error rates of subjects also increased. The relationship between e_h and λ is obtained (see Appendix A).

The values of the other parameters are set according to human factor experimental studies: human service rate $\mu = 0.588$ tasks/sec (see details in Appendix D) and human queuing system capacity as 7 [26]. In addition, task arrival rate λ and c are set between 0.1 and 2.5 tasks/s and from -1 to its own upper bound [can be obtained by (8)], respectively. From this, the maximum value of e_h can be obtained (close to 0.09). Since it is assumed that the error rate of the automatic machine is larger than that of the human operator, $e_m = 0.1$ is set. In addition, according to the context of each scenario, relevant parameters can be fixed or flexible to obtain the optimal allocation strategies.

To simplify the term of the strategies, all of the allocation strategy numbers are coded from 1 to 7. Strategy n means that any pending tasks are allocated to the human operator if there are $(n-1)$ tasks in the human operator.

C. Results

In each scenario, first, the results of the optimal algorithm using interactive e_h are shown. Then, a comparison between optimal and conventional algorithms is discussed. Finally, the potential applications of the results in intelligent transportation systems (ITS) design related to the case study are described.

1) Minimize the Human Operator Workload Given the Arrival Rate and System Error Rate Constraint: Scenario 1 is to determine q_j (routing strategy) so that the human operator workload is minimized given a task arrival rate λ and an overall error rate tolerance E_T. From Fig 4(a)–(c), the general relationship between the workload and the task arrival rate can be obtained. With an increase of the task arrival rate, both the workload and the strategy number increase. This is consistent with Bi and Salvendy [27], who found that a high task arrival rate significantly increased the mental workload. Similar experimental results can also be found in [28] and [29].

Taking Fig. 4(c) as an example, if the arrival rate is less than 1.1 tasks/s, the strategy number will be 1, which means that the human operator finishes processing the current task before the arrival of the next task. When the arrival rate increases from 1.1 to 1.2 tasks/s, the strategy number varies from 1 to 2 accordingly. At the same time, human workload increases compared with lower arrival rate conditions. The mechanism of this result is that when one more task goes into the human operator, it is this additional task that causes a sudden change in the workload of the human operator.

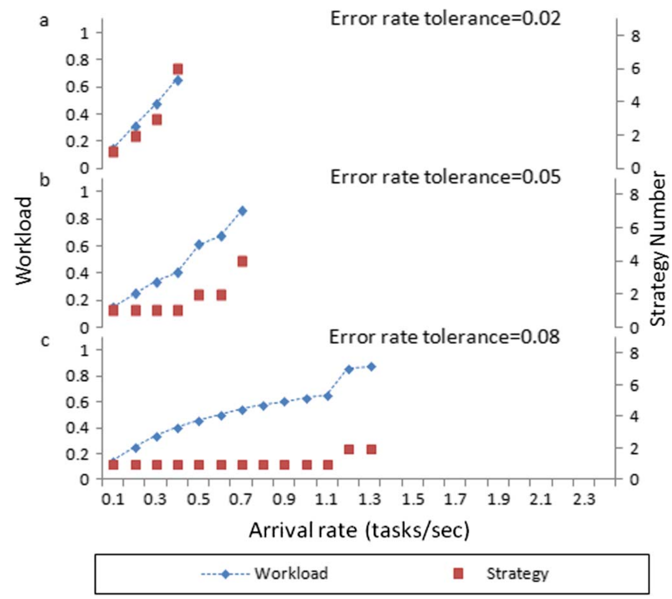

Fig. 4. Relationship between workload and strategy number versus arrival rate in different conditions of error rate tolerance.

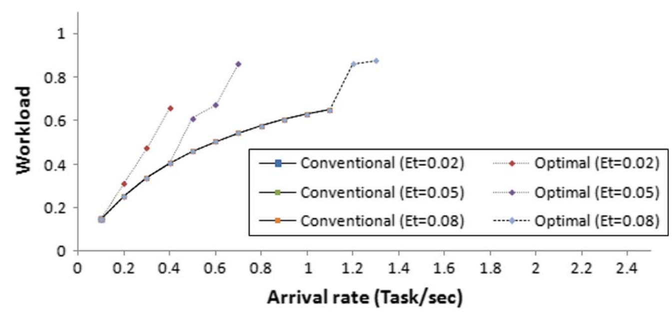

Fig. 5. Workload comparison between conventional and optimal algorithms.

The results of the comparison are shown in Fig. 5: given strategy 1, the optimal algorithm is identical to the conventional one. However, the optimal algorithm works with a larger range of task arrival rates than the conventional algorithm.

In the police officer's routine, this optimal algorithm can be applied if he/she is busy with another task. Based on our interview with police officers, besides speeding detection task, a police officer usually handles other tasks while driving (e.g., communicating with dispatch center/other police cars through radio). When QM-ITA is applied, it assigns speeding detection tasks to the automatic machine to minimize the police officers' workload in these multitasking situations.

2) Minimize Overall System Error Rate Given the Human Operator Workload Tolerance and Arrival Rate: Scenario 2 is to determine q_j so that the overall system error rate e is minimized given the task arrival rate λ and workload tolerance U_T. Fig. 6 shows that with an increase of arrival rate in general, the overall system error rate increases while the strategy number decreases. This is consistent with existing human

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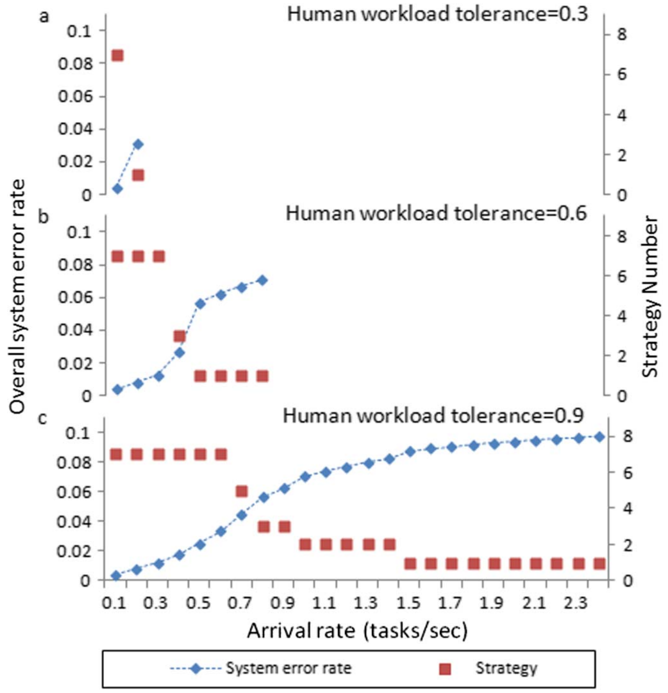

Fig. 6. Relationship between error rate and strategy number versus arrival rate in different conditions of workload tolerance.

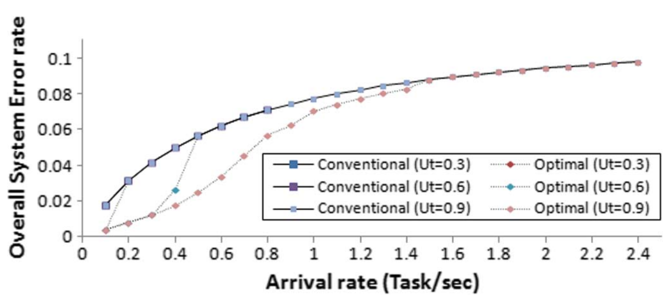

Fig. 7. Error rate comparison between conventional and optimal algorithms.

factor studies that show that the error rates of human–machine systems increased when the task arrival rate was relatively high [25], [30], [58].

A comparison between the two algorithms is presented in Fig. 7. At lower arrival rates, the system error rates of optimal algorithm are less than that of the conventional algorithm.

The optimal algorithm may potentially be applied when the objective of the system is to minimize the overall system error rate. In this case study, the goal of the system is to detect speeding vehicles as accurate as possible. Since the error rate of the human operator is lower than that of the automatic machine, QM-ITA would assign more tasks to the police officer so that the overall system error rate would be minimized, and the system is able to perform the speeding detection task more accurately. In addition, results of the overall system error from QM-ITA can be used to estimate and predict the error rate of the whole human–machine system given different information processing demands (i.e., arrival rate).

3) Maximum Acceptable Machine Error Rate Given the Human Operator Workload Constraint and Arrival Rate: This scenario is to determine q_j (routing strategy) so that the maximum acceptable e_m is obtained, given workload tolerance U_T and task arrival rate λ values. Fig. 8 shows the results of the maximum acceptable machine error rate $(Max\ E_m)$: With an increase of arrival rate, both $Max\ E_m$ and strategy number decrease. This result is consistent with existing experimental findings that suggest that high task arrival rates lead to high human error rates (e.g., [25] and [30] in general and [51] in driving[4]). Since QM-ITA captures the speed–error tradeoff of human, when the task arrival rate increases, the human error rate e_h increases, which produces higher requirements (lower $Max\ E_m$) on the automatic machine.

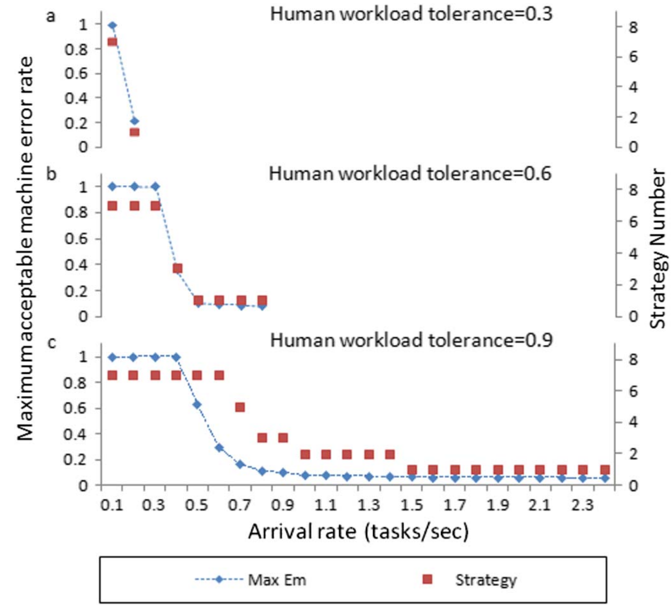

Fig. 8. Relationship between maximum acceptable E_m and strategy number versus arrival rate in different conditions of workload tolerance.

On the other hand, when the arrival rate is low, $Max\ E_m$ is equal to 1, indicating $Max\ E_m$ has no effect on the overall system error rate. At this point, the human operator handles all of the tasks, and it does not matter how large $Max\ E_m$ is.

The patterns of $Max\ E_m$ shown in Fig. 8(c) are dissimilar to the patterns in Fig. 8(a) and (b). As the arrival rate increases, the value of $Max\ E_m$ starts to decrease before the strategy number changes, and the turning points of $Max\ E_m$ emerge when the arrival rate is equal to 0.5 tasks/s. $Max\ E_m$ decreases from this arrival rate point (arrival rate $= 0.5$ tasks/sec) since the automatic machine attempts to process tasks. However, this does not change the strategies due to a high workload tolerance ($U_T = 0.9$), which allows the human operator to process most of the tasks.

The results of the comparison between the two algorithms are presented in Fig. 9. In most conditions, the optimal algorithm works better than the conventional one. When the arrival rates are low, the human–machine system equipped with the optimal algorithm is able to process, at most, seven tasks. Given the same error rate tolerance, the more tasks processed by the human operator, the larger $Max\ E_m$. Therefore, the value of

[4]For example, when a driver is a performing a dual task (e.g., using a cellar phone while driving, the arrival rates of information increase (driver has to process both driving information and cellar phone's information in cognition) compared with a single task situation), the error rate of drivers in dual tasking significantly increases [51].

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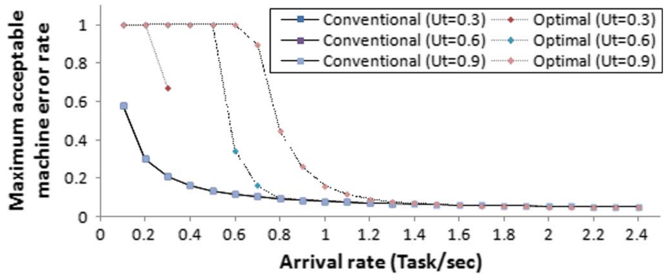

Fig. 9. Maximum acceptable E_m comparison between conventional and optimal algorithms.

$Max\ E_m$ of the optimal algorithm can be much greater than that of the conventional algorithm.

In terms of the application of the results of QM-ITA, first, it can help ITS designers to determine the maximum acceptable error rate of the automatic machine under different circumstances. This maximum acceptable error rate of the automatic machine $Max\ E_m$ provides a target of the ITS so that designers can achieve it via improving programming or/and training recognition algorithms (e.g., E_m should be lower than 0.2 when the task arrival rate is over 1 task/s and human workload tolerance is at 0.9). Second, the results can also help ITS designers determine under which level of arrival rate an automatic machine is needed and/or the time when an automatic machine starts to work to help the human operator process the coming tasks. Taking Fig. 8(c) as an example, when the task arrival rate is lower than 0.5 tasks/s, $Max\ E_m$ is 1. This indicates the following: 1) an automatic machine is needed under situations with task arrival rate higher than 0.5 tasks/s; or 2) if an automatic machine is already installed, when the task arrival rate is higher than 0.5 tasks/s, that machine starts work to assist the human operator.

4) Maximum Acceptable Task Arrival Rate Given Human Operator Workload and Overall System Error Rate Constraint: Scenario 4 is to determine q_j (routing strategy) so that the maximum task arrival rate λ can be obtained given the system error rate tolerance E_T and the human operator workload tolerance U_T. Fig. 10 shows the relationship between the maximum acceptable task arrival rate and strategy number versus error rate tolerance under different conditions of the human operator workload tolerance.

From Fig. 10, it can be concluded that, in general, with an increase in error rate tolerance, the maximum task arrival rate increases while the strategy number decreases. As the workload tolerance increases [comparing Fig. 10(c) with Fig. 10(a) and (b)], the maximum task arrival rate increases in general. This result is consistent with previous empirical findings in human factors (e.g., [53] and [54]): A young operator with higher workload tolerance would able to process more tasks than an elder operator with lower workload tolerance in the same time period (i.e., higher task arrival rate).

The comparison in Fig. 11 shows the following: 1) The optimal algorithm results in a higher maximum acceptable arrival rate than the conventional algorithm under different conditions of workload tolerances; and 2) the optimal algorithm can be used when the error rate tolerance is low, where the conventional algorithm does not demonstrate a feasible solution (e.g., the error rate tolerance is 0.01).

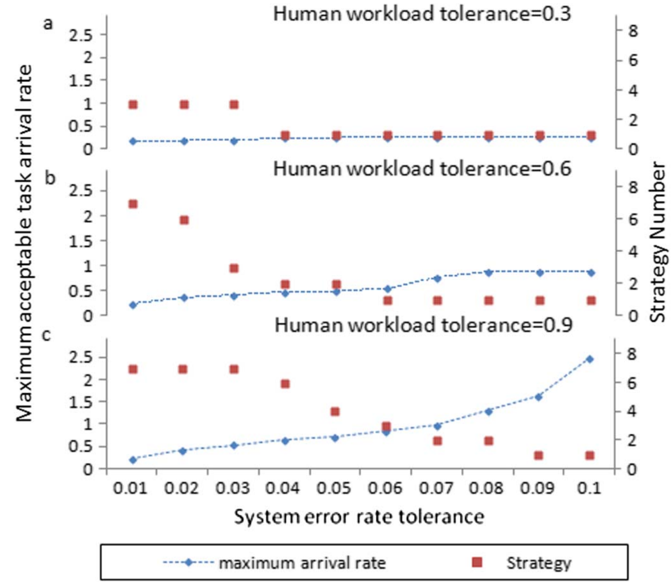

Fig. 10. Relationship between maximum acceptable arrival rate and strategy number versus error rate tolerances in different conditions of workload tolerances.

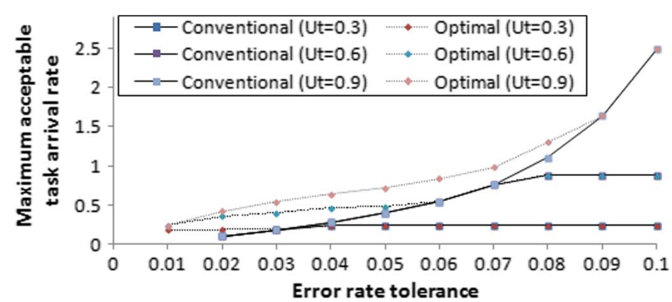

Fig. 11. Maximum arrival rate comparison between conventional and optimal algorithms.

This scenario is to determine the maximum acceptable task arrival rate. Using the case study as an example, the task arrival rate is the amount of vehicles arriving within a certain area where a police officer monitors. If the rate goes beyond the maximum acceptable λ, a police officer equipped with QM-ITA will be unable to handle all the vehicles arriving within this area. Therefore, based on QM-ITA's suggestion in this scenario, he or she would either call for assistance from other police officers or slow down the traffic in some way (e.g., make the police vehicle visible to the traffic) so that the arrival rate of the information to the human–machine system is reduced. For example, if there are three vehicles every second needing to be inspected, one police officer equipped with QM-ITA can handle one vehicle every second based on QM-ITA's suggestion [e.g., in Fig. 10(c), when the system error rate tolerance is 0.07, the maximum task arrival rate is close to 1 task/s, which means the human–machine system can process 1 vehicle per second]. Therefore, he/she must call another two police officers equipped with QM-ITA.

IV. Discussion

QM-ITA defines and optimizes the dynamic task allocation between human operator and automatic machine, quantifying

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the nonlinear relations between task arrival rate, overall system error rate, error rate of the automatic machine, and human workload. Integrating a cognitive model of mental workload, speed–error tradeoff, and the closed-form equations with global optimum solutions, this work may provide useful quantitative computational results for designers of in-vehicle system to develop corresponding algorithms. It is anticipated that the proposed model may enhance intelligent transportation systems by offering a useful approach to manage task allocation in a way of dynamically allocating the tasks between the human and automatic machine to minimize the workload of human operator, minimize the overall system error rate, propose the maximum acceptable error rate of automatic machine, and suggest the maximum acceptable task arrival rate.

QM-ITA can be applied in human–machine systems to improve their safety and performance. First, in many practical situations, operators are occupied by a primary task, and additional information loaded on the operators may affect the performance and safety. In these situations, QM-ITA can be used to avoid overwhelming the driver with information from these secondary tasks (see Section III-C1). Second, in certain human–machine systems in practice, minimizing the overall error rate of the whole system is the most important concern for its use [47, Sec. 3.3.2], [48, Sec. 3.3.2]. QM-ITA can be applied to minimize this overall error rate of the whole system. Third, in practice, on the one hand, designers may be uncertain if an automatic machine is really needed in a human–machine system or not. On the other hand, in the situation when an automatic machine is needed, it is difficult for designers of automatic machines to reach 0% error rate or improve the accuracy of an automatic machine by 5% via the change of programming or/and training of automatic machine. In these situations, QM-ITA can be used to determine 1) if an automatic machine is needed or not (e.g., if a human–machine system works in the max $E_m = 1$ situation, the automatic machine may not be needed), and 2) if an automatic machine is needed, what is its maximum acceptable error rate to reduce hardware and software costs (see Section III-C3)? Fourth, in practice, the information processing capacity of a human–machine system is usually limited; if an intelligent system like QM-ITA is able to determine the maximum arrival rate of information to be processed by one human–machine system, it can help operators or managers in real settings to determine how many such kind of human–machine systems are needed (see Section III-C4).

Since the queueing model was developed in Excel Visual Basic Application module, it can be implemented without installing advanced software environment. An optimal allocation strategy is obtained as long as the real-time arrival rate and workload information is received by QM-ITA, with the preprogrammed objective, constraints, and other system parameters.

QM-ITA can work together with the queueing network-model human processor (QN-MHP) adaptive workload management system (QN-MHP AWMS) [5] in driving situations. Once QM-ITA assigns a task to the human operator, it is processed by QN-MHP AWMS (as shown in Fig. 12), and QN-MHP AWMS intelligently regulates the interarrival time among these tasks and then sends them to a human operator. Before this regulatory process, the arrival rate of some tasks

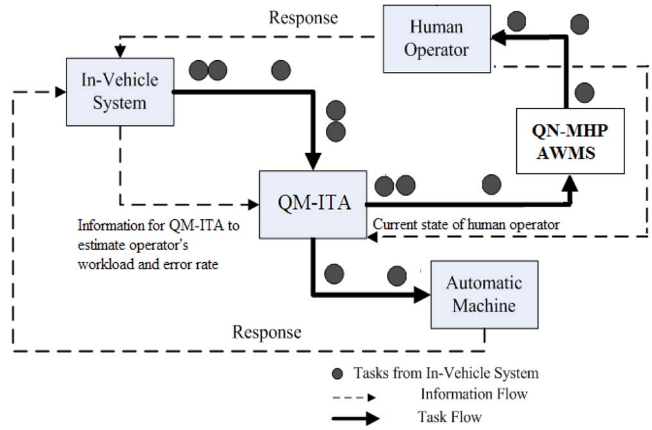

Fig. 12. QN-MHP AWMS and QM-ITA working together in a human–machine system.

can be quite short, which may overload the human operator (see the dots close to each other on the task flow from QM-ITA to QN-MHP AWMS in Fig. 12). During this regulation/process, without sacrificing the overall processing time, tasks arrive at the human operator with a comfortable rate to reduce human workload and error rate (see the dots on the task flow from QN-MHP AWMS to the human operator in Fig. 12).

QM-ITA currently works under the assumption that the error rate of the automatic machine is greater than the human operator ($e_m > e_h$); however, if $e_m < e_h$, QM-ITA sends all the tasks to the automatic machine, and the human operator is no longer needed in the system.

There are several limitations of the current work that might be addressed in future work. In practice, the task allocations between the human operator and the automatic machine are complex (e.g., the human operator may play a supervisory role in a human–machine system to monitor the machine, or the human operator performs some relatively difficult tasks, and these tasks are never assigned to machines). The task allocation modeled currently represents one aspect of the theory applied (i.e., the automatic machine can process tasks as human but with higher error rate). To account for other aspects and situations in task allocations, new equations of the human workload and error rates of the system need to be built. Future studies should consider and model other possibilities of task allocations when a machine and human operator play different roles in the system. Although there is consistency between the current and empirical results, as described in each scenario, all of the results of this paper were obtained from the model's derivation, and they should be verified by empirical studies in the future.

APPENDIX A
ESTIMATION OF HUMAN ERROR RATE

Based on existing literatures in human factors [6], [55]–[57], Figs. 13 and 14 show the relationship between response accuracy, error rate, and reaction time.

Since error rate $= 1 -$ accuracy, we can derive the inverse relationship between the response error rate and reaction time, i.e., speed–error tradeoff (see Fig. 14). It is assumed that the error rate of the human operator e_h is less than the error rate of the automatic machine e_m, which is $e_h < e_m$, and the

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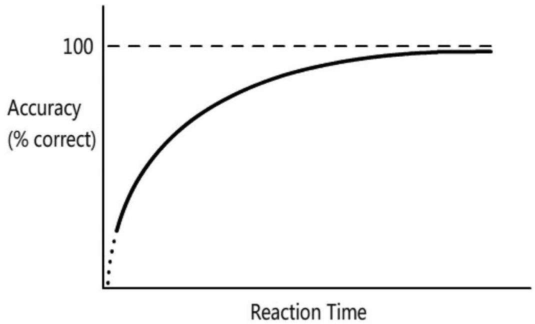

Fig. 13. Speed–accuracy tradeoff (revised from [6]).

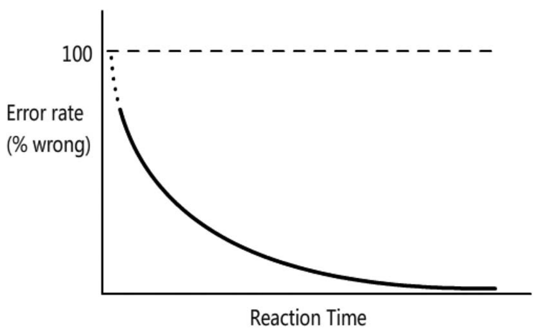

Fig. 14. Speed–error rate tradeoff (revised from [6]).

relationship between human error rate and reaction time follows the equation ($e_h \geq 0$ and $RT \geq 0$)

$$e_h = \frac{A}{A + RT} \tag{A1}$$

where A is the constant of the speed–error tradeoff.

In addition

$$\frac{1}{\lambda} = RT + C \tag{A2}$$

where RT means reaction time of a human. An interval between two stimuli is $1/\lambda$, and it is also equal to the human reaction time (RT) plus a certain rest time (C) in general.

By combining the two equations, the human error rate can be calculated by

$$e_h = \frac{A}{A + \frac{1}{\lambda} - \mathrm{C}}. \tag{A3}$$

Mulert [25] reported the error rates and reaction times of 60 trials. Based on the experimental data, we are able to determine that $\mathrm{A} = 0.04$. Therefore, the speed–error tradeoff follows the equation

$$e_h = \frac{0.04}{0.04 + \frac{1}{\lambda} - \mathrm{C}}. \tag{A4}$$

APPENDIX B
ESTIMATION OF HUMAN WORKLOAD AND SYSTEM ERROR RATE

q_j is defined as the probability that a task will be assigned to the human operator, given the condition that there are j tasks currently in the human operator, and p_j is defined as the probability that there are j tasks in the human operator of all c states. Therefore, $\sum_{j=0}^{c} q_j p_j$ is the expected probability that tasks will be distributed to the human operator in QM-ITA for all c states, and $(\sum_{j=0}^{c} q_j p_j)\lambda$ is the expected number of tasks assigned to the human operator for all c states.

Human workload of secondary tasks can be modeled by the human operator utilization ρ, and the relationship of workload WL and ρ is expressed as [42]

$$WL = a\rho + b = a\frac{\left(\sum_{j=0}^{c} q_j p_j\right)\lambda}{\mu} + b \tag{B1}$$

where parameters a and b are the constants in representing the direct proportional relationships between the averaged utilizations and the subjective responses ($a > 0$).

By applying basic queueing theory into the human operator, which is treated as a whole, the utilization is able to be obtained by

$$\rho = \frac{\left(\sum_{j=0}^{c} q_j p_j\right)\lambda}{\mu}. \tag{B2}$$

Let the error rate of the human operator be e_h and the automatic machine error rate be e_m, and the error rate of system e can be quantified as follows:

$$\begin{aligned} e &= P(e|\text{human})P(\text{human}) + P(e|\text{machine})P(\text{machine}) \\ &= e_h \sum_{j=0}^{c} q_j p_j + e_m \sum_{j=0}^{c} (1 - q_j) p_j \\ &= \sum_{j=0}^{c} p_j \left(e_h q_j + e_m (1 - q_j)\right). \end{aligned} \tag{B3}$$

APPENDIX C
DERIVATION OF THE SOLUTIONS TO THE OPTIMAL ALGORITHM

Scenario 1 (Minimize Workload): We know that

$$\begin{aligned} e &= \sum_{j=0}^{c} p_j \left(e_h q_j + e_m (1 - q_j)\right) \\ &= e_m \sum_{j=0}^{c} p_j + (e_h - e_m) \sum_{j=0}^{c} p_j q_j \leq E_T. \end{aligned}$$

Since $\sum_{j=0}^{c} p_j = 1$, we can have

$$\sum_{j=0}^{c} p_j q_j \geq \frac{e_m - E_T}{e_m - e_h}.$$

Finally, the objective inequality can be obtained as

$$\rho = \frac{\left(\sum_{j=0}^{c} q_j p_j\right)\lambda}{\mu} \geq \frac{e_m - E_T}{e_m - e_h} \frac{\lambda}{\mu}. \tag{C1}$$

Scenario 2 (Minimize Error Rate): Since

$$\rho = \frac{\left(\sum_{j=0}^{c} q_j p_j\right)\lambda}{\mu} \leq U_T.$$

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It can be obtained that

$$\sum_{j=0}^{c} q_j p_j \leq U_T \frac{\mu}{\lambda}.$$

Therefore

$$\begin{aligned} e &= \sum_{j=0}^{c} p_j \left(e_h q_j + e_m(1-q_j)\right) \\ &= e_m - (e_m - e_h) \sum_{j=0}^{c} q_j p_j \\ &\geq e_m - (e_m - e_h) U_T \frac{\mu}{\lambda}. \end{aligned} \tag{C2}$$

Scenario 3 (Maximum Error Rate of Machine): We have already known

$$\sum_{j=0}^{c} q_j p_j \leq U_T \frac{\mu}{\lambda}.$$

Hence

$$\frac{1}{1-\sum_{j=0}^{c} q_j p_j} \leq \frac{1}{1-U_T \frac{\mu}{\lambda}}.$$

Meanwhile

$$\begin{aligned} e_m &= \frac{E_T - e_h \sum_{j=0}^{c} q_j p_j}{\sum_{j=0}^{c} (1-q_j) p_j} \\ &= e_h + \frac{E_T - e_h}{1-\sum_{j=0}^{c} q_j p_j} \\ &\leq e_h + \frac{E_T - e_h}{1-U_T \frac{\mu}{\lambda}}. \end{aligned} \tag{C3}$$

Scenario 4 (Maximum Task Arrival Rate): It is known that the workload should not exceed the constraint

$$\rho = \frac{\left(\sum_{j=0}^{c} q_j p_j\right) \lambda}{\mu} \leq U_T.$$

Then

$$\lambda \leq U_T \frac{\mu}{\left(\sum_{j=0}^{c} q_j p_j\right)}. \tag{C4}$$

We also know that the error rate should not exceed the constraint

$$\sum_{j=0}^{c} p_j \left(e_h q_j + e_m(1-q_j)\right) \leq E_T.$$

Then

$$\frac{1}{\sum_{j=0}^{c} p_j q_j} \leq \frac{e_m - e_h}{e_m - E_T}.$$

Finally, the task arrival rate is subject to (C4) and (C5)

$$\lambda = \frac{\mu \rho}{\left(\sum_{j=0}^{c} q_j p_j\right)} \leq U_T \mu \frac{e_m - e_h}{e_m - E_T}. \tag{C5}$$

APPENDIX D
ESTIMATION OF HUMAN SERVICE RATE IN THE CASE STUDY

The estimation of the service rate of the human operator can be obtained by estimating the processing time. First, the human operator receives visual information from the system environment (information perception). The human operator then makes his/her decision based on the visual stimuli (decision making). Responses to stimuli are then sent back to the system environment (response execution).

In [5] and [43], the experimental results of processing time of two secondary tasks, which are speeding detection task and the radio message response task are reported. Based on there results, we are able to estimate the processing time of the speeding detection task.

Information Reception: An existing study [43] estimated that the processing time of visual radar reading is 676 ms. In addition, the processing time of auditory hearing is estimated as 300 ms.

Decision Making and Response Execution: The experimental results of the processing time of secondary tasks are obtained by previous work [5], [43], which is 3 s. An existing study [44] found that the processing times of decision making and response execution of auditory-manual response task and visual-manual response task are the same. At this point, letting T be the processing time of decision making and response execution of the visual-manual response task, we have $300 + T + 676 + T = 3000$ ms. Solving the equation, $T = 1012$ ms. We can obtain the processing time of visual-manual response, which is $676 + 1012 = 1688$ ms. Round it up to 1.7 s. Therefore, the service rate of the human operator $\mu = (1/1.7) \cong 0.588$ tasks/s.

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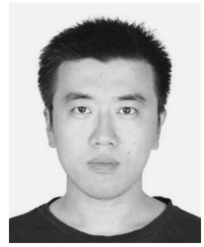

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