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Research article

Automated argumentation for collaboration among cyber-physical system actors at the edge of the Internet of Things

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ABSTRACT

The force of automation is paving the path for cyber-enabled systems to transform every facet of human life. Decisions and actions emanating from systems with common objectives must be made coherent with respect to target objectives. Automated argumentation is a collaboration tool for groups of agents with potentially conflicting impulses. The process of argumentation identifies contradictions and ameliorates coherence among disparate actions. It is a fully distributed approach with applications in edge computing for the Internet of Things. After review of basic tenets of using argumentation for untangling opposing positions, a case study of cyber-enabled vehicles changing traffic lanes illustrates interactions that rely on argumentation. A NetLogo simulation implements the methodology described in this work. The approach presented here is also a clarion call for collaborations needed in other similarly diverse and distributed scenarios.

1. Introduction

The term Internet of Things (IoT) is used to describe a system where the Internet is connected to the physical world via ubiquitous sensors and actuators. The resulting pervasive network is comprised of numerous machine agents equipped with sensors and the ability to perceive context. Originally coined in 1999, today the term Internet of Things designates the dynamic global network of Internet-enabled devices of various kinds. Virtual and physical devices integrated in the IoT have identities, virtual personalities, intelligent interfaces, as well as sensing, communication and decision making capabilities [1], and as a result of the virtually unlimited addressing capability of IPv6, their number can grown unhindered and at great speed.

Even though the IoT is currently largely vertical [2] and heterogeneous, the expectation is that in the future smart devices will seamlessly network with each other [3] behind the scenes. In 2006, the term cyber-physical systems (CPS) was first conceived and referred broadly to integrations of computation with physical processes [4]. Today the term is most often used to describe smart devices - active machine agents interacting with one another and proactively making decisions and taking action. A large number of these CPS are agents in the IoT. Each agent is designed to receive sensory data and perform problem solving that produces an output. The output may be a mere perception or an action to perform. The world is currently

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experiencing an inexorable proliferation of pervasive and ubiquitous cyber-enabled actors (CAs) - algorithmically controlled mechanisms involving networked devices and their decision-making modules [5,6]. CAs are the proactive components of cyber-physical systems. Whereas physical components of CPS (e.g., robots, sensors, and other various devices) are tangible, embodied, and occupy physical space; cyber components are largely intangible, disembodied, and location-independent. In contrast to CPS entities, which are viewed as passive objects or things, CAs (also referred to as agents or actors) are active and may behave proactively. As an example, from this perspective, smart vehicles as cyber-physical systems are empowered with agent overlays that provide deliberate decision-making capabilities based on actionable intelligence collected from the multitude of smart sensors the vehicles are equipped with. No further processing by a human agent or a centralized authority is necessary when agents are able to communicate with each other and have arbitration mechanisms in place to resolve inevitable conflict. This emerging type of computing, called edge computing [7], where data is collected, stored and analyzed at the source promises faster, scalable, and more responsive IoT systems. The edge computing approach moves intelligence from the cloud to the edge, i.e. to smart devices themselves, and enables efficient real-time decision making. Should devices not have the capabilities to handle the computation burden required of them, they can shift some of the latency sensitive data processing to network devices instead of to the cloud. This approach is known as fog computing [8].

Cyber-enabled actors may be embodied agents equipped with sensors and actuators performing automated tasks (e.g. different deployed security systems, robot swarms) or disembodied agents inhabiting parts of the Internet and monitoring and initiating automated actions (e.g. Twitterbots that follow and post tweets). In isolation, the scope of such CAs may be rather narrow and their functionality could remain restricted to independent actions serving larger systems. Naturally, there is mounting effort to incorporate more advanced cyber-enabled actors into interconnected, complex networks (e.g. guarding a large public facility). Inevitably, these endeavors bring along the need for mechanisms that monitor and ascertain congruence among disparate actions of a group of CAs thus creating a collaborative environment for actors. More advanced smart agents that sense and collect relevant data about the environment and are equipped with information processing and decision making capabilities means that information processing, decision making, and conflict resolution can be moved to the edge of the system. This will make use of the advantages of edge-centric computing - exploiting the computational, storage and communication power of modern smart devices while pushing the frontier of computing applications away from a centralized authority and redistributing it to the edge of the network [9]. It will improve scalability, tackle issues of message relay delay, simplify additional required infrastructure, and will provide a local distributed computing environment which in turn will improve real-time performance [10]. Fast and reliable performance is especially important in constantly changing environments like vehicle traffic.

Advanced autonomous smart agents will try to proactively take action. That will, as a matter of course, lead to conflicts with other agents in the proximity, which brings the need for mechanisms for arbitration and conflict resolution. One technique that offers itself to this scenario is automated argumentation [11]. Argumentation is a multi-agent system approach that views a pool of intended actions of heterogeneous agents as a collection of abstract arguments. The mechanism then uses these arguments to identify possible congruence concerns and to arrive at a satisfactory resolution of conflicts in favor of a common objective. This work will lay the foundations for designing collaborative settings for collections of CAs. Smart vehicles (i.e. driverless and cyber-enabled) is an arena for a class of cyber actors that exhibits potential compatibility issues among decisions. This paper reviews a general case for the application of automated argumentation among CAs and then focuses on issues of lane selection in smart vehicles as a concrete example.

The vast populations of CAs will soon dwarf human population. Cyber actors must make decisions on behalf of humans in order to advance the unavoidable trajectory toward automation. This results in a large number of machine-to-machine interactions and a great volume of data that if effectively wielded can positively contribute to society. However, reminiscent of Isaac Asimov's Three Laws of Robotics [12], to assure the safety and predictability of agent behavior, there is a need for the creation of systems of rules and policies that embody desired objectives and govern all CA actions. It is conceivable that there will be decisions made by machine agents that will be unpopular, at odds with human needs, or rife with ethical issues. For instance, a driverless vehicle must determine the best course of action when confronted with an unavoidable collision [13]. Even though complete autonomy of vehicles is still prohibited by the Geneva [14] and Vienna [15] Conventions on Road Traffic, competition among countries for potential future profits will inevitably create challenges to existing legal constraints. Legal and ethical considerations remain outside of this work's current scope but it is a virtual certainty that the rapid advancement of smart vehicle technology will eventually place autonomous traffic agents on the road. Modern vehicles are cyber-physical systems benefiting from advanced sensors and computational power the combination of which has led to the development and deployment of advanced driver-assist systems. These systems are a precursor to the integration of V2X (vehicle-to-vehicle and vehicle-to-infrastructure) communication into future automobiles [16]. The actual communication infrastructure is out of the scope of this work; the attention here is limited to argumentation as a form of negotiation among cyber-enabled actors in general and smart vehicles in particular. The presented approach can be adapted and extended to numerous scenarios. Negotiation and reasoning among humans have been an inspiration for modeling automated argumentation but human involvement unavoidably brings underlying politics, implicit agendas, and possible behavior-altering strategic incentives. With those taken out of the equation, CA arguments are modeled as atomic proclamations, the general idea for which was posited in earlier work [17]. The approach and implementation presented here are entirely new and not previously reported. The distributed nature of the approach enables small groups of devices to self-organize at the edge of the network so the enormous scale characteristics of the IoT are not taken advantage of.

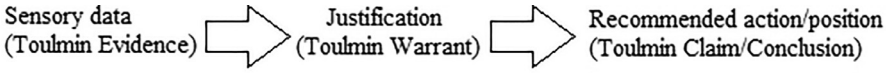

Fig. 1. An illustration of a Toulmin style argument.

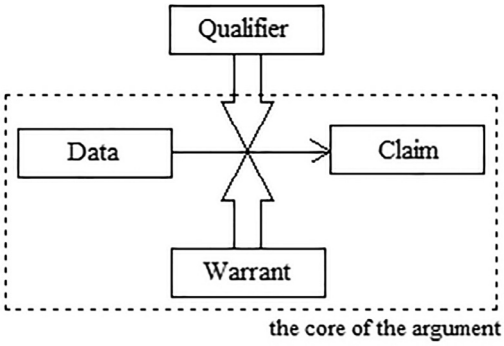

Fig. 2. Components of the Toulmin model of argumentation.

However, IoT technology governs the heterogeneous devices and their interconnectivity within the dynamically changing local network, which utilizes the argumentation layer presented in this work.

This paper is organized as follows: Section 2 outlines the process which results in the production of arguments; Section 3 details the expert systems for CA smart vehicles; Section 4 further elaborates details of argumentation during vehicle lane changes, Section 5 discusses challenges and applications, and Section 6 summarizes the methods presented.

2. Genesis of arguments

An argument is a pair of sensed data and an output. The internal argument structure ⟨sensed condition, then warrant; therefore, recommended action⟩ is illustrated in Fig. 1. Arguments built this way follow the Toulmin model of argumentation [18] shown in Fig. 2.

For an arbitrary domain, an expert system is typically structured as a set of rules partitioned into subsets that are either in the form ⟨**if** condition-x **then** conclusion-y⟩ for situation assessment purposes or in the form ⟨**if** conclusion-y **then do** action-k⟩ for action selection purposes. A "condition-x" is a combination of conditions sensed in the environment (Toulmin Evidence) while a "conclusion-y" is a perception. An "action-k" is an action to be performed. An inference system is the component of the expert system that gathers conditions matching the "condition-x" part of rules. It then fires the applicable rules and determines a winning "conclusion-y" (Toulmin Warrant). Inference works on all applicable action rules that arbitrate among competing actions to determine a winning "action-k" (Toulmin Conclusion) to be executed. Running inference on the expert system yields argument components.

Consider the arguments labeled x_1 and x_2. The warrant portion is simplified for illustration purposes only. In this proposed approach, warrants will be produced as a result of using a model that formulates and propagates danger/safety levels for each room based on modeled dynamics of a moving assailant posing danger to occupants [19].

- x_1 = Since the room is quiet and there is no motion; then the room is safe; therefore, you should stay in the room.
- x_2 = Since the room smells of gun powder and there is no motion; then the room is dangerous; therefore, you should leave the room.

As illustrated, arguments are byproducts of reasoning as in expert systems [20]. Once generated, each argument can be labeled as an atomic entity. As a whole, there will be a large number of arguments and since they are generated by different agents, inconsistencies and contradictions are inevitable. Arguments pertaining to a specific objective can be contrasted in the context of the objective. The relative contribution of an argument toward an objective can be used to give it a higher precedence over lower valued arguments.

To participate in the process of argumentation, in true edge computing fashion, each agent is expected to perform its own independent reasoning that can be approximately modeled as an expert system. Each cycle of an agent's reasoning process will produce an outcome that can be considered an atomic argument. Once agents have generated arguments, the system will maintain them in argument pools indexed by the environmental contexts of their genesis primarily identified by the goal (objective) of the agent that created them. The competition among arguments is only meaningful when they pertain to a common purpose. A contradiction between a pair of arguments is identified as an attack. In the example presented above, argument x_1 attacks x_2 and vice versa. For each objective, the collection of attacks forms an attack graph. The process of argumentation is largely a process of identifying a group of arguments that are the most compatible for producing an objective. The chosen set of arguments will be used to guide the agent's actions in the world. The model of argumentation

Table 1
Lane characteristics of a simulated three-lane highway.

	Emission levels (1–10)	Maximum speed (1–10)	Minimum speed (1–10)
Lane 3	10	10	7
Lane 2	7	6	4
Lane 1	4	3	1

presented here is fully distributed and performed with arguments independently generated by a group of different agents. Arguments compete within specific purposes. Agents who generate the selected arguments will act on them while the system will discard the remainder of arguments. The next section in this paper elaborates on the argumentation process of a group of driverless vehicles using specific contexts.

3. An expert system for vehicular lane selection

The expert system (ES) for lane selection among smart vehicles developed here utilizes a Toulmin style form of argument formation. It embodies two main components: (a) an inference engine, and (b) an inter-agent argumentation resolution component. The ES of an agent is able to infer and analyze context sensed from the environment and determine the optimal action to take. For the chosen action it generates an argument which competes with arguments created by other agents' expert systems. With an argument an agent stakes a claim over the next position it seeks to occupy should the chosen action be taken from the current position the agent is in. The argument resolution component takes the argument representing the selected best potential action and attempts to realize it through argumentation with agents with conflicting interests. Vehicles vying for positions within the current road configuration puts traffic agents in the same vicinity at odds with one another. Automated argumentation resolves these conflicts by arbitrating among positions. Agents being equipped with both expert systems and argumentation components pushes interaction and conflict resolution computation to the edge of the IoT network and distributes and localizes it within a small subset of agents in the same neighborhood. Working within a limited group of agents improves communication reliability and speed while performing decision-making and computation at the source improves real-time performance.

In general, an ES can be used for generating inferences as well as for postmortem analysis of conclusions. For the purposes of the work presented here, the focus is on how to generate inferences as arguments and on how to arbitrate among them. There will be need for analysis for the purposes of continual design revision for ES in certain case studies. For instance, for interactions among cyber-enabled things in a semi-stationary facility (e.g. a warehouse), ES can be used as a pattern detection and analysis tool aiming to improve future interactions. Here, the scenario of interest is the producing of winning arguments for ad-hoc vehicular lane changes and for this case study the teleological analytic powers of the developed ES are not considered further.

In order to communicate, agents must exchange messages. In the absence of a centralized arbitration authority, when argumentation is performed in a fully distributed manner at the edge, message exchange cost may present a challenge. Instead of exchanging two messages with the cloud (sending an argument and receiving the argumentation decision), an agent will have to flood the local network with its argument. However, in many cases physical constraints will limit the local network size to agents in the immediate proximity, so issues with scalability may not always be as dire as they appear at first glance. Message exchange, trust, and synchronization mechanisms as well as network infrastructure and communication protocol particulars are out of the scope of this work.

3.1. The environment

The environment in which the expert system is developed for the scenario presented here consists of a simulated three-lane expressway with each lane having characteristics pertaining to (i) *maximum speed*, (ii) *minimum speed*, (iii) and *emission level*. These features are assigned valid values between 1 and 10 with 1 being the lowest emission level or speed and 10 being the highest. As shown in Table 1, the top lane, Lane 3, is characterized by the maximum overall speed but also the maximum emission level. These indicators decrease as lanes change down. Lane 1 is the slowest but most emission-friendly lane. These conditions were chosen to simulate and simplify real world multi-lane expressway structure.

The vehicle agents themselves are defined as having (i) *current speed*, (ii) *preferred speed*, (iii) a binary *amenability rating*, and (iv) a level of *objective emphasis*. For simplicity, these attributes are valued between 1 and 10, with 10 denoting the highest weighted value. While the current speed attribute is explicitly defined as the speed at which the vehicle is traveling, for the test bed simulation the objective emphasis and preferred speed attributes are randomly generated within the feasible ranges for each vehicle. The amenability rating refers to the willingness of a vehicle to cede its claim to a projected lane position to another vehicle whilst in argumentation with said vehicle. The objective emphasis attribute denotes the level of prioritization a vehicle currently places on its main objective. This case study considers three potential objectives: agents may choose to prioritize minimizing personal travel time, reducing lane congestion, or reducing global emissions. By maintaining an objective, vehicles on the road are working against some or all of the remaining objectives. For example, a

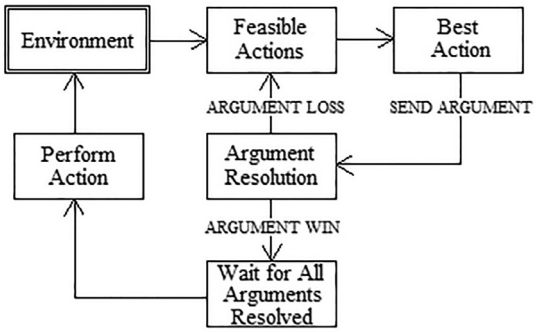

Fig. 3. The life cycle of argument formation, conflict resolution, and action enactment.

vehicle focused on minimizing its travel time will likely select to drive in a faster lane than a vehicle focused on minimizing its emissions would choose, since faster speeds come with higher emissions. Thus, the action of choosing a faster lane taken to satisfy a travel time objective adversely affects the global emission levels and therefore works against the emissions reduction objective. The tendency of agents focused on reducing emissions to choose the slowest lane and the inclination of vehicles interested in reducing travel time to choose the fastest lane result in higher congestion levels in the slow lane and fast lane, respectively, and therefore work against the congestion reduction objective. These objectives combined with the other vehicle attributes comprise the abstract concepts relevant to the test bed presented here.

Some design choices had to be made in order to not overly complicate the scenario. The test bed already simplified the speed and emission attributes and limited the possible objectives. Also for simplicity, the choice was made to disregard vehicle performance and structure characteristics even though in the real world those will influence and restrict the speed at which a vehicle can travel and the emission levels it can produce. Other assumptions made here include the prevailing laws governing the travel of vehicles from one lane to another. Without restriction of generality, it is assumed that once a vehicle starts to travel to a different lane the movement will be perpendicular to the vehicle's current position and the agent will immediately relinquish current lane attributes and adjust behavior to fall within the restrictions of the new lane. As for the argumentation process amongst vehicles, by taking into account its current objective every agent in the test bed casts a single vote for each argument involved in the arbitration process, including its own. In addition, it is assumed that every vehicle in the immediate environment is taking part in the argumentation process with no consideration given to the propagation of information; how vehicles build and maintain network links and how long it takes to transfer arguments and votes along those links is irrelevant for this work. Arbitration takes place in a distributed fashion with no central authority. All vehicles are peers and can communicate with each other and there is no extraneous vehicle on the road such as an emergency vehicle or a rogue agent that may not participate in peer level argumentation.

3.2. Inference engine

The inference system component of the expert system is responsible for formulating an argument corresponding to a best potential course of action determined from sensed environment data. As seen in Fig. 3, environmental conditions are evaluated to determine all current feasible actions that can be taken by the vehicle. The five possible atomic actions, whose derivations are shown in Algorithm 1, are: (1) *move up one lane*, (2) *move down one lane*, (3) *accelerate*, (4) *decelerate*, and (5) *maintain speed*. The conditional rule sets pertaining to these five actions consider system priority, basic physical constraints, and argumentation constraints. A vehicle can move up if the lane above is within the bounds of the environment, it is not "claimed" by another vehicle, and is not currently occupied. Similar conditions of bounds and availability apply to the action of moving down. Maintaining speed is contingent on there not being a vehicle in the space ahead in conjunction with the lack of a conflicting interest from a vehicle of a different lane for the space. Acceleration and deceleration are dependent on the current lane maximum and minimum speed limits, with the acceleration rule set also being dependent on the availability of the space ahead in the current lane.

A lane being "claimed" by another is a concept introduced by the "loss" of argumentation for a desired projected global configuration posited by a vehicle. When deciding on the feasibility of an action, a vehicle must take into account the possibility and consequence of losing an argument for a projected expressway position. Every argument brought forth by a vehicular agent puts it at odds with other cyber-enabled vehicles in its vicinity and the outcome of the argumentation round becomes the basis of the next possible future action. A "win" leads to implementation of the desired action. A "loss" provides further context for the inference system to then reevaluate and form a new feasible actions set. The inference engine uses context taken from the environment, as well as from argument losses, and formulates all potential actions, as shown in Fig. 3. Upon feasible action derivation, the best action in accordance with the ES objective is determined. The argument for this respective action encapsulates the projected position that the vehicle expects to occupy as a result of their chosen action and also encapsulates the vehicle identification. The arguments of all agents are consolidated into an argument pool where

Algorithm 1 Feasible action derivation.

```
if Lane Above in Bounds && Not Claimed && Not Occupied then
    Can Move Up = true;
end if
if Lane Below in Bounds && Not Claimed && Not Occupied then
    Can Move Down = true;
end if
if Space Ahead Not Claimed && Not Occupied then
    Can Maintain Speed = true;
end if
if Current Speed Not Below Lane Min then
    Can Decelerate = true;
end if
if Current Speed Below Lane Max && Space Ahead Not Claimed && Not Occupied then
    Can Accelerate = true;
end if
```

the overseeing system identifies conflicting arguments. Two arguments are in conflict if they project two vehicles to enter the same global expressway position. The arbitration process can be performed with social voting. The overseeing system gathers votes from each vehicle. A vote represents a vehicle's stance on an argument and each vehicle casts an accept or reject vote for each argument in the pool. Votes are tallied and after the social support for each argument is known, conflicts between arguments are resolved, with each argument with the most support within a conflicted arguments subset of the entire argument pool being assigned the win. Upon approval and modification of all argument actions such that there are no longer any conflicts between arguments, each winning agent will then perform their chosen action or will perform the default action in the event of a loss.

Once the inference engine has determined all feasible actions, rule sets pertaining to each of the objectives determine the best action for the said objective. In the current testbed, these ES objectives may be in one of three priority modes: (1) *global emissions*, (2) *local lane congestion*, or (3) *personal travel time*. The local lane congestion objective is concerned with reducing the congestion of the vehicle's current lane. The personal travel time objective aims to attain and if possible exceed the vehicle's preferred speed thus minimizing travel time. Finally, the global emission objective's target is to reduce the global emission levels generated by all vehicles on the road. The current dominating objective for a vehicle directly affects the arguments the vehicle will formulate and bring forth. The following three arguments follow the Toulmin model and the structure presented in Section 2. They exhibit possible conclusions and actions pertaining to each objective.

- Personal Travel Time Objective: a_1 = Since my current lane has a maximum speed limit below my adjusted preferred speed and the lane above is available; then faster speed in the lane up is possible and will reduce travel time; therefore, move up one lane.
- Global Emission Objective: a_2 = Since my lane has a minimum speed limit above my emission adjusted preferred speed and the lane below is open; then a move to a slower lane is possible and will reduce emissions; therefore, move down one lane.
- Local Lane Congestion Objective: a_3 = Since my lane has a high relative congestion and the lane above me is open, within my adjusted preferred speed range, and has low relative congestion; then moving up a lane will benefit my local lane congestion and satisfy my adjusted preferred speed requirement; therefore, move up one lane.

The expert systems corresponding to each objective are seen in Algorithms 2–4. For the personal travel time and global emission objectives, the motivation behind travelling into a higher or lower lane are dependent on the adjusted speed of the vehicle and the vehicle's preferred speed. The adjusted speed is comprised of the preferred speed and a speed factor. For the personal travel time objective, as seen in Algorithm 2, a vehicle is more willing to ignore its preferred speed in favor of higher speeds (line 1, 9, 17), which will result in lowering personal travel time in accordance with its dominating objective. This speed factor, the level at which the preferred speed may be ignored, comes directly from the vehicle's objective emphasis; in other words, the priority the vehicle places on an objective directly impacts how willing they are to ignore their preferred speed.

For the global emission objective, as shown in Algorithm 3, vehicles are willing to drive slower (line 1, 9, 17) in order to travel in a lane of lesser speed and thus lower emission rate. One may note that, for travel time base objectives, as seen in the pseudocode in Algorithm 2, a vehicle focused on maximizing its speed will choose to move up to a faster lane over accelerating (line 6). Assuming that the dominant mode of reasoning runs in a blocking fashion, if a vehicle is travelling below its adjusted speed and can either move up to a faster lane or accelerate, it will choose to move up. This is due to the blocking nature of "Best Action" being assigned to "Move Up" which overwrites the previously assigned "Accelerate" decision.

The same is true when a travel time prioritizing agent has to make a decision in what fashion to travel at a slower speed. The vehicle would choose to decelerate and remain in its current lane (line 14) before moving to a slower lane. For

Algorithm 2 Conclusion derivation rule sets for the personal travel time objective.

```
if Current Lane Max < Preferred Speed + Speed Factor then
    if Can Accelerate then
        Best Action = Accelerate;
    end if
    if Can Move Up then
        Best Action = Move Up;
    end if
end if
if Current Lane Min > Preferred Speed + Speed Factor then
    if Can Move Down then
        Best Action = Move Down;
    end if
    if Can Decelerate then
        Best Action = Decelerate;
    end if
end if
if Current Lane Min == Preferred Speed + Speed Factor then
    if Can Maintain Speed then
        Best Action = Maintain Speed;
    end if
end if
```

Algorithm 3 Conclusion derivation rule sets for the global emission objective.

```
1:  if Current Lane Max < Preferred Speed - Speed Factor then
2:      if Can Move Up then
3:          Best Action = Move Up;
4:      end if
5:      if Can Accelerate then
6:          Best Action = Accelerate;
7:      end if
8:  end if
9:  if Current Lane Min > Preferred Speed - Speed Factor then
10:     if Can Decelerate then
11:         Best Action = Decelerate;
12:     end if
13:     if Can Move Down then
14:         Best Action = Move Down;
15:     end if
16: end if
17: if Current Lane Min == Preferred Speed - Speed Factor then
18:     if Can Maintain Speed then
19:         Best Action = Maintain Speed;
20:     end if
21: end if
```

emission-based objectives, the opposite holds true. As seen in Algorithm 3, an emission agent that is about to increase speed is more willing to accelerate in its own lane (line 6) rather than moving up to a higher emission lane and when slowing down it's more inclined to move down to a slower and thus more emission friendly lane (line 14) rather than decelerate and remain in its current lane.

The ES for congestion-based objectives is handled similarly within this test bed, with the exception that the computed adjusted speed has a slightly more complex algorithm. An agent focused on local lane congestion is influenced by highway lane congestion conditions but only to the extent that the agent is willing to be influenced (e.g., based on the agent's objective emphasis value). To calculate the adjusted speed, the agent first evaluates the lane conditions of the lanes above, below, and the current lane by generating a "cost" of the lanes above and below, as shown in Algorithm 4. The amount of emphasis, or awareness, the agent places on the congestion objective directly affects that cost. Let the maximum level of congestion for a lane be 1. The current lane has a cost calculated as the difference between the maximum lane congestion and the current lane congestion multiplied by the level of awareness of the agent. The process is repeated for the lanes above and below, if applicable. The cost of moving up a lane is thus the difference between the congestion cost of the lane

Algorithm 4 Conclusion derivation rule sets for the local lane congestion objective.

LaneNCost : Awareness * (1 - Relative Lane Congestion)

LaneNPlusCost : Awareness * (1 - Relative Lane Above Congestion)

LaneNMinusCost : Awareness * (1 - Relative Lane Below Congestion)

UpLaneCongCost : LaneNPlusCost - LaneNCost

DownLaneCongCost : LaneNMinusCost - LaneNCost

AdjustedTopSpeed : Preferred Speed + UpLaneCongCost

AdjustedLowSpeed : Preferred Speed - DownLaneCongCost

```
if Current Lane Max < AdjustedTopSpeed then
    if Can Move Up then
        Best Action = Move Up;
    end if
end if
if Current Lane Min > AdjustedLowSpeed then
    if Can Move Down then
        Best Action = Move Down;
    end if
end if
if Current Speed > Preferred Speed then
    if Can Decelerate then
        Best Action = Decelerate;
    end if
end if
if Current Speed < Preferred Speed then
    if Can Accelerate then
        Best Action = Accelerate;
    end if
end if
if Current Speed == Preferred Speed then
    if Can Maintain Speed then
        Best Action = Maintain Speed;
    end if
end if
```

above and the congestion cost of the current lane, whereas the cost of moving down a lane is the difference between the congestion cost of the lane below and the congestion cost of the current lane. At this point, the agent can use these cost values to assist in the reasoning behind lane changes from the congestion perspective. The adjusted speed of the vehicle is calculated as a range. The lane congestion costs for the two neighboring lanes (if applicable) represent a de facto congestion factor used to adjust the preferred speed. Lane changes due to congestion will only be made by an autonomous vehicle agent if it makes sense within the context of its preferred speed.

Through these algorithms, given the same environmental context, the expert systems of vehicles prioritizing different objectives will be able to formulate their chosen actions and generate the arguments to bring forth in order to attempt to win the right to implement them.

3.3. Inter-agent argumentation resolution

The inter-agent argumentation resolution component implemented atop this test bed is a methodology that employs the use of social abstract argumentation (SA) [21,22]. In SA each agent within the group casts a “vote” for each argument within the argumentation pool. Agents who posit arguments that have little social support, but do not take part in any conflicts, carry out their corresponding actions regardless of the levels of acceptance from the remaining agents. Conversely, if an agent posits an argument which is in conflict with other arguments and it loses by gathering little social support from the group, then the agent must concede, update its inference engine to mark the lost target position as claimed, and further generate a new best action. If an argument wins the argumentation round, the agent it belongs to can implement the action attached to it.

3.3.1. Social abstract argumentation

Social abstract argumentation requires all vehicles within the section of highway under consideration to vote on what arguments they view most align with their specific objectives and don't hinder their own planned actions. The inference engine of each agents determines the best next action and forms an argument corresponding to the projected position the vehicle aims to occupy should the action be successfully implemented. The framework used to model argumentation among agents within the system is postulated in Definition 1.

Definition 1. An *argumentation framework* $F = \langle A,\ R,\ V_a \rangle$ consists of a set of arguments, A, a set of relations between arguments, R, and a set of votes for the arguments, V_a where:

- A is finite. An argument $a_i \in A$ is a pair $a_i = \langle i,\ p_i \rangle$ composed of a vehicle i, and the very next highway position p that the vehicle is projected to occupy based on the best action generated by its inference engine;
- R is finite. A relation between two arguments a_i and a_j is denoted as a binary attack relation (a_i,a_j) such that argument a_i attacks argument a_j, further denoted as $(a_i \rightarrow a_j)$;
- V_a is finite. Each vote $v \in V_a$ takes the form $v_{a_i} = \langle a_i,\ v_+, v_- \rangle$ where $a_i \in A$, and v_+ denotes a vote for argument a_i, while v_- denotes a vote against argument a_i.

Conflicts are formed when two arguments are found to be in competition for the same global position as stated in Definition 2.

Definition 2. The set of binary relations between arguments, R, is comprised of all conflicting arguments in the set of arguments, A. The inference engines of vehicles i and j have determined the next best positions, respectively, as p_i and p_j. Upon detection of conflict, the corresponding arguments are paired into an argument relation and added to the existing set R of relations between arguments:

$\forall a_i \in A \Leftrightarrow \exists a_j \in A$ s.t. $p_i \equiv p_j \Rightarrow R = R \cup \{(a_i \rightarrow a_j), (a_j \rightarrow a_i)\}$

For each argument $a_i \in A$ there exists social support $v_{a_i} = \langle a_i,\ v_+, v_- \rangle$, that contains all of the approval votes v_+ and the rejection votes v_- cast for a_i.

Definition 3. The set of argument votes V_a registers the social approval or rejection of any given vote cast in the argumentation round. Every argument a_i has a corresponding $v_{a_i} = \langle a_i,\ v_+, v_- \rangle$ which encompasses the social support for a_i:

$\forall a_i \in A\ \exists v_{a_i} \in V_a$ s.t. $a \equiv v_{a_i}$

To model the argumentation framework described in Definitions 1–3, a semantic framework S, is introduced in Definition 4.

Definition 4. A *semantic framework* $S = \langle \Psi,\ \Gamma,\ \neg \rangle$, consists of a vote evaluation function, Ψ, a conflict reduction function, Γ, and a unary negation operator, $\neg$, where for two arguments $a_i,\ a_j \in A$,

$\neg(a_i \rightarrow a_j) \equiv (a_j \rightarrow a_i)$

A function that converts v_{a_i} to a corresponding value of social approval $v_{+/-}$, gives the social approval for a given argument a_i. The difference between the votes for (v_+) and against (v_-) an argument a_i impacts $v_{+/-}$ such that $v_{+/-} = v_+ - v_-$.

Definition 5. A *vote evaluation function*, Ψ, accepts votes for an argument a_i and returns a scalar value of approval $v_{+/-}$ for a given argument a_i.

$v_{+/-} = \Psi(v_{a_i})$

To resolve ties among arguments who garner the same level of social support, the amenability level attribute of the conflicting arguments must be taken into consideration. Amenability is a binary value of either 1, to indicate that the agent postulating an argument is willing to concede if tied with another agent positing a conflicting argument, or 0, where the agent will not concede to another agent in the event of a tie. If both agents have the same amenability value, then there is no winner, and both lose as a result.

Definition 6. A *tie resolution function*, T, considers the argument relations $r_i,\ r_j \in R$ and the amenability levels of their aggressing arguments, denoted as c_{r_i} and c_{r_j}, respectively, to resolve a tie in social support between the two arguments. The loser, or losers, of the operation are returned into a set $\ell = T(r_i, r_j)$:

$$\ell = \left\{ \begin{cases} r_i & \text{if } c_{r_i} > c_{r_j}, \\ r_j & \text{if } c_{r_i} < c_{r_j}, \\ r_i, r_j & \text{if } c_{r_i} \equiv c_{r_j} \end{cases} \right\}$$

A conflict reduction function is necessary to resolve all conflicting arguments identified within the set of relations, R. The function reduces the set of relations R to a conflict-free set R_r with the help of the set of argument votes V_a using the process outlined in Definition 7.

Definition 7. A *conflict reduction function*, Γ, accepts a set of argument votes, V_a, and a set of relations, R, and reduces R to a conflict-free set of relations, R_r, with $R_r \subseteq R$. The vote evaluation function, Ψ, determines the social support for each pair

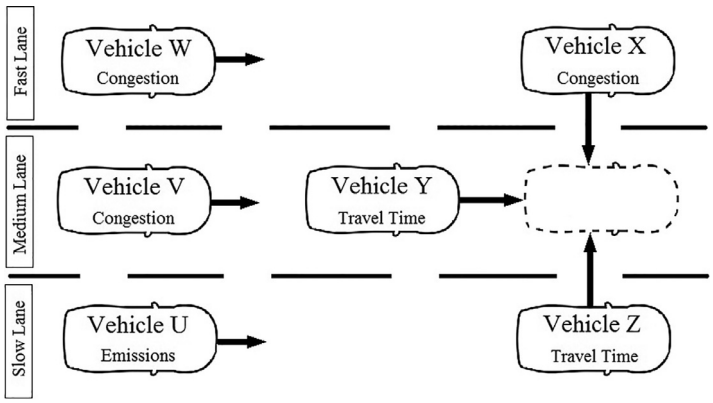

Fig. 4. Social abstract argumentation among vehicles on a highway example.

of conflicting arguments a_i and a_j involved in the attack relations r_i and r_j in which a_i and a_j are the respective aggressor. The relation the aggressor of which has garnered less social support is removed from the set. Should the social support for both aggressor arguments end in a tie, the tie resolution function, T, is utilized to determine if either agent will collaborate and abandon their claim to the desired position. Applying the conflict reduction function repeatedly for all conflicts delivers a conflict-free set $R_r = \Gamma(R, V_a)$:

$$\forall r_i \in R \Leftrightarrow \exists r_j \in R\, s.t.\, r_i \equiv \neg r_j \Rightarrow R_r = R \setminus \left\{ \begin{cases} r_j & \text{if } \Psi(v_{a_i}) > \Psi\left(v_{a_j}\right), \\ r_i & \text{if } \Psi(v_{a_i}) < \Psi\left(v_{a_j}\right), \\ T\left(r_i, r_j\right) & \text{if } \Psi(v_{a_i}) \equiv \Psi\left(v_{a_j}\right) \end{cases} \right\}$$

4. Social abstract argumentation for autonomous vehicle lane changes example

The principal features of the argumentation procedure presented in this work can be illustrated with an example scenario as shown in Fig. 4. This scenario was implemented and verified in NetLogo and utilizes Algorithms 1 through 4 and the Expert System model outlined in Section 3.

4.1. Inference engine argument generation

Consider a 3-lane highway with six autonomous vehicle agents travelling at certain speeds and acting in accordance with their main objective. Of these vehicles, three prioritize local lane congestion (V, W, X), two focus on their personal travel time (Y, Z), and one has a global emission objective (U). The inference engines of both Vehicle X and Vehicle Z chose lane change actions to the lane position directly ahead of Vehicle Y. Each vehicle in the group generates an argument in accordance with its inference engine's conclusions and adds it to the argumentation pool. The actions tied to the argument can only be implemented once all conflict in the argumentation pool is resolved and a determination is made whether the vehicle agent is allowed to proceed.

Recall that an argument is comprised of the vehicle identification and the projected next highway position it aims to occupy as a result of the next best action determined by its inference engine. For simplicity, in this scenario the arguments are labeled with their corresponding vehicle identification. Thus, the set of all arguments, A, generated by the vehicles within the scenario is:

$A = \{U, V, W, X, Y, Z\}$

4.2. Social voting

Vehicle X currently gains the most utility from arguing for a configuration that both vehicle Y and vehicle Z are at odds with. No other disputes over imminent positioning changes are present within this set of vehicles for this round of argumentation. Arguments generated by X, Y, and Z will pairwise be in conflict and the attacks between them will make up the set of binary relations R.

$R = \{(X \to Y), (X \to Z), (Y \to X), (Y \to Z), (Z \to X), (Z \to Y)\}$

In each argumentation round all agents in the system cast votes to determine the corresponding social support for each of the arguments in the pool. Each agent confers with their own inference engine and determines if the argument will negatively affect their next move. Congestion agents will disapprove of another vehicle entering their lane, emissions agents

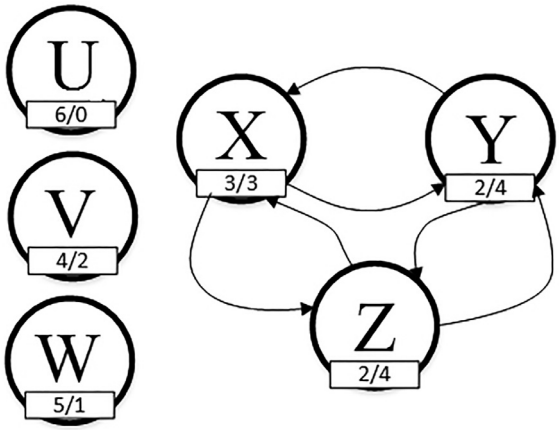

Fig. 5. Social abstract argumentation example - attack graph with argument votes.

Table 2
Determination of votes for arguments X, Y, and Z.

Vehicle (Objective)	Vote for X	Vote for X reasoning	Vote for Y	Vote for Y reasoning	Vote for Z	Vote for Z reasoning
U (Emission)	V_+	X is moving to a lower emission lane	V_-	Y is not moving to lower emissions	V_-	Z is moving to a higher emission lane
V (Congestion)	V_-	X is entering my lane	V_-	Y is congesting my lane	V_-	Z will congest my lane
W (Congestion)	V_+	X is moving out of my lane	V_+	Y is not hindering me	V_+	Z is not hindering me
X (Congestion)	V_+	I am X	V_-	Y is taking my desired position	V_-	Z is taking my desired position
Y (Travel time)	V_-	X will hinder my speed	V_+	I am Y	V_-	Z will hinder my speed
Z (Travel time)	V_-	X is taking my desired position	V_-	Y is taking my desired position	V_+	I am Z

will only approve of other agents staying in or moving to the slowest lane, and travel time agents will approve any argument except those that impede their ability to accelerate, maintain speed, or move to a different lane.

In the example shown in Fig. 4, the corresponding attack graph representing all arguments in set A, their relations contained in set R, and the votes cast in relation to them, are depicted in Fig. 5. The set V_a contains the social support $v_{a_i} = \langle a_i, v_+, v_- \rangle$ for each argument a_i. Each social support tuple in the set is comprised of the argument, the votes for it and the votes against it. For this test case, the set V_a was verified in a NetLogo implementation of this model and was calculated to be:

$$V_a = \{\langle U, 6, 0\rangle, \langle V, 4, 2\rangle, \langle W, 5, 1\rangle, \langle X, 3, 3\rangle, \langle Y, 2, 4\rangle, \langle Z, 2, 4\rangle\}$$

Vehicle U's next best action is to remain in its lane. Agent U casts a positive vote for its own argument. Its chosen action is not in conflict with any of the actions the remaining 5 agents plan to take - vehicle U is not looking to enter lanes congestion focused vehicles V, X, and W are currently in, and it won't hinder travel time focused vehicles Y and Z, so they all cast approval votes for U's argument. Argument U thus receives 6 for votes and implements its chosen action at the end of the argumentation round. Vehicle V posits an argument according to which it plans to remain in its lane. It will receive two votes of disapproval - by vehicle U because it's not in the lowest emission lane and not moving to it, and by vehicle X because it congests the lane X wants to be in. Vehicle W decides to remain in its current lane which garners a negative vote from vehicle U, since W is not driving in or moving to a lower emission lane. The vote tally and reasoning for the conflicting arguments X, Y, and Z is shown in Table 2.

4.3. Argument resolution

Now that the attack relations have been determined and all agents' votes have been gathered, the set of conflicting arguments has to be reduced down to a conflict-free set $R_r = \Gamma(R, V_a)$ with the help of the conflict reduction function from Definition 7. This reduced set contains two remaining attack relations $R_r = \{(X \to Y), (X \to Z)\}$. The set of winning arguments is seen in Fig. 6. Arguments U, V, and W are in the set of winners because they were not in conflict with any other argument. Arguments Y and Z lose out to argument X because they both had weaker social support.

The argument relations found in R_r represent the conflicting actions that have been approved by the agents in the group. Any agents that are the aggressor of any relation contained within the resulting set of the operation, $R \backslash R_r$ (in this example agents Y and Z), are forced to amend their choice of best action to the automatically accepted state of "decelerate." The

Fig. 6. Social abstract argumentation example - set of winning arguments after conflict reduction.

remaining agents either have no conflicting argument relations or were elected as the top choice among the conflicting relations and will be allowed to proceed with their selected actions at the end of the argumentation round. After the assigned actions are implemented by all agents and the next round of argument formation, conflict rectification, and action enactment, will start again.

4.4. Analysis

The illustrative example presented here was implemented and verified in a NetLogo simulation.

The next round of argumentation puts vehicle W at odds with vehicle Y. Vehicle W posits an argument reflecting its wish to remain in the fast lane and maintain its speed. Having lost the position directly ahead to vehicle X in the previous round, vehicle Y puts forth an argument for moving up to the fast lane. Vehicle W is opposed to that move since it would increase the congestion in its lane. Both Y and W's arguments garner the same social support from the group and the outcome is decided based on the amenability levels of each agent. In the same round, vehicle Z is not able to move up a lane because it is blocked by vehicle X so it chooses to accelerate until in subsequent rounds it is able to try to move up to the middle lane.

In the current model, each agent votes on each argument posited by another agent in isolation. In the first round, as seen in Table 2 vehicle W voted for vehicle X moving out of its lane but it also voted for the arguments of vehicles Y and Z, which were in direct competition with vehicle X for the middle lane position. Positive votes for Y and Z could have sabotaged the ability of vehicle X to change lanes, even though X leaving the lane would have been preferred by W in accordance with its congestion objective. In the following round vehicle V votes for vehicle Y leaving the lane they currently share but it also votes for vehicle W, since W is not currently negatively affecting it. Casting positive votes for both W and Y even though vehicle V has a vested interest in vehicle Y winning the argument is not the best strategy for the agent. An added layer of strategy during the voting process where the agent considers the conflict relations that may directly affect it before it casts its votes is a possible future improvement of the model.

5. Discussion

Even though the example presented here is of driverless vehicles, the approach outlined in this work can be implemented and utilized in any context that requires any kind of smart device to perform negotiation with other agents. Even simple devices can be argumentation-enabled. As long as a device is equipped with an expert system capable of forming arguments based on sensed data, it can take part in the argumentation process. Argumentation resolution capabilities can be delegated within the IoT if the agents are not capable or equipped to perform this task, or the additional energy drain resulting from ES decision making and computation cannot be sustained. If the edge cannot support it, the resolution component can reside in the cloud but to ensure low latency, a better choice would be to shift resolution authority to the fog. In most scenarios, security issues created by malicious devices at the perceptual, physical, and data link layers of the IoT should be given consideration [23]. Existing mechanisms to identify malicious edge devices [24] can be employed before a device is allowed to take part in the argumentation process. Depending on the scenario and heterogeneity and capabilities of participating CPS, integration issues may have to be addressed as well [25]. Reliability of links within the argumentation group will either have to be maintained or a mechanism to forward arguments, votes and results will have to be put into place. Scalability may become an issue depending on the size of the group. In that case, a central authority in the cloud or the fog may be needed to facilitate the argumentation process.

Automated argumentation can be used to aid devices in forming coalitions to reach a common goal. It can also be applied to allow devices to negotiate to achieve individual objectives. It can provide agents with the ability to settle conflict autonomously or aided by a central authority. Industrial applications of machine-to-machine argumentation are limitless. Within smart cities - in transportation, aside from negotiated lane changes, argumentation can be used in vehicle platooning, parking spot assignment and in directing traffic at intersections. It can also be used in autonomous multi-agent systems devoted to security or search-and-rescue by enabling robot swarms to efficiently self-organize and divide the area of operations. Within the context of smart energy and smart living, argumentation can be a useful tool in energy conservation and reduction of waste - e.g. smart power supply controllers negotiating power consumption and down time with connected devices. Argumentation among autonomous "things" can be applied anywhere within the IoT where conflict may arise when devices communicate and negotiate with each other.

The model presented in this work represents a stride toward fully autonomous negotiation between machines. It augments the ability of interconnected cyber-physical systems to communicate with other agents in the IoT. It affords a fair and organized distributed model of communication to reach decisions that will be accepted by all agents taking part in the argumentation process. It is a simple but powerful tool for unsupervised collaboration and negotiation through communication requiring minimal resources.

6. Conclusion

This work addressed the need for codifying interaction among actors on the burgeoning Internet of Things with automated argumentation that extends abstract Dung-style argumentation with social voting. It illustrated how expert systems can be used to produce Toulmin-style arguments. These arguments are generated based on the overarching objectives of the peer agents that generate them and are then grouped for competition. The presented approach is fully distributed and benefits from the advantages of IoT edge computing - real time performance is improved as computation is performed at the source. A prototyped implementation of the automated argumentation model and corresponding inference system that accounts for cyber enabled vehicles engaging in negotiation over lane selection was presented. A social abstract argumentation model for conflict resolution among autonomous vehicles seeking to change lanes on a multi-lane highway was introduced. Without restriction of generality and for simplicity, a limited set of shared objectives that govern vehicular agents' patterns of driving was used to illustrate the methodology. A natural extension for further research is to consider argument conflicts that arise from agents possessing heterogeneous objectives. The methodology presented in this work heralds a step toward automated negotiation through automated argumentation. Many other cyber-physical environments embody stages for opposing positions that may benefit from automated argumentation as a tool for collaboration.

Declarations of interest

None.

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