IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 1, 2018, accepted February 2, 2018, date of publication February 6, 2018, date of current version March 12, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2803051

An Agent-Based Inference Engine for Efficient and Reliable Automated Car Failure Diagnosis Assistance

SALAMA A. MOSTAFA[1], AIDA MUSTAPHA[1], AHMED ABDULBASIT HAZEEM[2], SHIHAB HAMAD KHALEEFAH[3], AND MAZIN ABED MOHAMMED[4]

[1]Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, Parit Raja 86400, Malaysia
[2]Anbar General Director of Education, Iraq Ministry of Education, Anbar 31001, Iraq
[3]Faculty of Computer Science, Almaaref University College, Anbar 31001, Iraq
[4]Planning and Follow Up Department, University Headquarter, University of Anbar, Anbar 31001, Iraq

Corresponding author: Salama A. Mostafa (semnah@yahoo.com)

This work was supported in part by the Ministry of Higher Education under Grant FRGS Vot 1557 and in part by UTHM under Post-Doctoral Grant VotD004.

ABSTRACT There are many difficulties and challenges involved in cars failure and malfunction diagnosis. The diagnosis process involves heuristic and complex series of activities and requires specific skills and expertise. A basic toolkit and assistance software are imperatives to help the car drivers to at least identify the source of car failure or malfunction, especially, when the location of the event does not permit immediate help. It enables the car driver to take an initiative in knowing the car condition and try to repeat the car. Expert systems are widely used to embody the diagnosis expertise into machines. However, improving the expert systems' inferencing capability and diagnosis accuracy are still open research topics. Consequently, this paper proposes an agent-based inference engine for the car failure diagnosis expert system that is named automated car failure diagnosis assistance (ACFDA). The agents' goal is to maximize the efficiency of the overall performance of the ACFDA system by deliberating a number of inferencing tasks and tuning the inferencing logical flow. Additionally, the agents' collective effort provides reliable solutions that best fit the users' inputs. The ACFDA system is experimentally tested by 15 relevant candidates. The test results show that the system efficiently and reliably performs the diagnosis to the most given car failure cases. The system can be integrated into cars or can be used as a separate gadget to assist the car drivers in car failure diagnosis and repair.

INDEX TERMS Car failure diagnosis, knowledge-based system, expert system, software agent, inference engine.

I. INTRODUCTION

In the current time, cars play an important role and become very necessary for different walks of humans' life. The cars are the most popular transportation methods in many parts of the world [1]. Appling automotive and assistance technologies in cars at present and in the future, are very important features for most of the cars' users [2]. Some people are spending time in their cars more than spending time with their family. Subsequently, integrating smart devices and applications in cars have become a competitive merit for all car makers. Assisting a car driver about the car's condition can be a popular and outstanding feature [3].

There are many cases where car failure causes are very simple and can be handled by the car driver if the driver has a basic knowledge about cars [1], [3]. It is an essential need when the failure incidence occurs far from car service shops or garages such as suburbs, highways or uninhabited places [4]. An example of car failures that can be handled by a novice user engine overheating. it can result from low water level in the radiator which does not involve defective car parts. Hence, the car driver in many situations should be able to perform the first level of diagnosis.

Mostly, car failures require skilled automotive technicians or car mechanics such as a dead injector or fuel pump [3]. The advance car failures diagnosis is only limited to highly skilled automotive technicians or car mechanics. However, cars' specifications are always and quickly changing due to environmental and economic factors [2]. This change results from the emergence of innovative technologies such as hybrid engines or electric motors. Throughout these changes, even skilled car mechanics are straggling to handle some car failures or malfunctions.

The success in handling diagnosis of a car failure manly depends on the individual's experience and experts. A specific diagnosis experience of a domain can be acquired from experts and collect in computer applications to be used by inexpert individuals [5]. Artificial intelligence techniques have been successfully applied by researchers, institutions, and firms in different diagnosis domains [6]–[9]. Knowledge-based systems, expert systems, software agents, fuzzy logic and neural network are some examples [10]–[15].

Expert systems are widely used in many diagnosis applications including cars failure diagnosis [3]. The expert systems use heuristic algorithms to reason over a stored knowledge and formulate solutions [16]. Many facts and rules are to be applied in order to catch the car failure causes which entails reasoning capabilities. Applying software agents to perform reasoning tasks for expert systems is visible in the literature. The agents are useful in dynamically exchanging data and collaboratively handling multiple streams of events [17]. For instance, Cardoso [18] proposes a multi-agent expert system. The system incorporates rule-based agents to form its inference engine. The inference engine obtains the autonomous capabilities of a multi-agent system including communication, coordination, and collaboration.

In general, this paper manifests the importance of adopting an expert system for cars failure diagnosis. Consequently, the paper includes the development of an Automated Car Failure Diagnosis Assistance (ACFDA) system. The ACFDA systems use a proposed agent-based inference engine. This research contributes the design and development of the agent-based inference engine and a Multi-agent System Collaborative (MASC) module.

The remainder of this paper proceeds as follows. Section I presents car failure diagnosis that is followed by the related work in Section III. Section IV presents the design and the implementation of the ACFDA system. Section V outlines system testing and presents the results. Section VI discusses the research contributions, limitations and finding. Finally, Section VII presents the conclusion and proposes future work.

II. CAR FAILURE DIAGNOSIS

The failure diagnosis operation, in general, is a heuristic and complex series of activities as shown in Figure 1. It entails a prior knowledge and experience regarding the diagnosed subject; such as a human, animal, plant, or machine [12]. The manual failure diagnosis is represented by humans' observations and the rules of thumb in diagnosing a particular problem. The observations provide information about the behavior of the diagnosed subject [11]. The rule of thumb includes checking the parts that are more related to the problem with the consideration of the intended and normal state of their performance [5]. A human who diagnoses a particular problem of a machine (electrical or mechanical) needs to have different types of knowledge about the machine include the machine's physical properties, fundamental, tacit, along with common sense diagnosis knowledge [1]. The diagnosis knowledge of an individual is acquired and improved through practice across time. The practice helps an individual to develop its knowledge and later become an expert [19].

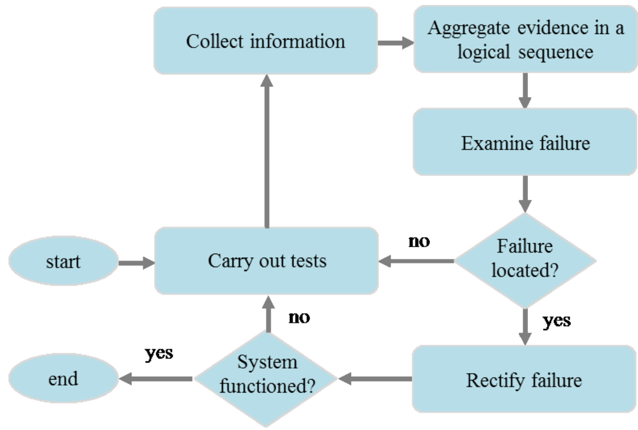

FIGURE 1. General framework of failure diagnosis.

There are different types of vehicles and each of which utilizes different types of technology. For instance, the engine of a car might run on petrol, gas, diesel, electrical, or hybrid power. Subsequently, expert mechanics or mechanical engineers usually specialize in specific types of vehicles [20]. Consequently, cars are exposed to failure or malfunction incidences that unexpectedly break them down. There are many causes of cars failure including the problems in the engine system, cooling system, braking system, transmission system, electricity, and wiring. The variety of the types and potential causes complicate the cars failure diagnosis process. Cars failure and malfunction diagnosis in general built upon the knowledge of a car's parts, their locations and applying a logical failure diagnostic routine [3]. The following algorithm 1 presents a common diagnosis routine of a car failure.

Algorithm 1 The Diagnosis Steps of a Car Failure

step1: identify irregularities of the car during different run states;
step2: search for physical symptoms such as leaking or broken parts;
step3: deliberate on the possible problems and filter out irrelevant targets;
step4: assess the targeted problem conditions;
step5: apply solutions to the targeted problem;
step6: verify the successfulness of the applied solutions;

The automated failure diagnosis is applying a number of procedures to automatically detect and identify faulty parts. It is one of the challenges that the artificial intelligence tries to solve. Its challenge results from the need for a reasoning technique that is capable of emulating the diagnosis processes of the human brain [19]. Automated car failure diagnosis becomes an interesting subject in Artificial Intelligence research [9]. There are a number of automated diagnosis techniques available together with their reasoning algorithms [12]. These techniques include the following components [3], [16]:

1. Domain knowledge.
2. Data acquisition methods to collect symptoms.
3. Variation rules to identify expected and actual states.
4. Assessment methods to detect inconsistencies.
5. Inference methods to generate solutions.

A knowledge-based system is a part of Artificial Intelligence science that aims to produce intelligent machines and computer programs [9]. An expert system is a type of a knowledge-based system that embodies a particular domain expertise such as a particular medical [7] or mechanical [8] diagnosis domain. Usually, an expert system interacts with users via a dialogue to get inputs of a problem in order for the system to extract the problem's symptoms. The direction of the dialogue is based on inputs of the user. The inputs can be extracted by providing series of questions and collecting responses or using an information sheet to be entered into the system [2]. The expert system then processes the symptoms as facts and offers solutions and suggestions [16]. At the same time, the user can take the initiative to supply information that the expert system did not ask for to improve the diagnosis results.

III. RELATED WORK

Our literature review reveals that agent-based expert system is yet to be applied in car failure diagnosis. Subsequently, to cover the scope of this work, we divide the literature review into two parts as follows.

A. CAR FAILURE DIAGNOSIS EXPERT SYSTEMS

Expert systems have been developed for a wide range of applications to perform reasoning tasks in diagnosis, control, and detection research fields [16]. The first expert system for technical fault diagnosis is developed at MIT in the early 1970's [19]. Recently, expert systems have been proposed for cars failure diagnoses. Milanović *et al.* [6] propose a car automotive diagnostic model based on hybridization of an expert system and decision support system. The failure diagnosis is made by the expert system and the process of the replacement of a faulty component is made by the decision support system. This hybrid system is practically tested and the test results show that the system increases the efficiency of labor and reduces the mental workload of the workers.

Nabende and Wanyama [21], develop an expert system for a heavy load vehicles diagnosis, known as Heavy Duty Diesel Engines (HDDEs). They propose Bayesian Network technology for modeling the inference engine of the HDDEs. The HDDEs faults diagnosis expert system has a high potential for rapid diagnosis revealed a hidden fault in the engine and re-recommendation proper procedures of corrective actions. The results show that employing an expert system in such domain is highly useful. Heavy-duty diesel engines require high skills and extensive experience in the field of mechanics. The limitation of the work is the simplicity of the knowledge base in which a very limited number of facts and rules are applied.

In the work of Aggarwal *et al.* [9], they model an expert system for cars failure diagnosis and repair. They propose a recursive inference engine that its applicable rules perform according to the phases of matching, selecting and executing. The knowledge base has a complex structure and contains a large number of facts and rules. The system takes into account many factors affecting the expert system such as the time and level of expertise. The prototype of this system is not promoted to be used as a complete application due to time and resource limitations.

Similarly, Mostafa *et al.* [3] present the imperatives for an expert system in developing car failure detection models. They address the problem of cars failure diagnosis and the need for applying the expert system in this field. Subsequently, they develop a Car Failure and Malfunction Diagnosis Assistance System (CFMDAS). The CFMDAS consists of three main parts which are the knowledge acquisition the graphical user interface and expert system. The expert system has a conventional forward chaining interface engine. The CFMDAS system is found to be highly useful in assisting mechanics for failure detection and training purposes.

Roanes-Lozano *et al.* [4] develop a portable knowledge-based system for cars failure notification. The system consists of three main important parts: a knowledge base, an inference engine and a user interface which has a standard dashboard of a car. The inference engine has a mathematical model and works based on algebraic architecture. The system helps the driver to be aware of the dashboard icons conditions and meanings. The driver interacts with the system to identify the car conditions based on the dashboard lights indications. The system is developed as a mobile application to alarm the driver on a possible failure and helps the driver to handle the failure.

B. AGENT-BASED EXPERT SYSTEMS

There are several studies that integrated software agents in expert systems. The aim of the studies is to improve the quality and accuracy of the overall systems' performance [22]. The agent provides proactive capabilities and the multi-agent provides deliberative capabilities to the systems [23]. These capabilities make the systems feasible to analyze some possible interactions among modules at design time and hence efficiently handle complexities and anomalies [24]. The following are some examples of deploying agents in expert systems.

Sridhar [25] proposes a framework of distributed multi-agent to improve the accuracy of an expert system. The agents interact with users to collect relevant information then combine it with the knowledge base data to discover a high order data or global knowledge. The framework includes data mining algorithms to retrieve and/or extract useful data of facts and rules from the knowledge base. The framework is applied in a knowledge-based medical diagnostic system for calculi disease.

Arsene *et al.* [24] propose a collaborative multi-agent framework in an expert system for an online healthcare system. The framework is used to manage and contribute to medical specialists' collective diagnosis. It has three key components: software agents for search and collaboration, a Bayesian network for uncertainty reasoning, and ontology for domain knowledge representation and management. The domain knowledge includes the history of the patients in the form of evidence, causes, effects. Each agent assists a physician in searching the domain knowledge, propagating beliefs and performing the collaborative diagnosis.

Muntean and Donea [26] propose an agent-based expert system for tourist guide mobile application. The expert system includes a knowledge base of Artificial Intelligence Markup Language (AIML) and a Global Positioning System (GPS) database. The GPS-database includes information and coordinates of tourist attraction places such as historical monuments, hotels, restaurants, hospitals and, embassies and user-defined locations. The agents collect and track a user position via the GPS databases and dynamically map the position of the user with the targeted places. The agents interact with the user via a query interface, perform inferencing tasks on the AIML and GPS-database, and return answers to the user in natural language.

IV. THE ACFDA SYSTEM

This research proposes an agent-based expert system for cars failure diagnosis called the Automated Car Failure Diagnosis Assistance (ACFDA) system. The ACFDA system is used to evaluate car conditions and recommends the best actions to be carried out by its targeted users, who are car drivers and junior car mechanics. The diagnosis covers possible repairs, whether on-site or at a workshop depending on the urgency of the problem. The system also provides a tow service. The ACFDA system is implemented in Java using Java Expert System Shell (Jess) as the expert system development platform and Java Agent DEvelopment (Jade) as a multi-agent system development platform. The ACFDA system is tested by a number of car mechanics and drivers to ensure its correct diagnosis to cars failures. The ACFDA system architecture consists of four main components which are knowledge acquisition, knowledge base, agent-based inference engine and user interface. The components are detailed in the following subsections. Figure 2 shows the architecture of the ACFDA system.

A. THE KNOWLEDGE ACQUISITION

Knowledge acquisition is an essential step in developing an expert system. In order for the expert system to solve a problem that requires a human expert, it needs a sufficient knowledge of the domain expertise to be stored in its knowledge base. The source of the knowledge base highly depends on the domain, which in this research, would include the domain experts, existing sources such websites, catalogs and maintenance guides as well as knowledge growth. The domain experts are represented by mechanics, engineers, and scholars. The knowledge growth results from the agents' modification to the Jess based on the human validation to the diagnosis process. The conducted knowledge acquisition methods, their difficulties, and usages are shown in Table 1.

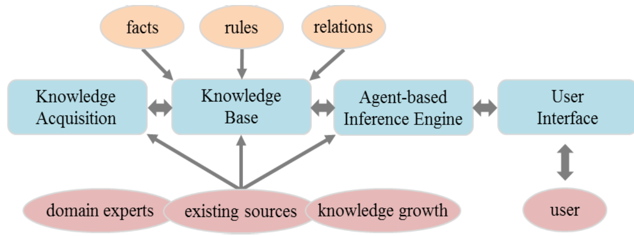

FIGURE 2. Architecture of the ACFDA system.

TABLE 1. Data acquisition methods and properties.

Source	Method	Difficulty	Usage
domain experts	interviewing experts	high	medium
existing sources	adopting from others	low	high
knowledge growth	learning	high	low

The acquired data represents straightforward and easy to handle failures by a car driver. The data is represented as sets of facts, rules, and relations of car failure diagnosis. It also includes texts, audio, and images which are mainly used for explanation and guiding purposes. Table 2 presents a sample of the acquired data.

TABLE 2. Data samples.

Type	Description	Example
fact	a piece of information	Car's battery needs charging
rule	a conditional statement	If fuel tank is empty Then fill it up
text	an explanatory information	This type of failure requires a car service center
audio	spoken words of a natural language	
image	a visual representation	

B. THE KNOWLEDGE BASE

The facts include diversities of attributes, structure, entities such as predicates of rules (expressions that defines the constraints of the rules) or arguments. The rules have different depths and include meta-rules. The rules are divided into three categories: Start-up rules which contain 12 main rules, run-stable rules which contains 8 main rules, and movement rules which contains 17 main rules. The categories are adopted from [10] and the rules are mainly adopted from [3], [6] and [20]. Figure 3 shows the structure of the knowledge base.

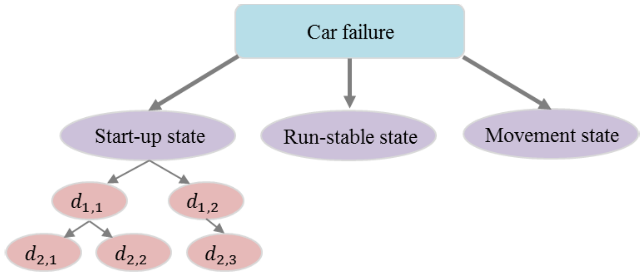

FIGURE 3. Car failure diagnosis states.

The start-up state addresses problems that may occur when a person tries to start-up a car. For example, an engine does not work, some sounds noticed, or engine worked ones and stopped. These problems could be caused by one or more failures including battery, wiring or dynamo. The run-stable state addresses the problems that may occur after starting up the car but the car fails to move. The corresponding failures of this state are related to the brake system, cycle on-off or gearbox system. The movement state addresses problems that may occur during a car's movement. The corresponding failures of the movement state are related to the fuel system, oil pressure, water temperature, or wiring problems. The knowledge base also contains suggestions to the users that explains the application of the solutions.

C. THE AGENT-BASED INFERENCE ENGINE

The ACFDA system has an agent-based inference engine and works based on a forward chaining algorithm. This type of inference engine considers the options of facts and rules applications and tracks or chains the conditions that direct to an outcome. The forward chaining algorithm uses a basic rule-based system strategy of a cause and effect implies a conclusion. For instance, a *car_radiator_water_level* is low (cause), *engine_temperature* is high (effect) and this change of the temperature results *damage_engine* (conclusion). Consequently, the agent-based inference engine maps a user's inputs with rules and their corresponding data including facts, texts, audio, and images. It works on the three categories of pre-assigned car failure diagnosis data as explained before. The agents implement seven inferencing tasks to direct the execution flow of the diagnosis process. The inferencing tasks are presented as follows:

- t_1: *interact with a user (inputs/outputs);*
- t_2: *search for an appropriate query based on the user's inputs;*
- t_3: *retrieve relevant facts from the knowledge base based on the user's inputs;*
- t_4: *search for appropriate rules to be applied to the facts;*
- t_5: *decide on the conflict of applying multiple rules;*
- t_6: *decide on the outputs that best satisfy the user's inputs;*
- t_7: *update the knowledge base with a new knowledge when required;*

The agents have a collaborative architecture that deliberates on carrying out inferencing tasks according to the diagnosis conditions [27], [28]. A major advantage of the collaborative multi-agent system architecture is the balance between the interoperability and the autonomy of individual agent. The agents' goal is to maximize the efficiency of the overall performance by reducing the inferencing tasks and generate reliable solutions that best fit the users' inputs [29], [30].

The agent-based inference engine has a collaboration module of a multi-agent system, MASC. This module assists the agents in performing a collaborative plan and prevents a possible conflict between their plans. The plans consist of a set of inferencing tasks. The agents deliberatively choose the tasks and perform a number of pre-compiled actions to complete the tasks. Figure 4 shows the collaborative architecture of the agent-based inference engine in which three agents are deployed to decide on the seven inferencing tasks.

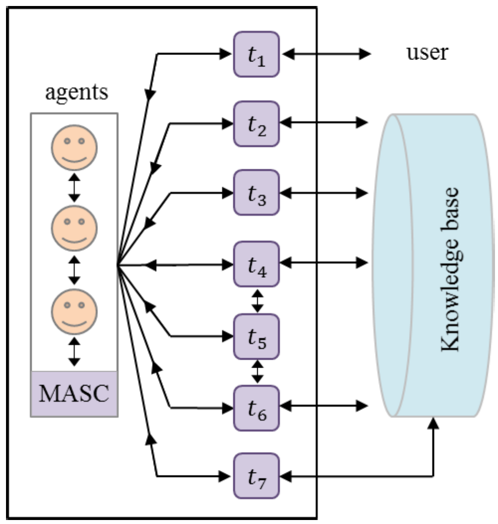

FIGURE 4. Architecture of the agent-based inference engine.

Based on Figure 4, if a user enters an input after t_1, then the agents select the task t_2. Tasks selection can be sequential if the diagnosis is simple, or deliberative if the diagnosis is complex. A diagnosis is deemed as complex when the system fails to reach a solution directly and performs several revisions to its queries. The system needs to revise some of its activities such as reconsidering pursuing t_2 or t_4. This revision might result in conflict in agents' decisions in which each agent might select a different sequence of tasks. The following explains the collaboration mechanism of a multi-agent system to revise the inferencing process of the expert system.

Let G^α be a group of agents that operate in a system; α be an agent in which $G^\alpha = \{\alpha_1, \alpha_2, \ldots\}$; and $T = \{t_1, t_2, \ldots\}$ are the possible tasks that each of the G^α can perform according to a collaborative plan, P in which the $P \subseteq T$. Let an individual agent, α_i has a set of beliefs B_i that represents its perception of its environment, E, including an inferencing complexity belief, B_i^C, and a plan revise belief, B_i^R; the α_i

operates according to a plan, p_i; the α_i frequently updates its beliefs using a *belief revision function* (*brf*), $brf : B_i \rightarrow B_i$. The α_i updates its p_i when there is a significant change in its beliefs of B_i^C and B_i^R using *plan revised function* (*prf*) as follows:

$$prf : (B_i^C \times B_i^R \rightarrow B_i) \times p_i \Rightarrow p_i \tag{1}$$

The G^α has a collaboration module of a multi-agent system MASC that helps in managing and coordinating the performance of the agents in a system. Each agent has its own plan, p and the p has a set of inferencing tasks in specific sequence $p^t = \{t_1, t_2, \ldots\}$. The agents use the MASC module to form a collaborative plan through applying a *tasks choice function* (*tcf*) to distinguish between the selection of different tasks.

$$tcf(p^t) \begin{cases} r_{i,j} = 1, & \exists\, t_j \in T : t_j \in p^t \\ r_{i,j} = 0, & otherwise \end{cases} \tag{2}$$

where r is an element that denotes an agent's choice of planned tasks, i is an index of an agent, j is an index of a task, and $i, j = \{1, 2, \ldots\}$.

The *tcf* forms a plans relation matrix, R. The agents' use the R to map the plans and induces the collaborative plan, P of a multi-agent system:

$$R = \begin{array}{c} \\ \alpha_1 \\ \alpha_2 \\ \alpha_n \end{array} \begin{array}{c} \begin{array}{ccc} t_1 & t_2 & t_m \end{array} \\ \begin{bmatrix} r_{1,1} & r_{1,2} & r_{1,m} \\ r_{2,1} & r_{2,2} & r_{2,m} \\ r_{n,1} & r_{n,2} & r_{n,m} \end{bmatrix} \end{array}, \tag{3}$$

where n denotes the number of agents and m denotes the number of tasks of the inference engine.

The agents apply a *tasks intensity function* (*tif*) in the MASC module to decide on the consideration of a particular pattern of tasks, P. The *tif* includes (4) to measure the intensity, v, of the chosen patterns of tasks in which the intensity of a $p_i^v = \{v_1, v_2, \ldots, v_m$. Then it maps the R with the p_i^v to form the new P.

$$v_i = \frac{\sum_{i=1}^{n} r_{i,j}}{n} \tag{4}$$

For example, suppose that there are four agents, $G^\alpha = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4\}$ and six types of tasks, $T = \{t_1, t_2, t_3, t_4, t_5, t_6$ of a multi-agent system. Each agent deliberates the options of the tasks and selects a specific number of tasks with specific sequence as its plan based on its perception in which $\rightarrow \alpha_1$: *deliberation* $p_1^t = \{t_1, t_3, t_5\}$, $\rightarrow \alpha_2$: *deliberation* $p_2^t = \{t_2, t_3, t_5\}$, $\rightarrow \alpha_3$: *deliberation* $p_3^t = \{t_1, t_3, t_4\}$, and $\rightarrow \alpha_4$: *deliberation* $p_4^t = \{t_1, t_2, t_5\}$. The agents use the MASC to generate the relation matrix, R then apply $tif : R \times p_i^v \rightarrow P$ and generate the collaborative plan as described in Figure 5.

A simplified model of the ACFDA system based on the agent-based inference engine is shown in Algorithm 2.

Algorithm 2 The ACFDA Model

```
begin;
initial < S^S: solution state, S^F: failure state, S^Q:
   query state, S^A: answer state, S^C: complexity state,
   S^R: revise state, S^K: knowledge base state,
   B : {B^S, B^F, B^Q, B^A, B^C, B^R, B^K, ...} >;
User: selects a S^F;
G^α do until valid S^S:
      G^α do i until n:
            brf : B_i → B_i;
            prf : B_i × p_i ⇒ p_i;
      end-do;
      tif: R× ⇒ p_i^v P;
      G^α do j until m:
            switch (P_j)
                  case 1: /*t_1^*/; break;
                  ...
                  case 7: /*t_7^*/; break;
                  default: /*revise*/ break;
            end-switch;
      end-do;
      if found S^S:
            recommend solution;
            assist user;
            User: apply solution;
            User: validate solution;
            set S^S;
      otherwise:
            set S^C;
            set S^R;
      end-if;
end-do;
assist user;
end.
```

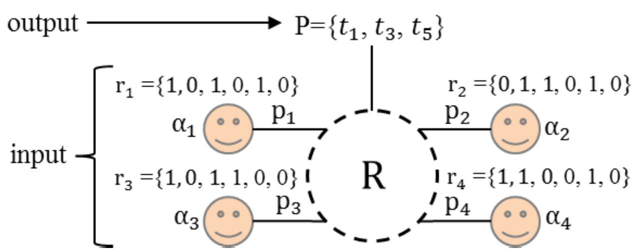

FIGURE 5. Collaborative relationship of the agents.

D. THE USER INTERFACE

The ACFDA system runs a diagnosis of a car failure through interactive sessions via a graphical user interface. The system provides a step-by-step guide to the user with a set of explanation along the diagnostic activities. The user interface is divided into four types, which are the (1) main user interface, (2) query user interface, (3) solution user interface, (4) assistance user interface, and finally (5) knowledge base

FIGURE 6. Main user interface of the ACFDA system.

user interface. The system diagnosis a car failure through interaction session with a user. When the system is started the main user interface is displayed on the screen and asks the user to choose one of the three car states as shown in Figure 6. The user is expected to choose a state that is particular to the problem that the car has.

Following Figure 6, the diagnostic flow starts when the user selects the failure state according to the car condition. The system then interacts with the user by starting a query session until the user answers all the queries. The user interface is represented as a menu which displays the questions to the user and the user answers with YES or NO. Subsequently, the system will propose a solution based on the answers by the users. The system is meant to deal with novice users that could benefit from simple diagnosis to solve problems. The ACFDA is also equipped with user assistance features. The application will guide the users on what they should do to solve the problem. As the last resort, the system provides a help service that lists all car repair and tow services from different cities in Malaysia.

V. THE RESULTS AND EVALUATION

The ACFDA system testing encompasses two test phases in order to evaluate the performance quality of the system. An initial test precedes each of the test phases to check the functionalities of the system. This test covers all the possible diagnosis problems that the system might encounter. It is meant to verify that the inference engine and the knowledge base are performing correctly. Subsequently, (I) the first test phase implements the proposed agent-based inference engine that has deliberative features. (II) The second test phase implements a conventional forward chaining inference engine that has sequential features. This type of inference engines chains or tracks the conditions of rules that direct the system to an outcome. The system has the same initial state for the two test phases. The candidates for the tests are 15 persons (10 car drivers and 5 mechanics). Each test phase consists of 15 attempts and considers specific and similar failures of a car. The failures are selected to cover the start-up, run-stable, and movement car failure states for which each state is equally tested with five attempts. The test results are divided into the same three categories of start-up, run-stable- and movement results.

(I) The results of the agent-based deliberative inference engine: The diagnosis results of the start-up state show that the required diagnostic steps to reach a solution on average is 10, the average time to do the diagnosis is 0.56 seconds, the revision state occurs six times (ones a run in average), the average number of tasks is 44, the human evaluation of the logical flow of the run in average is 88% and the overall diagnosis success rate is 100%. The run-stable diagnosis results show that the required diagnostic steps to reach a solution on average is 9, the average time to do the diagnosis is 0.54 seconds, the revision state occurs five times (ones a run in average), the average number of the performed tasks is 40, the human evaluation of the logical flow of the run in average is 92% and the overall diagnosis success rate is 100%. Finally, the diagnosis results from the movement state show that the required diagnostic steps to reach a solution on average is 9, the average time to do the diagnosis is 0.64 seconds, the revision state occurs six times (ones a run in average), the average number of the performed tasks is 46, the human evaluation of the logical flow for a test in average is 88% and the overall diagnosis success rate is 100%. Table 3 presents the results of the agent-based deliberative inference engine.

TABLE 3. Results of the agent-based inference engine.

car state	test	steps	time (s)	revise	tasks	flow	success
start-up	1	10	0.54	1	44	5	successful
	2	9	0.48	1	40	5	successful
	3	11	0.62	2	52	4	successful
	4	11	0.72	2	52	4	successful
	5	8	0.45	0	32	4	successful
run-stable	1	8	0.51	0	32	5	successful
	2	10	0.61	2	48	4	successful
	3	9	0.53	1	40	5	successful
	4	8	0.49	0	32	5	successful
	5	10	0.57	2	48	4	successful
movement	1	12	0.81	3	54	4	successful
	2	10	0.47	2	48	5	successful
	3	8	0.68	0	42	3	successful
	4	9	0.74	1	45	5	successful
	5	8	0.52	0	42	5	successful

In table 3, the car state column contains the tested cars' state of failure; the test column contains the number of tests for each of the tested states; the steps column contains the number of diagnostic steps of a test that are taken to reach a solution; the time column contains the diagnosis time of a test in second (excluding human respond time); the revise column contains the occurrence of the revision process of a test; the task column contains the number of tasks of a test; the flow column contains the human evaluation of the logical flow for a test (the value of 1 indicates low and 5 indicates high flow); and the success column contains the overall diagnosis success state of a test.

(II) The results of the conventional sequential inference engine: The start-up diagnosis results show that the required diagnostic steps to reach a solution on average is 9, the average time to do the diagnosis is 0.53 seconds, the average number of tasks is 46, the human evaluation of the logical flow of the run in average is 80% and the overall diagnosis success rate is 80% with one attempt that is considered unsuccessful. The run-stable diagnosis results show that the required diagnostic steps to reach a solution on average is 8, the average time to do the diagnosis is 0.49 seconds, the average number of the performed tasks is 41, the human evaluation of the logical flow of the run in average is 88% and the overall diagnosis success rate is 100%. Finally, the results of the movement diagnosis show that the required diagnostic steps to reach a solution on average is 9, the average time to do the diagnosis is 0.56 seconds, the average number of the performed tasks is 49, the human evaluation of the logical flow of the run in average is 76% and the overall diagnosis success rate is 80%.

The results of the conventional sequential inference engine are convenient in general. Meanwhile, the results of the agent-based inference engine are better than the conventional inference engine. Figure 7 shows the summary of the ACFDA system performance using (I) the agent-based deliberative and (II) conventional sequential inference engine in the three car failure states. The overall results of the agent-based inference engine show that the required diagnostic steps to reach a solution on average is 9, the average time to do the diagnosis is 0.58 seconds, the revision state occurs six times (ones a run in average), the average number of tasks is 43, the human evaluation of the logical flow of the run in average is 89% and the overall diagnosis success rate is 100%.

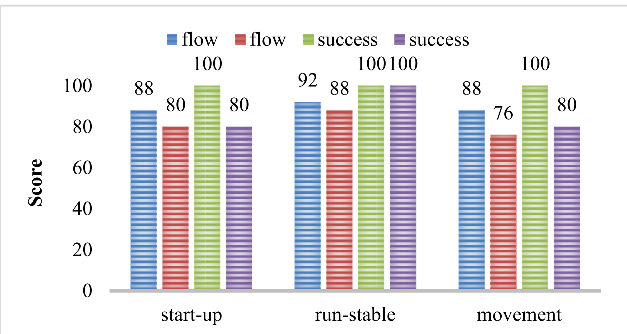

FIGURE 7. Evaluation results of the two inference engines.

The overall results of the conventional inference engine show that the required diagnostic steps to reach a solution on average is 9, the average time to do the diagnosis is 0.52 seconds, the average number of tasks is 45, the human evaluation of the logical flow of the run in average is 81% and the overall diagnosis success rate is 86%. Consequently, the results imply that the overall required time to get a satisfactory diagnosis and the human evaluation to the diagnosis are relatively convenient. Subsequently, the agent-based inference engine increases the required diagnostic steps but decreases the number of tasks which slightly increases the diagnosis time. In return, it increases the logical flow of the run and the diagnosis success rate. The variation of the diagnosis time is affected by the diagnosis steps, the corresponding tasks, and the revision operation. Figure 8 depicts this relationship in the three car failure states.

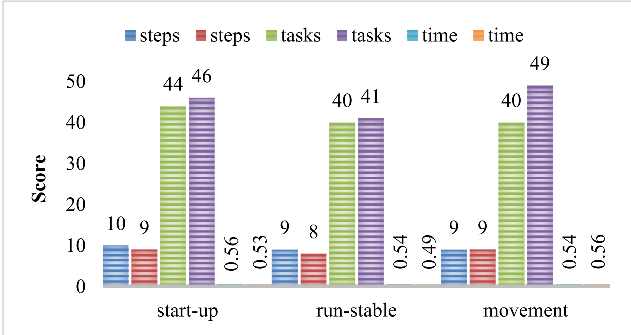

FIGURE 8. Relationship between the diagnosis and time of the two engines.

Although the sequential behavior is less complicated but not good enough to handle some anomalies of uncommon diagnosis cases or user inputs. The deliberate inference engine can revise and do backtracking without completing unnecessary tasks. However, the system is tested by experienced or guided users, in order to show its superiority over the conventional system, it should be tested by common users and in a real-world environment.

The ACFDA system is compared against existing systems including the specifications of the diagnosis method, the type of users, the online or offline access ability, the availability of a friendly user interface, the development platform, and the existence of additional services. Ultimately, the evaluation results prove that the ACFDA system has the characteristics of efficient and reliable expert systems. It has the merits of adequate response time, high accuracy, easy usage, interactivity and ability to be integrated into multiple platforms.

VI. DISCUSSION

Expert systems are computer programs that manifest intelligent solutions by acquiring and inferencing humans' knowledge and expertise to solve challenging problems. The expert system embodies humans' knowledge of a particular expertise to accomplish particular tasks of a domain. The application of the expert system in the diagnosis domain entails interaction with users to obtain relevant information from the users. The system performs the diagnosis according to reasoning processes over the obtained information. It applies a heuristic mechanism to its existing knowledge and proposes solutions.

In general, cars failure and malfunction diagnosis are built upon the knowledge of a car's parts, their locations and applying a logical failure diagnostic routine [3]. There are many needs for an automated car failure diagnosis system. It is essential in the emergency and difficult situations when the driver of the car in places that are far from car services. In this work, we study, design, implement, test and evaluate an expert system for car failure and malfunction diagnosis. The ACFDA system is able to perform the diagnosis of 15 car failures. The results of the tests show the ACFDA system is found to be successful and useful. The logical flow and consumed diagnosis time of the ACFDA system are also found to be very convenient to the users. The system can be used as a software kit by drivers that have basic knowledge or experience on car parts or junior mechanics.

This research contributes the design and development of an agent-based inference engine. Additionally, it contributes the MASC as a collaboration module of a multi-agent system. The MASC assists the agents in generating a collaborative plan and prevents a possible conflict between the agents' planning decisions. The research finds that integrating a system like the ACFDA within cars can be practical and particularly useful. The ACFDA system provides early diagnosis of some types of failure or malfunction which could prevent greater damage or serious accidents. The limitation in the present design of ACFDA is that the knowledge base is tailored to a specific type of cars and users, and the users need to have prior knowledge about their cars. The system can be further improved by enhancing its knowledge base contents which will further reflect the usefulness of the proposed contributions.

VII. CONCLUSION

This paper presents some recent issues of automated cars failure diagnosis and the application of the expert system on cars failure diagnosis. It attempts to develop an expert system for cars failure diagnosis to efficiently control a car failure diagnosis process and generate reliable results. Subsequently, the paper proposes an agent-based inference engine for developing an Automated Car Failure Diagnosis Assistance (ACFDA) system. The ACFDA system assists the car driver to take the initiative and try to fix the car or at least learn the car condition. The system is experimentally tested by a number of car mechanics and drivers. The test results show that the ACFDA system has successfully performed diagnosis in most of the tested car failure cases and confirm its usefulness. The system can be integrated into cars or be used as a mobile application to assist car drivers.

The possible future improvements to be made to the system are updating the knowledge base with new car failures. A more futuristic work is making the system able to perform a fully-automated diagnosis by connecting it directly to the problematic parts of the car and automatically alarms the driver when specific incidences or failures occur.

REFERENCES

[1] D. O. Olanloye, "An expert systems for diagnosing tractor failure and malfunction," *Int. J. Adv. Stud. Comput., Sci. Eng.*, vol. 2, no. 6, pp. 27–33, 2013.

[2] C. Saridakis, S. Tsafarakis, P. Delias, G. Baltas, and N. Matsatsinis, "Optimizing differentiation and commonality levels among models in car line-ups: An empirical application of a nature-inspired heuristic mechanism," *Expert Syst. Appl.*, vol. 42, no. 5, pp. 2323–2335, 2015.

[3] S. A. Mostafa, M. S. Ahmad, M. A. Mohammed, and O. I. Obaid, "Implementing an expert diagnostic assistance system for car failure and malfunction," *Int. J. Comput. Sci. Issues*, vol. 9, no. 2, pp. 1–7, 2012.

[4] E. Roanes-Lozano, J. L. Galán-García, and G. Aguilera-Venegas, "A portable knowledge-based system for car breakdown evaluation," *Appl. Math. Comput.*, vol. 267, pp. 758–770, Sep. 2015.

[5] Z. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3757–3767, Jun. 2015.

[6] D. D. Milanović, M. Misita, D. Tadić, and D. L. Milanović, "The design of hybrid system for servicing process support in small businesses," *FME Trans.*, vol. 38, no. 3, pp. 143–149, 2010.

[7] P. S. K. Patra, D. P. Sahu, and I. Mandal, "An expert system for diagnosis of human diseases," *Int. J. Comput. Appl*, vol. 1, no. 13, pp. 71–73, 2010.

[8] J. G. Rolim and M. Moreto, "An expert system based approach for diagnosis of occurrences in power generating units," in *Expert Systems for Human, Materials and Automation*, vol. 17. Rijeka, Croatia: InTech, 2011, pp. 327–350.

[9] R. Aggarwal, S. Jain, Y. Jindal, and N. Verma, "Approach towards car failure diagnosis-an expert system," *Int. J. Comput. Appl.*, vol. 1, no. 23, pp. 61–64, 2010.

[10] A. T. Al-Taani, "An expert system for car failure diagnosis," *IEC (Prague)*, vol. 5, pp. 457–560, Aug. 2005.

[11] R. Isermann, *Fault-Diagnosis Systems: An Introduction From Fault Detection to Fault Tolerance*. Berlin, Germany: Springer, 2006.

[12] W. Budiharto, "The development of an expert car failure diagnosis system with Bayesian approach," *J. Comput. Sci.*, vol. 9, no. 10, pp. 1383–1388, 2013.

[13] M. A. Mohammed, "Design and implementing an efficient expert assistance system for car evaluation via fuzzy logic controller," *Int. J. Comput. Sci. Softw. Eng.*, vol. 4, no. 3, pp. 60–68, 2015.

[14] M. A. Mohammed, B. Al-Khateeb, and D. A. Ibrahim, "Case based reasoning shell frameworkas decision support tool," *Indian J. Sci. Technol.*, vol. 9, no. 42, pp. 1–8, 2016.

[15] M. K. A. Ghani, M. A. Mohammed, M. S. Ibrahim, S. A. Mostafa, and D. A. Ibrahim, "Implementing an efficient expert system for services center management by fuzzy logic controller," *J. Theor. Appl. Inf. Technol.*, vol. 95, no. 13, pp. 3127–3135, 2017.

[16] C. Angeli, "Diagnostic expert systems: From expert's knowledge to real-time systems," in *Advanced Knowledge Based Systems: Model, Applications & Research*, vol. 1, P. Sajja and R. Akerkar, Eds. TMRF e-Book, 2010, pp. 50–73. [Online]. Available: http://www.tmrfindia.org/eseries/ebook.html#content

[17] C. Bădică, L. Braubach, and A. Paschke, "Rule-based distributed and agent systems," in *Proc. Int. Workshop Rules Rule Markup Lang. Semantic Web*, 2011, pp. 3–28.

[18] H. L. Cardoso. (2007). Integrating Jade and Jess. JADE. [Online]. Available: http://jade.tilab.com/doc/tutorials/jade-jess/jade_jess.html

[19] W. T. Scherer and C. C. White, III, "A survey of expert systems for equipment maintenance and diagnostics," in *Knowledge-Based System Diagnosis, Supervision, and Control*. New York, NY, USA: Springer, 1989, pp. 285–300.

[20] N. Y. Asabere and S. Kusi-Sarpong, "Mves: A mobile vehicle expert system for the automobile industry," *Int. J. Eng. Res. Appl.*, vol. 2, no. 6, pp. 1108–1123, 2012.

[21] P. Nabende and T. Wanyama, "An expert system for diagnosing heavy-duty diesel engine faults," in *Advances in Computer and Information Sciences and Engineering*. Dordrecht, The Netherlands: Springer, 2008, pp. 384–389.

[22] S. A. Gutierrez and J. W. Branch, "A comparison between expert systems and autonomic computing plus mobile agent approaches for fault management," *Dyna*, vol. 78, no. 168, pp. 173–180, 2011.

[23] S. A. Mostafa, M. S. Ahmad, A. Mustapha, and M. A. Mohammed, "A concise overview of software agent research, modeling, and development," *Softw. Eng.*, vol. 5, no. 1, pp. 8–25, 2017.

[24] O. Arsene, I. Dumitrache, and I. Mihu, "Expert system for medicine diagnosis using software agents," *Expert Syst. Appl.*, vol. 42, no. 4, pp. 1825–1834, 2015.

[25] S. Sridhar, "Improving diagnostic accuracy using agent-based distributed data mining system," *Inform. Health Soc. Care*, vol. 38, no. 3, pp. 182–195, 2013.

[26] M. V. Muntean and A. Donea, "A hybrid intelligent agent based expert system for GPS databases," in *Proc. 8th Int. Conf. Electron., Comput. Artif. Intell. (ECAI)*, 2016, pp. 1–4.

[27] K. S. Macarthur, R. Stranders, S. D. Ramchurn, and N. R. Jennings, "A distributed anytime algorithm for dynamic task allocation in multi-agent systems," in *Proc. AAAI*, Aug. 2011, pp. 701–706.

[28] K. Govil, "A smart algorithm for dynamic task allocation for distributed processing environment," *Int. J. Comput. Appl.*, vol. 28, no. 2, pp. 13–19, 2011.

[29] S. Kraus and T. Plotkin, "Algorithms of distributed task allocation for cooperative agents," *Theor. Comput. Sci.*, vol. 242, no. 1, pp. 1–27, 2000.

[30] Q. Kang, H. He, and J. Wei, "An effective iterated greedy algorithm for reliability-oriented task allocation in distributed computing systems," *J. Parallel Distrib. Comput.*, vol. 73, no. 8, pp. 1106–1115, 2013.

SALAMA A. MOSTAFA received the B.Sc. degree in computer science from the University of Mosul, Iraq, in 2003, and the M.Sc. and Ph.D. degrees in information technology from Universiti Tenaga Nasional, Malaysia, in 2011 and 2016, respectively. He is currently a Member of Postdoctoral Staff with Universiti Tun Hussein Onn Malaysia, Malaysia. His research interests are in the area of software engineering, artificial intelligence and their integration including software agents and intelligent autonomous systems.

AIDA MUSTAPHA received the B.Sc. degree in computer science from Michigan Technological University, in 1998, the M.Sc. degree in computer science from the National University of Malaysia, Malaysia, in 2004, and the Ph.D. degree in artificial intelligence focusing on dialogue systems from Universiti Putra Malaysia in 2008. She is currently the Deputy Dean of the Center for Research and Development, Universiti Tun Hussein Onn Malaysia. She is also an Active Researcher in the area of computational linguistics, soft computing, data mining, and agent-based systems.

AHMED ABDULBASIT HAZEEM received the M.Sc. degree in computer science from Universiti Kebangsaan Malaysia in 2016. He is currently the Anbar General Director of Education, Iraq Ministry of Education, Anbar. His research interests include artificial intelligence and expert systems.

SHIHAB HAMAD KHALEEFAH received the B.Sc. degree in computer science from the University of Anbar, Iraq, in 2013, the M.Sc. degree in computer science from Universiti Kebangsaan Malaysia in 2016. He is currently a Lecturer with the Faculty of Computer Science, Almaaref University College. His research interests include artificial intelligence, image processing, and pattern recognition.

MAZIN ABED MOHAMMED received the B.Sc. degree in computer science from the University of Anbar, Iraq, in 2008, and the M.Sc. degree in information technology from Universiti Tenaga Nasional, Malaysia, in 2011. He is currently pursuing the Ph.D. degree with the Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka, Malaysia. His research interests include artificial intelligence, biomedical computing, and optimization.