An Architecture of a Multi-Agent System for SCADA
Dealing With Uncertainty, Plans and Actions

Sarah Calderwood, Weiru Liu, Jun Hong and Michael Loughlin
School of Electronics, Electrical Engineering and Computer Science,
Queen's University Belfast, Belfast, U.K.

Keywords: Autonomous Agents, Multi-Agent Systems, Sensors, SCADA, Uncertainty, Plans, Actions, Fusion.

Abstract: This paper presents a multi-agent system approach to address the difficulties encountered in traditional SCADA systems deployed in critical environments such as electrical power generation, transmission and distribution. The approach models uncertainty and combines multiple sources of uncertain information to deliver robust plan selection. We examine the approach in the context of a simplified power supply/demand scenario using a residential grid connected solar system and consider the challenges of modelling and reasoning with uncertain sensor information in this environment. We discuss examples of plans and actions required for sensing, establish and discuss the effect of uncertainty on such systems and investigate different uncertainty theories and how they can fuse uncertain information from multiple sources for effective decision making in such a complex system.

1 INTRODUCTION

Uncertainty (Graham and Jones, 1988; Halpern, 2003) is pervasive in sensor network based systems and control systems. Information may be incomplete or approximated due to limitations in the equipment used to collect data or introduced by the algorithms that process the data. It is sometimes infeasible to exactly describe an environment, a particular situation, a future outcome or the possibility of multiple outcomes. Plans are derived from system goals and, taking into account the current environmental conditions, they define a series of actions that aim to achieve those goals. For example a grid connected solar powered house may need to take an action such as *demand additional electricity from the National Grid* based upon information received from other sensors or based upon other specific plans for that particular situation. A sensor may have accuracy limitations that might introduce doubt whether this action should take place. Uncertain information may cause a catastrophic error if this uncertainty is not dealt with properly.

Robust uncertainty modelling theory is required to represent, reason and adequately represent reliabilities associated with the sources of uncertain information. Examples of theories include Dempster-Shafer theory of evidence (Shafer, 1976) and possibility theory (Dubois and Prade, 2011).

In a multi-agent system, agents communicate, cooperate, compete and co-ordinate accordingly with the other agents in order to minimize the degree of uncertainty that arises to accomplish their individual and global goals. Since agents collect uncertain information from different sources, it becomes necessary to fuse (or combine) uncertain information from multiple sources in order to determine the most plausible model of the environment. Therefore developing suitable fusion algorithms within each chosen theory is important. In this paper we will investigate these issues and illustrate how these uncertainty modelling and fusion approaches can be integrated into multi-agent systems.

The rest of the paper is structured as follows. Section 2 provides a background stating the basic terms. Section 3 describes a simplified power supply/demand scenario. Section 4 defines goals, plans and actions for normal operation of three agents. Section 5 describes the sensing environment and factors contributing to uncertainty. Section 6 models uncertainty and how to fuse uncertain information using theories. Section 7 summarises conclusions and future work.

Calderwood S., Liu W., Hong J. and Loughlin M..
An Architecture of a Multi-Agent System for SCADA - Dealing With Uncertainty, Plans and Actions.
DOI: 10.5220/0004594603000306
In *Proceedings of the 10th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2013), pages 300-306
ISBN: 978-989-8565-70-9

2 MULTI-AGENT SYSTEMS AND SCADA

Multi-Agent Systems (Jennings and Wooldridge, 1998; Wooldridge, 2002) are comprised of interacting autonomous agents that are well suited for applications in a dynamic, unreliable situation. Such systems provide robust models for representing complex and real world environments such as power systems. Multi-agent systems gather information from sensors and other agents through communication, and then reason with dynamic environments to make rational and timely decisions or actions.

Typical multi-agent systems adopt a centralised architecture (Pipattanasomporn et al, 2009) but problems arise because of the need to integrate increasingly diverse components and to scale to larger deployments. In addition the complexity and unpredictability of the environment present unique problems for centralised solutions.

Decentralised systems offer the necessary control and level of integration to help components work together and provide a methodology that helps to distribute tasks (Jennings et al, 1995).

There are many advantages in using multi-agent systems including increased fault and noise tolerance, increased flexibility in design and scalability, enhanced security and increased efficiency. To demonstrate and validate these advantages simulations will be created using a simplified power supply/demand scenario. This is beyond the scope of this paper.

SCADA (Supervisory Control and Data Acquisition) is a proven and successful technology consisting of a centralised system that monitors and controls industrial processes, particularly in large scale critical infrastructures such as power generation and power transmission (Daneels and Salter, 1999; McArthur et al, 2007; Arghira et al, 2011). SCADA systems are attractive solutions in these application domains by virtue of their flexibility, simplicity, reliability and ability to work autonomously in real time. SCADA does however have a number of restrictions due to the centralised control architecture especially in the areas of flexibility, scalability and resilience to failure or attack (Yang et al, 2006).

Uncertainty in SCADA systems arises when sensor data or inferred knowledge cannot be deemed accurate. Applications must deal with inherent noise/error in sensor data or knowledge as well as uncertainty, incompleteness and inconsistent or conflicting data from multiple sources (Sobh and Mahmood, 2002). Humans have traditionally supervised such problems to reason and resolve issues. In traditional SCADA deployments the human supervisor takes the role of encapsulating and handling inherent uncertainties arising from incompleteness and inconsistencies. Intelligent multi-agent systems need to perform this role autonomously.

Domain knowledge captures environmentally specific regulations, norms, restrictions, exceptions and other domain-specific information. This knowledge is used to generate plans of actions for a system in a given state to achieve particular goals. Agents need this knowledge to operate and reason with collected sensory information for achieving their objectives. Each agent may have its own specific knowledge in addition to some common knowledge shared amongst agents.

Domain knowledge is either elicited from domain experts who are specialists in a chosen application area or learned from domain specific datasets.

A common approach to capturing domain knowledge is to use production rules that can readily be represented and executed using Prolog. For example a rule reacting to the reading of the voltage and frequency of an overhead service line in a normal state can be formatted as

If Voltage(Reading) $\in$ (228V, 252V) $\wedge$
Frequency(Reading) = 50Hz
Then Transmit(Electricity) $\wedge$ Update(Meter)

Goal and action modelling helps to achieve automated intelligent control, reducing the need for human interaction and executing in real-time to suit various environmental conditions that may arise in the system such as uncertainty, security issues or component failure. From a description of possible states of the world, the desired goals and a set of possible actions, a plan can be determined that is guaranteed from any of the initial states to generate a sequence of actions that leads to one of the goal states.

3 POWER SCENARIO

For the purpose of illustration, this paper will use in its simplest form, a grid connected solar system for successful power generation and supply (see Figure 1). This is part of a larger scenario for power generation, transmission and consumption. It consists of three agents (a substation, a distribution transformer, a house) and multiple sensors to measure voltage, frequency etc. Other agents required will aid decision making, record status and events, retrieve data from equipment as shown in Figure 2. The approach can be readily transferred to similar applications operating in other SCADA-related domains.

Power from Grid. We assume electricity has been generated at a power station and transmitted over transmission lines to a *substation* located near to consumers. The AC frequency of the power supply is 50 Hertz (Hz).

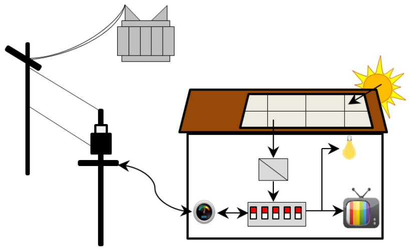

Figure 1: A simple grid connected solar system.

Substation transformers reduce high voltage electricity to lower voltage electricity. Medium/low voltage *distribution transformers* convert the power from *main distribution lines* to 240 volts (V) to serve residential loads. Electricity is delivered on low voltage *overhead service lines* to a *meter* located inside the building. A *fuse box* will trip to protect from problems such as short-circuits or appliance faults.

Solar Power. When the sun shines, *solar photovoltaic panels* generate direct current (DC). An *inverter* converts DC into 240V alternating current (AC) suitable for household appliances. A *meter* measures electricity production and consumption. Excess electricity is fed into the *National Grid* where credit is given by a utility company. If solar becomes unavailable then accumulated credits are used to offset electricity drawn from the grid. Reverse power flow causes problems such as voltage control, power quality issues, difficulty of isolation for maintenance etc.

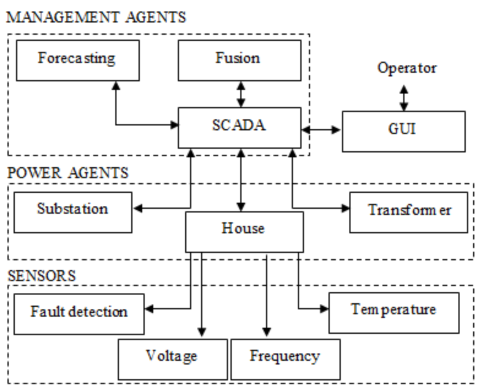

Figure 2: A sample solution of the SCADA agents and sensor architecture for simplified power scenario.

4 GOALS, PLANS AND ACTIONS

For the purpose of illustration we use, in its simplest form, three agents for solar power generation and distribution (a substation, a distribution transformer, a house) each equipped with the relevant sensors.

The goals, plans and actions are captured in the AgentSpeak programming language (Rao, 1996; Bordini et al, 2007). AgentSpeak is an agent-oriented programming language based on logic programming and the BDI architecture for autonomous agents.

Goals. The pro-active behaviour of agents is possible through the notions of goals. A goal is a desired state of the world. Each agent will have individual goals that they strive to independently achieve depending on their state (for example normal, emergency, failure, recovery).

For example the house agent has a goal to deliver sufficient power to household appliances at an acceptable voltage level and AC frequency. More specially, to achieve this goal the house (fusebox, meter etc.) must be switched on with the power supply operating at 50Hz and the voltage between 228V and 252V (nominal voltage allows $\pm 5\%$).

Similarly a goal to switch off a working transformer for maintenance requires informing the participating components e.g. substation, consumers etc. of the goal in order that they can react appropriately to the overall system goals for this situation.

Plans. Each emerging situation (determined from the information provided by sensing/observing agents in the environment) must be complemented by a plan of actions to follow to transform the initial situation to one that satisfies some goal.

An AgentSpeak plan has the general structure of:

```
triggering event : context <- body
```

where the triggering event denotes the events that the plan handles or a goal an agent needs to see achieved. The context represents the circumstances in which the plan can be used and the body is the course of action to be used to handle the event if the context is believed true at the time a plan is executed.

```
Substation Agent:
+!startSystem: true <- switchOnSystem;
 runSystem.
+!runSystem: on(system) <- !startHouse;
 !startTransformer.

Solar House Agent:
+!startHouse: on(system) <- solarHouseOn;
 !runHouse.
+!runHouse: on(house) <- checkHouseSensors;
 !runningHouse; !runHouse.
+!runningHouse: on(house) & frequency(50) &
 (voltage(228) | voltage(252)) & on(fusebox) &
 on(appliance) & meter(credit+1) <-
 workSolarHouse.
+!runningHouse: on(house) <- switchOffHouse;
.send(system, untell, on(house));
.send(transformer, untell, on(house)).
```

```
Transformer Agent:
+!startTransformer: on(system) & on(house) <-
 switchOnTransformer; !runTransformer.
+!runTransformer: on(transformer) <-
 checkTransformerSensors; !runningTransformer;
 !runTransformer.
+!runningTransformer : on(transformer) &
 on(house) & (voltage(228) | voltage(252)) &
 frequency(50) <- workTransformer.
+!runningTransformer: on(transformer) &
 on(solarPower) <- switchOffTransformer;
.send(system, untell, on(transformer));
.send(house, untell, on(transformer)).
```

Actions. For the normal operation of the generation and distribution of solar power these typical actions may be executed for the above plans. These actions are specific to each agent and may rely on further actions taken by other agents simultaneously.

```
switchOnSystem
Preconditions:  ¬on(system)
Effects:  on(system)

solarHouseOn
Preconditions:  ¬on(house)
Effects:  on(house)

workSolarHouse
Preconditions:  on(house)
Effects:  on(solarPower)

checkHouseSensors
Preconditions: on(house)
Effects: on(solarPower) & frequency(50) &
(voltage(228) | voltage(252)) &
on(fusebox) & on(appliance) & on(meter)

switchOnTransformer
Preconditions:  ¬on(transformer)
Effects:  on(transformer)

workTransformer
Preconditions:  on(transformer)
Effects:  on(gridPower)

checkTransformerSensors
Preconditions: on(house) & on(transformer)
Effects: on(gridPower) & frequency(50)
(voltage(228) | voltage(252))
```

These plans and actions can be further refined to account for the real complexity in a working power system.

5 SENSING ENVIRONMENT FOR MULTI-AGENT SYSTEMS

In a real-world multi-agent system, the environment plays a prominent role. Constantly sensing the environment provides situational awareness and allows an agent to adapt to environmental changes by selecting or generating new plans as needed to ultimately ensure agents meet their own goals.

The environment can be considered to include all aspects of a system that are not owned or hosted within an agent, including the infrastructure by which agents communicate.

Certain environmental aspects may become unavailable to an agent but which are required for decision making about further actions. Informed guesses may be required to progress. Uncertainty is an issue that may arise and will have an impact on plan selection. The following four aspects are factors that contribute to uncertainty in a SCADA system such as power distribution.

Supply and Demand Issues. Supply and demand is a dynamic balance made more difficult because there are no scalable methods of storing electricity. It is difficult to predict and generate exactly the amount of electricity required for consumer needs and to protect the grid from power overload and damage. Blackouts occur if demand exceeds supply and brownouts occur if power supply drops below demand. Maintenance of this balance is challenging. Output from solar panels and other renewable sources are favoured over fossil fuel based resources and generating power stations may suspend generation temporarily until any surplus electricity has been redistributed.

Future Popularity of Electricity and Consumers Behaviour. It is predicted that electricity will be increasingly relied upon to meet new demands for electric heating, air conditioning and electric vehicles. The unpredictable behavioural effects of consumers, changes in their geographical distribution, the effect of economic incentives etc. will also impact the potential demand making it hard to estimate and plan for future needs. For example if the price of electricity becomes more expensive then consumers may be more careful with usage.

Data Acquisition. Uncertainty arises from sensing instrumentation or techniques used to make the measurement. Moreover there is the possibility of humans, systematic errors or external deliberate intrusions compromising the reliability of data. For example the measurement or updating of a voltage sensor could be broken or a human may introduce an error when interpreting a sensor reading. The precision and accuracy of the sensor could be significant to the problem i.e. voltage is within a certain range and frequency is an exact value.

Unpredictability of External Events. Uncertainty arises if components required to distribute electricity are tampered. This can be accidental or malicious. Projections of human behaviour are not easily amendable to prediction. Uncertainty may be embedded into environmental factors that are out of our control (e.g. humidity), weather conditions (e.g.

wind, lightning), operational events (e.g. component failure) and economic events (increased electricity prices, costs to repair components) etc. Agents need to predict future events based on many different types of information and environmental factors. It can be impossible to be certain that events will occur. Different sources will have different degrees of reliability when agents make use of their information.

It is advantageous to handle properly uncertain sensor information to enhance the performance of an agent system. A multi-agent system that has adopted measures to minimise uncertainty will reduce the chances of failure/disaster occurring e.g. if new evidence has been collected or observed and introduced to the system an agent's beliefs will need to be revised or updated to take into account new information. It will also result in better autonomous decision making because robust uncertainty handling would limit the need for human interaction and so allow for real-time situational awareness.

6 UNCERTAINTY MODELLING

Many techniques have been developed for representing and processing uncertainty depending on the information given.

6.1 Dempster-Shafter Theory (DST)

This theory (Shafer, 1976) extends probability theory and offers a mechanism to combine uncertain information from distinct sources (represented by belief functions) using Dempster's combination rule. Mass values are assigned to sets of possibilities rather than singleton events. This model can cope with varying degrees of precision.

Definition 1: A frame of Discernment

Set $\Omega=\{\omega_1,...\omega_n\}$ is called a frame of discernment(frame) if one and only one ω_j is true at a time.

Example 1. data acquisition - assume there are two voltage sensors on a distribution line and we want to monitor the readings. For simplicity, assume the reading[1] is either Normal(n) or Abnormal(¬n), then $\Omega = \{n, \neg n\}$.

Definition 2: Basic Belief Assignment (BBA)

Let m be a function on Ω as m: $2^\Omega \rightarrow [0,1]$ then m is a BBA *iff* $\sum A\ m(A)=1$. When $m(\varnothing)=0$ is required, it is called a mass function.

Example 2. Each sensor (S_1) will contribute its observations by assigning beliefs over Ω. The mass function derived from sensor S_1 reading is denoted by m,

$m(\{n\})=0.5,\ m(\{\neg n\})=0.3,\ m(\Omega)=0.2$

If $m(\varnothing)\neq 0$, m is referred to as self-inconsistent, which is equivalent to the open world assumption. This means this is something we do not know therefore it is not modelled in Ω or the sensor information is wrong.

Definition 3: Pignistic Transformation

In order to aid decision-making we use pignistic transformation (Smets, 2004) which transforms a BBA to a probability function.

Let m be a BBA on Ω. Its associated pignistic probability function $BetP_m$: $\Omega \rightarrow [0,1]$ is defined as:

$$\mathrm{BetP}_m(\omega) = \sum_{A\subseteq\Omega,\omega\in A} \frac{1}{|A|}\frac{m(A)}{1-m(\emptyset)},\ m(\emptyset)\neq 1$$

where $|A|$ is the cardinality of subset A.

Example 3. Using Ex. 2,

$$\mathrm{BetP}_m(\mathrm{n}) = \frac{m(\{n\})}{|\{n\}|} + \frac{m(\{\Omega\})}{|\Omega|} = 0.6$$

Similarly $\mathrm{BetP}_m(\neg\mathrm{n}) = 0.4$.

This means that it is highly likely voltage on the cable is Normal, so no immediate actions are needed.

6.2 Possibility Theory

Dubois and Prades (2011) theory is suitable for modelling an agents knowledge that is incomplete, therefore complementing probability theory.

Definition 4: Possibility Theory

Let Ω be a frame of discernment consisting of a set of possible solutions.

A fundamental function in possibility theory is a *possibility distribution* $\pi : \Omega \rightarrow [0,1]$. π is said to be *normal* iff $\exists\omega_0 \in \Omega$ such that $\pi(\omega_0) = 1$. $\pi(\omega)$ means the maximum likely possibility of ω being true.

Example 4. Using Ex. 2, $\pi(n)=1$, $\pi(\neg n) = 0.5$

A possibility distribution is more like a quantitative comparison of its alternatives. This is more suitable when evidence is less precise to define either a probability function or a mass function. It has been proved that any possibility distribution π can be converted into a mass function.

6.3 Fusing Uncertain Information

In a complex system, certain information collected from different or multiple sources such as data from sensors or agents can be fused to derive more precise beliefs and help achieve situation awareness. Perceptions can be built which allows the selection of appropriate plans. By retrieving agent goals a decision can be made on the actions to execute.

[1]It is possible to define a set of voltage values as the elements of a frame.

Different theories will deploy different combination mechanisms. For example, Dempsters combination rule for DS theory (Shafer, 1976), states that the rule cannot be applied if pieces of information are almost conflicting or coming from sources that may have influenced one another.

Defintion 5: Dempster's Combination Rule
Given two mass functions m_1 and m_2, their combined mass function is:

$m_{1\oplus 2}(C)=m_1\oplus m_2(C)=(1/1-k)\sum_{A\cap B=C\neq\varnothing} m_1(A)\, m_2(B)$

$k = \sum_{A\cap B=\varnothing} m_1(A)\, m_2(B)$ where k is the degree of conflict.

For each proposition such as Normal(n), this theory gives a rule of combining sensor S_1 and S_2 observation m_1 and m_2 respectively.

Table 1: This table shows the results of using the combination rule.

$m_2 \downarrow m_1 \rightarrow$	$\{n\}$,0.6	$\{n,\neg n\}$,0.4
$\{n\}$,0.4	$\{n\}$,0.24	$\{n\}$,0.16
$\{n,\neg n\}$,0.6	$\{n\}$,0.36	$\{n,\neg n\}$,0.24

Therefore $m_{1\oplus 2}(\{n\})$=0.76, $m_{1\oplus 2}(\{n,\neg n\})$=0.24. This reading indicates the voltage on the line is normal.

For heterogeneous uncertain information, we can merge mass functions (m) with possibility distributions (π), after π can be converted into another m'. This then allows m and m' to be combined using DS values (Hunter and Liu, 2006).

As a result of uncertainty, agents have chances to take different plans to achieve the same goal. They need to evaluate which plan to take under such utility through a selection function that is still to be developed.

7 CONCLUSIONS AND FUTURE WORK

Uncertainty models are approximations because it is infeasible to eliminate uncertainty entirely. It becomes necessary to model a problem domain, incorporating appropriate fusion algorithms, in such a way that is suitable for the type of uncertainty evident in the system to capture the true nature of the real world domain.

Forthcoming research will involve the design and implementation of a multi-agent SCADA system taking the power system as an example, dealing with uncertainty, multi-source information, as well as their effects on agent goals and plans. To recognise different environments, goals, plans and actions will be incorporated using sensor data and domain knowledge. A selection function will be developed to decide which plan is most appropriate to achieve the goal depending upon the prevailing circumstances. This can help in future decision making and planning. The AgentSpeak language has been used to model plans and goals. Jason (Bordini et al, 2007) will be used to develop a BDI agent architecture for the SCADA power control. We plan to integrate our BDI architecture with the Electronic Institutions framework (Arcos et al, 2005) in order to model norms/regulations.

REFERENCES

Arcos, J. L., Esteva, M., Noriega, P., Rodrguez-Aguilar, J. A. and Sierra, C. (2005). Engineering open environments with electronic institutions. In *Engineering applications of artificial intelligence*. 18(2), 191-204.

Arghira, N., Hossu, D., Fagaraan, I., Iliesc, S.S. and Costianu, D.R. (2011). Modern scada philosophy in power system operation A survey. In *UPB Scientific Bulletin, Series C: Electrical Engineering*. 73(2), pp. 153-166.

Bordini, R. H., Hubner, J. F., Wooldridge, M. (2007). *Programming Multi-Agent Systems in AgentSpeak using Jason*. John Wiley and Sons.

Daneels, C. and Salter, W. (1999). What is SCADA? In *International Conference on Accelerator and Large Experimental Physics Control Systems*. Italy, 339-343.

Dubois, D. and Prade, H. (2011). On possibility theory, formal concept analysis and granulation: Survey. In *Applied and Computational Mathematics*. 10(1), pp. 10-19.

Graham, I. and Jones, P. (1988). *Expert systems: knowledge, uncertainty and decision*. Chapman and Hall.

Halpern, J. (2003). *Reasoning about uncertainty*. The MIT Press, Cambridge, Massachusetts, London, England.

Hunter, A. and Liu, W. (2006). Fusion rules for merging uncertain information. In *Information Fusion Journal*. 7(1):97-134.

Jennings, N. R., Corera, J. M. and Laresgoiti, I. (1995). Developing industrial multi-agent systems. In *1st Int. Conf. on Multi-Agent Systems (ICMAS '95)*. 423-430.

Jennings, N. and Wooldridge, M. (1998). *Agent Technology: Foundations, Applications, and Markets*. Springer, Berlin.

McArthur, S. D. J., Davidson, E. M., Catterson, V.M., Dimeas, A. L., Hatziargyriou, N. D., Ponci, F. and Funabashi, T. (2007). Multi-agent systems for power engineering applications - Part I: Concepts, approaches, and technical challenges. In *IEEE Transactions on Power Systems*. 22(4), pp. 1743-1752.

Pipattanasomporn, M., Feroze, H. and Rahman, S. (2009). Multi-agent systems in a distributed smart grid: Design and implementation. In *IEEE/PES Power Systems Conference and Exposition*. PSCE 2009.

Rao, A. (1996). Agentspeak(l): BDI agents speak out in a logical computable language. In *Agents Breaking Away*. Springer.

Shafer, G. (1976). *A Mathematical Theory of Evidence. Theory of Evidence.* Princeton University Press.

Smets, P. (2004). Decision making in the TBM: the necessity of the pignistic transformation. In *International Journal of Approximate Reasoning*. 133-147.

Sobh, T. and Mahmood, A. (2002). Recovering structure uncertainties from noisy sense data. In *Computers and Electrical Engineering. IEEE/PES Power Systems Conference and Exposition.* 28(2), pp. 127-141.

Wooldridge, M. (2002). *An Introduction to Multiagent Systems*. Wiley, New York.

Yang, Z., Ma, C., Feng, J. Q., Wu, Q. H., Mann, S. and Fitch J. (2006). A multi-agent framework for power system automation. In *International Journal of Innovations in Energy Systems and Power*. Vol. 1, no. 1.