POTENTIAL IMPACT ASSESSMENT OF COMMON CAUSE FAILURES AND HUMAN ERRORS IN EXISTING AND FUTURE POWER PLANTS

František Janíček — Ivan Darul’a — Martin Brezina

At present time, the assessment of common cause failures is an important part of reliability and risk analysis. This paper deals with common cause failures, causes and mechanism of rising common cause failures in nuclear power plant systems. The paper presents a scheme and methods for evaluation of common cause failures in risk and reliability analyses in nuclear power plants. Reliability and risk analyses are very important for increasing the safety and reliability of nuclear power plant operation.

Keywords: reliability, common cause failures, human errors

1 INTRODUCTION

Common cause failures are multiple unit failures due to a single cause [1]. In the nuclear power industry, the last (few) years have seen a growing interest in the combat against common mode failures of plant systems. Human errors during plant operation and maintenance can lead to common mode failures of plant systems. In many reliability models, random failures of components result only in system failures. In real situations, however, systems are sometimes affected by environmental factors such as human errors or variations of the electrical power. Although the linkage of human failure to common cause failures in complex systems is undeniable, it is often underestimated in reliability analyses [2]. Therefore, the subject of human errors and common cause failures (CCF) has attracted considerable attention in this paper.

2 COMMON CAUSE FAILURES

We can define a common cause failure as any instance in which multiple units or components fail due to a single cause. In general, common cause failures are categorised according to their cause into four groups [1] and [7]:

- Hardware: Random equipment failures due to causes inherent to the affected component
- Human: This group includes errors during plant operations, errors during equipment testing and maintenance, and errors during the design, manufacturing and construction.
- Environmental: This group involves such events which are external to the equipment but internal to the plant. The same factors, such as a dust, dirt, humidity and temperature, affect also the internal components.
- External: Events that begin outside the plant and lead to abnormal environmental loading of the equipment. They include events such as fire, flood and earthquake, which could affect every system of the plant.

3 METHODS OF CCF ASSESSMENT AND MODELLING

The methods and models of common cause failures can be categorised in several different ways, based on the number of parameters, their assumptions regarding the cause, coupling mechanism, and the impact of common cause failures [1].

The categories, as for the number of parameters required for modelling common cause events, are:

- Single parameter models
- Multiple parameter models

With respect to how multiple failures occur, there are two categories:

- Shock models
- Non-shock models

The shock models estimate the frequency of multiple component failures by assuming that the system is subject to common cause shocks at a certain rate and estimating the conditional probability of failure of components within the system, given the occurrence of shocks. The common cause failure frequency is a product of the shock rate and the conditional probability of failure.

Finally, except for the basic parameter model, all common cause models estimate the probability of basic events indirectly, ie through the use of other parameters. In general, the types of parameters, estimation methods and data requirements vary from one model to another. However, with the current state of data that involves large
uncertainties, given is a consistent treatment of data in all cases.

3.1 Single parameter models

The single parameter models refer to those parametric models that use one parameter in addition to the total component failure probability to calculate the common cause failure probabilities. The most widely used single parameter model, and the first such model to be applied to common cause events in applied risk and reliability analysis, is known as the beta factor model [6]. According to the beta factor model, a fraction ($\beta$) of the component failure rate can be associated with common cause events shared by the other components in a common group. According to this model, whenever a common cause event occurs, all components within the common cause group are assumed to fail. Therefore, based on this model, for a group of $m$ components, all $Q_k$ (probability of basic event involving $k$ specific components, $l \leq k \leq m$) are zero, except $Q_1$ and $Q_m$. The last two quantities are written as

\[ Q_1 = (1 - \beta)Q_t \]
\[ Q_m = \beta Q_t \]

This implies that

\[ \beta = \frac{Q_m}{Q_1 + Q_m} \]  

The total failure probability of one component is given as $Q_t = Q_1 + Q_m$, when $Q_2 = \cdots = Q_{m-1} = 0$

3.2 Multiple parameter models

For a more accurate analysis of systems with higher levels of redundancy, models that represent a range of impact levels of redundancy, models that represent a range of impact levels that common cause events can have, are more appropriate. These models involve several parameters with which to quantify the specific contribution of various basic events.

Four such models are selected here to provide adequate representation of the methods that have been proposed (Table 1). In the non-shock model category the Multiple Greek Letter (MGL) model and the alpha factor model are discussed. The binomial failure rate model represents the shock model category.

3.2.1 Multiple Greek Letter model

The Multiple Greek Letter model (MGL) [4] is the most general of a number of recent extensions of the beta factor model. In this method, other parameters in addition to $\beta$ are introduced to distinguish between common cause events affecting different numbers of components in a higher order redundant system. The MGL parameters consist of the total component failure frequency, which includes the effect of all independent and common cause contributions to that component failure, and a set of failure fractions, which are used to quantify the conditional probabilities of all the possible ways a common cause failure of a component can share with other components in the same group if a given component failure has occurred. For a system of $m$ redundant components and for each given failure mode, $m$ different parameters are defined. For example, the first four parameters of the MGL model are:

$Q_t$ - total failure frequency of component due to all independent and common cause events,

$\beta$ - conditional probability that a common cause of a component failure will be shared by one or more additional components,

$\gamma$ - conditional probability that a common cause of a component failure that is shared by one or more components will be shared by two or more components additional to the first,

$\delta$ - conditional probability that a common cause of a component failure that is shared by two or more components will be shared by three or more components additional to the first.

The general equation that expresses the frequency of multiple component failures due to common cause $Q_k$ in terms of MGL parameters is given in Table 1.

3.2.2 Alpha factor model

The difference between the $\alpha$ factor parameters and the MGL parameters is that the former are system failure based while the latter are component failure based [5]. The $\alpha$ factor parameters are thus more directly related to the observable number of events than are the MGL parameters. Like the MGL model, the $\alpha$ factor model develops common cause failure frequencies from a set of failure ratios and the total component failure rate. The parameters of the $\alpha$ factor model are defined. As before:

$Q_t$ - total failure frequency of each component due to all independent and common cause events

plus

$\alpha_k$ - fraction of total frequency of failure events that occur in the system involving the failure of $k$ components due to common cause

and $\alpha_1 + \alpha_2 + \cdots + \alpha_m = 1$.

The general equation relating the basic event probabilities, $Q_k$, to the $\alpha$ factor model parameter is given in Table 1. As we can see, the key difference between $\alpha$ in this model and the parameters of the MGL and $\beta$ factor models is that the former is a fraction of the events that occur within a system, whereas the latter are fractions of component failure rates.
Table 1.

<table>
<thead>
<tr>
<th>Model</th>
<th>Model Parameters</th>
<th>General form for multiple component failure frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-shock model, direct estimation approach</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basic parameter</td>
<td>$Q_1, Q_2 \ldots Q_m$</td>
<td>$Q_k = Q_k, \quad k = 1, 2 \ldots m$</td>
</tr>
<tr>
<td>Non-shock model, single parameter indirect estimation approach</td>
<td>Beta factor</td>
<td>$Q_k = (1 - \beta)Q_t, \quad k = 1$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$0, \quad m &gt; k &gt; 1$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\beta Q_t, \quad k = m$</td>
</tr>
<tr>
<td>Non-shock models, multi parameter indirect estimation approach</td>
<td>Multiple Greek letters</td>
<td>$m - l$ parameters</td>
</tr>
<tr>
<td></td>
<td>$Q_t, \beta, \gamma, \delta$</td>
<td>$Q_k = \frac{1}{(m-1)} \left( \prod_{i=1}^{k} \rho_i \right) (1 - \rho_{k+1}) Q_t$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\rho_1 = 1, \rho_2 = \beta, \rho_3 = \gamma, \ldots \rho_{m+1} = 0$</td>
</tr>
<tr>
<td></td>
<td>Alpha factor</td>
<td>$Q_t, \alpha_1, \alpha_2, \ldots \alpha_m$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$Q_k = \frac{k}{(m-1)} \frac{\alpha_k}{\alpha_t} Q_t, \quad k = 1, \ldots m$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\alpha_t = \sum_{k=1}^{m} k \alpha_k$</td>
</tr>
<tr>
<td>Shock model approach</td>
<td>Binomial failure rate</td>
<td>$Q_k = \mu \rho^k (1 - \rho)^{m-k}, \quad k \neq m$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\mu \rho^m + \omega, \quad k = m$</td>
</tr>
</tbody>
</table>

3.2.3 Binomial failure rate model

The binomial failure rate (BFR) [3] model considers two types of failures. The first represents independent component failures; the second type is caused by shocks that can result in failure of any number of components in the system. According to this model, there are two types of shocks, lethal and non-lethal. When a non-lethal shock occurs, each component within the common cause component group is assumed to have a constant and independent probability of failure. The name of this model arises from the fact that, for a group of components, the distribution of the number of failed components resulting from each non-lethal shock occurrence follows a binomial distribution. The BFR model is therefore more restrictive because of these assumptions than all other multiparameter models presented in Table 1.

When a lethal shock occurs, all components are assumed to fail with a conditional probability of unity. Application of the BFR model with lethal shocks requires the use of the following set of parameters:

$Q_t$ - independent failure frequency for each component,

$\mu$ - frequency of occurrence of non-lethal shocks,

$p$ - conditional probability of failure of each component, given a non-lethal shock,

$\omega$ - frequency of occurrence of lethal shock.

The general form of the probability of basic events according to the BFR model is given in Table 1.

3.2.4 Illustrative example

As an example of presented models we consider a system of three identical components $A$, $B$ and $C$, with a two out three-success logic. These components form a single common cause component group. The component-level fault tree is shown in Figure 1, with the following minimal cut-sets: $\{A, B\}; \{A, C\}; \{B, C\}$.

The reduced Boolean representation of the system failure in terms of minimal cutsets of the component-level fault tree is

$$S = AB + AC + BC.$$ (3)
The expansion of this component-level Boolean expression down to the common cause impact level can be illustrated by representing each component-level basic event as a subtree, such as that shown in Figure 2, in which it is assumed that common cause failures can lead to either two or three components failing simultaneously.

![Component-level fault tree](image)

**Fig. 1.** Component-level fault tree

![Basic event subtree for component A](image)

**Fig. 2.** Basic event subtree for component A

The equivalent Boolean representation of the total failure of component A is

\[ A_T = A_I + C_{AB} + C_{AC} + C_{ABC} \]  

where are \( A_T \) - failure of component A from independent causes, \( A_I \) - failure of component A from independent causes, \( C + AB \) - failure of components A and B from common causes, \( C_{AC} \) - failure of components A and C from common causes, \( C_{BC} \) - failure of components B and C from common causes, \( C_{ABC} \) - failure of components A, B and C from common causes.

When all the components of this two-out-of-three system are expanded similarly, the following minimal cut-sets are obtained:

\[ \{A, B\}; \{A, C\}; \{B, C\} \]
\[ \{C_{AB}\}; \{C_{AC}\}; \{C_{BC}\} \]
\[ \{C_{ABC}\} \]

The reduced Boolean representation of the system failure in terms of these cut-sets is

\[ S = A_I B_I + A_I C_I + B_I C_I + C_{AB} + C_{AC} + C_{ABC} \]  

and the algebraic equation in terms of the probabilities of the basic events is

\[ P(S) = P(A_I)P(B_I) + P(A_I)P(C_I) + P(B_I)P(C_I) \]
\[ + P(C_{AB}) + P(C_{AC}) + P(C_{BC}) + P(C_{ABC}), \]  

where \( S \) is the failure of the whole system, \( P(X) \) - is the probability of event \( X \).

It is a common practice in risk and reliability analysis to assume that the probabilities of similar events involving similar types of components are the same. According to this approach we get

\[ P(A) = P(B) = P(C) = Q_1, \]
\[ P(C_{AB}) = P(C_{AC}) = P(C_{BC}) = Q_2, \]
\[ P(C_{ABC}) = Q_3. \]  

This is called the symmetry assumption.

The system failure probability can be written as

\[ Q_S = 3Q_1^2 + 3Q_2 + Q_3. \]  

In general, for the basic events corresponding to a common cause group of \( m \) components, we can define \( Q_K \) - probability of basic event involving \( k \) specific components and \( k \in (1, m) \).

**Beta factor.**

Using the beta factor model with our example, the terms representing the basic event in (8) are written as

\[ Q_1 = (1 - b)Q_t, \]
\[ Q_2 = 0, \]
\[ Q_3 = bQ_t \]  

As one can see, the beta factor model requires that an estimate of the total failure rate of the component be provided from generic sources of data and that a corresponding estimate for the beta factor also be provided.

**Multiple Greek Letter model.**

To see how parameters of MGL model can be used, consider the tree component system, (8). The maximum number of components that can share a common cause is three \((m = 3)\). Therefore \( \gamma \) is the conditional probability that the common cause of failure of a component will be shared by exactly two additional components, and \( \delta = 0 \).

Then

\[ Q_1 = (1 - \beta)Q_t, \]
\[ Q_2 = \frac{1}{2}\beta(1 - \gamma)Q_t, \]
\[ Q_3 = \beta\gamma Q_t. \]  

**Beta factor.**

Using the beta factor model with our example, the terms representing the basic event in (8) are written as

\[ Q_1 = (1 - b)Q_t, \]
\[ Q_2 = 0, \]
\[ Q_3 = bQ_t \]  

As one can see, the beta factor model requires that an estimate of the total failure rate of the component be provided from generic sources of data and that a corresponding estimate for the beta factor also be provided.

**Multiple Greek Letter model.**

To see how parameters of MGL model can be used, consider the tree component system, (8). The maximum number of components that can share a common cause is three \((m = 3)\). Therefore \( \gamma \) is the conditional probability that the common cause of failure of a component will be shared by exactly two additional components, and \( \delta = 0 \).

Then

\[ Q_1 = (1 - \beta)Q_t, \]
\[ Q_2 = \frac{1}{2}\beta(1 - \gamma)Q_t, \]
\[ Q_3 = \beta\gamma Q_t. \]
The unavailability of a two-out-of-three system in terms of MGL parameters is

\[ Q_S = 3(1 - \beta)^2Q_t^2 + \frac{3}{2}\beta(1 - \gamma)Q_t + \beta\gamma Q_t. \quad (12) \]

The \( \beta \) factor model is a special case of the MGL model. In this example, the MGL model reduces to the \( \beta \) factor model if \( \gamma = 1 \).

**Alpha factor model.**

Probabilities of basic event of three component system in terms of the a factor model parameters are written as

\[
\begin{align*}
Q_1 &= \frac{\alpha_1}{\alpha_t} Q_t, \\
Q_2 &= \frac{\alpha_2}{\alpha_t} Q_t, \\
Q_3 &= \frac{3\alpha_3}{\alpha_t} Q_t, \\
\end{align*}
\]

where \( \alpha_t = \alpha_1 + 2\alpha_2 + 3\alpha_3 \).

The system unavailability for our example is given by

\[ Q_S = 3 \left( \frac{\alpha_2}{\alpha_t} \right)^2 Q_t^2 + \frac{3}{2} \frac{\alpha_2}{\alpha_t} Q_t + \frac{3}{3} \frac{\alpha_3}{\alpha_t} Q_t. \quad (13) \]

**Binomial failure rate model.**

Probabilities of the basic model for this model are

\[
\begin{align*}
Q_1 &= Q_t + \mu p (1 - p)^2, \\
Q_2 &= \mu p^2 (1 - p), \\
Q_3 &= \mu p^3 + \omega, \\
\end{align*}
\]

\[ Q_S = 3 \left[ Q_t + \mu p (1 - p)^2 \right]^2 + 3 \mu p^2 (1 - p) + \mu p^3 + \omega. \quad (15) \]

\[ Q_S = 3 \left[ Q_t + \mu p (1 - p)^2 \right]^2 + 3 \mu p^2 (1 - p) + \mu p^3 + \omega. \quad (16) \]

**4 HUMAN ERROR AND HUMAN RELIABILITY ANALYSIS**

With incidents in the recent time such as the Three Mile Island nuclear incident and the Chernobyl nuclear disaster etched vividly in the public psyche, human reliability in nuclear industry has come under question. To its credit, for the last decade the nuclear industry has been struggling with the concept of identifying and reducing the risk related to running nuclear power plants by implementing the techniques associated with probabilistic risk assessment (PRA) and human reliability analysis (HRA).

A fundamental assumption of HRA is that human failure can be analysed and quantified as any other component of a system. This is not a realistic approach since human errors cannot be easily quantified because there is no real consensus on what constitutes and causes an error. The ability to determine human failure rates has evolved from a combination of engineering judgement, limitations for human intervention as determined by plant phenomenology, and what we know about human performance from behavioural sciences. Behavioural sciences devoted to the study of human performance are seen at the first glance to be ideally suited to determining human reliability. Although the human reliability can be determined in a fashion similar to that used in evaluating reliabilities of components, the human factors cannot be determined with the same precision as the performance parameters of electrical, mechanical or electronic systems. On the other hand, no machines can perform with such human qualities as perception, recognition, and decision making, which are of great importance in operating a nuclear power plant. The operation of a nuclear system involves some major elements of uncertainties, which may lead to an unexpected course of events requiring decision making, and probably reiteration on standing decisions.

An operator, eg, cannot be represented by a simple control element in the reactor control and protection system. However, compared to reactor components, the operators are less stable since they are subject to such effects as physiological and psychological conditions, work environment, motivation, learning, boredom, and fatigue. The operator is also influenced by noise, workspace, operating console layout, operating procedures under different situations, communications, logistics and system organization. The operator reliability can be defined as: "the probability that the operator will successfully complete an operation task as intended at any required stage in the nuclear power plant operation stage within a required minimum time". The operator reliability is essential to nuclear power plant safety analysis due to the major role of the operator in the plant performance.

Performance shaping factors (PSFs) are those factors that affect the ability of personnel to carry out tasks. PSFs become extremely important when looking for means of improving the human performance. When these factors adversely affect the performance of a given task, there is an opportunity for improving the performance by making the PSFs more favourable. PSFs analysis provides a basis for human error probability (HEP) quantification and for identifying potential corrective actions to improve the operator performance.

**5 ANALYTICAL MODELING OF HUMAN RELIABILITY AND FORMAL METHODS FOR ESTIMATING HUMAN RELIABILITY**

Standard reliability analysis techniques use the usual fault tree or reliability block diagram approaches. The modelling of human performance has been more or less restricted to fault tree or HRA event tree representation. It is worth noting that HRA event trees work forward in time. Fault trees on the other hand, begin with the end point and work backward in time.

The FAULT TREE is a graphical model of all parallel and sequential combinations of faults that lead or result in the undesired event (Top event).
The HRA EVENT TREE models the potential operator actions in response to an initiating event and the actions and failures associated with the normal conduct of operations throughout various plant evolutions. Typically, the branches of the HRA event tree represent a binary decision/action path in which the correct performance and the incorrect performance are the two choices.

Some other methods that are used by the HRA community: expert estimation, confusion matrix, human cognitive reliability, success likelihood index and technique for human error rate prediction (THERP). Of these, THERP is the best known and most highly referenced.

EXPERT ESTIMATION is frequently used in HRA to estimate human error probabilities. We present five techniques for estimation:

1) paired comparison procedure,  
2) ranking and rating procedure,  
3) direct numerical estimation,  
4) indirect numerical estimation,  
5) multiattribute utility procedure.

Direct numerical estimation is the most commonly used.

Two measures of quality for the elicitation and use of expert opinion are “substantive goodness” and “normative goodness”. Substantive goodness refers to the knowledge of the expert relative to the problem at hand. Normative goodness, on the other hand, refers to the expert’s ability to express that knowledge in accordance with the calculus of probabilities and in close correspondence with his or her actual opinions. It is generally accepted that both types of expertise are equally important. The available research indicates that:

- the methods by which expert opinions are elicited can have a significant effect on the accuracy of the resulting estimates, and
- some of the most common techniques for combining estimates from different sources tend to yield less accurate results than other equally simple approaches.

CONFUSION MATRIX (cm).

The major focus of the confusion matrix is event misdiagnosis. The cm is designed to determine the probability of an operator not to diagnose an accident event correctly. The cm identifies accidents with similar signatures to determine the failure probability. The technique is based on the principle that accidents with similar signature may lead to confusion of the crew and, therefore, to misdiagnosis.

HUMAN COGNITIVE RELIABILITY (HCR) model quantifies the time dependent non-response probability of control room operators performing tasks. Strictly speaking, it does not produce a HEP, although analysts use it as such. The HCR model is a normalized time reliability curve, the shape of which is determined by the dominant human cognitive process associated with the task being performed (skill-based, rule-based or knowledge-based behaviours). The analyst determines the type of the cognitive process, estimates the median crew response time and the time available to the crew and uses the HCR model to quantify the non-response probability.

Unfortunately, some of the errors made at Three Mile Island, and at Chernobyl seem to have little to do with time and much to do with thinking. This next gap that HRA must bridge is related to modelling and quantifying errors that are cognitive.

SUCCESS LIKELIHOOD INDEX METHOD -MULTIATTRIBUTE UTILITY DECOMPOSITION. SLIM-MAUD uses an interactive computer-based approach, MAUD, to elicit and organize expert opinion within the framework of the SLIM. The approach is based on the assumption that the expert can estimate the failure rates associated with task performance or at least select reasonably other values and allow the software to perform the estimate for them. The activities that can be modelled during a SLIM session include operations, maintenance, in-service test or calibration exercises.

The end result of a SLIM-MAUD session is a probability estimate that can be used in HRA fault and event trees.

TECHNIQUE FOR HUMAN ERROR RATE PREDICTION (THERP) is an in-depth and widely used method for modelling and quantifying human reliability. Of the models discussed, it is the only complete model because it provides a mechanism for modelling as well as for quantifying [9], [11] and[12]. The method is based on performing a task analysis that describes the tasks to be performed by the operator, maintainer or crew. Along with describing individual tasks, various PSFs are collected to modify probabilities. The task is then graphically represented in PRA event trees. THERP allows failure rate estimates to be changed based upon the operator or crew stress and the dependence between tasks. The three types of HEPs from THERP are as follows:

- Nominal HEP, HEP when PSFs have not yet been accounted for or are unknown for the system under evaluation.
- Basic Human Error Probability. BHEP with PSFs considered without considering the influence of other tasks.
- Conditional Human Error Probability. Modification of the BHEP to take account of the influence of other tasks or events.

6 CONCLUSIONS

Common mode failures where more than one component may fail together from a common cause become of significant concern in the commercial nuclear power plant field. Human errors during plant operation can lead to a common mode failure of plant systems. During the last decade it has become self-evident that to minimise the
probability of failures, the human factor must be taken into account. With the Chernobyl nuclear disaster etched vividly in the public psyche, human reliability in nuclear technology has come under question [10]. The methods presented in this paper support the effort to develop tools to help the society to cope and coexist in a safe and peaceful manner with the high-risk nuclear power plant technology.

Acknowledgement

This paper has been accomplished under Grant No 1/7604/20 of Slovak Grant Agency.

References


Received 25 May 2001

František Janíček (Prof, Ing, PhD), graduated in power engineering from the Slovak University of Technology in 1979. In 1984 he gained the PhD degree. In 1999 he was appointed Professor in power engineering. Since 1990 until now he has been a member of the Scientific Council FEI, and since 1995 a member of the Supervisory Board of the Western Slovak Energy Distribution Company. He is the founding member of the Slovak Committee of the World Energy Council. Professor Janíček is the Head Manager of the Project ”Qualification of Selected Electric Equipment of the Nuclear Power Plants in Slovakia and in the Czech Republic”, Since 2000, Professor Janček has been the Dean of the Faculty of Electrical Engineering and Information Technology of the Slovak University of Technology in Bratislava.

Ivan Darula (Doc, Ing, PhD), graduated in power engineering from the Slovak University of Technology in 1966. In 1981 he gained the PhD degree. Mr. Darula joined the department of Power Engineering of Faculty of Electrical Engineering and Information Technology in 1970. He is currently Associate Professor of FEEIT, Slovak University of Technology Bratislava, where his activities include teaching and research. His primary research interests are power stations and renewable energy.

Martin Brezina (Ing), graduated in power engineering from the Slovak University of Technology in 1999. He is currently PhD student at the department of Power Engineering of Faculty of Electrical Engineering and Information Technology, Slovak University of Technology in Bratislava. His main activities are teaching and research in the area of secured systems and reliability of auxiliary in the Nuclear Power Plant.