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Measurement-based Estimation of the Composite Load Model Parameters

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Abstract – Power system loads have a significant impact on a system. Although it is difficult to precisely describe loads in a mathematical model, accurately modeling them is important for a system analysis. The traditional load modeling method is based on the load components of a bus. Recently, the load modeling method based on measurements from a system has been introduced and developed by researchers. The two major components of a load modeling problem are determining the mathematical model for the target system and estimating the parameters of the determined model. We use the composite load model, which has both static and dynamic load characteristics. The ZIP model and the induction motor model are used for the static and dynamic load models, respectively. In this work, we propose the measurement-based parameter estimation method for the composite load model. The test system and related measurements are obtained using transient security assessment tool(TSAT) simulation program and PSS/E. The parameter estimation is then verified using these measurements. Cases are tested and verified using the sample system and its related measurements.

Keywords: Composite load model, Measurement-based parameter estimation

1. Introduction

Electricity is generated and consumed simultaneously in electric power systems. Generator dynamics are actively studied, whereas load dynamics are ignored because they are thought to have little effect on power systems. However, loads have a significant impact on a system. In order to effectively analyze the dynamics of a power system, the loads are considered along with the generators in a transient security analysis. Power system planners and operators attempt to accurately model the loads in order to analyze their systems. However, accurately describing the loads in a mathematical model is very difficult. A load consists of several components that have very different dynamic characteristics. In addition, these characteristics change over time.

Two basic methods are used for load modeling: the component-based method and the measurement-based method. The former is based on the load components found on a bus, and the latter is based on measurements from a power system [1]. The static load model consists of constant impedance, constant current and constant power, which is defined as the ZIP model. This model has been widely used in load modeling. However, the simulation results produced by the ZIP model often show deviation from field test results. This indicates the inefficiency of the ZIP load model [2]. The composite load model has both static and dynamic load characteristics and has been the focus of many studies. Reference [3] concluded that the composite load model provides closer dynamic response to the measured data than the static load model itself. The measurement-based load modeling has an advantage in terms of the direct monitoring of true dynamic load responses. The load model parameters are also easily updated when the load dynamics change.

There are two important factors in load modeling: determining the mathematical model that represents the load characteristics, and estimating the parameters of the determined mathematical model [4-6]. In this paper, the composite load model is used for the load model. The ZIP model and the induction motor model are used for the static and dynamic load models, respectively. We discuss a parameter estimation method to determine the composite load model parameters.

2. The Composite Load Model

The static and dynamic load models are classified according to the voltage effect on the load. If the load variation depends only on instantaneous voltage input and is unrelated to the preceding voltage inputs, the static load model is used. However, if the load characteristics are affected by all voltage inputs over time, then the dynamic load model is used. For example, an electric lamp represents a static load, whereas an induction motor represents a dynamic load. As mentioned in the introduction, practical loads consist of several components. As a result, the recently-proposed composite load model has been widely adopted by many researchers [2, 7].

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The composite load model is described by a physical load model that unifies the static and dynamic load characteristics (Fig. 1) [8]. The static load model is described by the ZIP model, whereas the dynamic load model uses the induction motor model.

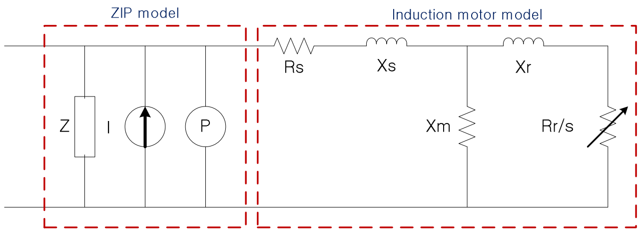

Fig. 1. The composite load model

Eqs. (1) and (2) represent the composite load model and are respectively expressed as:

$$P = P_{ZIP} + P_{motor}, \quad (1)$$

$$Q = Q_{ZIP} + Q_{motor}, \quad (2)$$

where P_{ZIP} and Q_{ZIP} are the active and reactive powers for the ZIP model, respectively. In addition, P_{motor} and Q_{motor} are the active and reactive powers for the induction motor model, respectively.

2.1 The ZIP Model

The voltage dependency of the loads is determined using the polynomial model found in [9].

$$P_{ZIP} = P_0\left[a_p\left(\frac{V}{V_0}\right)^2 + b_p\left(\frac{V}{V_0}\right) + c_p\right] \quad (3)$$

$$Q_{ZIP} = Q_0\left[a_q\left(\frac{V}{V_0}\right)^2 + b_q\left(\frac{V}{V_0}\right) + c_q\right] \quad (4)$$

This static load model is referred to as the ZIP model, because it consists of a constant impedance (Z), a constant current (I), and a constant power (P). The parameters of this model are the coefficients a_p to c_p and a_q to c_q, which define the proportion of each component.

2.2 The Induction Motor Model

The dynamic load model is referred to as the induction motor model. The static load model equation is algebraic, whereas the induction motor model is expressed using both differential equations in (5) to (7) and algebraic equations in (8) and (9).

$$\frac{dE_d'}{dt} = -\frac{1}{T_0'}\left[E_d' + (X - X')I_q\right] + \omega_0 s E_q' \quad (5)$$

$$\frac{dE_q'}{dt} = -\frac{1}{T_0'}\left[E_q' - (X - X')I_d\right] - \omega_0 s E_d' \quad (6)$$

$$\frac{ds}{dt} = \frac{1}{2H}\left[T_m - T_e\right] \quad (7)$$

$$I_d = \frac{1}{R_s^2 + X'^2}\left[R_s(V_d - E_d') - X'(V_q - E_q')\right] \quad (8)$$

$$I_q = \frac{1}{R_s^2 + X'^2}\left[R_s(V_q - E_q') - X'(V_d - E_d')\right] \quad (9)$$

$$T_0' = \frac{X_r + X_m}{\omega_0 R_r}, \quad X = X_s + X_m$$

$$X' = X_s + \frac{X_m X_r}{X_m + X_r}$$

$$T_m = T_{m0}\left[A(1-s)^2 + B(1-s) + C\right]$$

$$T_e = E_d' I_d + E_q' I_q$$

In the equations above, R_s is the stator resistance, X_s is the stator reactance, X_m is the magnetizing reactance, R_r is the rotor resistance, X_r is the rotor reactance, and H is the motor inertia.

Eqs. (10) and (11) represent the active and reactive power for the induction motor model and are respectively given by:

$$P_{motor} = V_d I_d + V_q I_q, \quad (10)$$

$$Q_{motor} = V_d I_d - V_q I_q, \quad (11)$$

where V_d and V_q are d-axis and q-axis voltages of a bus, respectively.

In this model, the parameters were K_m, R_s, X_s, X_m, R_r, X_r, and H. We assumed that parameter A was 1.0. For the composite load model, a very important parameter that should be identified was the motor load proportion. This is expressed by:

$$K_m = \frac{P_{motor}}{P_0}, \quad (12)$$

where P_0 is the initial active load on the bus, and P_{motor} is the initial motor load [10].

3. The Parameter Estimation

The parameter estimation is an important part of the determined load model. In this paper, the measurement-based method was used for load modeling. There are 13 estimated parameters. In order to calculate these, it is necessary to find the parameters that minimize the error function between the measured value and the simulated value expressed by:

$$\min_{p \in Z} \varepsilon(p) = \min_{p \in Z} \frac{1}{2} \sum_{k=1}^{N} [(P_{measured} - P_{simulated})^2 + (Q_{measured} - Q_{simulated})^2] \tag{13}$$

where p is the estimated parameter vector, N is the number of data samples, and Z is the parameter space.

The concept of parameter estimation in the measurement-based method is described in Fig. 2 [11].

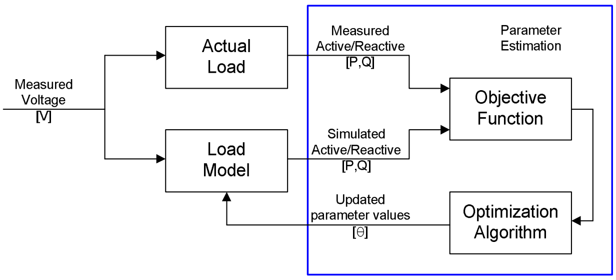

Fig. 2. Procedure for the parameter estimation

In order to estimate load model parameters, a non-linear least square method was adopted in this paper. The least square method can converge into a local minimum, and is sensitive to the initial values of the parameters. However, it has a fast convergence characteristic that can be applied in real time [12, 13]. Fig. 3 shows a simplified diagram of the estimation process.

The Runge-Kutta method was used to calculate the initial states of E_d', E_q', and the motor slip(s). These initial states were obtained by solving the differential equation using the initial parameters. The parameters that satisfy Eq. (13) were then modified using the optimization process.

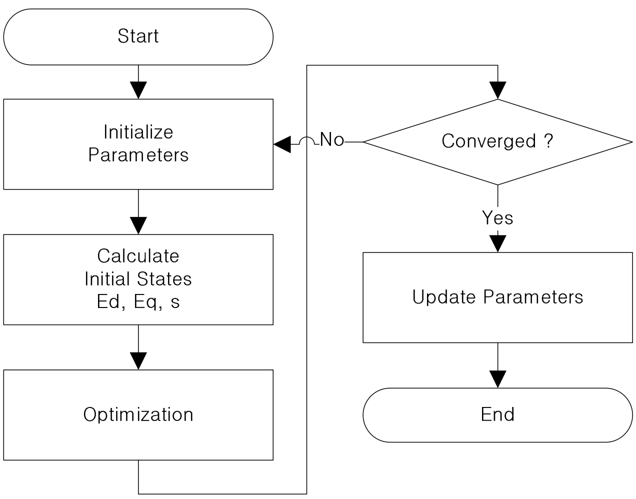

Fig. 3. The estimation flow chart

4. The Developed Program Summary

In this section, we describe the functions of the developed program for parameter estimation. In the program, a graphical user interface (GUI) was implemented to increase the users' convenience. Fig. 4 shows the initial page of the developed program.

The initial page of the program consists of three parts, details of which are described below.

① Data selection

The data file, which includes the measurements, can be selected. The data comprises voltages, active power, and reactive power at the load buses.

② Estimation set-up

The convergence conditions can be set for the least square method. This part also has components for selecting the initial parameter type. Random and traditional values can be selected for the initial values of the parameters.

③ Range of initial parameter

The initial values of the parameters can be set using the lower and upper boundaries.

Fig. 5 represents the result page of the program. Once the calculation is converged, the estimated results are displayed in the page. The program's result page has two parts.

④ Result chart

If the program converged, the simulated values are displayed along with the measured values in the chart.

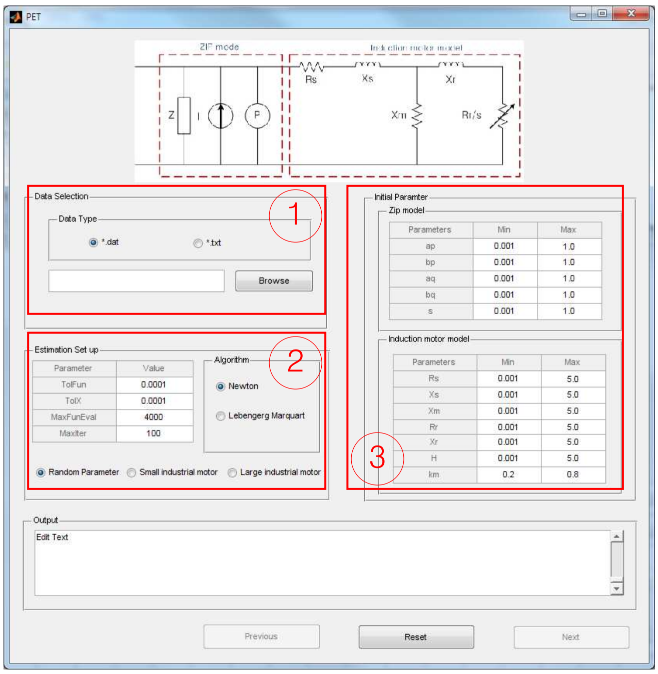

Fig. 4. Initial page of the program

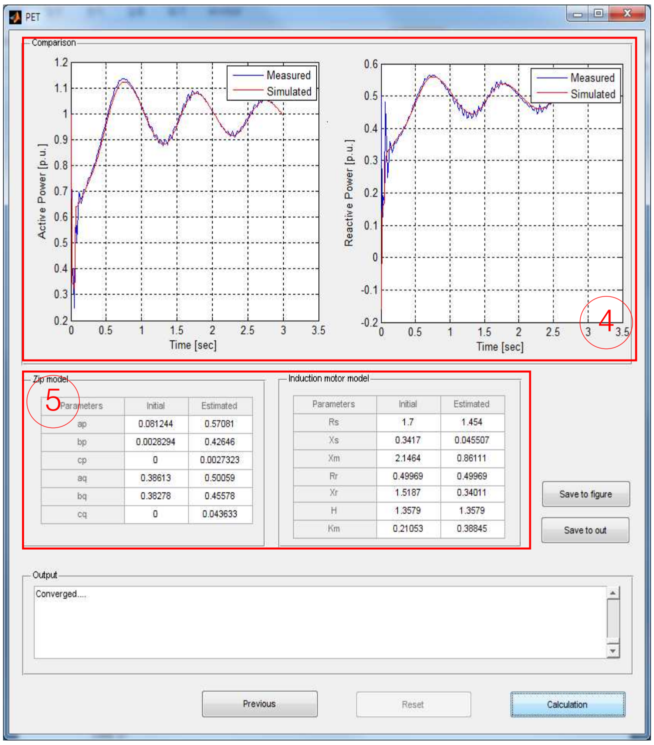

Fig. 5. Result page of the program

⑤ Results table

After convergence, the estimated parameters are written in a table along with the initial parameters.

5. The Case Study

The test system used for the simulation is presented in Fig. 6. It consists of 23 buses and 6 generators. This is an example test system in PSS/E [14].

5.1 Case 1

In order to obtain measurements, a three-phase fault contingency was applied to branches 151 and 152 for 0.3 seconds. This occurred 1.5 seconds after starting the simulation. The PSS/E dynamic simulation was used in obtaining the simulation data.

The sampling data obtained at bus 203 showed the voltages, active powers, and reactive powers. The data were used for parameter estimation. Comparisons between the measured values and simulated values are expressed in Figs. 7 and 8, respectively. The estimated parameters are given in Table 1. The model error value is smaller than 0.001, hence, the parameters are accurately estimated.

Table 1. The estimated parameters

Parameter	Estimated	Parameter	Estimated
ap	0.0016586	Rs	0.73482
bp	0.001	Xs	0.30475
cp	0.99734	Xm	3.044
aq	0.0010041	Rr	0.009
bq	0.0053353	Xr	0.37157
cq	0.99366	H	1.5
error	0.000993	Km	0.79426
ZIP	20.574%	Motor	79.426 %

5.2 Case 2

In order to obtain the measurements, a three-phase fault contingency was applied to branches 151 to 201 for 3 cycles. This occurred 2 seconds after starting the simulation.

The TSAT program was used for obtaining the simulation data. The sampling data obtained at bus 3005 showed voltages, active powers, and reactive powers. The data were then used for parameter estimation.

We tested two cases in order to perform the estimation. One began from random values for the initial parameters,

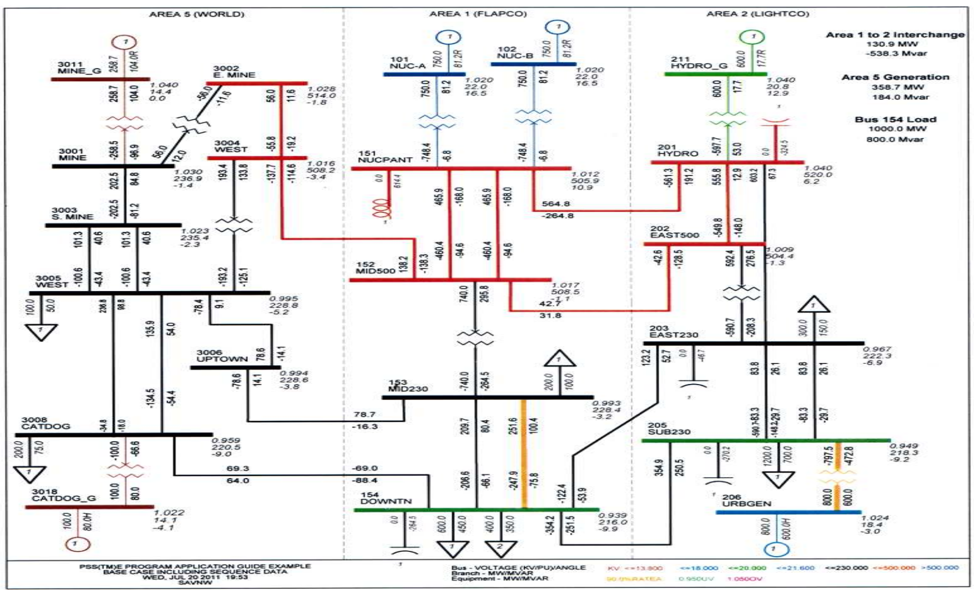

Fig. 6. Test system

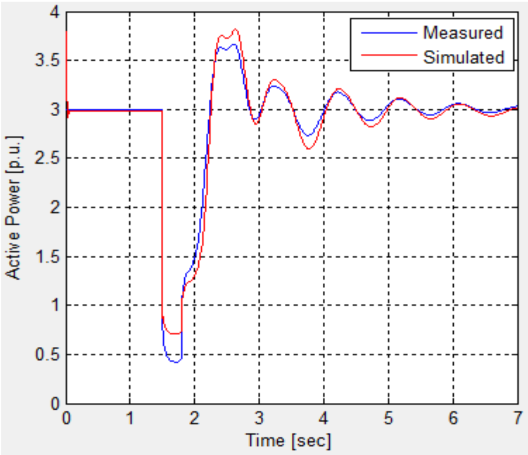

Fig. 7. Comparison of active powers

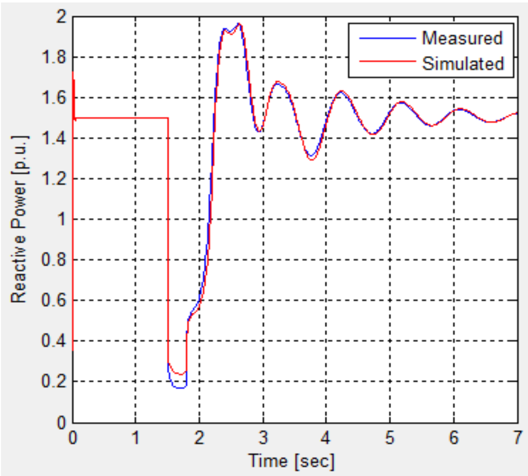

Fig. 8. Comparison of reactive powers

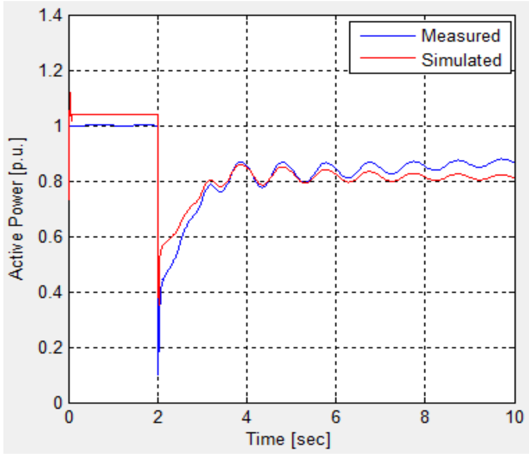

Fig. 9. Comparison of active powers

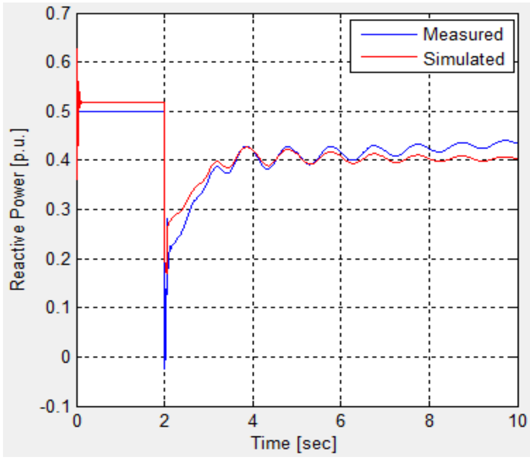

Fig. 10. Comparison of reactive powers

and the other began from the typical values for the initial parameters. The convergence condition was such that the model error was smaller than 0.001.

5.2.1 Random initial values

The results were obtained by selecting the random values for the initial parameters. Comparisons between the measured and simulated values are expressed in Figs. 9 and 10, respectively. The estimated parameters are given in Table 2. As can be seen, the parameters are accurately estimated because the estimated values have errors smaller than 0.001.

5.2.2 Typical initial values

The results were obtained by selecting the typical values for the initial parameters. Comparisons between the measured and simulated values are expressed in Figs. 11 and 12, respectively. The estimated results are given in Table 3.

Table 2. The estimated parameters

Parameter	Estimated	Parameter	Estimated
ap	0.001	Rs	2.1919
bp	1	Xs	0.17653
cp	-0.001	Xm	2.0992
aq	0.02836	Rr	0.20528
bq	0.99975	Xr	1.8197
cq	-0.028112	H	2.1221
model error	0.00938	Km	0.28526
ZIP	71.414%	Motor	28.526%

Table 3. The estimated parameters

Parameter	Estimated	Parameter	Estimated
ap	0.001075	Rs	0.86073
bp	0.001	Xs	0.24993
cp	0.99792	Xm	2.5543
aq	0.0012872	Rr	0.009
bq	0.0014299	Xr	0.30694
cq	0.99728	H	1.5
error	0.0045	Km	0.7535
ZIP	24.65%	Motor	75.35%

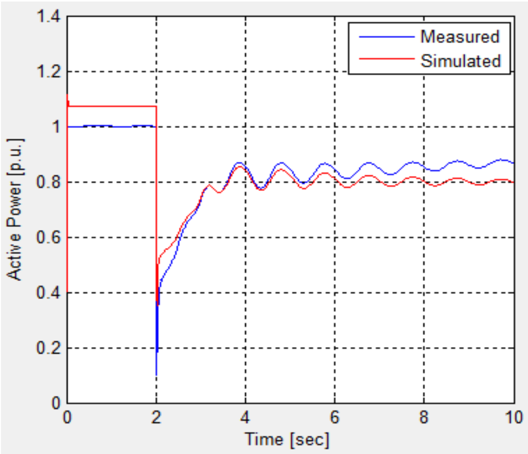

Fig. 11. Comparison of active powers

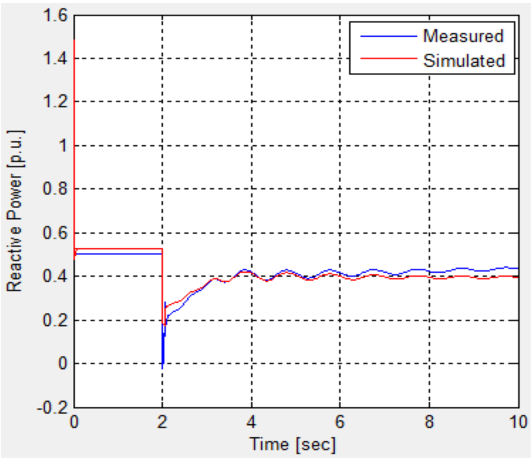

Fig. 12. Comparison of reactive powers

6. Conclusion

Due to the technological advancements in computers, metering devices and communication networks, gathering operational data from power systems has become much easier. When a disturbance occurs in a power system, the measurements from monitoring devices, such as digital fault recorders, phasor measurement units and power quality monitors, are now available to develop load models that reflect the load variation with time.

The traditional component-based load model has some drawbacks. The types and characteristics of the loads, as well as the load composition information must be known. The change of the load characteristics over time cannot be reflected in the model as well. Conversely, the measurement-based estimation method used in this paper has certain advantages over the component-based method, such as the ability to show the actual load behavior during disturbances. Given that loads are time variant, load models should be verified with actual measurements.

In this paper, we proposed the composite load model and the WLS-based parameter estimation method. The parameters for the determined load model were estimated using the measured data. We implemented a GUI program to increase the users' convenience. The developed program was proven to be effective in estimating the load model parameters. Furthermore, the calculation time is faster than that used in heuristic methods, such as genetic algorithm and particle swarm optimization method. Although the variability assessment of composite load models and sensitivity analyses of load model parameters should be further studied, the measurement-based parameter estimation method proposed in this paper showed a closer look at the real-time power system loads and their dynamic characteristics.

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